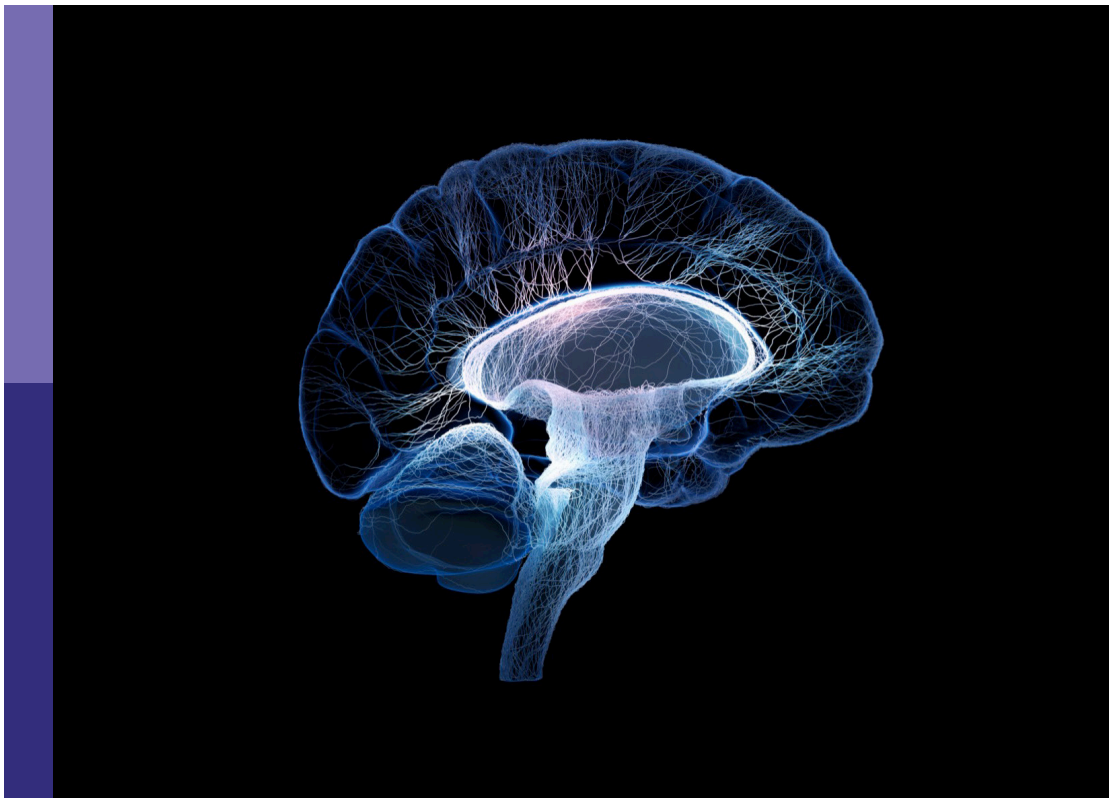
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Consumer neuroscience - foundation, validation, and relevance

Edited by
Thomas Zoëga Ramsøy, Hilke Plassmann, Carolyn Yoon and Joseph T. Devlin

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Consumer neuroscience - foundation, validation, and relevance

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Conceptual Closure Elicited by Event Boundary Transitions Affects Commercial Communication Effectiveness

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While our experience of the world may appear continuous, recent evidence suggests that our experience is automatically segmented and encoded into long-term memory as a set of discrete events. Event segmentation is an important process in long-term memory encoding with evidence pointing to experiences occurring around event boundaries being better recognized subsequently. Neuroimaging studies have shown increased activity in the hippocampus and other nodes of the default mode network (DMN) when encountering an event boundary. We have previously demonstrated that the steady state topography (SST) measure of brain activity at a left inferior frontal scalp sites is correlated with the strength of long-term memory encoding. More recently, we have noted that event boundaries occurring in naturalistic stimuli such as television advertising trigger a transient drop in activity at the inferior frontal scalp sites, an effect we have termed *Conceptual Closure*. In this study, SST measures of brain activity were recorded in 50 male participants as they viewed a first-person journey through a 10-room virtual art gallery. We hypothesized that the transition from one room to another would serve as an event boundary which would triggers increased hippocampal and DMN activity while correspondingly decreasing activity in task positive networks in the vicinity of the inferior frontal cortex thus eliciting Conceptual Closure. A permutation test confirmed the hypothesis in that the appearance of the door between gallery rooms was associated with Conceptual Closure in that we observed a significant drop in brain activity at the left hemisphere inferior frontal scalp site at this point in time. Finally, we illustrate the real-world impact of Conceptual Closure by considering the commercial effectiveness of a television advertisement that exhibited Conceptual Closure at points of branding. The television advertisement was broadcast before and after it was re-edited to minimize Conceptual Closure at the time the advertising brand was being featured. Minimizing Conceptual Closure at the time of branding and key message was associated with significant increased commercial effectiveness of the advertisement.

Keywords: event boundary, long-term memory encoding, steady state visual evoked potential, prefrontal cortex, conceptual closure

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INTRODUCTION

While our experience of the world may appear continuous, recent evidence suggests that our experience is segmented and encoded into long-term memory as a set of discrete events (Zacks and Swallow, 2007; Kurby and Zacks, 2008). Such segmentation appears to be automatic and operating on multiple timescales with finer temporal components constituting subcomponents of larger scale segments (Swallow et al., 2009). In the current study, we examine the impact of event boundaries on long-term memory encoding. The motivation for this study emerged from our observation of the brain activity correlates of long-term memory encoding when viewing naturalistic time extended stimuli such as television advertisements or television programs. We found that event boundaries in the viewed material were frequently associated with transient drops in long-term memory encoding and the current study aims to examine this effect using a naturalistic stimulus with repeated, well-defined and consistent event boundaries. We conclude our report with an illustrative example of the potential impact of such event boundaries on the commercial effectiveness of a television advertisement.

Evidence for segmentation of experience was originally suggested by the inter-subject consistency of the location of event boundaries in video content (Newtson, 1973; Newtson et al., 1977; Speer et al., 2003). Event segmentation also appears to play a role in long-term memory encoding with evidence pointing to material occurring around an event boundary being better recognized subsequently (Swallow et al., 2009). While events occurring around an event boundary appear to be better recognized, there is evidence that working memory is updated at an event boundary. For example, participants walking through a doorway in a virtual reality experience exhibit reduced recall for content and events prior to walking through the doorway, presumably an event boundary (Radvansky and Copeland, 2006).

Neuroimaging studies also indicated changes in brain activity when encountering an event boundary. For example, higher levels of brain activity were observed when encountering an event boundary in either film or reading (Kurby and Zacks, 2008; Zacks et al., 2010; Ben-Yakov et al., 2013). Furthermore, while increases in brain activity have been observed to coincide with the occurrence of consciously identified event boundaries, there may be other events that are processed as event boundaries but are not consciously recognized as such. Nakano et al. (2013), Nakano (2015) examined the brain activity correlates of blinks. They found that blinks tend to occur at what the authors describe as 'breakpoints' or points in time coinciding with event boundaries such as a pause in speaking or the end of a sentence while reading (Nakano et al., 2013). The blink related changes in brain activity reported by Nakano et al. (2013), Nakano (2015) reveal richer detail in the changes in brain activity associated with blink related event boundaries. Specifically, brain activity increases immediately following blinks were primarily restricted to the default mode network (DMN), including the hippocampus while activity in the dorsal attention network, a task positive network, was reduced (Nakano et al., 2013, Nakano, 2015). This was interpreted as a transient disengagement from sensory or external perception and the engagement of *internally oriented* networks (Nakano, 2015).

Earlier observations of enhanced long-term memory encoding for events occurring around the times of event boundaries led researchers to examine the relationship between hippocampal activity and event boundaries (Ben-Yakov et al., 2013, 2014; Ben-Yakov and Henson, 2018). In the most recent study (Ben-Yakov and Henson, 2018), brain activity was measured while participants viewed either an 8.5 min unfamiliar film or a 120 min film they had first viewed some years previously. Five independent observers identified the occurrence of event boundaries in the films and the *event boundary strength* of an event boundary was defined as the number of observers (more than one) that identified the specific event boundary. The findings were consistent with the stated hypothesis in that only hippocampal activity increased monotonically with *event boundary strength*. Furthermore, a data-driven approach indicated that the times of hippocampal activity peaks were associated with the occurrence of event boundaries.

While much of the research concerning the processing of event boundaries have focused on memory processes and especially hippocampal activity, a recent study has revealed a temporal hierarchy of event boundary processing in a number of cortical regions. Using a data driven approach, researchers observed transitions in stable patterns of brain activity as participants viewed an episode of a television serial (Baldassano et al., 2017). These transitions formed a temporal nested hierarchy with the most rapid transitions occurring in the primary visual and auditory cortices, longer transitions occurring in the multimodal cortices and the longest transitions observed in the hippocampus. The longest hippocampal transitions also coincided with human labeled event boundaries.

In summary, both behavioral and brain imaging studies of event boundaries processing suggests that event boundaries trigger transitions in brain activity in a range of cortical regions that occur on multiple time scales and form a nested temporal hierarchy with DMN and hippocampal transitions occurring on the longest time scale. At the level of the DMN and hippocampus, event boundaries trigger subsequent increased activity and a simultaneous reduction in task positive networks such as the dorsal attentional network.

Along with the hippocampus, the ventro-lateral prefrontal cortex (vlPFC) is also known to play an important role in long-term memory encoding. During a memory task, targets associated with higher levels of activity at the vlPFC are better recognized subsequently, an effect known as the 'differential neural activity based on memory' and referred to as *Dm* (Buckner et al., 1999; Paller and Wagner, 2002; Blumenfeld and Ranganath, 2007). We have previously demonstrated the *Dm* effect at an inferior frontal site using steady state topography (SST) an evoked potential methodology (Silberstein et al., 2000a). The SST methodology makes use of the steady state visual evoked potential (SSVEP) which is elicited by a diffuse peripheral 13 Hz sinusoidal visual flicker presented at the same time that participants view centrally presented video content The SSVEP phase variations in turn indicate SSVEP latency changes that we interpret in terms of regional brain activity changes with SSVEP latency decreases

or *phase advance* indicating increased activity and vice versa (Silberstein et al., 2000b; Kemp et al., 2004). Depending on the context and ease of understanding, we will use the terms *SSVEP latency* and *activity* interchangeably (Silberstein, 1995; Silberstein et al., 2016, 2017, 2019).

Our choice of the SST methodology for this study was based on a number of factors. Firstly, unlike transient evoked potentials such as N200 or P3b, SST is well suited to the study of time extended cognitive tasks such as the ones described in the current study. In addition, the SST methodology is highly resistant to the common sources of EEG artifacts such as muscle activity, blinks and eye movements (Silberstein, 1995; Gray et al., 2003). Finally, the SST measures of brain activity appear to be suitably sensitive to cognitive processes such as visual attention and long-term memory encoding (Silberstein et al., 1990, 2000a,b; Silberstein and Nield, 2008).

In the above mentioned *Dm* study (Silberstein et al., 2000a), we measured variations in 13 Hz SSVEP phase while 35 participants viewed naturalistic television content including unfamiliar advertisements sourced overseas. Advertising images coinciding with SSVEP latency minima or peaks in activity at the left hemisphere lateral frontal scalp site FC5 located between C3 and F7 (overlaying the vlPFC) were better recognized 7 days later than advertising images coinciding with times of minimum activity at this site (66.0% vs. 37.9%, d.f. = 34, $t = 7.1$, $p < 5 \times 10^{-8}$). As hypothesized, the *Dm* effect was largest at FC5 and the correlation between the 7-day recognition score and the SST measure of activity was only statistically significant at FC5 after correcting for multiple comparisons (Silberstein et al., 2000a).

In the current study, we use SST to examine variations in brain activity while participants encountered event boundaries in a virtual first-person journey through a 10-room art gallery. Each of the rooms displays three paintings that were always viewed at the same pace and followed by an opening door leading to the next gallery room. We hypothesize that the first-person journey through the open door to the next gallery room constitutes an event boundary and that such event boundary will be associated with a transient reduction in activity at FC5, the left hemisphere site we have previously shown to demonstrate a robust *Dm* effect. Our choice of the doors separating the gallery rooms as the event boundaries was based not only on the fact that the doors were the actual boundaries between participants viewing a different trio of paintings but also published reports that passing through doorways triggered reductions in access to memory of items in the preceding room (Radvansky and Copeland, 2006; Radvansky et al., 2011). These findings suggest that doorway passages are processed as event boundaries. In addition, we base our hypothesis of a transient reduction in activity at this site on accumulated evidence that the left and right vlPFCs are nodes of task positive cortical networks. Specifically, the right vlPFC is considered a node of the ventral attentional network (Vossel et al., 2014) while the left vlPFC plays an important role in speech as well as the cognitive control of memory processes (Badre and Wagner, 2007; Blumenfeld and Ranganath, 2007). As both left and right vlPFCs are components of task positive networks, the widely observed negative correlation between DMN activity and task positive networks (Buckner et al., 2008) suggests that the increases in DMN activity associated with the experience of event boundaries should be associated with a transient reduction in activity at the left hemisphere site FC5.

MATERIALS AND METHODS

Participants

The sample comprised 50 male participants, mean age 34.1 years (SD = 12.6 years, range 18–59 years). All were screened for the presence of pre-existing medical, neurological or psychiatric conditions, including epilepsy. Participants were recruited via a recruitment agency and all testing was conducted on the premises of Neuro-Insight Pty Ltd. The study was approved by the Swinburne University Human Research Ethics Committee as application SUHREC2014/029.

Procedure

Participants viewed a first-person journey through a 10-room virtual art gallery that was created by the multi-media software company *Opaque Media*. Each room of the gallery exhibited three well known paintings and was entered through a hinged door that opened on approach. Participants spent 35 s in each of the 10 rooms and the entire viewing period occupied 380 s. The timing of the appearance of each painting as well as the appearance of the door to the next room after entering a room was identical for all of the 10 rooms. Views of one of the gallery rooms in 5 s increments are illustrated in **Figure 1**.

The task was presented on a video monitor subtending 24° vertically and 46° horizontally. The stimulus used to evoke the steady state visually evoked potential (SSVEP) was a white spatially diffuse 13-Hz sinusoidal flicker with a modulation depth of 45% and subtending a horizontal angle of 160° and a vertical angle of 90°, which was superimposed on the visual fields. This flicker was present throughout the task and special goggles enabled subjects to simultaneously view the cognitive task and the sinusoidal flicker.

Data Acquisition

Brain electrical activity was recorded from 20 scalp sites illustrated in **Figure 2** and these were positioned and labeled according to the International 10-10 system (Acharya et al., 2016). Electrode locations FC5 and FC6 are located closest to the left and right VLPFC respectively. The average potential of both mastoids served as a reference while an electrode located at FPz served as a ground. Brain electrical activity was amplified and bandpass filtered (3 dB down at 0.1 Hz and 30 Hz) before digitization to 16-bit accuracy at a rate of 400 Hz. The major features of the signal processing have been described (Silberstein et al., 2016). Briefly, the SSVEP was determined from the 13-Hz single-cycle cosine and sine (or real and imaginary) Fourier coefficients that were then smoothed using a 10 stimulus-cycle cosine weighted smoothing window. At the stimulus frequency of 13 Hz, this yields a temporal resolution of 380 ms or half the 10-cycle window width because of the cosine weighting. The cosine smoothing window was then shifted 1 stimulus cycle and

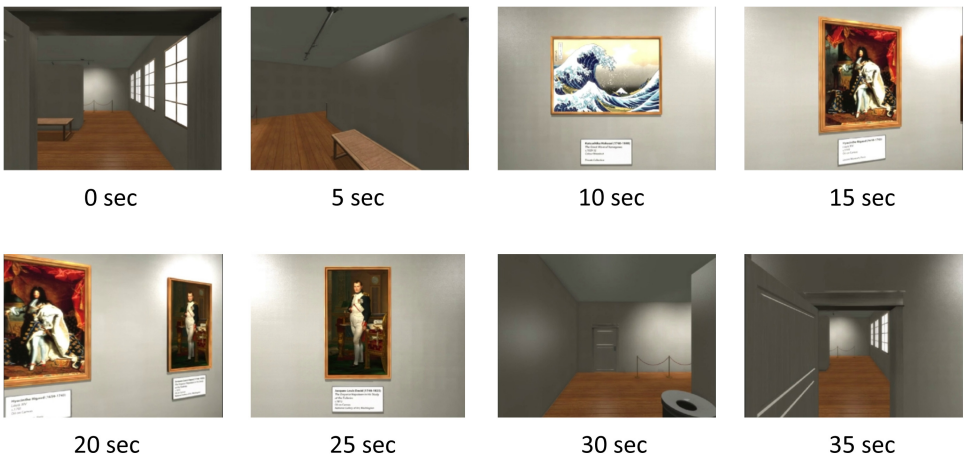


FIGURE 1 | The timing of events in a room in the virtual gallery are illustrated. During the 35 s period in each room, the exit door comes into view at the 30 s mark while the passage through the doorway to the next room occurs at the 35 s mark.

the coefficients were recalculated for this overlapping period. This process was continued until the entire 380 s of activity was analyzed. An identical procedure was applied to data recorded from all recording sites.

For each participant, the SSVEP data at each electrode associated with the 35 s epoch following the entrance to the next room was averaged across all of the 10 rooms.

For each participant, the mean phase of the SSVEP at each electrode evaluated over the first 5 s epoch following the entrance to the next room was set to zero before separately averaging the real and imaginary components of the SSVEP time-series across the 10 rooms. The SSVEP time series data at each electrode was then averaged across all participants to create the pooled SSVEP phase time-series data.

Statistical Analysis

We used a permutation test to evaluate the hypothesis that the SSVEP phase at the FC5 site will exhibit a transient reduction at the time the exit door of the gallery room is viewed. We used a permutation test rather than a parametric test such as Student's t for two main reasons. Firstly, parametric tests are based on the assumption that the test parameter is distributed normally. As the SSVEP phase data is not distributed normally, we used the permutation test which does not depend on any assumption of normality. In addition, the permutation test provides exact probabilities (Blair and Karniski, 1993). These features have led biomedical researchers to consider permutation tests as the preferred statistical methodology (Ludbrook and Dudley, 1998).

Our NULL hypothesis is that there is no statistical difference in SSVEP phase at the time the exit door is viewed compared to the mean SSVEP phase during the first 5.0 s of the trial. The mean of the first 5 s of the trial are used as the reference level as during this interval no paintings have been viewed in the current room. The mean SSVEP phase evaluated over the first 5.0 s of the trial is subtracted from all the SSVEP phase values in the 35 s epoch yielding an SSVEP phase difference time series for each electrode. To conduct the permutation test, a random subset of SSVEP phase difference time series are multiplied by −1 and a new average determined. This multiplication by −1 is equivalent to interchanging the SSVEP mean of the first 5 s and the SSVEP value at a given point in time and is consistent with the NULL hypothesis where it is assumed that the SSVEP phase is as likely to exceed the reference level as it is to be exceeded by the reference level. This process is repeated 100,000 times and the number of times where the permuted average of the SSVEP phase difference is equal to or less than the observed value at the 30 s point in time (the time of the appearance of the door) is determined. This number when divided by the number of permutations (100,000) yields the exact one-sided p-value of the observed SSVEP phase difference occurring under the NULL hypothesis. This process was repeated for all 20 recording sites.

As the hypothesis of this study is that the appearance of the exit door will be associated with a transient reduction in activity at electrode site FC5, we only consider the statistical significance of the activity on the appearance of the exit door at the 30 s point in time.

RESULTS

The SST based measures of activity during the 35 s epoch are illustrated in **Figure 2** and the first appearance of the door at the 30 s mark is associated with a transient activity reduction that is most prominent at left frontal sites FC5 and C3.

Table 1 lists the exact probability of falsely rejecting the NULL hypothesis at the 30 s point in time for all electrode sites. While our hypothesis only refers to effects at electrode site FC5 we will extend our consideration beyond this single site and thus adjust the experiment wide p level to account for the 20 comparisons considered. After applying a Bonferroni correction for the 20 comparisons, only sites FC5 and C3 demonstrate an experiment wide effect significant at the corrected $p < 0.01$ level. Applying a less conservative criterion of an experiment wide effect significant at the corrected $p < 0.05$ level indicates a significant effect at

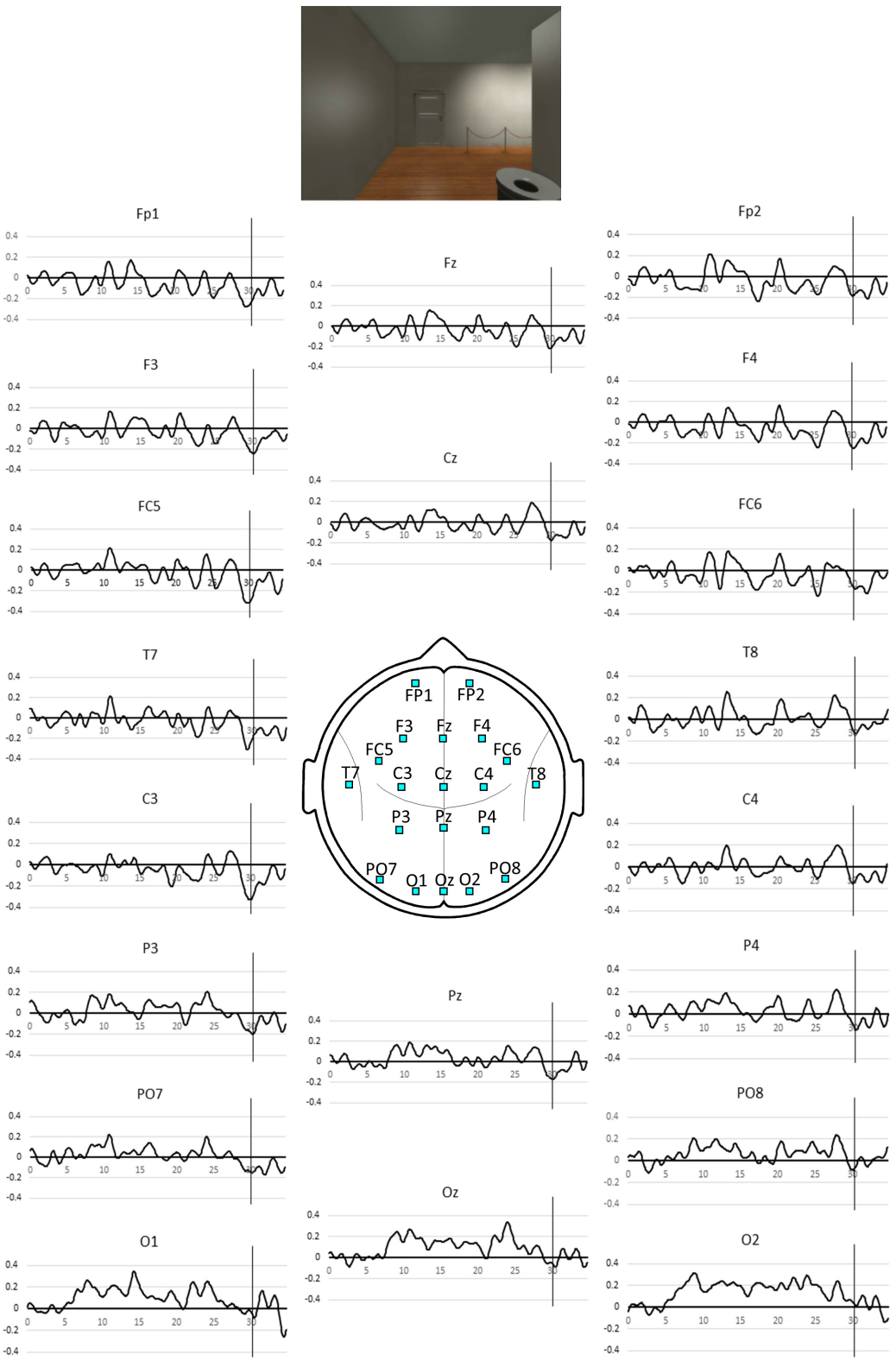


FIGURE 2 | Pooled SSVEP phase averaged over the all gallery rooms for the 35 s period spent in each room. Positive values indicate *phase advance* or increased activity and negative values, *phase lag* or reduced activity. The vertical line indicates the 30 s mark coinciding with the appearance of the exit door as illustrated above. The associated *p*-values for the NULL hypothesis that the observed SSVEP phase at the 30 s mark is not less than the mean value during the first 5 s in the room are listed in **Table 1**.

TABLE 1 | Exact probability of rejecting the NULL hypothesis that activity at the 20 recording sites is not less than the mean of the initial 5 s value.

Electrode	*p*	Electrode	*p*	Electrode	*p*
Fp1	0.0045			FP2	0.0270
F3	0.0062	Fz	0.0103	F4	0.0043
FC5	0.0002**			FC6	0.0783
T7	0.0134			T8	0.0840
C3	0.0002**	Cz	0.0178	C4	0.0385
P3	0.0011*	Pz	0.0198	P4	0.0542
PO7	0.0201			PO8	0.1972
O1	0.3129	Oz	0.1697	O2	0.6308

One asterisk indicates that the effect is significant at the experiment wide $p < 0.05$ level after correcting for multiple comparisons, that is $p < 0.05/20$. The two asterisks indicate that the effect is significant at the experiment wide $p < 0.01$ or $p < 0.01/20$.

the left parietal site P3. Statistically, the strongest effect was observed at FC5 and C3 where both are associated with a value of $p = 2 \times 10^{-4}$. Using the $r_{\text{equivalent}}$ approach suggested by Rosenthal and Rubin (2003) to determine experimental effect size of this SSVEP reduction, we see that the effect size is $r = 0.52$, which is considered a large effect (Cohen, 1988).

In summary, we note that the strongest effects associated with the appearance of the door at the 30 s mark are restricted to the left frontal sites.

DISCUSSION

Our hypothesis was confirmed in that the appearance of the event boundary represented by the 'virtual gallery door' was associated with a robust transient drop in activity at FC5 the left frontal scalp site overlaying the ventro lateral prefrontal cortex (vlPFC). Given the recognized role of the vlPFC in long-term memory encoding (Buckner et al., 1999; Blumenfeld and Ranganath, 2007) and our previous work demonstrating a *Dm* effect for the SSVEP phase at FC5 the scalp site (Silberstein et al., 2000a), our current findings suggest that an event boundary triggers a transient reduction in long-term memory encoding. Such a reduction is consistent with the fMRI findings of Nakano et al. (2013), Nakano (2015) who interpreted their findings of blink related activity reduction in nodes of the dorsal and ventral attentional networks in terms of event boundaries causing a 'transient disengagement from external perception and the engagement of internally oriented network,' presumably such as the default mode network. Interestingly, Nakano et al. (2013) observed a blink related activity reduction at the right vlPFC while we observed the event boundary related reduction at FC5 located in the vicinity of the left vlPFC. We suggest two possible factors may have contributed to this difference. One could be the different events used to initiate data acquisition in our respective studies. We used explicit events (doorways) that are widely considered to comprise event boundaries (Radvansky and Copeland, 2006; Radvansky et al., 2011, 2015). By contrast, the Nakano et al. (2013), Nakano (2015) studies focused exclusively on blink related changes in brain activity. While event boundaries are associated with blinking, not all blinks are associated with event boundaries. For example, lapses or reductions in attention also cause increased blinking (McIntire et al., 2014). The possible contribution of factors other than event boundaries to the Nakano et al. (2013), Nakano (2015) right vlPFC findings is thus consistent with the right vlPFC comprising a node of the ventral attentional network (Vossel et al., 2014) and such attention effects are observed most consistently in the right hemisphere rather than the left (McIntire et al., 2014).

Another possible contributing factor is that participants in the Nakano studies were told that their recollection of the material viewed while in the scanner would be tested after the scan. By making the task one of memory recall, it is possible that this reduced the impact of event boundaries on long-term memory encoding and hence attenuated the event boundary related drops at the left vlPFC.

Our findings are also consistent with those of Ben-Yakov et al. (2014), Ben-Yakov and Henson (2018) who reported increased hippocampal activity immediately following the occurrence of event boundaries in a film viewed by participants. Increased activity in the hippocampus and other DMN nodes when perceiving an event boundary would result in transient decreased activity in task-oriented networks including the vlPFC (Buckner et al., 2008). This would in turn be associated with a transient reduction in attention and long term memory encoding. As the transient reduction in long-term memory encoding following an event boundary occurs in conjunction with increased hippocampal activity, this suggests that this transient reduction coincides with better encoding of the experience preceding the event boundary.

We observed a frontal left hemisphere bias in the strength of the event boundary related drop in SSVEP phase. This was the case even though the viewing material was primarily pictorial with no speech and text restricted to the painting labels. This left hemisphere bias is consistent with our earlier report on the SSVEP *Dm* effect (Silberstein et al., 2000a) as well as numerous studies pointing to a preferential role for the left vlPFC in the control of both encoding and retrieval of long-term memory (Badre and Wagner, 2007; Blumenfeld and Ranganath, 2007). Furthermore, our findings suggest that the left prefrontal and frontal cortex play an important role in not only encoding information into long-term memory but also in the segmentation of time extended events and the identification of high-level event boundaries. In summary, our findings point to the left frontal cortex playing an important role in interposing a transient drop in long-term memory encoding on the perception of an event boundary.

While our hypothesis is confirmed in that activity at the left frontal site FC5 showed a sharp drop at the event boundary, the findings of Ben-Yakov and Henson (2018) call into question the underlying mechanism we proposed for the event boundary effect. We proposed that the drop in vlPFC activity was driven by an increase in DMN and hippocampal activity at the event boundary. However, Ben-Yakov and Henson (2018) reported bilateral and approximately equal increases in hippocampal activity on encountering an event boundary. If the vlPFC drop was determined by increased ipsilateral hippocampal activity,

then we might expect to see a drop in both left and right vlPFC activity or at scalp sites FC5 and FC6. We suggest that two possible explanations may account for the inconsistency between the neural mechanism proposed to account for the vlPFC event boundary effect and our observation of an overwhelmingly left hemisphere effect. One possibility is that the interaction between hippocampus and vlPFC may differ between left and right hemispheres. This would be consistent with the differing roles of the left and right vlPFC. The left vlPFC is known to play a crucial role in the control in both encoding and retrieval of information from long-term memory (Badre and Wagner, 2007). By contrast the right vlPFC is involved in non-memory processes such as response inhibition, etc. (Levy and Wagner, 2011).

Another possibility is suggested by a consideration of Event Segmentation Theory which proposes that an 'event comprehension systems' make predictions about upcoming events and an event boundary is identified when a prediction of upcoming events is in error (Swallow et al., 2009). Such prediction errors are associated with increased hippocampal theta activity suggesting increased encoding in long-term memory (Paller and Wagner, 2002; Garrido et al., 2015). A magnetoencephalography study of brain activity responses to a sequence of pictorial stimuli that violate expectations indicated that an EEG theta frequency mismatch signal is generated in a network comprising the hippocampus and ventro-medial prefrontal cortex (vmPFC) (Garrido et al., 2015). The authors report that it is the vmPFC that drives hippocampal activity when expectations are violated and that this effect is restricted to the left vmPFC and hippocampus. Such a left hemisphere bias is also consistent with our findings.

One possibility that must be considered is the extent to which our findings are due to visual sensory effects rather than the appearance of an event boundary. If sensory driven changes in visual attention were responsible for our observations, we would expect to see such changes reflected in activity at occipital sites (Silberstein et al., 1990). We consider this possibility unlikely for the following reason. While the appearance of the 'door' was associated with a robust SSVEP phase reduction at left frontal sites FC5 and C3, none of the occipital sites demonstrated statistically significant changes or differences with respect to the reference level at this time. However, while the SSVEP phase values at occipital sites are consistent with our suggestion that the effects at FC5 and C3 are unlikely to be triggered by visual sensory effects, our experimental design and methodology does not allow us to completely eliminate this possibility. For example, it may be possible that changes in activity at some components of the visual processing system in either the dorsal or ventral visual processing systems may account for our observations at FC5 and C3. One possibility suggested by a reviewer is that the Limited Capacity Model of Motivated Mediated Message Processing (LC4MP) may provide an alternative interpretation for our findings (Lang, 2006). Specifically, changes in the visual environment in moving from one gallery room to the next engages increased visual processing resources which in turn decreases performance in a 'secondary task' such as long-term memory encoding. One interesting approach suggested by the reviewer is a study where the visual environment remains unchanged while the event boundary is presented verbally, such as in the conclusion of a narrative or a verbal joke.

A point which we believe warrants comment is the relatively strong effect size of the observed event boundary related drop in SSVEP phase at FC5 (r = 0.52). We observed a comparably large effect size in our original report describing the *Dm* effect evaluated with the SSVEP (Silberstein et al., 2000a). While signal to noise considerations may play a role in contributing to the experimental effect size, we suggest that more fundamental aspects of neural information processing in the cortex may play an important role. Specifically, we suggest that the 13 Hz frequency used to elicit the SSVEP may be an important factor influencing the effect size. This is suggested in the light of recent findings concerning the neural mechanisms mediating sensory-driven or 'bottom-up' and cortical control or 'top down' information flows within the cortex. While these are briefly described here, readers seeking a more detailed description are referred to Silberstein et al. (2016). It is now recognized that both 'bottom-up' and 'top-down' intracortical communication processes are mediated by synchronous oscillations. Recent work examining the difference between the information flows reveals that they are mediated by oscillations in different frequency ranges. Specifically, bottom-up communication appears to be mediated predominantly by synchronous oscillations in the EEG gamma frequency range (40–80 Hz) while top-down communication is mediated predominantly synchronous oscillations in the EEG high alpha-low beta range (10–20 Hz) (Von Stein et al., 2000; Markov et al., 2014; Fries, 2015). Our choice of 13 Hz as the frequency used to elicit the SSVEP means that our responses (measurements, recorded findings) are likely to be driven predominantly by top-down processes that among other things would modulate long-term memory encoding. In other words, our SST methodology may be particularly well suited to measuring top-down processes and this may contribute to the strong effect size we have observed.

We have termed event boundary related transient drop in the SST based measure of activity at FC5 and C3 *Conceptual Closure*. We have frequently observed what we take to be Conceptual Closure when recording SST brain activity in naturalistic time extended stimuli such as television advertisements (Silberstein and Nield, 2008). While Conceptual Closure appears at obvious event boundaries such as the screen changing color or music ending, we have also observed it in more subtle indications of event boundaries such as two people standing to shake hands or a car driving into the distance. Consistent with our finding that long-term memory encoding at branding is associated with television advertising effectiveness (Silberstein and Nield, 2008) we have found that Conceptual Closure can have a significant negative impact of the commercial effectiveness of an advertisement if it coincides with the sole appearance of product branding or key message. This is typically the case where a television advertisement is structured as a narrative that describes the issue or problem to be addressed in the absence of an explicit or implicit representation of the brand or product in question. Frequently, the narrative concludes immediately before the appearance of the product or brand and thus the narrative conclusion is processed by the brain as an event boundary

triggering Conceptual Closure at the time the product or brand first appears in the advertisement. We have found this situation is more likely to be associated with consumers associating a competing brand with the advertisement.

Illustrative Case Study

The following case study is provided to illustrate the manner in which *Conceptual Closure* can be managed so as to enhance an advertisement's commercial effectiveness. It should be stressed that the following case study was undertaken as a standard commercial study for a client as advertiser. It is primarily presented here to illustrate how findings concerning *Conceptual Closure* are dealt with in a commercially relevant manner.

Neuro-Insight Pty Ltd. was commissioned to conduct a two-part advertising research study examining an advertising campaign by the client, NAB Ltd. a major Australian financial services provider for its superannuation fund, MLC. The design of the advertising campaign, named 'Save Retirement' was to encourage likely clients to seek retirement related financial advice from MLC. The campaign was launched in early 2014 and had been on air for approximately 3 months with independent tracking indicating the campaign was suffering from poor brand linkage in that an unacceptably high proportion of viewers were inclined to identify a competing brand as the advertiser.

In the first part of the study, Neuro-Insight evaluated the effectiveness of the original 30 s television advertisement on the basis of SST measures of long-term memory encoding (scalp site FC5) at the point of branding in the final 5 s of the advertisement. Recommendations on how to address identified deficiencies were made and implemented by the creative agency with a re-edited 30 s advertisement broadcast in the last quarter of 2014. The re-edited advertisement can be viewed at https://www.youtube.com/watch?v=ZbzKcTaOlXg. The original advertisement was on air for 3 months and the re-edited advertisement for a following 2 months. An independent market research firm was commissioned by the client to track the performance of both the original and revised advertisement. As this was a standard commercial study conducted by Neuro-Insight it was undertaken in accordance with the ESOMAR *International Code on Market, Opinion and Social Research and Data Analytics* and the Neuromarketing Science and Business Association (NMSBA) *Code of Ethics*. It should also be noted that the data recording procedures and equipment used in this case study are identical to those used in the preceding study and approved by the Swinburne University Human Research Ethics Committee as application SUHREC2014/029.

Studies of the original and re-edited advertisement were both conducted in Melbourne at the Neuro-Insight offices. Fifty participants (25 females) with a mean age of 54 years (range 45–64 years) participated in the first study undertaken in July 2014. Another group of 50 participants (25 males) with a mean age of 52 years (range 45–61 years) took part in the subsequent study undertaken in September 2014. Participants in both studies were recruited through a recruitment agency and had to satisfy a range of criteria such as age, employment status and financial decision-making responsibility as specified by the client. Nine participants in the first study (six females) also participated in the subsequent study.

In both studies, participants viewed the client television advertisement in the context of a typical television viewing experience. The advertisement was viewed as one of a group of four advertisements in an advertising break occurring in a typical prime time television program.

A total of three groups of advertisements or advertising 'breaks' were present in both studies with the presentation of the client advertisement counterbalanced in either the first or second advertisement break.

The advertisement was viewed in one of two groups of advertisements or advertising breaks. In both cases, the client advertisement occurred as the second advertisement in the break and was preceded by a different advertisement in each break. The order in which the advertisement was viewed was evenly rotated across the entire sample. All details of the procedure, data acquisition and analysis are the same as those described in the multi room gallery study described above.

Both versions of the advertisement featured a young boy and his grandfather visiting a futuristic 'museum' where a display features a happy older couple going for a drive in the country in their sports car, and by inference enjoying their retirement. As they look at the display, the young boy asks 'what are they doing' and the grandfather wistfully replies 'they are in retirement' and in retirement 'they can do anything they want.' In the original advertisement, a voice-over then suggests people speak to their financial advisor and subsequently the boy pulls his grandfather away and they both leave the display.

Analysis of the original advertisement indicated two transient reductions in long-term memory encoding in the final 7 s of the advertisement. The first at the 22.5 s mark coincides with the end of the story narrative and a verbal call to action. The second at the 24 s mark coincided with the boy pulling his grandfather from the 'retirement display.' We consider both drops in long-term memory encoding to be examples of *Conceptual Closure* as they occurred at clear event boundaries in the advertisement. The likely impact of Conceptual Closure on the effectiveness of the advertisement is indicated by the level of long-term memory encoding during branding during the final 3.5 s. The brand is only featured in the last 3.5 s of the original advertisement (final branding) and during this period, long-term memory encoding is low and in the lowest 8% of our database of financial services advertisements.

The main changes recommended for the revised advertisement were aimed at reducing the impact of *Conceptual Closure* at the time of branding. These included introducing the brand verbally and visually earlier to suggest a continuation of the original narrative while the grandfather and boy remain at the display. Furthermore, the scene triggering Conceptual Closure was edited out so that the boy and grandfather remained stationary throughout the advertisement. To accommodate these changes, the end of the narrative and call to action occurred 2 s earlier. The impact of these changes on long-term memory encoding at the times of branding was significant in that the level of long-term memory encoding at time of the newly branded scene peaked at the 96th percentile of our database of financial

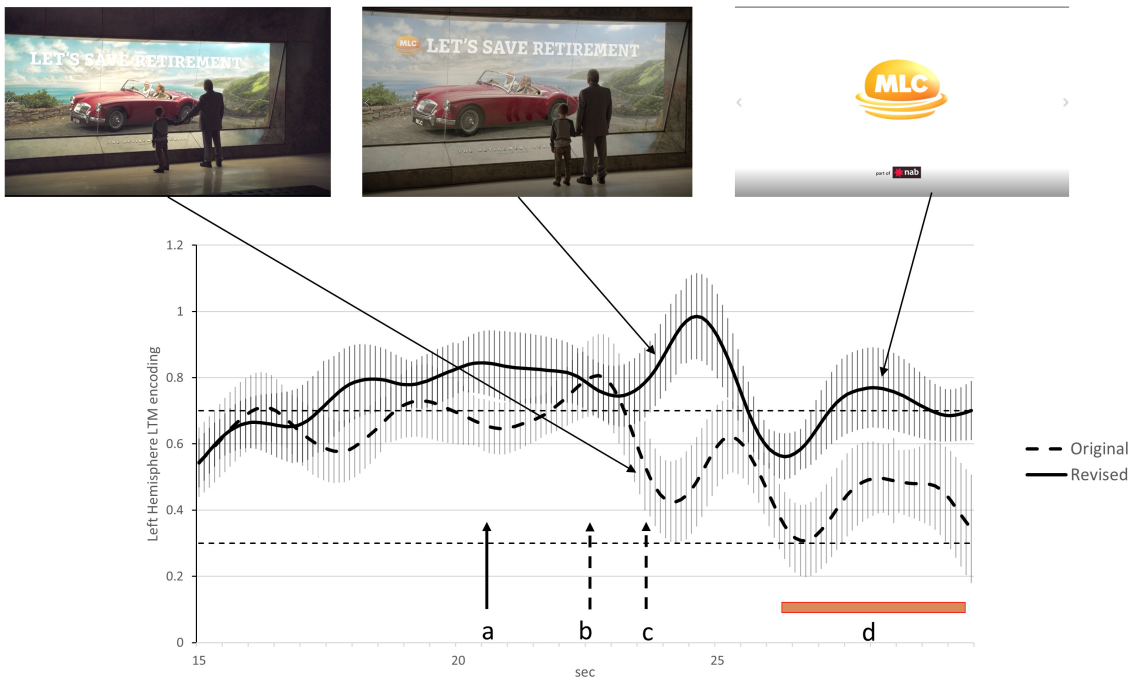


FIGURE 3 | Activity at FC5 indicating levels of long-term memory encoding for the last 15 s of the original and re-edited advertisements. The dashed line illustrates long-term memory encoding for the original advertisement while the solid line is the equivalent finding for the re-edited advertisement. The 84% confidence interval are included for both time series and when these do not overlap, the statistical significance of the difference between time series corresponds to $p < 0.05$ (Austin and Hux, 2002). The points in time where the narrative ends and the call to action starts in the original advertisement is indicated by the dashed arrows labeled 'b' while the dashed arrow labeled 'c' indicates when the child starts pulling his grandfather from the display cabinet. The solid arrow labeled 'a' indicates the point in time where the narrative end and the call to action starts in the re-edited advertisement. The brown bar labeled 'd' indicates the duration of the logo on the screen and final branding. The removal of the segment where the boy pulls his grandfather away from the cabinet appears to reduce the impact of Conceptual Closure and lead to higher long-term memory encoding during the final 3 s of the advertisement.

services advertisements while the final branding final visual branding was now at the 72nd percentile of our database of financial services advertisements. These differences in long-term memory encoding at the time of branding were significant at the $p < 0.05$ level and this is explained in more detail in the **Figure 3** legend.

During the 3 months period that the original advertisement was aired and the following 1 month where the re-edited advertisement was being broadcast, an independent market research firm conducted advertising tracking studies for the client. It was found that in the 3-month period when the original advertisement was being aired, the proportion of viewers who had seen the advertisement and correctly identify the brand (brand linkage) was considered low by the market research firm conducting the tracking study. However, in the first month that the re-edited advertisement was being broadcast, we were advised by the client that the market research firm conducting the tracking study reported that brand linkage had more than doubled, increasing by 120%. While the tracking findings are consistent with the SST indications of improved advertising effectiveness, we cannot exclude the possibility that other factors external to those determined by the client may have also contributed. However, the client is unaware of any such external factors that may have contributed to the advertisement's improved performance.

Limitations and Future Research

We acknowledge that one of the limitations of this study is that the experimental design does not enable us to include behavioral data to confirm the drop in long-term memory encoding on the appearance of the door. We have relied on extensive evidence from other laboratories on the role of the left ventrolateral prefrontal cortex and long-term memory encoding as well as our previous findings demonstrating the link between activity at FC5 long-term memory encoding to infer a drop in long-term memory encoding on the appearance of the event boundary. Nevertheless, the incorporation of a behavioral test of long-term memory encoding at the event boundary is a recommendation for future studies.

Another limitation concerns the limited amount of information that could be included in the illustrative case study concerning the effectiveness of the first and then the revised advertising phases. As this was a commercial study, the client has the final say on what, or if any commercially sensitive information concerning the study may be published. We are grateful to MLC for their permission to include the percentage increase in the brand linkage and advise that brand linkage data for the first and revised advertising phases has not been made available for publication.

CONCLUSION

Event boundaries can trigger a brief drop in long-term memory encoding or *Conceptual Closure*. While Conceptual Closure, in general may not compromise advertising effectiveness, it may do so if it occurs at the time that a key message or branding is presented. In the case study, we show how minor changes to a finished advertisement can modify the impact of Conceptual Closure and in turn significantly enhance advertising effectiveness.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Swinburne University Human Research Ethics Committee as application SUHREC2014/029. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

RS and GN conceived the project. SS and GN supervised development of video first person journey. RS and SS contributed to the experimental design. SS supervised the project. RS developed statistical analysis software for the study and analyzed the data.

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Neuro-Insight Pty Ltd. provided facilities for the study at no charge to the authors. Neuro-Insight Pty Ltd. also paid for the recruitment and reimbursement of participants. Neuro-Insight Pty Ltd. provided the services of SS to supervise the recording at no charge.

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Conflict of Interest: RS, SS, and GN are employed by Neuro-Insight Pty Ltd. and have a financial interest in Neuro-Insight Pty Ltd.

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Opportunities and Challenges for Using Automatic Human Affect Analysis in Consumer Research

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The ability to automatically assess emotional responses via contact-free video recording taps into a rapidly growing market aimed at predicting consumer choices. If consumer attention and engagement are measurable in a reliable and accessible manner, relevant marketing decisions could be informed by objective data. Although significant advances have been made in automatic affect recognition, several practical and theoretical issues remain largely unresolved. These concern the lack of cross-system validation, a historical emphasis of posed over spontaneous expressions, as well as more fundamental issues regarding the weak association between subjective experience and facial expressions. To address these limitations, the present paper argues that extant commercial and free facial expression classifiers should be rigorously validated in cross-system research. Furthermore, academics and practitioners must better leverage fine-grained emotional response dynamics, with stronger emphasis on understanding naturally occurring spontaneous expressions, and in naturalistic choice settings. We posit that applied consumer research might be better situated to examine facial behavior in socio-emotional contexts rather than decontextualized, laboratory studies, and highlight how AHAA can be successfully employed in this context. Also, facial activity should be considered less as a single outcome variable, and more as a starting point for further analyses. Implications of this approach and potential obstacles that need to be overcome are discussed within the context of consumer research.

Keywords: automatic human affect analysis (AHAA), machine learning, facial expression, spontaneous expressions, dynamic responses, consumer research

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INTRODUCTION

Emotions matter profoundly for understanding consumers' behavior in fast changing economic markets of modern life (McStay, 2016). While there exist various ways to assess emotions in the laboratory, most approaches that target bodily signals require sensors to be attached to the participant that are either less accurate or less practicable when used in the field (Küster and Kappas, 2013). Hence, automated methods of measuring facial emotional responses via contact-free video

recording tap into a rapidly growing market that presents opportunities but also risks (e.g., Gupta, 2018; Schwartz, 2019), and debate about false expectations (Vincent, 2019).

If consumer attention, social engagement, and emotional responses can be measured reliably and non-invasively, a broad spectrum of marketing decisions could be readily informed by objective data. As such, we need to examine *how well* new computational methods can predict consumer behavior, thereby moving away from questions that simply ask *whether* or not they can predict choice (Smidts et al., 2014). Further, it will be critical to measure neurocognitive choice processes in more naturalistic settings to facilitate the study of a broad spectrum of human behavior – including also disorders such as addiction and obesity (Hsu and Yoon, 2015). For example, such settings could include the elicitation of complex yet distinct mixed emotional states such as the feeling of *being moved* that is often described as pleasurable, but that can also involve crying and tears (Zickfeld et al., 2019). Viewing another's tears has been shown to elicit empathy and a wish to help (e.g., Küster, 2018). In turn, this might result in increased donations towards advertisements based on the feeling of being moved. Potentially, it might be possible to even simulate human-like empathy through affective computing (Picard, 1997), thereby creating an "empathic artificial intelligence" (McStay, 2018) that fundamentally transforms the future of consumer research and related fields. On the flipside, certain real-world applications of automatic human affect analysis (AHAA), such as the detection of unhappy emotional states of customers in retail stores (e.g., Anderson, 2017) appear to be vastly premature, if not downright unethical.

The current paper aims to critically discuss the growing role of AHAA in consumer research. It also highlights some of the most pressing barriers the field currently faces. We argue that automatic classification may provide substantial new leverage to the study of emotion and cognition in consumer neuroscience through both primary and subsequent machine analysis. While the tools available to date may not be as versatile, reliable, and proven to be valid across domains, they nevertheless represent an important advance in the area of AHAA with substantial potential for further development.

ABUNDANT CHOICES: CLASSIFIERS LACK CROSS-SYSTEM VALIDATION

In the past decades, early automated systems for facial affect recognition (Tian et al., 2001) were not readily available for use by the wider research community. In the wake of recent technical advances in video-based affect sensing, this has changed (Valstar et al., 2012). Today, researchers face a plethora of choices for selecting the best machine classifier. Besides covering a wide range of price tags, commercial systems differ in their technical features for facial analysis, as well as the ways in which users engage with the system (e.g., through APIs, SDKs). Among the "grizzled veterans" in the field of AHAA are the two software packages FACET (iMotions) and FaceReader (Noldus). Originally built upon another software called CERT (Littlewort et al., 2011), FACET was distributed by Emotient, whereas FaceReader was developed and first presented by VicarVision in 2005 (Den Uyl and Van Kuilenburg, 2005). Both systems have been used in a large number of scientific studies (e.g., Skiendziel et al., 2019; for a review see Lewinski et al., 2014a) as well as in consumer behavior (Garcia-Burgos and Zamora, 2013; Danner et al., 2014; Yu and Ko, 2017) and marketing research (Lewinski et al., 2014b; McDuff et al., 2015). Nonetheless, there are several other promising off-the-shelf classifiers available today that could be employed for the same purposes. These include *Affdex* (Affectiva), *FaceVideo* (CrowdEmotion), *Cognitive Services: Face* (Microsoft), *EmotionalTracking* (MorphCast), *EmotionRecognition* (Neurodata Lab), or *FaceAnalysis* (Visage Technologies). Moreover, some classifiers are freely available such as OpenFace (Baltrusaitis et al., 2016) or OpenCV (Bradski, 2000) to extract facial feature sets from video recordings.

Given the large and growing number of choices for academics and practitioners in consumer research, there still exists little "cross-system" (i.e., between competing products) validation research that could independently inform about the relative performance indicators of AHAA (Krumhuber et al., 2019). Out of the studies available to date, only a few have directly compared different commercial classifiers (Stöckli et al., 2018). Likewise, a small number of studies has tested AHAA against human performance benchmarks on a larger number of databases (Yitzhak et al., 2017; Krumhuber et al., 2019), thereby calling the generalizability of findings derived from single stimulus sets into question.

Ultimately, not only accuracy of AHAA needs to be evaluated, but also its validity and reliability in a broader sense (cf., Meyer, 2010; Ramsøy, 2019). First, certain concepts may require re-interpretation: For example, classic *test–retest reliability* by the machine classifier on identical stimuli tends to be perfect because the underlying algorithms remain fixed. Likewise, the issue of *inter-rater reliability*, i.e., different experimenters applying the same AHAA, may be irrelevant if all parameters are shared between experimenters. More critical, however, are questions of *convergent* and *external validity*. So far, most validation efforts have focused on the convergence between AHAA and human ratings, although initial evidence suggests that AHAA may correlate highly with facial electromyography (EMG; Kappas et al., 2016; Beringer et al., 2019; Kulke et al., 2020). However, much more work is still needed to compare AHAA against both facial EMG and expert annotations to determine its *convergent* and *discriminant validity*. *Generalizability* of AHAA study findings may be further limited in other ways. E.g., classifier performance may be substantially lower for spontaneous affective behavior (Dupré et al., 2019; Krumhuber et al., 2019). This issue often ties into the lack of information given about the stimulus materials originally used to develop or "train" a given AHAA system to fully evaluate generalizability toward similar novel stimuli.

Finally, AHAA needs to demonstrate an added value to predict consumer behavior. A few studies have begun to examine this question by predicting purchase intent from automatically detected facial expressions. For example, the FACET classifier has recently been employed to examine purchase intent toward vegetable juices, showing that AHAA-based facial expressions modulated consumer intent in concert with a number of other factors (Samant et al., 2017; Samant and Seo, 2020). Nevertheless,

it remains an empirical question to what extent expressions, as tracked by AHAA, translate to purchase intent and tangible real-world behavior.

Overall, we still know too little about the various contenders to choose between classifiers for different purposes. Once a commercial software package has been purchased, users typically have few options to reconsider their choice, as the cost of even a single system is often in the (higher) four- or (lower) five-digit range. Furthermore, available open-source solutions such as *OpenFace* still need to be tested with regards to their potential for supplementary behavioral analysis.

MISSING THE BEAT OF FINE-GRAINED EXPRESSION DYNAMICS

In the real world, faces are constantly in motion. As demonstrated by a growing body of research in cognitive science, the dynamics of facial movement convey communicative intent and emotion (for reviews, see Krumhuber et al., 2013; Krumhuber and Skora, 2016; Sato et al., 2019). While the role of fine-grained dynamics has been best explored in the context of smiling (e.g., Krumhuber et al., 2007, 2009), they are believed to impact emotion judgments and behavioral responses more generally (Sato and Yoshikawa, 2007; Recio et al., 2013). This renders expression dynamics to be of crucial importance for large areas of consumer research. Since online and TV advertisements frequently involve dynamic material involving human faces, their affective credibility depends on whether the content is perceived as genuine-looking and sincere. However, relatively little is known about the precise characteristics of expression dynamics in product evaluation beyond simple analyses of means (Peace et al., 2006). Teixeira and Stipp (2013) showed an inverted-U relationship between smile intensity and purchase intents of people who viewed advertisements – i.e., both very high and very low levels of humorous entertainment predicted lower purchase intent. Similarly, *joy velocity*, i.e., the speed of change in facial expressions of happiness, has been suggested to affect consumers' decisions to continue to watch or "zap" advertisements (Teixeira et al., 2012). Finally, humorous entertainment, as measured by smile intensity, may increase purchase intent when placed after, rather than before, brand presentation (Teixeira et al., 2014).

One reason for this comparative neglect of the dynamics of facial movement lies in its complexity. In traditional laboratory research, a limited number of factors can be manipulated simultaneously. Higher ecological validity of evoked facial activity, and more natural recording situations, typically make it more difficult to adequately control for possible confounds, as well as ensure sufficient statistical power. As shown in prior research (Ambadar et al., 2005), the impact of dynamic expressions is likely to be more than the sum of still images. While temporal information improves emotion recognition (Krumhuber et al., 2013), it is less clear how multi-peaked dynamic expression trajectories are weighted in the mind of the human perceiver. Also, it remains largely unknown how rich socio-emotional knowledge about the context of dynamic expressions shapes their perception (Maringer et al., 2011). Such applied questions are of imminent relevance for consumer research given that AHAA can provide per-frame classifications of large amounts of video data of human observers. For example, based on an analysis of more than 120,000 frames, Lewinski et al. (2014b) found context-specific features of facial expressions of happiness to be major indicators of happiness. Unfortunately, however, no well-established standards yet exist in terms of how best to pre-process and aggregate raw per-frame probabilities of machine classification.

Until now, many validation approaches consider only the peak response intensities or overall mean response envelopes of a perceiver's facial activity. From our perspective, this calls for more advanced and systematic ways of generating and testing hypotheses relating to short- to medium term expression dynamics. Such challenges may require the use of metrics that do not simply reduce complex facial movements to a single image, i.e., one that is representative of the prototypical peak expression. Instead, temporal segments of facial activity need to be weighted relative to other simultaneously present channels, without discarding nuanced expressions (Pantic and Patras, 2006; Valstar and Pantic, 2006; Dente et al., 2017).

While AHAA provides new avenues for more fine-grained and subtle expression analysis, certain use cases might fail to translate to future research. For example, it is unlikely that micro-expressions (Ekman, 2009; Matsumoto and Hwang, 2011) offer a promising theoretical approach toward a better understanding of expression dynamics in consumer research. Micro-expressions refer to brief displays (20–500 ms) argued to "leak" an individual's true emotional state before the expression can be actively controlled (Ekman and Friesen, 1969). While micro-expression analysis still enjoys substantial attention (see Shen et al., 2019), the concept is questionable and lacks empirical support as a validated theory, partly because micro-expressions are extremely rare (Porter et al., 2012) and of little practical relevance in understanding the multiple functions of emotions. As such, they could simply represent briefer and weaker versions of normal emotional expressions (Durán et al., 2017). In consequence, it seems worthwhile to focus future research efforts on other aspects, such as those that concern dynamic and spontaneous emotional behavior beyond the level of the individual frame.

FROM POSED STEREOTYPES TO SPONTANEOUS EXPRESSIONS "IN THE WILD"

Video-based affect classification can only be a useful tool for consumer research if patterns of naturally occurring responses can be reliably detected. Historically, AHAA has primarily been designed to achieve high accuracy in recognizing intense and stereotypical expressions provided by carefully instructed actors (Pantic and Bartlett, 2007). However, the narrow focus on individual posed emotions throughout psychology has been increasingly criticized because it has not been very helpful to understand the evolutionary functions of emotional expressions themselves (Shariff and Tracy, 2011). While promising methods for analyzing spontaneous behavior have been proposed, fewer efforts target the automatic analysis of spontaneous displays (Masip et al., 2014). This could be due to the rather limited

number of available databases with naturalistic and spontaneous expressions used to train and test machine classifiers. Often, these databases are also of lower recording quality which hinders objective measurement and analysis (Krumhuber et al., 2017).

Recent findings regarding the classification performance of posed expressions have been encouraging. For example, Stöckli et al. (2018) demonstrated acceptable accuracy in classifying basic emotions using the software packages FACET and Affdex. The authors calculated recognition accuracy for maximum intensity expressions extracted from two posed databases. However, when participants were asked to spontaneously respond to emotionally evocative pictures, accuracy for emotional valence (see Yik et al., 2011) was barely above chance level. Similar results have been reported by Yitzhak et al. (2017) using videos. Depending on the emotion in question, recognition performance of prototypical posed expressions typically ranged between 70 and 90%, with happiness being recognized most accurately. By contrast, the same classifier performed "very poorly" (Yitzhak et al., 2017, p. 1) on subtle and non-prototypical expressions. Overall, machine learning for spontaneous expressions is a difficult task, with performance rates varying as a function of classifier, emotion, and database (Dupré et al., 2019). Furthermore, the notion of what constitutes spontaneous facial behavior varies between the databases.

To make significant progress in the future, more work is still needed to create and validate large and diverse datasets of spontaneous expressions (Zeng et al., 2009). For example, efforts such as AffectNet (Mollahosseini et al., 2019) or Aff-Wild (Kollias et al., 2019) might help to close the gap toward predicting affective responses in the wild. Ideally, new databases should be publicly accessible to allow for independent verification of the results or modification of the computer models. Dedicated large scale efforts to obtain high quality "in-the-wild" dynamic facial response data will allow researchers to consistently address ethical challenges that require substantial consideration. E.g., the partial deception required to ensure unbiased responses can be ameliorated through standardized debriefing procedures. Further, spontaneous databases can be (re-)used for multiple cross-system validation studies, as well as for more specific consumer response analyses. By doing so, AHAA of spontaneous expressions may contribute to increasingly better predictions of real-world consumer responses while minimizing the burden on ethical data collection in the field. Finally, such an approach would also provide a benchmark for comparisons between the different algorithms. For example, although a large amount of online video data used for the training of *Affdex* has been one its major selling points (Zijderveld, 2017), this and similar systems still function like a "black box" that cannot be directly validated by other parties.

THEORETICAL ISSUES: A LACK OF COHERENCE

While some of the most pressing issues of AHAA concern practical limitations, theoretical issues equally need to be addressed. Importantly, the notion of a direct and hard-wired or "universal" link between facial expressions and subjective experience has been challenged in recent years. As argued by multiple researchers (Reisenzein et al., 2013; Hollenstein and Lanteigne, 2014; Durán et al., 2017), coherence between emotions and facial expressions may at best be moderate in strength, and sometimes even non-existent. Further, similar configurations of facial actions [i.e., Action Units (AUs)] may express more than one emotion or communicative intent (Barrett et al., 2019). This contrasts with existing views such as those proposed by Basic Emotion Theory (Ekman, 1992, 1999). In consequence, any facial activity, whether it is measured manually or automatically, cannot be assumed to directly reflect a person's emotional experience. Facial expressions are *not* the sole readout of underlying emotional states (Kappas, 2003; Crivelli and Fridlund, 2018). As a result, AHAA is essentially about the recognition of patterns and regularities in the data (Mehta et al., 2018).

Nevertheless, there are reasons to be optimistic when attempting to interpret facial expressions. First, spontaneous consumer responses might be more predictive of affective behavior than abstract and decontextualized situations as typically examined in the laboratory (Küster and Kappas, 2014). Such applied contexts could be more informative about the emotional experience of respondents, thereby increasing the magnitude and coherence of the response. Second, recent improvements in efficiency rendered by AHAA allows the processing of larger amounts of data than has previously been possible. This should increase overall robustness in study findings across domains, including larger-scale studies (Garcia et al., 2016). Third, results obtained via frame-based classification could be used as a starting point for further analyses based on machine learning despite low overall levels of emotion-expression coherence. For example, for the prediction of consumption choices between several products, it might not matter whether a given smile or frown reflects a full-blown emotion or something else (i.e., concentration, politeness) – provided the consumer's decision is predicted correctly.

Overall, we therefore propose to consider the wider context of emotional expressions rather than to limit investigations to a blind use of emotion labels provided by commercial machine classifiers without considering the wider context. Instead, it is commendable to think of these technologies as a means to "pre-process" large amounts of facial activity data at low cost. These pre-processed facial activity data can then itself be used as input features for machine learning methods to learn and predict human emotional behavior in context.

CONCLUSION

AHAA promises to revolutionize research in consumer neuroscience. However, even apart from general theoretical limitations, its validity and usefulness are likely to vary between different types of studies. Testing hypotheses about specific consumer responses may often depend on relatively small datasets of facial responses, rendering the decision of which software to use even more difficult. In many cases, freely available tools such as OpenFace may be a good entry point. However, there presently appears to be no single software tool on the

market that clearly outperforms all other machine classifiers. Hence, additional research is still needed to examine the reliability and predictive value of AHAA. Although the future of automatic affect sensing in consumer research looks promising, it is important to remain aware of its potential limitations. Social scientists can play an active role here to contribute to further development of this technology.

AUTHOR CONTRIBUTIONS

DK and EK developed the theoretical ideas. All authors contributed to the discussion and refinement of the presented perspective with regards to AHAA. DK and EK wrote the manuscript. MB and TS provided critical feedback. DK, EK, MB, and LS contributed to manuscript revision. All authors read and approved the final version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Love at First Glance but Not After Deep Consideration: The Impact of Sexually Appealing Advertising on Product Preferences

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In advertising studies, the impact of sexually appealing advertisements (hereafter "ads") on consumers' product preferences is highly controversial. This paper explores (1) how such ads affect consumers' product preferences at the gazing stage (initial stage of exposure to the ad) and evaluation stage (final product preference), and (2) which type of product (utilitarian vs. hedonic) is more suited to such ads. We used an electroencephalogram to record participants' product preferences at the gazing stage and self-reported product preferences at the evaluation stage. The results indicated that participants preferred ads with high sex appeal at the gazing stage and ads with low sex appeal at the evaluation stage. Further, compared to utilitarian products, hedonic products were more suited to sexually appealing ads. The findings suggest that the effect of such ads on consumers' product preferences varies depending on their cognitive stage and the type of product advertised.

Keywords: sexually appealing ads, utilitarian product, hedonic product, gazing stage, evaluation stage, EEG, product preference

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INTRODUCTION

Shopping is a necessary part of daily life, and advertising is a common way to advocate products. Instantly capturing consumers' attention is key to achieving high sales figures. The use of sex appeal in advertising is a common marketing strategy to attract consumers and promote awareness of the product.

The Controversy of Sexually Appealing Advertisements

Sexually appealing advertisements (hereafter "ads") promote products using erotic images or sexual words. For example, the pun of "old driver" has two meanings in China. One denotes a driver who has been driving for many years, the other denotes a person who often tells sexual stories or dirty jokes. Owing to the particularity of "sex," the use of sex appeal in advertising has been highly controversial. On the one hand, it can attract consumers' attention to products. On the other hand, because of moral factors, people might reject such ads. Therefore, the effect of sex appeal in advertising has been a focus in the advertising literature, and the findings have been rather inconsistent (e.g., Dudley, 1999; LaTour and Henthorne, 1994; Pope et al., 2004; Bushman, 2005). For instance, Dudley (1999) showed that increased physical exposure in ads (e.g., partial/total nudity) weakened consumers' willingness to buy the products. Bushman (2005) found that such

ads reduced consumers' memory regarding the product brand. LaTour and Henthorne (1994) revealed that consumers' purchase intention toward jeans decreased when posters with sexual content were used. Inversely, Pope et al. (2004) compared products with sexually appealing ads to those without and found that participants preferred the former.

Two Possible Factors to Reconcile the Controversy

Two factors may reconcile this controversy. One is the difference between the initial and final stages of product preference. In prior studies, participants' product preference was measured in an exposed environment. For example, LaTour and Henthorne (1994) evaluated sexually appealing ads by interviewing participants at a mall. Dudley (1999) asked participants to evaluate sex appeal by projecting advertisement images on classroom screens. When answering questionnaires or being observed by others, participants' product preferences may be influenced by social norms or their sense of shame. It is likely that their final assessment will differ from their initial preference. That is, people may have preferred ads with sex appeal at first glance but did not do so after deep consideration owing to social values. Many researchers have pointed this out (Neeley and Cronley, 2004; Putrevu, 2008). For instance, Putrevu (2008) inferred that sex appeal was a sensitive topic. People may lower their preference for these ads to cater to mainstream values and obtain others' approval. This may lead to differences in the final preference assessment versus the initial reaction. Neeley and Cronley (2004) found that because of the impact of social expectation bias, people overestimated behavior akin to socially acceptable mainstream values and underestimated behavior considered to be socially unpopular. Neeley and Cronley (2004) highlighted that social expectations often lead to differences between people's initial and final preferences. Therefore, it is necessary to explore the different effects of sexually appealing ads on product preferences between the initial and final stages.

The other factor is the type of product (utilitarian vs. hedonic). Utilitarian products have effective, useful, functional, necessary, and practical attributes (e.g., a wrench or spoon). Hedonic products have interesting, exciting, thrilling, and enjoyable attributes (e.g., chocolate or perfume) (Dhar and Wertenbroch, 2000; Voss et al., 2003). People often obtain utilitarian or hedonic information from ads. Therefore, appropriate ads enable people to obtain product information, thereby promoting their purchase intention. Many researchers have studied matching of product types with different advertising strategies to achieve better effects (Drolet et al., 2007; Geuens et al., 2011; Bart et al., 2014). For instance, Bart et al. (2014) analyzed data from 59 mobile advertising companies and found that the effect of mobile display ads for utilitarian products was better than for hedonic products. Drolet et al. (2007) found that utilitarian products with rational ads were more popular, while hedonic products with emotional ads were more popular. Geuens et al. (2011) found that emotional ads were more effective in advertising hedonic products. However, they did not have much of an impact on advertising utilitarian products. Ads with sex as the theme can also be considered emotional ads, as they evoke "sexual" emotions to attract consumers. Thus, hedonic products may be more suited to sexually appealing ads.

This paper investigates (1) how sexually appealing ads influence consumers' product preferences in the initial stage of being exposed to the ads and the final evaluation stage and (2) which type of product (utilitarian vs. hedonic) is more suited to such ads.

Electroencephalography for Measuring Advertising Effectiveness

In this paper, we used electroencephalography (EEG) to measure initial preference for sexually appealing ads. EEG is an electrophysiological monitoring method that records electrical activity in the brain. It analyzes the changes in people's brains through event-related potentials (ERP) or spectral content. It can record changes in the brain after a stimulus is presented in real time. Its high temporal resolution can detect people's brain responses to stimuli in the early, middle, and later stages. The EEG data were used to infer initial preferences for sexually appealing ads. EEG has many applications in advertising research (Ohme et al., 2010). For instance, Ohme et al. (2010) found significant differences in EEGs even though participants consciously reported no difference in preferences. Studies showed that the prefrontal cortex is associated with an individual's preferences (Ravaja et al., 2013; Telpaz et al., 2015), and prefrontal cortical data can be used to predict subjective preferences and choices. In a study by Ravaja et al. (2013), participants were asked to indicate their purchase intention toward 14 different products, and the results were compared with corresponding EEG data. The results showed that frontal alpha asymmetry may predict consumers' purchase decisions; a higher perceived need for a product and higher perceived product quality were associated with greater relative left frontal activation. Telpaz et al. (2015) also compared EEG data with subsequent subjective preferences and found that the N200 component of the central electrode of the prefrontal cortex predicted subjective preferences: the more the person preferred the product images, the more positive N200. However, late positive potential and positive slow waves were relatively better than N200. Additionally, Goto et al. (2017) found that N200, an early ERP component, reflected unconditional and automatic process-driven preferences through virtual shopping tasks. Based on previous studies, this paper selected the central electrode fz of the prefrontal lobe as the measuring electrode and the N200 component as the objective index of the initial advertising preference. N200 is a negative-going wave that peaks at 200–350 ms in the post-stimulus time frame and is found primarily over anterior scalp sites. N200 is considered to be related to initial cognitive assessment.

This paper also used the late frontal slow wave (LFSW), which is related to processing cognitive conflict. Studies have shown significant differences in the LFSW between conflict and non-conflict conditions when people process self-preference and social preference (Liu et al., 2004; McCleery et al., 2011). For example, McCleery et al. (2011) observed that the

LFSW components were more positive in conflicting situations (e.g., conflicts between self-values and social values) than in non-conflicting situations. We assumed that when preferences for sex appeal conflicted with social norms, the LFSW would be more positive. Therefore, we selected the LFSW component to investigate whether people came into conflict with social expectations while watching sexually appealing ads. Electrodes FP1 and FP2 on the left and right hemispheres were selected as the LFSW electrodes and 400–700 ms as the LFSW time window. Further, self-reported subjective product preference was also recorded as an important final preference.

In addition to analyzing ERP components in EEGs, we also analyzed the brain network. Based on the spatiotemporal organization theory of brain activity (Varela et al., 2001), higher-order cognitive processes and goal-oriented behavior synchronize dynamically with different regions of the brain through neural oscillations of different frequencies to form a unified functional network (Müller and Anokhin, 2012). We constructed a functional brain network based on the phase lag index (PLI) to explore the differences in brain networks triggered by different levels of sex appeal in ads and different types of products. "Small-worldness" has been shown to be one of the basic attributes of brain networks. A high "small-worldness" property indicates higher local clustering and shorter path length in brain networks (Micheloyannis et al., 2006; Zhao et al., 2018). For example, Micheloyannis et al. (2006), by constructing a functional brain network, found that participants with low education had a higher "small-worldness" property than those with higher education, supporting the hypothesis of neural efficiency. They assumed that subjects with low education needed a more optimized network organization structure to achieve cognitive tasks of equal levels of difficulty. Zhao et al. (2018) found through their intertemporal decision-making study that people's "small-worldness" attribute under the condition of loss aversion was larger than under the condition of benefit, implying that people have greater brain responses under the condition of loss. This means that the higher the "small-worldness" property, the more complex the functional brain network and the greater the brain response. Therefore, we chose "small-worldness" as the evaluation index of the brain network.

Experimental Overview

In this paper, we used EEG and behavioral reports to record participants' brain and behavioral responses (e.g., N200 in the initial stage, LFSW and subjective product preference in the final stage) to products with sexually appealing ads. We also examined which type of products (utilitarian vs. hedonic) were more suited to such ads.

MATERIALS AND METHODS

Participants and Design

A total of 25 healthy volunteers participated in this experiment. Data from four subjects were excluded because of errors in the recording of the EEG data. As a result, a total of 21 volunteers were fully analyzed (6 males, 15 females; mean age = 21.19 years ± 2.60). All participants were right-handed with no visual problems and no history of neurological diseases or mental disorders. All participants provided written informed consent prior to the experiment. The study protocol was approved by the Local Ethics Committee of Zhejiang University of Technology. This experiment was a two (sex appeal: high vs. low) × two (product type: utilitarian vs. hedonic) within-participants design.

High and low sex appeal pictures were selected from the study by Black and Morton (2017). Nudity is a common way to present sex appeal in ads. Based on the degree of nudity, we divided advertising pictures into two categories: high and low sex appeal ads.

In this experiment, 34 product images were selected for evaluation. The participants were provided with information on the difference between hedonic and utilitarian products in the following way: *Hedonic products focus on feelings and experiences and are fun, exciting, and enjoyable. Utilitarian products focus on functionality and utility and are effective, beneficial, functional, and practical. Utilitarian products highlight their functional and practical utilities.* Afterward, the participants were asked to evaluate the product type on a seven-point scale (1 = the most utilitarian to 7 = the most hedonic). Thirty volunteers were selected to classify these products. The results were as follows: utilitarian products included vacuum cups, condoms, chewable vitamin tablets, skincare products, shower gels, shampoos, and laundry detergent (M = 2.43), while hedonic products included massage oil, cakes, plush toys, potato chips, carbonated drinks, perfumes, music records, and entertainment magazines [M = 5.57, $t(29) = -15.099$, $p < 0.001$]. The experimental materials are shown in **Table 1**. Additionally, we screened the degree of sexual appeal of ads after combining sexually appealing advertising with product types through pre-experiments. Since some products showed little difference between high- and low-appeal ad scores and some products' high-appeal ad scores were not high, excluding these ads caused differences in the number of ad pictures under different conditions (high sex appeal utilitarian: 6; high sex appeal hedonic: 8; low sex appeal utilitarian: 5; low sex appeal hedonic: 9).

Procedure

Based on the experimental tasks of Telpaz et al. (2015), our experiment was divided into two stages. In the first stage, participants were asked to view each ad image and think about

TABLE 1 | Examples of experimental materials.

Type	Example	Example	Example	Example
Utilitarian products	 Chewable tablets	 Shampoo	 Condoms	 Vacuum cup
Hedonic products	 Music album	 Plush toys	 Cake	 Perfume

their preferences for the ad, and the corresponding EEG data of the participants were recorded at this stage. The aim was to measure the individual neural activity for each specific ad. In the second stage, the participants were asked to subjectively evaluate their preference for the ads presented in the previous EEG stages.

Stage 1: EEG Measurement

The experiment was conducted in a soundproof room where the participants sat in front of a computer screen and put on an EEG electrode cap. They were asked to minimize their movements during the EEG experiment. The display of the stimuli and the acquisition of behavioral data were conducted using E-Prime software. All ad images were randomly presented on a standard computer screen. Only one ad image was presented in each trial. The participants were instructed to think about their preference for the ad. During the experiment, they were not required to make any substantive choices or other behavioral responses.

Figure 1A depicts the visual presentation of an ad. For each trial, a fixation cross of 800–1,200 ms was first presented, followed by an ad for 2.5 s. The participants were instructed to think about their preference for the ad. To maintain their concentration on the experiment, in 21 random trials (1 of the 21 presentations for each of the 28 items), after the fixation, they were asked to answer how many volleyballs were on the screen. To improve the signal-to-noise ratio, every ad in each block was randomly presented three times. Thus, a block had a total of 84 trials (i.e., high sex appeal utilitarian: 18 trials; high sex appeal hedonic: 24 trials; low sex appeal utilitarian: 15 trials; low sex appeal hedonic: 27 trials; with each ad shown three times). A total of seven blocks was repeated for a total of 588 trials. Participants were allowed a short break between each

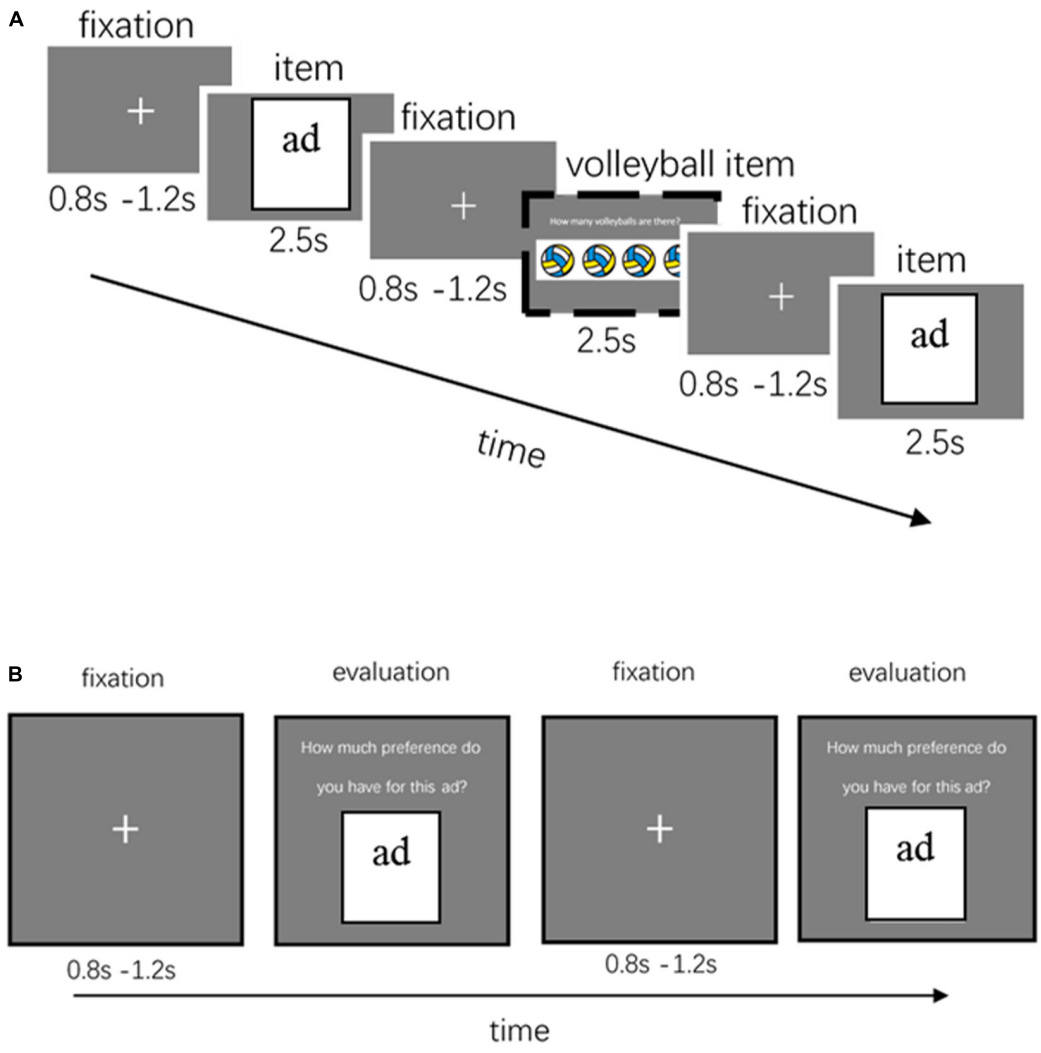


FIGURE 1 | Experimental design. **(A)** EEG Task. After 0.8–1.2 s fixation, the experiment randomly presented an ad; the participants were instructed to think about their preference for the ad. After 2.5 s, the next trial began. After presenting 28 ads, they were asked to answer how many volleyballs were on the screen, as shown in the dashed-border box, and they continued on to the EEG experiment after answering correctly. **(B)** Behavior Task. After 0.8–1.2 s fixation, the experiment randomly presented ads; the participants needed to evaluate their preference for the ad [seven-point scale ranging from "dislike a lot (= 1)" to "like a lot (= 7)"].

block (at the end of each block, the screen said that the subject could continue the task whenever he/she was ready by pressing the mouse button). The total duration of the EEG recording stage was 40 min.

For example, after a second of fixation, a high sex appeal hedonic ad was presented for 2.5 s. The participant was instructed to think how much he/she preferred the ad shown. After 28 trials, a picture of volleyballs was presented for 2.5 s. The participant was then asked to answer how many volleyballs were on the screen. At the end of the block, he/she could continue the task when ready by pressing the mouse button.

Stage 2: Behavioral Stage

At the end of the EEG measurement stage, the EEG electrode cap was removed, and the participant commenced the behavioral task after 10 min of rest. **Figure 1B** depicts the visual presentation for this task. For each trial, a fixation cross was first presented for 800–1,200 ms, then the screen randomly presented an ad image and the subjects were asked to rate how much they preferred this ad on a seven-point scale ranging from "dislike very much (= 1)" to "like very much (= 7)" for a total of 28 trials (high sex appeal utilitarian: 6 trials; high sex appeal hedonic: 8 trials; low sex appeal utilitarian: 5 trials; low sex appeal hedonic: 9 trials; each ad was present once). Thereafter, the participants filled in their demographic information, such as gender and age, were thanked for their participation, debriefed, and paid.

EEG Recording and Analysis

The EEG was taken from 64 scalp locations by electrodes mounted on an elastic cap with online reference to the left mastoid. The horizontal electrooculogram was recorded by two electrodes placed laterally on either side of the left and right eyes. The vertical electrooculogram was recorded by two electrodes located above and below the right eye. All electrode impedances were kept below 5 KΩ. All signals were sampled at 500 Hz, and the band-pass filtered frequency range was 0.01–100 Hz.

During the offline analysis, all EEG data were re-referenced to the mean of the left and right mastoids. A 20–Hz (24 dB/oct) low-pass filter was applied to all EEG data. The ocular artifacts in the data were removed via a regression procedure using Neuroscan software. Trials containing EEG sweeps with amplitudes exceeding ±80 μV were excluded. EEG data with a continuous duration of 1000 ms were extracted from each stimulus datum, including a 200 ms pre-stimulus period used as baseline.

In this experiment, the ERP components were analyzed using repeated-measures analysis of variance (ANOVA) in which sex appeal (high sex appeal vs. low sex appeal) and product type (hedonic vs. utilitarian) were used as within-participant factors. The time window of the frontal N200 component selected was 170–270 ms after stimulus presentation as peak amplitude, and the electrode selected was the fz electrode. The selection of the electrode and component time window was based on previous articles and visual inspection of the ERP grand average waveforms.

Construction of a Brain Function Network

The standard PLI quantifies the phase synchronization of two different time series by detecting non-zero phase difference coupling. The weighted phase lag index (wPLI) extends the PLI by increasing the phase difference between two time series (Vinck et al., 2011; Hardmeier et al., 2014). Therefore, in this study, we used the wPLI to measure the functional connection between electrodes (nodes). The steps for analyzing the weighted phase lag of each EEG signal were as follows: (1) classifying the EEG signals according to different frequency bands; (2) calculating the EEG signals with the wPLI for each frequency band, each condition, and each subject using HERMES software; (3) determining an appropriate threshold to maintain a connection density of 30% of the connected network in each frequency band (Bullmore and Bassett, 2011); (4) setting the values of connection values in each connection matrix that were greater than the threshold to one and values less than the threshold to zero.

Calculating the "Small-Worldness" Property

Based on the brain network connection matrix, we used the network's small-world index as an analysis index to explore the differences under each condition. The small-world attribute is equal to the clustering coefficient/characteristic path length of the network. Therefore, the clustering coefficient and shortest path length are the two most important parameters used to describe and characterize the small-world topology of a network.

The clustering coefficient reflects the local integration capability of a network. The clustering coefficient indicates the possibility that the neighbors of a certain node are neighbors to each other. The value of the clustering coefficient C_i of node i is equal to the ratio of the number of edges (e_i) connected between the neighbors of the node and the maximum possible number of connected edges [k_i (k_i−1)/2].

$$C_i = \frac{2e_i}{k_i(k_i - 1)}$$

In this paper, we used the average clustering coefficient of all nodes as the clustering coefficient of the network (Onnela et al., 2005). The shortest path length describes the information transmission capacity within a network. A path with the fewest edges between two nodes, i and j, is called the shortest path between the two points. The number of edges that the path passes is the shortest path length between nodes i and j, l_{ij}, and V is the set of nodes. The network shortest path length, L, describes the average of the shortest path length between any two nodes in the network.

$$L = \frac{1}{N(N-1)} \sum_{i,j \in v, i \neq j} l_{ij}$$

In this experiment, the method of calculating the "small-worldness" property was based on Hong et al. (2016). We chose the 300–800 ms post-stimulus period for the analysis. Then, we calculated the clustering coefficient and characteristic path length. The "small-worldness" index was defined as the ratio of the clustering coefficient and the characteristic path length.

All data were analyzed using SPSS 21.0, and the significance level was set at 0.05. The Bonferroni method was used to

correct the *post hoc* test of multiple comparisons. The important interactions were analyzed with simple-effects models.

RESULTS

EEG Results

N200

Inspired by Telpaz et al. (2015), we selected the N200 component of the fz electrode for analysis. Telpaz et al. found that the larger the magnitude of N200 in the mid-frontal electrode, the lower the preference for the item tested. The N200 component was analyzed via repeated-measures ANOVA, with sex appeal (high sex appeal vs. low sex appeal) and product type (hedonic vs. utilitarian) used as the within-participant factors. **Figure 2A** shows the ERP waveforms of the N200 component under the four conditions, and **Figure 2B** shows the topographic maps of the N200 component under those conditions. The results revealed that the main effect of product type was significant: $F(1, 20) = 5.315$, $p = 0.032$, $\eta_p^2 = 0.210$. The amplitude was significantly more negative with utilitarian product ads as opposed to hedonic product ads. This indicated that the participants preferred hedonic product ads over utilitarian ones. Further, the results also showed that the main effect of sex appeal was significant: $F(1, 20) = 9.678$, $p = 0.006$, $\eta_p^2 = 0.326$. The amplitude was significantly more negative for low sex appeal ads (vs. high sex appeal ads). This indicated that participants preferred high sex appeal ads over low sex appeal ads.

Moreover, we also found an interaction between the level of sex appeal and product type: $F(1, 20) = 14.871$, $p = 0.001$, $\eta_p^2 = 0.426$. As shown in **Figure 2C**, with low sex appeal, the amplitude of utilitarian product ads was significantly more negative than in hedonic product ads: $F(1, 20) = 19.70$, $p < 0.001$. However, no difference was observed in the amplitudes between utilitarian and hedonic product ads when sex appeal was high: $F(1, 20) = 1.14$, $p = 0.298$. This indicated that when sex appeal was low, the participants preferred hedonic product ads over utilitarian ones, and when sex appeal was high, there was no difference in their preferences.

LFSW

Since the LFSW is a late prefrontal slow wave, the FP1 and FP2 electrodes of the prefrontal lobe were selected as the left and right frontal lobe electrodes for analysis based on previous studies (e.g., Sabbagh and Taylor, 2000). We chose the LFSW component to explain whether people exhibit psychological activities that conflict with their own thoughts because of other reasons when they watch sexually appealing ads. The LFSW component was analyzed using repeated-measures ANOVA in which sex appeal (high vs. low sex appeal) and product type (hedonic vs. utilitarian) were used as the within-participant factors. **Figure 2E** shows the LFSW under the four conditions of the left hemisphere in this experiment. The results revealed that the main effect of sex appeal was significant in the left hemisphere: $F(1, 20) = 4.731$, $p = 0.042$, $\eta_p^2 = 0.191$. The amplitude was significantly more positive with high sex appeal ads as opposed to low sex appeal ads. However, we did not find any main effect of product type in the left hemisphere: $F(1, 20) = 0.936$, $p = 0.345$, $\eta_p^2 = 0.045$. There was an interaction between the level of sex appeal and the product type in the left hemisphere: $F(1, 20) = 0.005$, $p = 0.947$, $\eta_p^2 = 0.000$. **Figure 2F** shows the LFSW under the four conditions of the right hemisphere in this experiment. The main effect of sex appeal was significant in the right hemisphere: $F(1, 20) = 6.302$, $p = 0.021$, $\eta_p^2 = 0.240$. The amplitude was significantly more positive with high sex appeal ads than with low sex appeal ads. This indicated that high sex appeal ads may induce larger cognitive conflicts. However, neither a main effect of product type in the right hemisphere nor an interaction between the level of sex appeal and the product type in the right hemisphere were found: $F(1, 20) = 0.524$, $p = 0.477$, $\eta_p^2 = 0.026$; $F(1, 20) = 0.251$, $p = 0.622$, $\eta_p^2 = 0.012$.

"Small-Worldness" Property

We selected the "small-worldness" property developed by Hong et al. (2016) as the basic indicator of the brain network. The higher the "small-worldness" property, the more complex the functional brain network and the more brain areas that need to be activated. The "small-worldness" property was analyzed using repeated-measures ANOVA in which sex appeal (high sex appeal vs. low sex appeal) and product type (hedonic vs. utilitarian) were used as the within-participants factors. **Figure 2G** shows the "small-worldness" property of the delta band under the four conditions of this experiment, while **Figure 2H** shows the "small-worldness" property of the theta band. The findings were as follows:

(1) Delta band (δ: 0.1–4 Hz): The results revealed that the main effect for the product type was significant [$F(1, 20) = 33.993$, $p = 0.001$, $\eta_p^2 = 0.630$]. The "small-worldness" property was significantly higher in utilitarian product ads than in hedonic ones. There was no significant difference in sex appeal [$F(1, 20) = 2.450$, $p = 0.133$, $\eta_p^2 = 0.109$]. We also found an interaction between sex appeal and product type [$F(1, 20) = 6.863$, $p = 0.016$, $\eta_p^2 = 0.255$]. When the ad's sex appeal was low, the "small-worldness" property was significantly higher in utilitarian product ads than in hedonic ones [$F(1, 20) = 14.88$, $p = 0.001$]. However, there was no significant difference when the ad's sex appeal was high [$F(1, 20) = 0.2$, $p = 0.658$].

(2) Theta band (θ: 4.1–8 Hz): The results revealed that the main effect for the product type was significant [$F(1, 20) = 22.900$, $p = 0.000$, $\eta_p^2 = 0.534$]. The "small-worldness" property was significantly higher in utilitarian product ads than in hedonic ones. There was no significant difference in sex appeal [$F(1, 20) = 2.941$, $p = 0.102$, $\eta_p^2 = 0.128$]. We also found an interaction between sex appeal and product type [$F(1, 20) = 15.511$, $p = 0.001$, $\eta_p^2 = 0.437$]. When the ad's sex appeal was low, the "small-worldness" property was significantly higher in utilitarian product ads than in hedonic ones [$F(1, 20) = 25.91$, $p < 0.001$]. However, there was no significant difference when the ad's sex appeal was high [$F(1, 20) = 0.98$, $p = 0.333$].

(3) Alpha band (α: 8.1–12 Hz): The results revealed that there was no significant main effect for product type

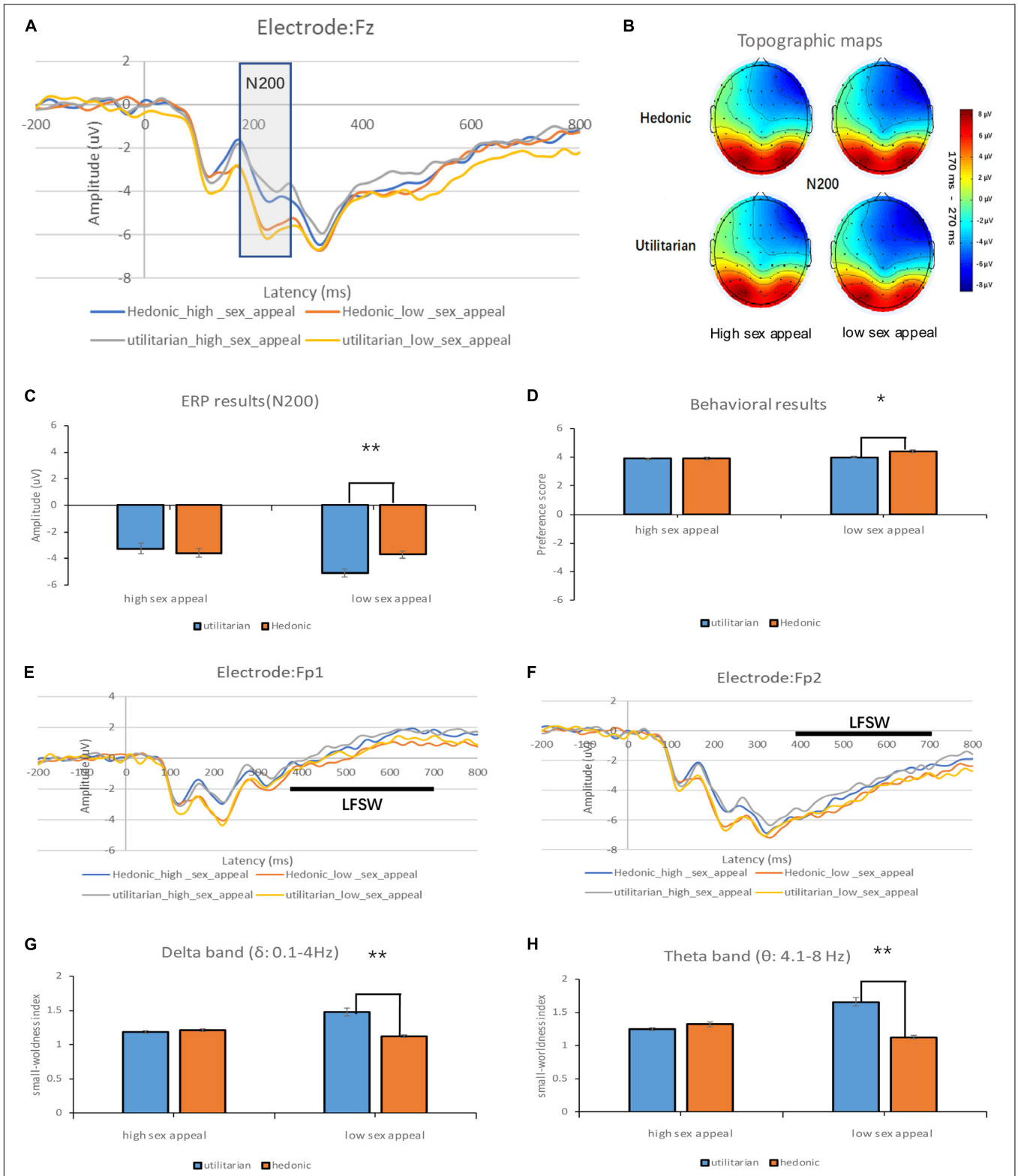


FIGURE 2 | Experimental results. **(A)** The results of the N200 component under four different conditions. There is a significant difference in the N200 peak between 170 and 270 ms after the stimulus was presented. **(B)** Topographic maps under four different conditions. **(C)** The average peak value of the N200 component under four different conditions. **(D)** The subjective preference score under four different conditions. **(E)** The results of the LFSW component under four different conditions. **(F)** The results of the LFSW component under four different conditions. **(G)** The small-worldness index in the delta band. **(H)** The small-worldness index in the theta band. (*$p < 0.05$, **$p < 0.01$).

[$F(1, 20) = 4.146$, $p = 0.055$, $\eta_p^2 = 0.172$] or sex appeal [$F(1, 20) = 0.142$, $p = 0.710$, $\eta_p^2 = 0.007$]. There was no interaction between sex appeal and product type [$F(1, 20) = 0.361$, $p = 0.554$, $\eta_p^2 = 0.018$].

(4) Beta band (β: 12.1–30 Hz): The results revealed that the main effect for the product type was significant [$F(1, 20) = 5.980$, $p = 0.024$, $\eta_p^2 = 0.230$]. The "small-worldness" property was significantly higher in utilitarian product ads than in hedonic ones, and the main effect for sex appeal was significant [$F(1, 20) = 10.281$, $p = 0.004$, $\eta_p^2 = 0.340$]. The "small-worldness" property was significantly higher when the ad's sex appeal was low than when it was high. There was no interaction between sex appeal and product type [$F(1, 20) = 0.361$, $p = 0.554$, $\eta_p^2 = 0.079$].

Behavioral Results

A two (sex appeal) × two (product type) repeated measurement ANOVA on ad preference was conducted. The results revealed that the main effect of sex appeal was significant $F(1, 20) = 5.644$, $p = 0.028$, $\eta_p{}^2 = 0.220$], indicating that the participants likely preferred low sex appeal ads ($M = 4.20$, $SD = 0.76$) over high sex appeal ads ($M = 3.91$, $SD = 0.79$). The main effect of the product type was not significant [$F(1, 20) = 2.690$, $p = 0.117$, $\eta_p^2 = 0.119$].

The interaction between sex appeal and product type was marginally significant [$F(1, 20) = 3.901$, $p = 0.062$, $\eta_p^2 = 0.163$]. As shown in **Figure 2D**, when the ad's sex appeal was low, participants preferred hedonic product ads over utilitarian ones [$F(1, 20) = 5.62$, $p = 0.033$]. However, there was no difference in preference between the utilitarian and hedonic product ads when their sex appeal was high [$F(1, 20) = 0.06$, $p = 0.815$]. This was consistent with the EEG results.

GENERAL DISCUSSION

This paper explored the effects of sexually appealing ads on utilitarian and hedonic product preferences. The results showed that the participants preferred high sex appeal ads at the gazing stage but preferred low sex appeal ads at the evaluation stage. Further, compared to utilitarian products, hedonic products were more suited to sexually appealing ads.

Sex Appeal and Its Effect on Advertising

Our paper contributes to the research on the controversy of sexually appealing ads. According to the behavioral results, people preferred low sex appeal ads over high sex appeal ones at the final evaluation stage, which is consistent with some previous studies (LaTour and Henthorne, 1994; Dudley, 1999). According to the ERP results, people preferred high sex appeal ads over low sex appeal ones at the initial gazing stage. The results of the LFSW indicated that sexually appealing ads induced larger cognitive conflicts.

We divided the process of experimenting with the ads into three steps: watching, thinking, and evaluating. Participants watched the ads first, then thought about the relevant factors of their preference, and finally made a preference evaluation. The N200 component, which was used to predict people's preferences, is an event-related-potential component. N200 is a negative-going wave that peaks at the 200–350 ms post-stimulus time frame. We used the N200 component as a preference assessment for the watching stage. The subjective assessment results belonged to the evaluation stage. The LFSW component is a late component that is generated by a person's independent thinking. Therefore, it can be considered as an indicator of mental activity in the thinking stage. In this paper, there was a difference in the LFSW between ads with different appeal intensity. We inferred that when people evaluated high sex appeal ads, conflicts arose because of their initial preferences and social expectations. However, the sexual content in the ads with low sex appeal was still within the socially acceptable range, which caused people to have different LFSWs.

Therefore, the psychological changes at the thinking stage caused the difference in preferences between the watching and evaluation stages. Further, sex appeal differences were observed in the beta band brain network. Low sex appeal ads showed stronger task-related modulations of the beta band brain networks than high sex appeal ads. This means that the beta band is related to preference evaluation and that, compared to high sex appeal ads, people may need more brain regions activated to participate in the evaluation of low sex appeal ads. This implies that people have a more in-depth understanding of low sex appeal ads. Sexually appealing ads may attract consumers at first, but excessive sexual content makes them lose interest in the ad; consumers do not make a deep evaluation of the ads. Thus, our participants had poor behavior evaluation scores and a low "small-worldness" property. In general, using sex appeal in advertising can immediately attract people's attention; as the degree of sex appeal increases, the attraction gets stronger, as verified by the ERP results. However, consumers may have negative reactions to excessive sexual content or may wish to set an example for others and thus do not further entertain high sex appeal ads. This is also evidenced by the "small-worldness" property of the brain network. As a result, the final evaluation deviated from the initial preference. This observation has also been verified by previous studies (Neeley and Cronley, 2004).

Cultural differences between the East and West may be another important reason for the inconsistent preferences in the early and later stages of reaction to strongly appealing ads. Many previous studies explored the impact of the cultural differences between East and West (e.g., Oyserman and Lee, 2008). Western culture is considered individualistic, encouraging people to express their inner state or feelings. Therefore, when people in such countries browse through sexually appealing ads, they may be more willing to follow their heartfelt thoughts and directly express their own internal state or feelings. Eastern cultures, however, highlight conservatism, observe social norms, and stress social harmony (Oyserman and Lee, 2008). Asian cultures tend to be collectivist, encouraging people to adhere to social values

(Tsai et al., 2007). Therefore, when viewing such ads, people in Eastern countries initially have a higher preference for sexually appealing ads but later change their initial thinking to meet social expectations.

Product Type and Sex Appeal

Our findings contribute to the literature on the effects of advertising for different types of products. Based on the ERP and behavioral results, low sex appeal ads were more effective in advertising hedonic products but not in advertising utilitarian ones. Consistent with emotional ads, sexually appealing ads were more suited to advertising hedonic products (Drolet et al., 2007; Geuens et al., 2011). Additionally, utilitarian and hedonic product ads were evaluated poorly when their sex appeal was high. This is consistent with previous studies: excessive sex appeal reduces people's purchase intention (LaTour and Henthorne, 1994; Dudley, 1999).

Theoretical and Practical Implications

Theoretically, the current paper explored two possible factors regarding the controversy about sexually appealing ads in previous studies. Our results suggested that the effect of sexually appealing ads on consumers' product preferences varies depending on their cognitive stage and the type of product advertised. People preferred ads with high sex appeal at the gazing stage but ads with low sex appeal at the evaluation stage. Further, compared to utilitarian products, hedonic products were more suited to sexually appealing ads.

Practically, using sex appeal in advertising is one of the commonly used strategies for marketers. Our findings suggest that for ads with high sex appeal, people may prefer them at the initial stage but not at the final stage because of social pressure. For ads with low sex appeal, their combination with hedonic products may produce positive advertising effects. During offline shopping where consumers are exposed to other individuals, high sex appeal ads may not be a smart way to advertise products as opposed to in online shopping, where the environment is relatively private. Additionally, advertising hedonic products with low sex appeal ads may be more effective than employing such ads for utilitarian products.

Limitations and Future Directions

Social Expectation Bias

Social expectation bias led to the reversal of stated preferences to sexually appealing ads. In public, the participants stated that they preferred the low sex appeal ads. Future studies should employ different process measures (e.g., "think aloud" protocols or post-rating interview data) to justify this explanation. There should be a high correlation between social desirability and the stated preference for low sex appeal ads. Open-ended responses may reveal participants' dislike for high sex appeal advertising for moral reasons. Another method would be to use procedures such as guaranteed private and anonymous data collection to minimize social expectation bias and emotional response display rules (e.g., Ekman, 2006). We believe that the stated preference reversal may be weaker or disappear altogether if privacy and anonymity are guaranteed[1].

Sample Size

We determined our sample size (N = 21) based on previous studies that used EEG (Barry et al., 2003; Daurignac et al., 2006) and studies related to ours (Telpaz et al., 2015), however, our small sample size is still a limitation. We call for future studies to test our findings using a larger sample.

N200

We used the N200 component as an early indicator of initial preference. Although prior studies suggest that it predicts initial subjective preferences, recent studies have shown that N200 is a weak measure of preference (Goto et al., 2017). Future studies can further test the effectiveness of N200 as an indicator of preferences or use other components to measure early preferences.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because the data cannot be shared for privacy restrictions. Requests to access the datasets should be directed to QW, 850703661@qq.com.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Local Ethics Committee of Zhejiang University of Technology. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

FH, LZ, and QS conceived and designed the experiments. YL and QW performed the experiments. YL, QW, and WX analyzed the data. FH and QS drafted the manuscript. QS and QW revised the manuscript. QS edited the manuscript.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Olfaction Modulates Inter-Subject Correlation of Neural Responses

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Odors can be powerful stimulants. It is well-established that odors provide strong cues for recall of locations, people and events. The effects of specific scents on other cognitive functions are less well-established. We hypothesized that scents with different odor qualities will have a different effect on attention. To assess attention, we used Inter-Subject Correlation of the EEG because this metric is strongly modulated by attentional engagement with natural audiovisual stimuli. We predicted that scents known to be "energizing" would increase Inter-Subject Correlation during watching of videos as compared to "calming" scents. In a first experiment, we confirmed this for eucalyptol and linalool while participants watched animated autobiographical narratives. The result was replicated in a second experiment, but did not generalize to limonene, also considered an "energizing" odorant. In a third, double-blind experiment, we tested a battery of scents including single molecules, as well as mixtures, as participants watched various short video clips. We found a varying effect of odor on Inter-Subject Correlation across the various scents. This study provides a basis for reliably and reproducibly assessing effects of odors on brain activity. Future research is needed to further explore the effect of scent-based up-modulation in engagement on learning and memory performance. Educators, product developers and fragrance brands might also benefit from such objective neurophysiological measures.

Keywords: inter-subject correlation (ISC), electroencephaloagraphy (EEG), attention, reliability, fragrance, olfaction

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INTRODUCTION

The flavors and fragrance industry has traditionally focused on the discovery and blending of raw ingredients to create taste and scent profiles for a wide range of product categories. While the process to extract, synthesize, formulate and deliver fragrance materials has advanced over the decades, the focus and methods for consumer testing remain largely unchanged – relying on creative briefs from brands, professional scent design, expert and technical evaluations, and the self-report ratings of sensory and naïve consumer panels to substantiate desired sensorial attributes and performance (Mattei et al., 2015).

In response to a growing demand from consumers the flavors and fragrance industry is increasingly focused on delivering proven functional benefits related to health and wellness that go beyond traditional approaches such as Aromatherapy (Hongratanaworakit, 2004) or anecdotal evidence (e.g., "lavender oil is good for sleep" or "peppermint oil is energizing").

The general effects of odors on cognitive function have been studied intensively (see **Table 1**). However, the evidence for effects of specific fragrances is sparse. Anecdotal evidence from aromatherapy and academic studies have shown that select essential oils can have a positive impact on cognitive functions, e.g., attention, alertness, learning and memory (e.g., Rasch et al., 2007; Moss and Oliver, 2012; Moss et al., 2014). However, few studies, if any, have systematically characterized the functional benefits of a broader range of scent materials that include both synthetic molecules and mixtures. Our goal is to identify objective neurophysiological measures of the effects of individual scents on cognitive function.

The effects of olfactory stimulation on brain activity have been well-characterized (Herz et al., 2004; Osterbauer et al., 2005; Gottfried et al., 2006; Li et al., 2008; Plailly et al., 2008; Howard et al., 2009), but the specific effects of different fragrances is not well-established (Brauchli et al., 1995; Martin, 1998; Lorig, 2000; Kroupi et al., 2014). In the current study, we employed a validated, cost-effective and practical approach based on electroencephalography (EEG). Traditional EEG research has largely employed event-related designs, which analyzes the immediate (<1 s) response after stimulus presentation. Due to the slower speed of delivery and sensory processing it has been difficult to do the same with odors (Lorig et al., 1993, 1999). Other approaches use oscillatory EEG activity which fluctuate on a slower time scale. For example, alpha activity (10 Hz oscillation) fluctuates in power on a scale of 10 s, and is known to be modulated by attention (Klimesch, 2012) but there are no consistent reports of olfaction on alpha activity (Lorig, 2000).

Instead, here we rely on a recent finding that EEG evoked activity can be significantly correlated between subjects while they watch naturalistic video stimuli, such as TV shows (Dmochowski et al., 2012), video advertising (Dmochowski et al., 2014), YouTube clips (Cohen and Parra, 2016), or movie trailers (Barnett and Cerf, 2017). Correlation of brain activity across subjects measured with functional MRI has been linked to memory and efficacy of communication (Hasson et al., 2008; Honey et al., 2012; Zadbood et al., 2017). Importantly, the level of this Inter-Subject Correlation in the EEG (ISC) is strongly modulated by attention (Ki et al., 2016) and is predictive of memory (Cohen and Parra, 2016), learning (Cohen et al., 2018; Bevilacqua et al., 2019) and audience retention (Cohen et al., 2017). The presumed mechanism for this in EEG is that attention increases evoked response magnitude and this in turn increases ISC (Ki et al., 2016; Poulsen et al., 2017). The main conclusion of this work is that ISC can be used as a marker of attentional engagement with naturalistic stimuli. In other words, ISC measures how alert subjects are as they perceive their natural environment. Here we propose to use ISC as an objective measure of the effects of scents on attentional engagement. Our specific hypothesis is that ISC of the EEG is modulated by exposure to fragrances during the viewing of a video narrative. In this work, we test this hypothesis directly with the goal to establish the ISC of the EEG as an objective measure for the impact of fragrances on alertness.

TABLE 1 | Summary of studies showing function benefits of scent exposure.

Topic	References
Smoking cessation	Arzi et al., 2014
Olfaction perception in sleep	Carskadon and Herz, 2004
Memory	Diekelmann and Born, 2010
Learning	Stickgold, 2012
Learning	Arzi et al., 2012
Clerical tasks associated with administration	Barker et al., 2003
Alertness and math computations	Diego et al., 1998
Anxiety reduction	Redd et al., 1994
Severity of labor pain	Yazdkhasti and Pirak, 2016
Pain tolerance	Prescott and Wilkie, 2007

RESULTS

Overview of Experiments and Objectives

Experiment 1 was a pilot experiment to test the effects of two odorants relative to a no-odor control. We used eucalyptol, considered an "energizing" odor (Moss and Oliver, 2012), and linalool, considered "calming" (Kuroda et al., 2005; Höferl et al., 2006). The primary outcome measure was ISC of the stimulus-evoked response while participants watched short animated autobiographical narratives (StoryCorps/Modern Love) video clips (see Cohen and Parra, 2016). The goal was to determine whether attentional engagement with the naturalistic audiovisual stimulus can be modulated by concurrent presentation of contrasting scents. The secondary outcome measures were traditional event related potentials and power of oscillatory activity.

Experiment 2 was a single-blind replication and optimization study, which sought to determine whether the results depended on the specific video clips used and what signal duration was necessary to obtain robust results. Here we used eucalyptol and limonene to test if the effect on ISC generalizes to other "energizing" odors such as limonene (Heuberger et al., 2001; Herz, 2009). Analysis focused on the primary outcome measures of ISC.

Experiment 3 was a double-blind screening study with 10 odors covering mixtures and single molecules with varying degrees of trigeminal stimulation (Doty et al., 1978). The goal was to test whether we obtain a differential effect of odors on ISC. Both participants as well as experimenters were blind to the nature or identity of the test odorants.

In all experiments, the videos were counterbalanced so as to appear equally often in all odor conditions. In all cases, ISC was compared with values within subjects to remove random variability across subjects.

Experiment 1: Eucalyptol Enhances ISC but Has No Effect on Odor-ERP or Alpha Power

Participants ($N = 19$) watched 6 video clips (2–3 min each, Cohen and Parra, 2016) in two blocks of three videos. Each block was paired with one of three odor conditions (eucalyptol, linalool

and no-odor vehicle), repeating each block three times such that all videos were paired with all odor conditions. Order of video blocks and odors were couterbalanced across subjects to control for temporal order effects. To prevent habituation, odors were presented in brief 6 s bursts repeated every 30 s (Tabert et al., 2007). The concentrations of the odorants were adjusted prior to the experiment to provide similar subjective intensity. To verify this, all subjects were asked to rate on a scale of 0 to 10 the "intensity" of each odor at the beginning of the experiment (**Figure 1**). Both odorants were perceived to be stronger than the no-odor control [eucalyptol: $t(18) = 13.66$, $p < 10^{-9}$; linalool: $t(18) = 11.5$, $p < 10^{-9}$]; all p values in this paper are two sided and computed with a paired t-test except where otherwise stated), but no different from one-another in intensity [$t(18) = 1.71$, $p = 0.10$]. Therefore, any difference we may find in the neural responses cannot be attributed to differences in perceived odorant intensity.

Inter-Subject Correlation of the stimulus-evoked EEG was measured using established techniques (Parra et al., 2018). We computed ISC values averaged over the 6 video clips corresponding to 18.7 min of EEG data. There was a significant increase in ISC when the videos were presented with eucalyptol as compared to both linalool and the no-odor control [**Figure 2**, left; linalool: $t(18) = 3.05$, $p = 0.007$, no-odor: $t(18) = 3.64$, $p = 0.0019$]. The EEG components that capture the largest correlation between subjects (**Figure 2**, right) were similar to previous results obtained for these video stimuli in the absence of olfactory stimulation (Cohen and Parra, 2016). This suggests that the increase in ISC is the result of a modulation of visual and auditory activity elicited by the audiovisual stimulus, rather than odor-evoked responses. It is interesting to note that both eucalyptol and linalool are trigeminal in nature (Doty et al., 1978), but only eucalyptol up-modulated ISC. Therefore, it is unlikely that the modulation is caused by an overall increase in alertness caused by trigeminal stimulation alone.

No Effect of Odors on ERP or Oscillatory Power

We also measured traditional event related potentials (ERPs) following the onset of odor exposure (**Figure 3**, left). Statistical testing of all electrodes and time delays up to 1 s after odor onset show no significant difference between odors and controls ($N = 722$ events in each condition; no time/electrode combination passes $p = 0.05$ after FDR correction for 32*256

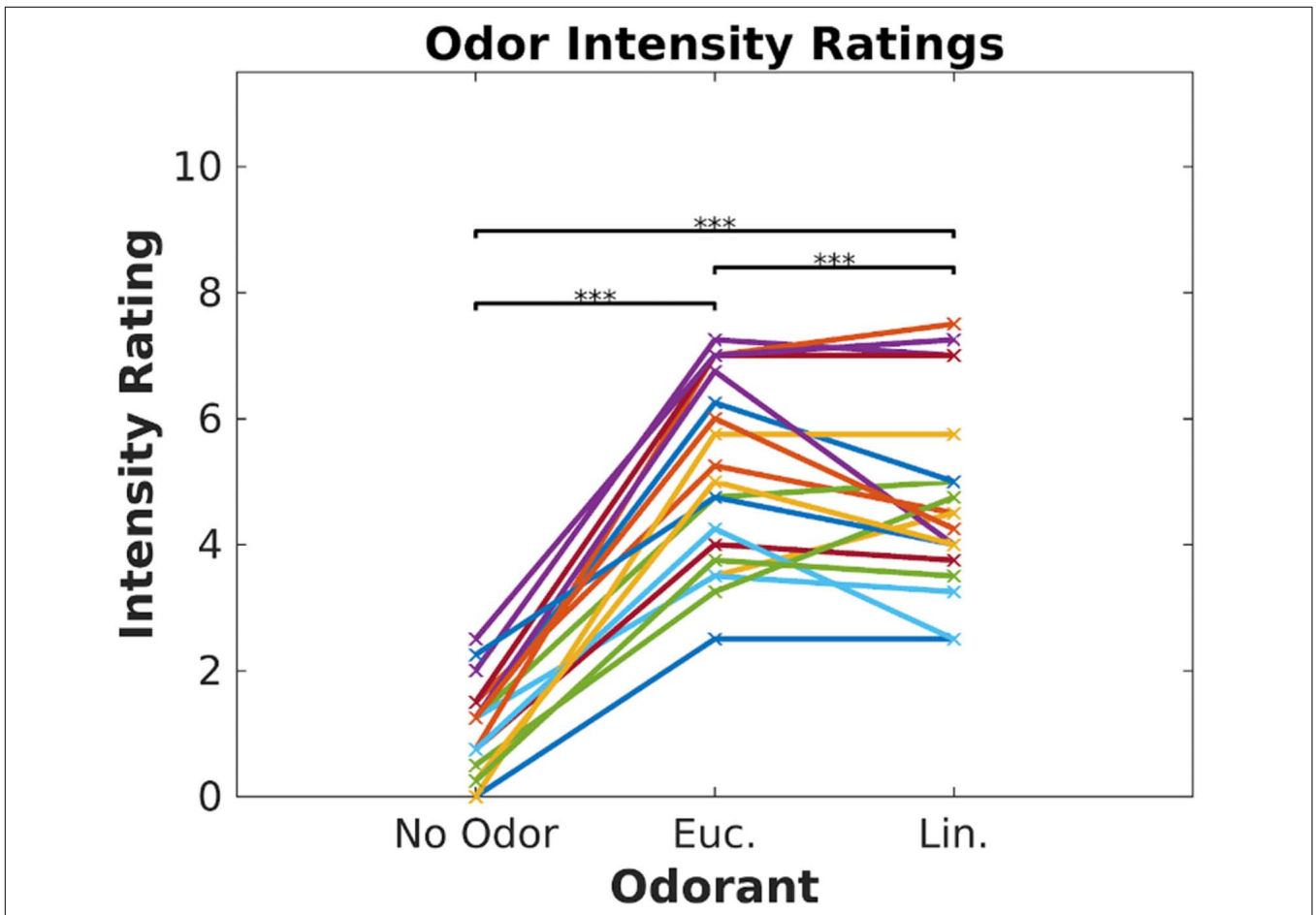


FIGURE 1 | Odor intensity was equalized for Eucalyptol and Linalool. Ratings of perceived intensity for the 2 odorants and the no-odor control in Experiment 1. Each participant is shown as a line and values are the mean of 4 repeated ratings per participant. The result of pairwise testing for significance is indicated as $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

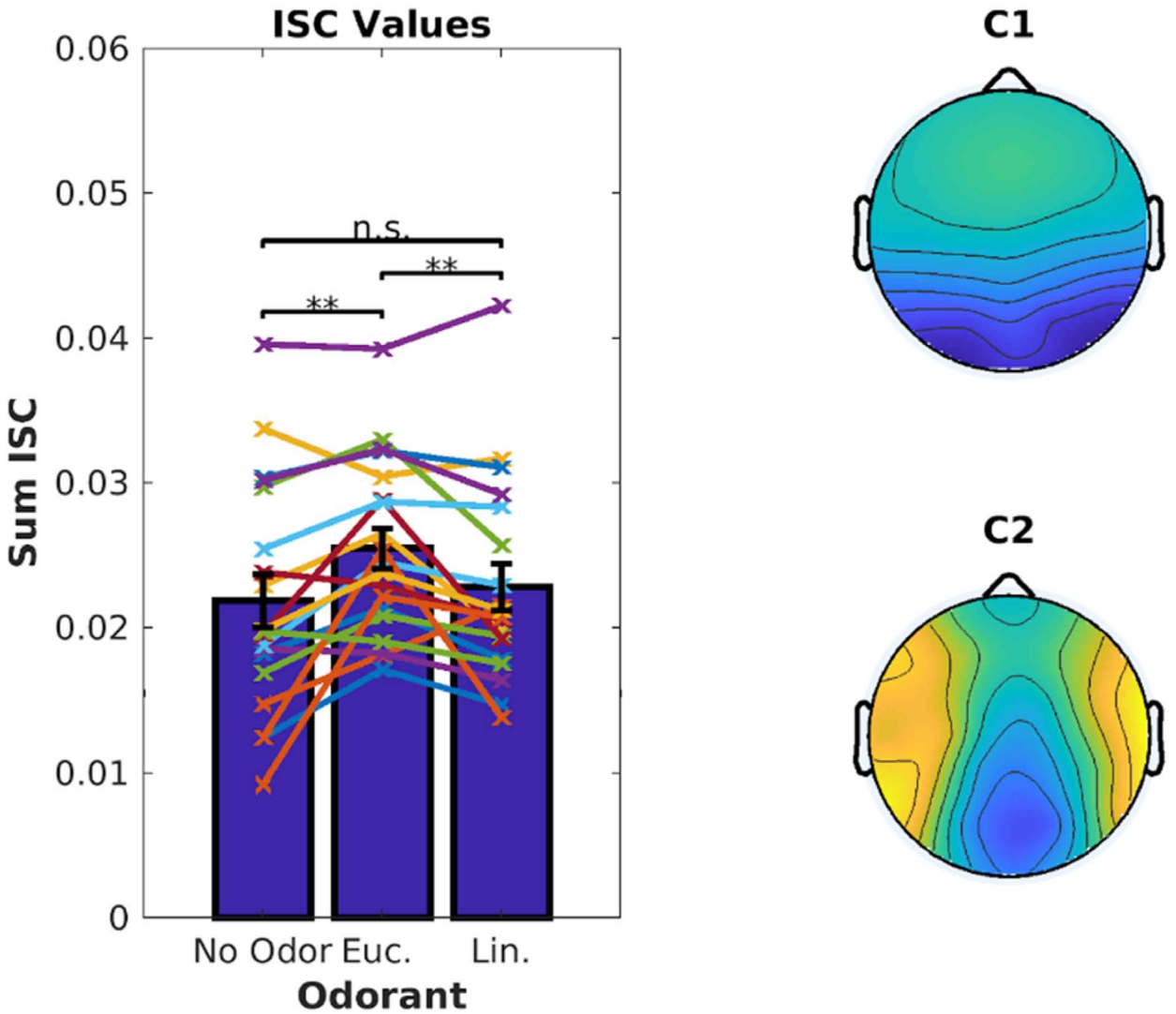


FIGURE 2 | Inter-Subject Correlation of the EEG during video presentation is enhanced by Eucalyptol, but not Linalool. Inter-Subject Correlation (ISC) is measured by combining signals from multiple EEG electrodes and measuring the correlation coefficient of the time courses between one subject and all others exposed to the same video clips. **Left:** ISC values for individual participants averaged across all videos for the 3 odor conditions shown as line graphs. The corresponding average values are shown as bars. **Right:** The combination of electrodes is reflected in components with a spatial distribution shown here across the scalp. These top two EEG components are maximally correlated between the participants.

comparisons). We also measured oscillatory power in that same time period, but now resolved by frequency between 0 and 20 Hz (**Figure 3**, right). There was no evident effect at any frequency or electrode. Thus, in this pilot study, we did not see an effect of odors on ERPs or oscillatory power, the two most conventional outcome metrics for EEG.

Experiment 2: Reliability and Scalability

Our ultimate goal was to perform routine biometric testing on a large number of fragrances and scents. Thus, the objective of Experiment 2 was to determine if the modulation of ISC depended on the specific videos used and whether we could use shorter video stimuli. We used the same six videos as in Experiment 1, but fixed the presentation order (**Figure 9**). Participants ($N = 14$) were exposed to eucalyptol and limonene as a second "energizing" odor (Heuberger et al., 2001; Herz, 2009) with low levels of trigeminal nerve activation at moderate intensity levels (Doty et al., 1978). Participants rated the two odors similarly in terms of odor intensity [**Figure 4**, left; ($t(13) = 0.039$, $p = 0.97$]. We also asked participants to categorize odors as "calming" or "energizing" (**Figure 4**, right). Both odors were judged in similar proportions as calming and energizing.

We first computed ISC combining all 6 video clips with ∼18 min of data per odor condition. As before, eucalyptol up-modulated participants' ISC compared to the no-odor control [**Figure 5**, left, $t(13) = 3.85$, $p = 0.002$]. Limonene did not increase ISC over the no-odor control [$t(13) = 0.41$, $p = 0.69$], and was

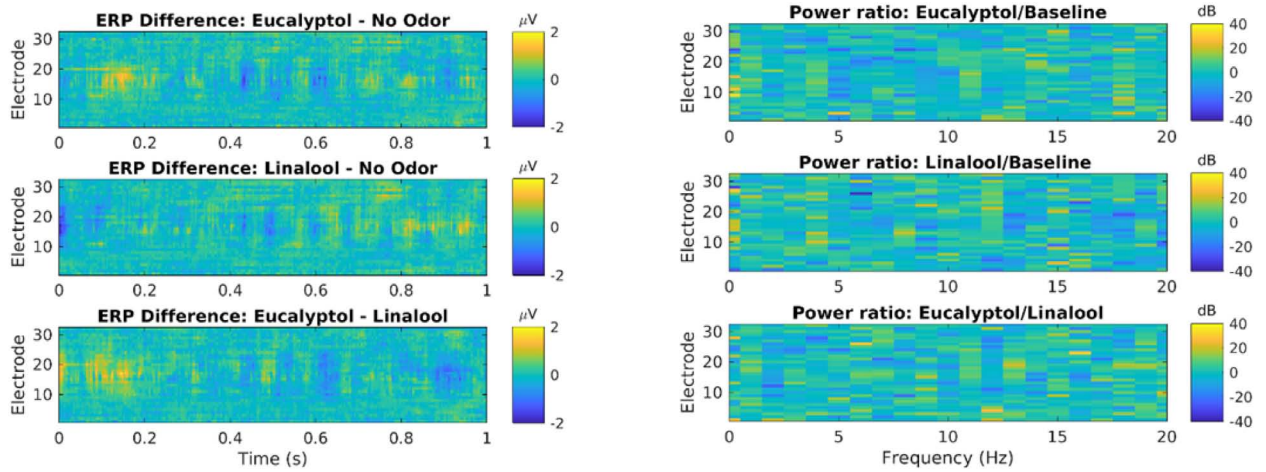


FIGURE 3 | Odor event-related potentials and oscillatory power are not significantly modulated by Eucalyptol of Linalool relative to no-odor control. **Left:** Event related potential (ERP) elicited by odor presentation, shown here for all electrodes as a time resolution of 2 ms. ERP is the average over all odor exposure events (722 odor presentations events from 19 subjects). Here the difference in ERP between different odor conditions is shown. Time is measured relative to odor onset. Statistical testing showed no significant difference (shuffle statistics, $N = 1000$ randomizations, only ∼1% of time-electrode bins cross a $p < 0.01$ threshold). **Right:** Power of oscillations of the EEG was analyzed in each electrode and different frequency bands. Shown are the log-power difference in the 1 s following odor exposure for different electrodes and frequency bins (0.5 Hz). No statistical testing was performed as there are no evident differences in power.

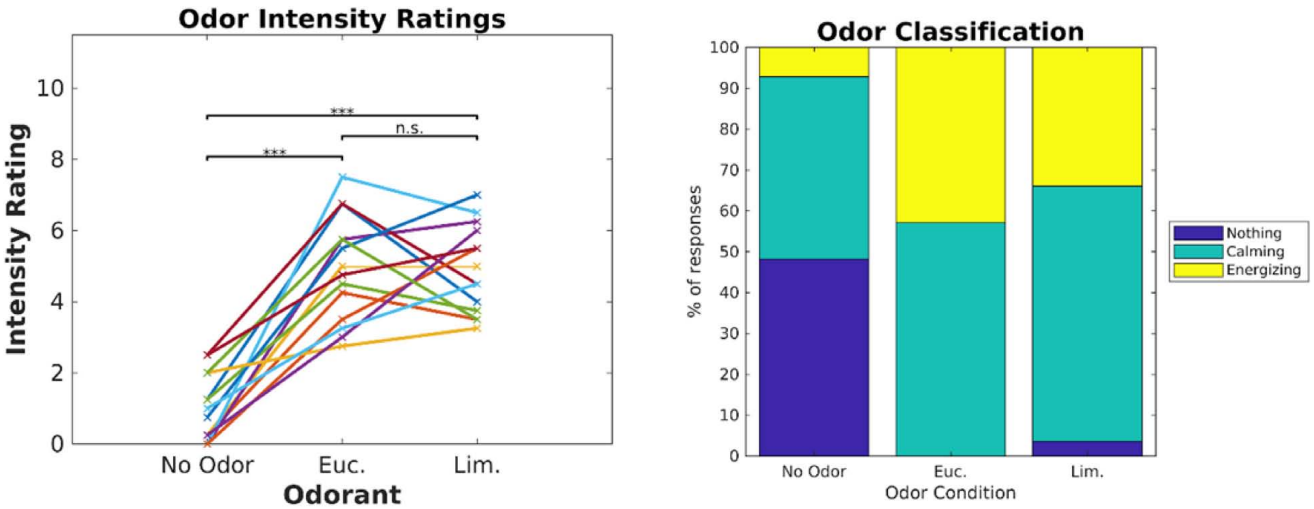


FIGURE 4 | Eucalyptol and Limonene were equalized in intensity and were similarly rated as "calming" or "energizing." **Left:** Individual ratings of perceived intensity for the 2 odorants and the no-odor control in Experiment 2. **Right:** Percent of participants that perceived the odorants as calming, energizing or neutral. The result of pairwise testing for significance is indicated as $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

lower than eucalyptol [$t(13) = 2.62$, $p = 0.021$]. This replicates the results of Experiment 1 for eucalyptol but does not apply to limonene which is traditionally considered to be energizing. Therefore, a boost in ISC should not be considered a measure of "energizing" effects of odors in the traditional sense of the aromatherapy literature.

We obtained similar results when we computed ISC with shorter data segments of ∼3 min from individual videos (**Figure 6**). The spatial distribution of the corresponding correlated components was also well-preserved, which further attests to the robustness of results with shorter data segments. To test if the choice of video clip has an effect on the modulation of ISC, we performed a three-way ANOVA (with subject as a random effect). As expected, we found again an effect for odor [$F(2) = 6.2$, $p = 0.0024$]. We also found an effect for video [$F(5) = 23.8$, $p < 10^{-9}$] indicating that some videos elicited higher ISC than others, but we found no interaction between video and odor [$F(10) = 1.15$, $p = 0.334$]. This suggests that odors modulate ISC similarly for different video clips. Although, given the shorter segments, one should note that on individual videos the expected trend is not preserved (e.g., video 2; **Figure 6**).

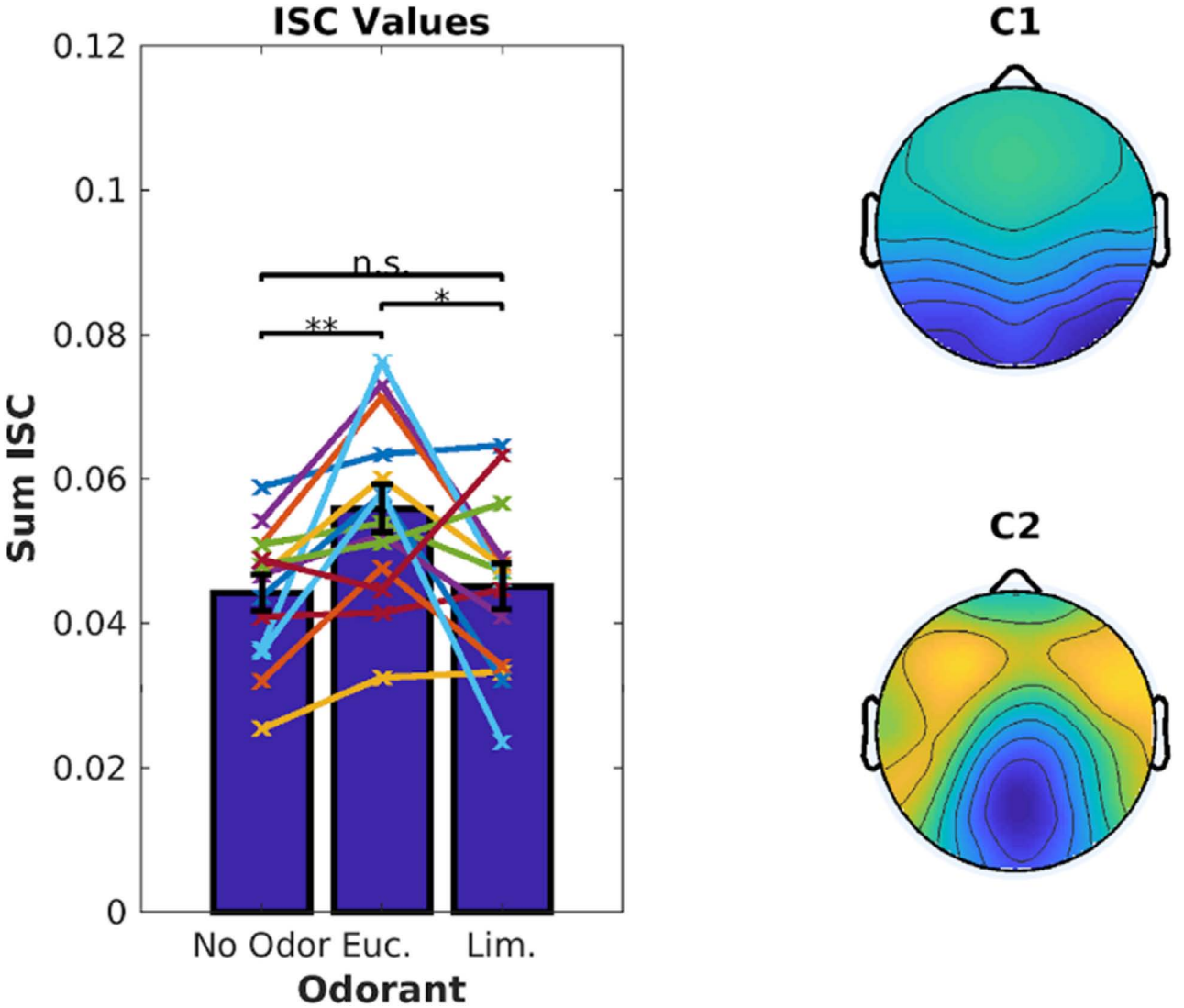


FIGURE 5 | Eucalyptol enhanced ISC but not Limonene. **Left:** ISC values for individual participants averaged across all 6 videos for the 3 odor conditions. Each line represents a participant. The corresponding average values are shown as bars. **Right:** The top 2 EEG components that are maximally correlated between the participants. They are similar to those in **Figure 2**. Result of pairwise testing for significance indicated as $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Finally, we repeated the oscillatory power analysis (as in **Figure 3**, right) and found no differences in power between Eucalyptol and Limonene relative to one another or relative to no-odor anywhere between 0 to 20 Hz (not shown).

Experiment 3: Differential Effect of a Battery of Odors on ISC

The results from Experiment 1 and 2 showed that odor based modulation of ISC can be reliably measured over a period of 3 min. Experiment 3 was designed to extend these findings to odors with a wide range of odor character, trigeminal quality and complexity (mixtures vs single molecules). Each participant (N = 20) watched a video clip paired with one odor, and again in a separate session on a separate day without the odor (see methods). The pairing of the 10 video clips with the 10 odorants was randomized, and the order of the odor/no-odor condition counterbalanced across the two sessions. Neither participants, experimenters or data analysts were aware of the name or nature of these odorants.

Participants were again asked to rate odor intensity and rate them as "energizing" or "calming" (**Figure 7**). A one-way repeated measures ANOVA found no difference in the subjective intensity ratings across odors [$F(9) = 0.93$, $p = 0.50$, **Figure 7**, top]. Generally, odorants were judged more often as calming, and this did not significantly differ between odorants [$F(9) = 0.46$, $p = 0.90$, **Figure 7**, bottom].

Overall, the odors enhanced ISC compared to no-odor control [**Figure 8**, top; $t(18) = 2.2$, $p = 0.038$]. There appears to be a difference between odorants on the degree to which

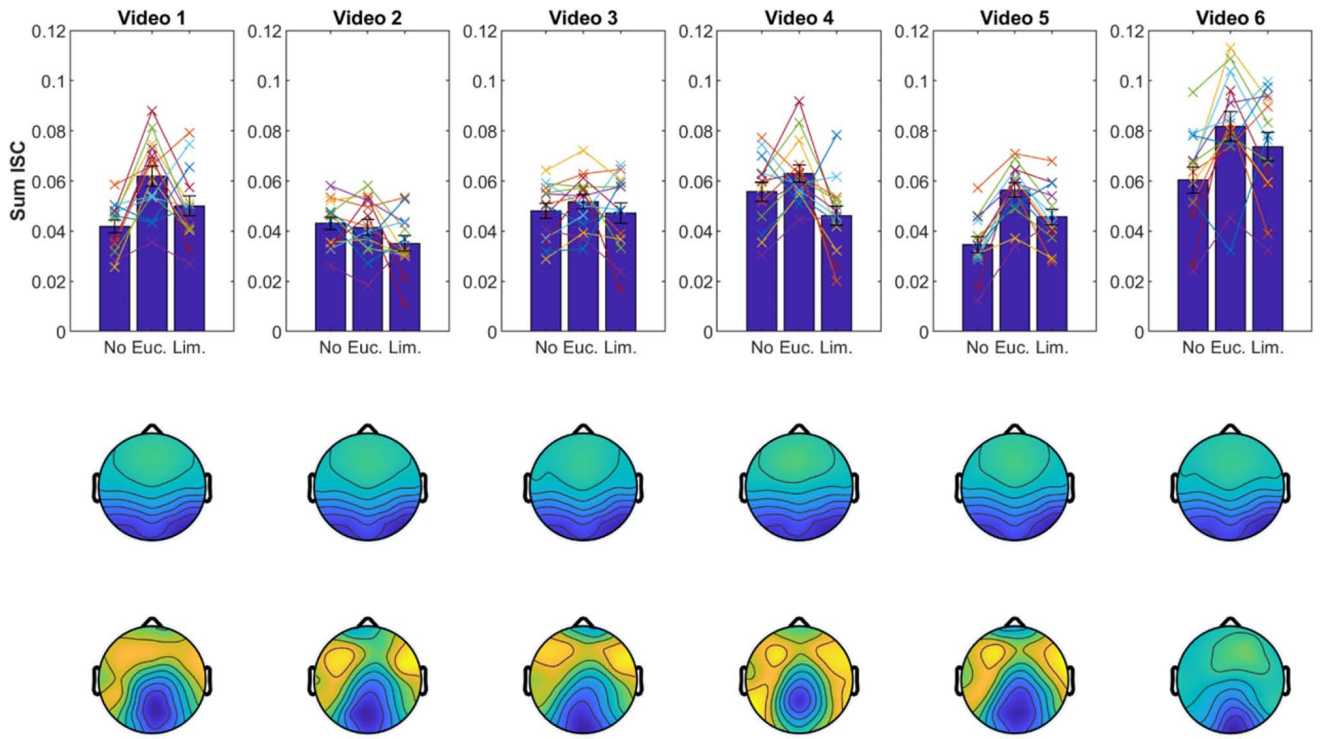


FIGURE 6 | Results replicate with shorter data segments. Same display as in **Figure 4** but ISC values and correlated components are computed separately for each video clip (∼3-min duration each).

they modulated ISC (**Figure 8**, bottom). However, a one-way repeated-measures ANOVA on the change in ISC does not resolve this effect [odor – non-odor: $F(9) = 0.67$, $p = 0.73$]. We found strongest modulation for Phenyl ethyl alcohol (PEA, rose) followed by Rosemary Oil and Eugenol, with a significant modulation for PEA [$t(18) = 2.3$, $p = 0.034$] and Eugenol [$t(18) = 2.12$, $p = 0.048$]. Interestingly, both PEA and Eugenol are considered to have low trigeminal effects at moderate perceived intensity levels, while Citral and Peppermint are known to have pronounced trigeminal effects (Doty et al., 1978). This further suggests that trigeminal stimulation is not driving the observed effects. Furthermore, the primary component of Rosemary Oil is Eucalyptol, which means that the up modulation with Eucalyptol has been replicated across 3 different experiments with 3 different sets of participants; lending further support to the robustness of this effect and our ability to reliably measure it.

DISCUSSION

In summary, we have shown that Inter-Subject Correlation of the EEG evoked by narrative auditory-visual stimuli is reliably and reproducibly modulated by olfactory stimuli and that this modulation is dependent on the particular odorant being presented. We have further shown that in odors across a range of olfactive qualities, this modulation is not dependent on the nature of the video, trigeminal nature of the odorant (**Table 2**), or whether the odorant is categorized as energizing or calming.

While we replicated results for eucalyptol in each of the 3 studies, the differences between 10 different odors could not be reliably resolved with a sample of 20 subjects. We ascribe this to the variability observed in ISC across subjects. For a systematic ranking of a larger number of odors, we thus recommend larger sample sizes. Subsequent studies may explore the reliability of odor ranking as a function of sample size. On the flip side, we do not believe that one requires as many electrodes as have been used here ($N = 32$). In practice, it may suffice to use 16 or even 8 electrodes, provided they are strategically placed. An additional caveat is the selection of videos. Here we used a set of 10 different short video clips to keep participants interested in the material. We do know that different stimuli will elicit different levels of ISC. By controlling with a no-odor condition with the same video clip we may have reduced some of this variability. However, it is possible that using different video material does add variability to the study. Future studies that seek to use ISC on a routine basis to evaluate odors may need to parametrize the dependence of the video stimuli used and possibly standardize the results.

The components with maximal ISC observed in this series of experiments are similar to those we observed previously with purely audiovisual stimulation (e.g., Cohen et al., 2017), suggesting that odorants modulate auditory-visual processing rather directly driving the neural response. This is confirmed by

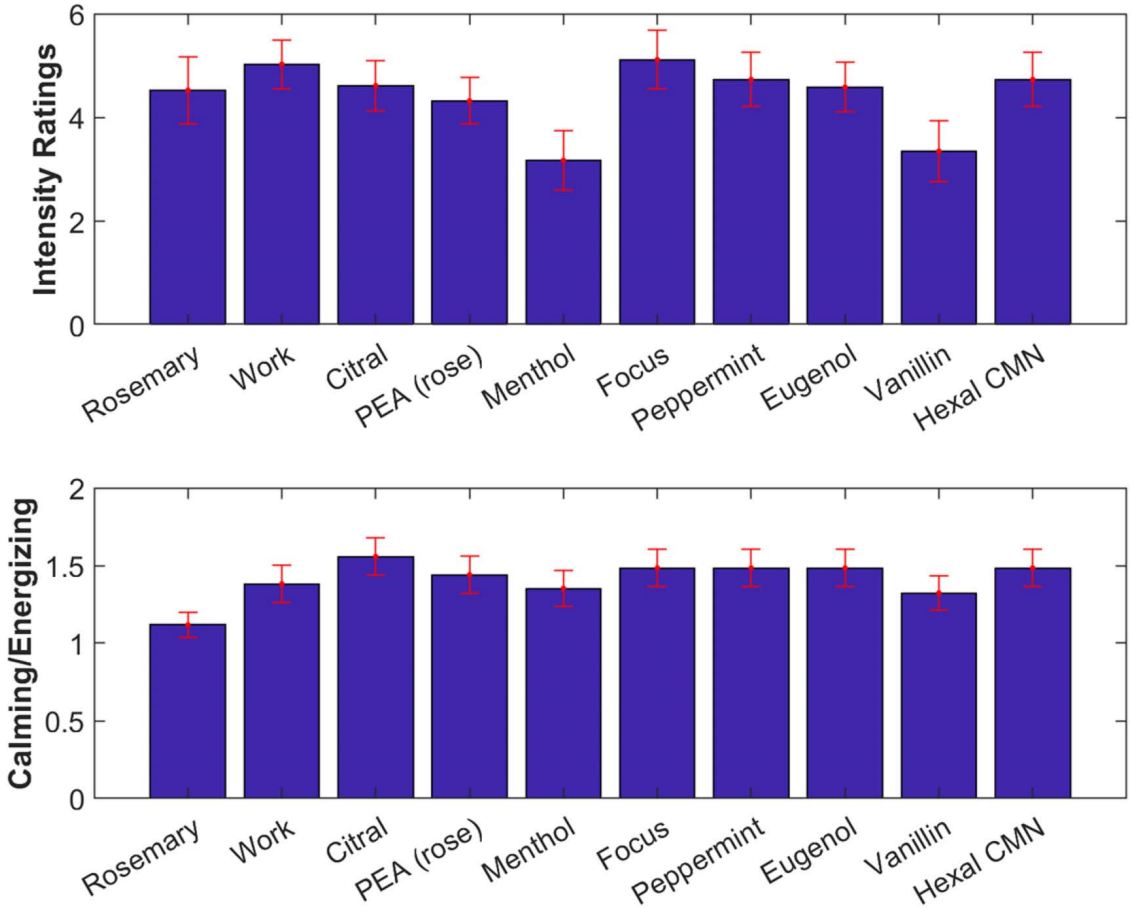


FIGURE 7 | All odorants tested were subjectively similar in intensity and quality. **Top:** Subjective intensity ratings averaged over all participants. Error bars (red) indicate standard error of the mean. **Bottom:** Ratio of number of participants rating odorants as calming vs energizing.

the lack of a direct observation of odor event-related potentials. The components of the EEG extracted with the present technique during video watching are known to be multisensory (Cohen and Parra, 2016). The spatial distributions of these components on the scalp are very similar to those earlier studies. Multisensory components that are broadly distributed are difficult to localize with EEG (if nothing else, because inverse modeling in EEG is an ill-posed problem). Nonetheless, earlier fMRI studies have attempted at localizing these components (Dmochowski et al., 2014) and identify correlated fMRI activity in the superior temporal sulcus likely due to auditory processing, as well as activity in the precuneus and anterior cingulate, which have been interpreted in that earlier study as self-referential processing. Further studies will need to be designed to explore the underlying neural mechanism for the effects observed here, specifically in the context of odors.

We have found here that odors modulate the EEG activity evoked by natural dynamic audiovisual stimuli. This is consistent with existing reports that odors can modulate visual and auditory event-related potentials. For example, odor modulate ERPs evoked by images of faces (Bensafi et al., 2002; Cook et al., 2015; Leleu et al., 2015; Syrjänen et al., 2018). Visual ERPs are also modulated when paired with congruent or incongruent olfactory stimuli (Seo et al., 2010; Robinson et al., 2015). Animal experiments also show a modulation of auditory evoked responses in the presence of odors (Halene et al., 2009). A recent study shows that ERPs in response to fearful images is modulated in infants by the scent of the mother (Jessen, 2019). This phenomenon was explained as an attentional effect (the presence of the mother allows the infant to attend less to threatening stimulus). Attention is well known to modulate the magnitude of auditory and visual evoked responses, this in turn results in increased ISC (Poulsen et al., 2017). Given the known modulation of ISC with attention (Ki et al., 2016), it is likely that varying attention accounts for the modulation observed here with different odors.

Despite this interpretation, one important caveat of the study is that we have used relatively small sample sizes here. Additionally, we have no behavioral readout of attention and therefore cannot draw strong conclusions in this regard. An alternative explanation is that the stimuli were physiologically arousing (Cuthbert et al., 2000) and this affected evoked response

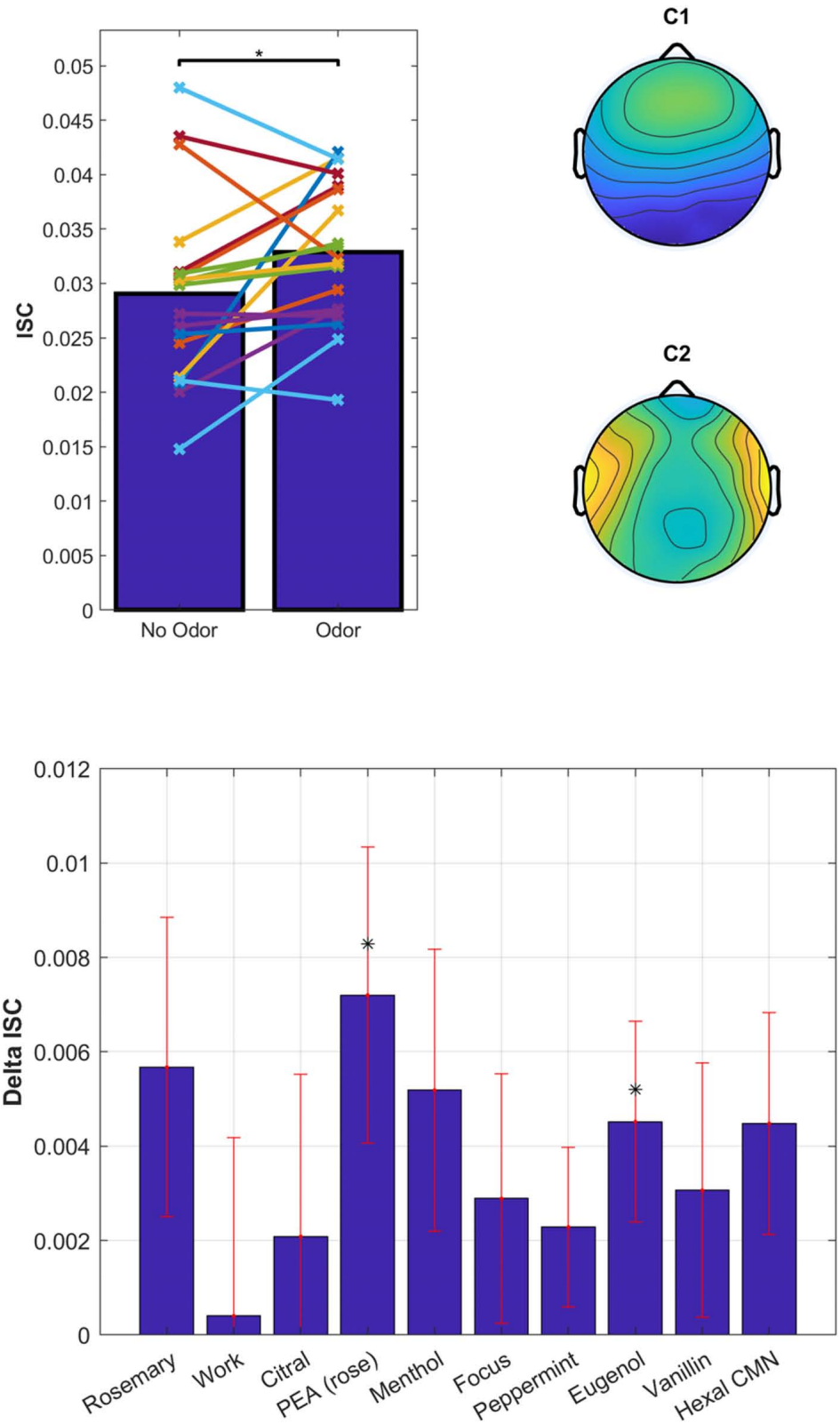


FIGURE 8 | Odorants have a differential effect on ISC of the EEG elicited by audiovisual stimuli. **Top:** ISC values averaged over all odorants and non-odorant conditions. Each line represents a participant (N = 20). Spatial distribution of the EEG components with the largest correlation suggestive of visual and auditory processing. **Bottom:** Delta ISC (odor minus non-odor) averaged across subjects. Error bars (red) indicate standard error of the mean.



FIGURE 9 | Study design used in Experiment 2. The order of videos was fixed and counterbalanced across participants. The no-odor control condition was always presented in-between the two odor conditions in order to minimize any carry over effects.

magnitudes without affecting attention. Ultimately, the blinded randomized sham-controlled trials we have performed here can only conclude that odors had an effect on ISC.

We analyzed alpha power given its established link to attention during sensory processing. Typically, alpha power is attenuated over sensory cortices during active and attentive processing of a visual or auditory stimulus (Foxe and Snyder, 2011). Yet, we did not find an effect of odor on alpha power. Given our interpretation of the effect of odor on ISC as a modulation of attention, this null result is particularly surprising. We had previously established that attention modulates both ISC of evoked responses as well as alpha power (Ki et al., 2016). But, the effect size of attention on alpha is quite a bit weaker than on ISC. It is possible that here, the attentional modulation was not sufficient to affect a measurable modulation of alpha power. In fact, ISC modulation is relatively weak here. An alternative explanation is that the effect of odor on audiovisual evoked response magnitude is direct (as discussed above). In that scenario, odors might not modulate attention toward the stimulus, but directly modulate sensory evoked responses.

We also did not find a modulation of potentials evoked by the odor itself, i.e., odor-evoked ERPs. In our reading of the literature, the odor-evoked ERP is relatively weak (Lorig et al., 1993, 1999). It may be that we did not collect long enough records or a sufficient number of subjects to resolve an attentional effect on what is already a weak ERP signal.

Given the extensive literature linking ISC modulation to attention and engagement with a natural audiovisual stimulus, we conclude that olfaction can have a differential modulatory effect on how alert we are when perceiving the natural world in a holistic and multisensory context. Importantly, previous studies have shown that ISC values while watching educational videos predict learning performance as measured by performance on a follow-up test like questionnaire (Cohen et al., 2018), or that subjects with higher ISC have better recall of episodic memories (Cohen et al., 2017). In future studies, we plan to explore if up-modulation in engagement driven by odors results in a similar increase in learning and memory performance. In doing so, Inter-Subject Correlation may help educators to improve attention and cognitive performance of students, as well as brands, to substantiate marketing claims made on the functional benefits of fragrances, which currently have to rely on more subjective measures of mood and emotion, or more broadly

TABLE 2 | List of odorants tested in Experiment 3.

Odorant	Category	Dosage (%)	Trigeminal
Peppermint oil	Essential oil	0.3	Yes
Rosemary oil	Essential oil	0.3	Yes
Citral refined	Molecule	1	Yes
Fragrance focus	Mixture	0.3	Yes
Fragrance work	Mixture	0.3	Yes
Hexyl Cinn Ald	Molecule	15	No
Vanillin	Molecule	0.3	No
Phen Ethyl Alc	Molecule	0.1	No
Eugenol USP	Molecule	0.3	No
Menthol	Molecule	3	Yes

TABLE 3 | Videos used in Experiment 1 and Experiment 2.

Vid ID	Duration	URL
1	3:17	https://www.youtube.com/watch?v=okF5UGpivR8
2	3:56	https://www.youtube.com/watch?v=yfWa9gI-Bks
3	3:03	https://www.youtube.com/watch?v=yAC-z8F0Mdw
4	3:17	https://www.youtube.com/watch?v=iGnCvLPZm84
5	3:02	https://www.youtube.com/watch?v=Nf3MM7jzkZw
6	2:07	https://www.youtube.com/watch?v=6m85l_UqM5I

TABLE 4 | Videos used in Experiment 3.

Vid Group	Vid ID	Duration	URL	Vid ID	Duration	URL	Total duration
A	1	3:17	https://www.youtube.com/watch?v=okF5UGpivR8	11	2:48	https://www.youtube.com/watch?v=gvdlaLHYUws	6:05
B	2	3:56	https://www.youtube.com/watch?v=yfWa9gI-Bks	12	2:33	https://www.youtube.com/watch?v=bW82E98FBCA	6:29
C	3	3:03	https://www.youtube.com/watch?v=yAC-z8F0Mdw	13	3:15	https://www.youtube.com/watch?v=ZPlaVilHr5M	6:18
D	4	3:17	https://www.youtube.com/watch?v=iGnCvLPZm84	14	2:44	https://www.youtube.com/watch?v=jZK7rayEptw	6:01
E	5	3:02	https://www.youtube.com/watch?v=Nf3MM7jzkZw	15	3:33	https://www.youtube.com/watch?v=YvDtOigTH-g	6:35
F	6	2:07	https://www.youtube.com/watch?v=6m85l_UqM5I	16	3:59	https://www.youtube.com/watch?v=eO7sKVKMO2s	6:06
G	7	2:22	https://www.youtube.com/watch?v=KtGbpTOk844	17	3:39	https://www.youtube.com/watch?v=KQF79ch6mA8	6:01
H	8	2:07	https://www.youtube.com/watch?v=Tlk4ocdavm0	18	3:56	https://www.youtube.com/watch?v=iRpKjghGQec	6:03
I	9	2:04	https://vimeo.com/76641635	19	4:18	https://www.youtube.com/watch?v=xSKuOccVVKg	6:22
J	10	1:34	https://www.youtube.com/watch?v=XypF2zV_LVs	20	5:51	https://www.youtube.com/watch?v=WNfvuJr9164	7:25

There were 10 video groups which consisted of a pair of videos totaling to a duration of at least 6 min.

defined cognitive constructs and dimensions such as "energizing" and "calming."

MATERIALS AND METHODS

Stimulus Presentation, Data Collection and Analysis

For all experiments, the odors were delivered via a modified OLFACT^{TM} (Osmic Enterprises, Inc., Cincinnati, OH, United States) olfactometer. The delivery of the odor was synchronized with the respiration cycle as measured by a nasal flow pressure transducer (SleepSense Product Code: SS-14833/E). The odor was delivered for 6 s at the onset of an inhalation phase with a 24 s inter-stimulus-interval (ISI) (Tabert et al., 2007).

32-channel EEG, fitted in accordance with the 10/20 standard layout, and nasal respiration were recorded with a BioSemi ActiveTwo System (BioSemi, Amsterdam, Netherlands) at a sampling frequency of 2,048 Hz. The audio-visual stimuli were presented via Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007) on a flat screen computer monitor.

EEG data pre-processing steps followed the procedure described in previous studies (Cohen and Parra, 2016) in order to remove eye-movement artifacts. Outlier samples, defined as values exceeding three times the distance between the 25th and 75th quartile of the median centered signal, were identified within each channel and replaced with zero-valued samples including 40 ms of signal before and after the outlier samples.

Inter-Subject Correlation

ISC calculations for each condition followed an identical procedure to that described in previous studies (Cohen and Parra, 2016; Parra et al., 2018). Briefly, signals are linearly combined across electrodes to form "components." These component signals are correlated across time between subjects. Each subject pair provides a correlation coefficient, and these are then averaged over all subject pairs involving one participant. Therefore, for each participant and component, there is one ISC value. These are then summed over the strongest correlated components to arrive at Sum ISC values. The linear weights for each component are derived from the data by maximizing Sum ISC computed for all available data. When reporting Sum ISC per odor, we use only data during that odor presentation. ISC was calculated using the sum of top two components of EEG signal that maximally capture the correlated responses across participants. In earlier studies, we used 3 or more components (Dmochowski et al., 2012, 2014; Cohen and Parra, 2016; Ki et al., 2016; Cohen et al., 2017, 2018). Here, however, in experiment 1 we found that the higher components (3 and higher) were not consistent across odors and therefore decided to limit to the first two for the first and subsequent experiments.

As in previous studies there is significant variation in ISC across subjects. We control for this by measuring only the change in ISC, e.g., difference to no-odor, or difference between odors. This means that we are doing within-subject control by using a paired t-test or, equivalently, repeated-measures ANOVA with subject as random effect.

Study Stimuli

Odor Samples

For Experiment 1, Eucalyptol was diluted to 10% in Triethyl Citrate (CAS# 77-93-0). Other oils used in Experiment 1 and 2 (Linalool and Limonene) were neat oils. All presented stimuli were presented at iso-intense levels (**Figures 1**, **4**, **7**). Triethyl Citrate was presented by itself as a no-odor control.

For Experiment 3, the ten materials shown in **Table 2** were presented at concentrations to ensure iso-intensity with those presented in Experiment 1.

Video Clips

For Experiments 1 and 2, the same set of six video clips were presented (**Table 3**). All videos were professionally produced and

TABLE 5 | Subject demographics per experiment.

Experiment	Total	Number of female	Age (mean)	Age (SD)
1	19	11	20.2	3.6
2	14	8	20.6	2.8
3	20	13	20.9	2.1

TABLE 6 | Latin Square Williams design in Experiment 3.

	Vid Group 1	Vid Group 2	Vid Group 3	Vid Group 4	Vid Group 5	Vid Group 6	Vid Group 7	Vid Group 8	Vid Group 9	Vid Group 10
Subject 1	1	2	3	4	5	6	7	8	9	10
Subject 2	2	3	4	5	6	7	8	9	10	1
Subject 3	10	1	2	3	4	5	6	7	8	9
Subject 4	3	4	5	6	7	8	9	10	1	2
Subject 5	9	10	1	2	3	4	5	6	7	8
Subject 6	4	5	6	7	8	9	10	1	2	3
Subject 7	8	9	10	1	2	3	4	5	6	7
Subject 8	5	6	7	8	9	10	1	2	3	4
Subject 9	7	8	9	10	1	2	3	4	5	6
Subject 10	6	7	8	9	10	1	2	3	4	5
Subject 11	1	2	3	4	5	6	7	8	9	10
Subject 12	2	3	4	5	6	7	8	9	10	1
Subject 13	10	1	2	3	4	5	6	7	8	9
Subject 14	3	4	5	6	7	8	9	10	1	2
Subject 15	9	10	1	2	3	4	5	6	7	8
Subject 16	4	5	6	7	8	9	10	1	2	3
Subject 17	8	9	10	1	2	3	4	5	6	7
Subject 18	5	6	7	8	9	10	1	2	3	4
Subject 19	7	8	9	10	1	2	3	4	5	6
Subject 20	6	7	8	9	10	1	2	3	4	5

Additionally, each video was presented to each participant under a no-odor control condition. Therefore, a participant watched the same video twice – once with odor and once without odor.

of engaging narrative content and previously used in ISC studies (Cohen and Parra, 2016). For Experiment 3, there were 10 groups of videos used, where each of the 10 pairs of videos had a total duration of at least 6 min (**Table 4**).

Study Participants

For each study, a separate group of young male and female participants between 18 and 24 years old were recruited and provided written informed consent (**Table 5**). All participants self-reported normal ability to smell and had no known allergies to scent materials. All data collection and procedures were approved by Western Institutional Review Board (WIRB).

Experimental Design

All experiments followed a within-subject design. For Experiment 1, participants watched all 6 videos under all odor conditions – linalool, eucalyptol & no-odor condition. The videos were presented in blocks of three videos, with only one odor presented in any given block. The order of videos within each block, as well as the order of blocks for a given odorant, was randomized between participants. The presentation order of odorants was counterbalanced between participants. All participants evaluated the intensity of the odors on a 0–10 scale at the beginning of the session.

For Experiment 2 the same six videos as in Experiment 1 were used, but the order in which the videos were presented was fixed (**Figure 9**). This allowed us to perform ISC analysis on a subset of the videos to determine minimum length needed for a reliable response (results not presented), as well as determine if the delta (odor vs no-odor) depends on the specific films selected. All other aspects of the experiment design were identical to Experiment 1.

For Experiment 3, a set of 10 video groups were selected (each group consisted of a pair of videos totaling to a duration of at least 6 min) and tested in the presence of 10 odors (see **Table 2**). Here, a Latin Square Williams design was used so that each video group and olfactory stimulus was paired with each other and all video groups were presented with a no-odor control. The order of odors and video groups were pseudo-randomized and counterbalanced across participants. The complete design is shown in **Table 6**. The data was collected over two 60-min sessions for each participant.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Western Institutional Review Board (WIRB). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

LP, PD, AJ, and MT designed the experiment. PD performed the research. PD and LP analyzed the data. LP, PD, AJ, and MT wrote the mansucript. All authors contributed to the article and approved the submitted version.

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The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Measuring Neural Arousal for Advertisements and Its Relationship With Advertising Success

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Abundant research has established the important role of ad-evoked feelings on consumers' reaction to advertising. However, measurement of feelings through explicit self-report is not without its limitations. The current study adds to previous work by showing a sophisticated way of first estimating how arousal is represented in the brain via an independent task (using EEG), and thereafter using this representation to measure arousal in response to advertisements. We then estimate the relationship between the identified process (arousal) and external measures of ad effectiveness (as measured by notability and attitude toward the ad). The results show that the neural measure of arousal is positively associated with notability of ads in the population at large, but may be negatively associated with attitude toward these ads. The implications for the application of EEG in ad testing and for understanding the relationship between arousal and effective advertising are discussed.

Keywords: EEG, advertising, arousal, consumer neuroscience, neuromarketing, attitudes

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INTRODUCTION

Advertising is an important means for companies to convey to consumers what they have to offer and thereby brings together supply and demand. The successfulness of advertising is an important factor in increasing the sales of products and services. Multiple marketing research techniques are currently applied to develop effective ads and to assess their effectiveness. These methods range from self-report measures and focus groups to the more innovative autonomic measures and brain imaging techniques in small so-called "neural focus groups" (e.g., Poels and Dewitte, 2006; Ariely and Berns, 2010). In the present study, we specifically investigate the impact of arousal in response to advertisements as measured with EEG and assess the relationship between this "neural arousal" measure and measures of advertising effectiveness in an independent larger sample of the population.

For companies, it is important to assess consumers' responses to advertisements before spending substantial amounts of money on the broadcasting of an advertisement. These responses include consumers' judgments or cognitions about advertisements, but, critically, also consumers' first reactions and "feelings" in response to ads are deemed to be important (e.g., Burke and Edell, 1989). Abundant research has established that ad-evoked feelings are strong predictors of consumers' response to advertising (Edell and Burke, 1987; Holbrook and Batra, 1987; Stayman and Aaker, 1988; Burke and Edell, 1989; Olney et al., 1991; Morris et al., 2002; Pham et al., 2013).

An important component of these ad-evoked feelings is arousal (e.g., Holbrook and Batra, 1987). Arousal is a fundamental aspect of emotion and is defined as the intensity or level of activation of

one's (emotional) response (Lang and Bradley, 2010). Over the years, multiple studies in advertising have shown a positive relationship between measures of arousal and advertising effectiveness such as attitude toward the ad (Holbrook and Batra, 1987; Olney et al., 1991), attitude toward the brand (Holbrook and Batra, 1987), purchase intention (Morris et al., 2002), and viewing time (Olney et al., 1991).

In all the above-mentioned studies, consumers' feelings in response to advertisements have been measured using self-reports. Although certainly not without merit, such reports, particularly when they involve reporting on feelings or other internal states, do have their limitations. In addition to the fact that people are limited in their ability to reflect accurately on their internal mental processes, concerns with social desirability compound this problem (Nisbett and Wilson, 1977; Wiles and Cornwell, 1990). Moreover, the ability to report on mental states requires cognitive processing, which may interfere with or even change the originally evoked feelings (Poels and Dewitte, 2006). Although the use of non-verbal graphical scales such as the well-known Self-Assessment Manikin (SAM) may reduce the amount of cognitive processing required (e.g., Morris et al., 2002), it still requires introspection and reflection on mental processes which largely occur outside our awareness (Zajonc, 1980).

Implicit techniques that measure physiological consequences (of psychological antecedents) in response to advertisements, share the advantage that they are free of the cognitive biases described above. A relatively new development in marketing is the application of brain imaging to measure the direct implicit response of the brain toward products, brands and advertisements (Plassmann et al., 2015). Electroencephalography (EEG) is the most popular of these methods in neuromarketing practice, particularly in ad testing (Smidts et al., 2014), because of its relatively low costs and high temporal resolution compared to, for example, functional magnetic resonance imaging (fMRI) (Ariely and Berns, 2010).

EEG is a non-invasive method to record brain activity by means of measuring voltage changes at the scalp. Decades of research have shown that oscillations in the EEG signal in certain frequency ranges can be associated with specific psychological processes in the brain (e.g., Basar et al., 1999). One of these frequency ranges, or frequency bands, in the EEG signal is the alpha frequency band which is defined as oscillations between 7 and 12 Hz. Desynchronization of the alpha band or "alpha suppression" in response to opening the eyes has been observed since the first application of EEG by Berger (1929), see also Barry et al. (2007). EEG studies investigating arousal showed that the processing of emotional arousing stimuli is related to alpha suppression (e.g., Simons et al., 2003; DeCesarei and Codispoti, 2011, but see Aftanas et al., 2002; Uusberg et al., 2013).

The generally adopted procedure in experimental studies investigating emotional arousal presents participants with stimuli from the International Affective Picture System (IAPS, Lang et al., 2008) (e.g., Müller et al., 1999; Keil et al., 2001; Aftanas et al., 2002; DeCesarei and Codispoti, 2011; Uusberg et al., 2013). These standardized and validated photographs depict various scenes, objects and people, and have been shown to evoke emotional states varying along the two dimensions of valence and arousal. Viewing arousing stimuli enhances cortical excitation compared to viewing neutral or less arousing stimuli, and thereby reduces alpha activity (DeCesarei and Codispoti, 2011).

Whereas measuring this type of brain activity and inferring a specific psychological process from this measurement is simple and straightforward, it is also problematic because it involves reverse inference (Poldrack, 2006; Lee et al., 2017). The fact that inducing high arousal leads to observing alpha suppression (forward inference), does not warrant the reverse inference that observing alpha suppression in a particular instance must mean that arousal is high. This logic is only valid if arousal is the only process that would lead to alpha suppression, which is not the case since also attention, memory demands and general alertness suppress alpha oscillations (Klimesch, 2012). Furthermore, also other frequency bands have been related to arousal, for example increased gamma band activity (30–65 Hz) has been observed in response to emotional arousing pictures compared to neutral pictures (Müller et al., 1999; Keil et al., 2001). This so-called reverse inference problem thus undermines most of the techniques used in neuromarketing practice today.

In the current study, we therefore first applied a so-called "functional localizer task" to search for patterns of EEG oscillations that we could objectively and independently estimate via an independent task as being associated with arousal. We adopted the same procedure that is generally used in other studies investigating emotional arousal, hence we presented the participants with IAPS stimuli. The oscillatory EEG activity evoked by the arousal dimension of these pictures will be used as the measure of arousal.

In addition, although EEG can be fruitfully applied to measure the implicit arousal response to advertisements, it is crucial to show that the inferred psychological process is actually relevant for advertising. We therefore investigated whether arousal evoked in response to the ads, as measured neurally in a relatively small group of individuals, is associated with measures of advertising effectiveness in the population at large. Even though EEG is currently the main method applied in neuromarketing practice, evidence on the relationship between EEG oscillations and measures of advertising effectiveness is limited (Chang, 2017). In only a handful recent studies, EEG-based measures have been shown to be related to market-level success (Boksem and Smidts, 2014; Dmochowski et al., 2014; Venkatraman et al., 2015; Barnett and Cerf, 2017). While the aim of the current study is not predicting market success, it would add to this previous work by showing the specific role of arousal in response to advertisements, as inferred from an EEG measure estimated via an independent task in one and the same study, in relation to measures of advertising effectiveness in a separate, larger sample of the population.

Advertising effectiveness can be defined in multiple ways, since there are several different communication objectives for advertising. A first communication objective is increasing awareness in consumers, in order to be able to rely upon memory, either recall or recognition, before or at the moment of the purchase decision (Percy and Rossiter, 1992). Research on personal theories of practitioners in advertising revealed that professionals in the field see capturing consumers' attention

as their main goal in order to break through "the clutter" of other advertisements and daily life (Kover, 1995; Nyilasy et al., 2013). A second objective of advertising is generating a favorable attitude toward the ad because of its influence on brand attitude (MacKenzie et al., 1986; Brown and Stayman, 1992) and subsequent behavior (Ajzen and Fishbein, 1977). In the present study, we obtained ratings from a large sample of the population on notability and attitude toward print advertisements as measures of advertising effectiveness covering these two communication objectives (awareness and attitude toward the ad).

In sum, in the present study we first applied a localizer task in order to functionally localize arousal-related patterns of oscillatory EEG activation. After having estimated how arousal is represented in the brain, we measured arousal evoked by print advertisements, and related those neural measures of arousal to measures of ad effectiveness in the population, consisting of self-reported ratings of notability and attitude toward the ad.

MATERIALS AND METHODS

Participants

The sample for the EEG study consisted of thirty-one students (16 female, age range = 19–27 years, $M = 22.3$, SD = 2.5) recruited from the university population. They all had normal or corrected-to-normal vision and had no history of neurological illness. In return for their participation they received 30 Euros.

The population sample consisted of an external consumer panel of 1,260 participants of the same nationality as that of the EEG participants (650 female, age range = 18–88 years, $M = 54.1$, SD = 12.4). These participants were randomly drawn from a consumer panel that is representative of the Dutch adult population (18 years and older), by a certified market research firm. Their educational background covered the whole range from low (23%), to intermediate (35%), to high (42%).

Tasks

EEG Functional Localizer Task

In this task, we showed our 31 participants 100 standardized and validated photographs from the International Affective Picture System (IAPS, Lang et al., 2008) while we recorded their EEG, in order to functionally localize arousal-related patterns of activity. We selected photographs at the low and high ends of the arousal dimension, and at the negative and positive ends of the valence dimension in order to keep a balanced design and to control for valence of the stimuli. This results in four picture categories, each containing 25 photos: positive valence/low arousal, negative valence/low arousal, positive valence/high arousal, and negative valence/high arousal. Averaging the mean normative ratings on arousal and valence of all our selected pictures results in the following mean ratings per picture category (on a scale from one to nine): positive valence = 7.32/low arousal = 3.56, negative valence = 3.56/low arousal = 3.61, positive valence = 7.12/high arousal = 6.52, negative valence = 2.73/high arousal = 6.75 (see **Supplementary Appendix 1**). Stimuli were presented for 3,000 ms, with an interstimulus interval of 1,500 ms. We instructed participants to empathize with the situation depicted and try to imagine being in that situation.

Print Advertisements

The stimuli in this task consisted of 150 real print advertisements from the United States from the Starch database (GfK MRI United States) and Ads of the World, in order to guarantee that they were new to our European participants and thus to control for familiarity of the ads. The ads pertained to five product categories: cars, gadgets, food, beauty, and fashion. Only women viewed the beauty and fashion advertisements, and only men the cars and gadgets advertisements. Both women and men viewed the food advertisements. During the EEG study, the advertisements were presented for 5,500 ms with an interstimulus interval of 1,500 ms. Brain activity was recorded while participants viewed the advertisements.

Participants from the population sample rated a random subset of 10 ads on two measures of ad effectiveness as part of an online survey: *Notability of the ad*, and *Attitude toward the ad* (nine items averaged), in order to capture effectiveness of the advertisement in the population at large (for more details on the items, see **Supplementary Appendix 2**). We created one measure of *Attitude toward the ad* out of the nine items, because the items mutually correlated significantly at the level of $p < 0.01$ (ranging from $r = 0.59$ to $r = 0.93$), Cronbach's α was .96, and a principal component analysis (PCA) returned only one component explaining 84% of the variance. All items were Z-transformed at the advertisement level. The descriptives of the raw scores at the advertisement level indicated that the 150 ads differed substantially both in Notability and Attitude (see **Table 1**).

Since the population sample is more diverse in age and level of education than the EEG sample, we checked whether a subsample of the population sample with similar characteristics as the EEG sample (relatively young and highly educated) differed in their ratings of the print advertisements from the overall sample. Ratings appeared to be robust to differences in age and education (see **Supplementary Appendix 3**).

EEG

Recording

The EEG data was acquired using the BioSemi Active Two system with 64 active Ag-AgCl electrodes. Additional flat type electrodes were placed on the right and left mastoid, and in the eye region in order to record eye movements or electro oculograms (EOGs). Electrodes were placed below and above the left eye in line with the pupil to record vertical EOGs, and at the outer canthi of both eyes to record horizontal EOGs. The EEG and EOG signals were

TABLE 1 | Descriptives of raw scores on notability and attitude toward the ad at the advertisement level (5-point scale).

	M	SD	Min	Max
Notability	3.51	0.32	2.77	4.11
Attitude	2.90	0.27	2.22	3.52

sampled at a rate of 512 Hz, and digitally low-pass filtered with a 128 Hz cut-off (3 dB).

Preprocessing

All preprocessing was done in Brain Vision Analyzer software (BVA; Brain Products). The data was first down-sampled to 256 Hz, then re-referenced to the averaged mastoids, and filtered with a low cutoff filter of 1 Hz and a notch filter of 50 Hz with a slope of 48 dB/octave. We split the continuous data into 100 segments (one for each IAPS picture) for the functional localizer task, and 90 segments (one for each ad) for the print ad task, with segments lasting from stimulus onset until 2.5 s after stimulus onset. Then, we applied Gratton and Coles ocular correction to correct for eye movements as implemented in BVA, and a standard artifact detection and rejection procedure in which segments were rejected that contained jumps larger than 30 μV/ms, amplitude differences exceeding 150 μV/200 ms, and amplitude differences below 0.5 μV/100 ms. Note that only the channels that contained artifacts were deleted within the given segment, and not the entire segment. For all segments, we decomposed the signal into components of frequencies ranging from 1 to 128 Hz using a Fast Fourier Transform (FFT) (BVA, using a 10% hamming window). The resulting spectral data was exported to Matlab (Mathworks).

Data Reduction

We then estimated how (at which frequencies in the signal) and where (at which electrodes on the 64-channel cap) the difference between low and high arousal is most pronounced across participants. To achieve this, we tested on the first (participant) level, whether the affective category that the presented picture belonged to could be used to predict the EEG data. To this end, we first log transformed the EEG data for normalization purposes. We then regressed the EEG data onto three independent variables (IV's): arousal, valence, and the interaction of valence and arousal, respectively. Even though our main interest is arousal, for completeness, we also checked the differentiation in brain activity for valence, and for the interaction between valence and arousal. Per participant, the regressions were performed at each electrode and each frequency.

Then, at the second level (i.e., the group level), the resulting regression coefficients (i.e., one for each electrode-frequency combination) were used to test the overall arousal effect across participants. Here, we searched for a cluster of frequencies and electrodes where the regression coefficients consistently deviated from zero across participants using (one-sample) *t*-tests. That is, we searched for activity that represents a difference between low and high arousal states in a similar fashion across participants (Step A in **Figure 1**). More specifically, we use a cluster-based permutation test [from the Mass Univariate ERP Toolbox; (Groppe et al., 2011)] to search for how and where on the scalp, the difference between low and high arousal is consistently represented in the EEG data across participants. The reported *p*-values are corrected for multiple comparisons via this permutation test. The test is based on a "cluster mass" statistic, and the output consists of a cluster of data points (frequencies, electrodes) where an effect is present across participants, with a family-wise-error corrected *p*-value for that cluster, thresholded at $p < 0.05$. The result of this analysis is a cluster of frequencies and electrodes where the activity represents a difference between low and high arousal states in a similar fashion across participants. We will therefore refer to this this cluster as the arousal Frequency by Region of Interest (F-ROI).

Using this method, we obtained a cluster of frequency-electrode combinations at which the EEG activity evoked by high and low arousal images differed significantly, in the alpha frequency band (7–12 Hz) on central electrode locations (see section "Results"). No such robust effects of valence (main effect and interaction with arousal) were observed so the valence dimension will not be discussed further. Since the literature on valence often reports asymmetry-effects (e.g., Davidson, 2004), we additionally transformed the data to specifically search for asymmetrical effects where we subtracted for each electrode, data at the electrode at the exact opposite side of the other hemisphere (except for the midline electrodes). We did not find additional significant clusters based on this transformed data.

Calibration

After having defined how arousal is represented in the brain across participants, we conducted individual calibration on this data to take heterogeneity of the brain response into account (Step B in **Figure 1**). Although we found a similar *pattern* of brain activity in response to the low versus high arousal pictures across participants in step A, this does not necessarily mean that the specific/exact EEG response to the low and high arousal pictures is the same across participants. Differences in properties of the skull, in the orientation of the neuronal sources and coherences between the sources, in addition to differences between responses at the neuronal source, result in heterogeneity of EEG responses across participants (Teplan, 2002). We conducted the individual calibration by performing a logistic regression for every participant. We took the (Z-transformed) EEG data from the arousal F-ROI, averaged across the selected frequencies and electrodes, to serve as independent variable, and the IAPS picture category as the dependent variable (DV: low versus high arousal). The participant specific coefficients that resulted from the logistic regressions can be used in the next step of the analysis on the EEG data obtained while viewing the print ads, in order to scale the EEG responses to the ads, to the standardized and validated levels of arousal of the IAPS pictures.

Estimating Arousal in Print Ads

In the next step of the analysis pertaining to the print advertisements, the EEG data that was recorded while viewing the print ads was also first transformed to the frequency domain. We then selected EEG data from the arousal F-ROI as determined in the first step of the analysis, but measured while viewing the print ads, for every participant. In addition, we scaled this activity in response to the ads for every participant, to the arousal level of the standardized and validated set of IAPS pictures. We did this by using a logistic function. For every participant, the selected (Z-transformed) activity from the arousal F-ROI was averaged across the electrodes and frequencies to serve as a predictor. We

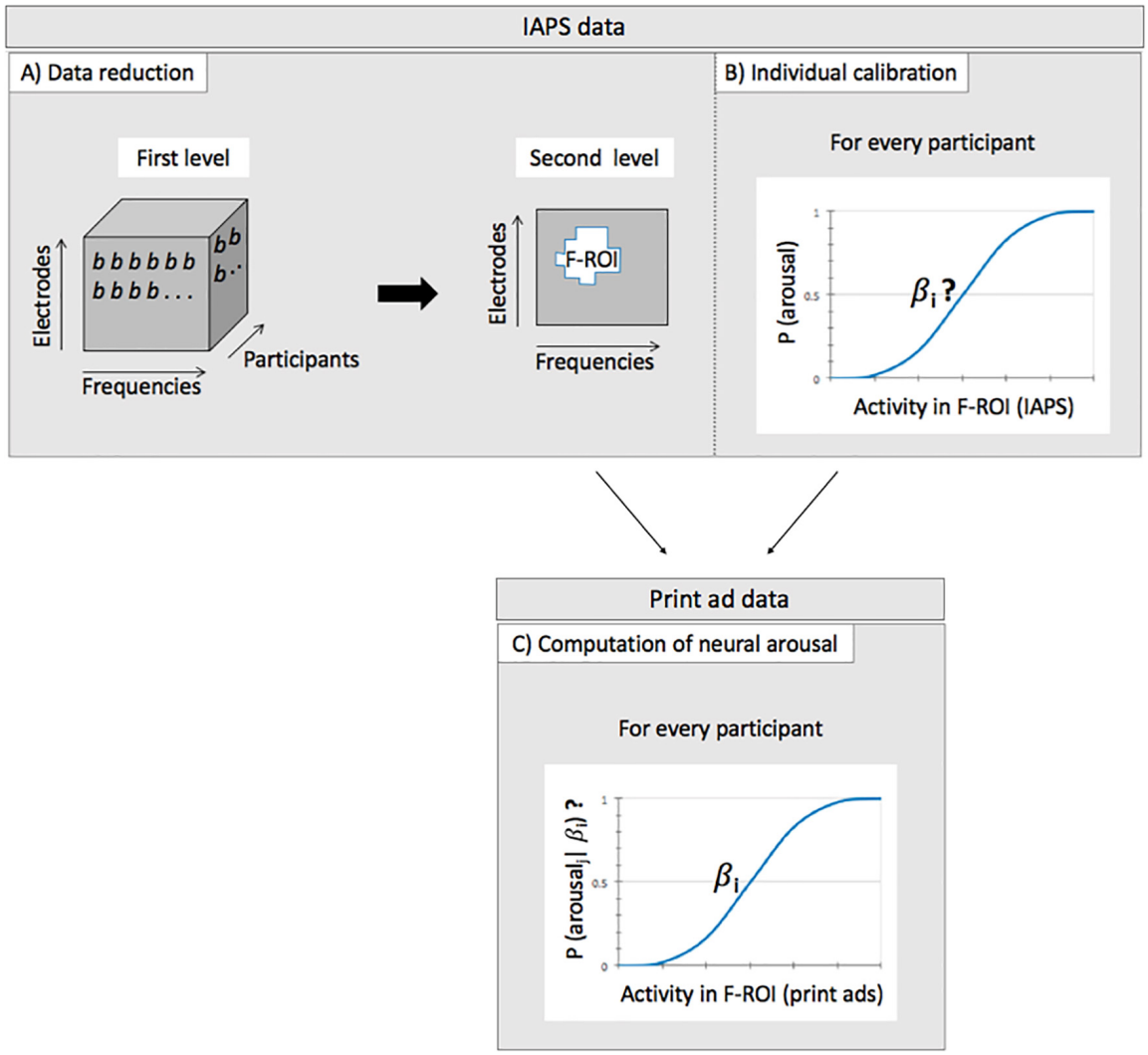


FIGURE 1 | Schematic representation of the different steps of the analysis of assessing neural arousal per ad. Step **(A)** and step **(B)** are performed on the IAPS data, step **(C)** on the print ad data. **(A)** Data reduction by searching for how and where in the brain, the difference between low and high arousal is consistently represented in the EEG data across participants. This step results in an arousal Frequency by Region of Interest (F-ROI). **(B)** Individual calibration of the data as defined in panel **(A)**, by searching for each participant for the optimal relation between the participants' specific EEG response on the one hand (in the F-ROI) and the IAPS pictures on the other hand (DV = low vs high arousal; logistic regression). This step results in participant specific coefficients (indicated by β_i) that link EEG activity and arousal level. **(C)** Computing for each participant *i* and print ad *j*, the probability that a print advertisement evokes neural arousal by selecting activity from the arousal F-ROI that is obtained while viewing the print ads (and given β_i).

then used the participant specific coefficient that was computed in the second step of the analysis and a logistic function, to estimate the probabilities that the advertisements evoked arousal for that participant, based on the EEG activity in the F-ROI (Step C in **Figure 1**).

Finally, per ad, the estimated arousal probabilities were averaged across participants to arrive at a neural arousal score for each print ad, thus making the advertisement our focal unit of analysis.

Importantly, it should be noted that the individual calibration was performed to take heterogeneity in the EEG response to a specific print ad across multiple participants into account. That is, the same EEG response to a specific print ad, will indicate more arousal for this ad if it originates from someone who reacts *less* to the high arousing IAPS pictures, than when it originates from someone who reacts *more* to these same high arousing IAPS pictures. When someone is less easily aroused in general, and thus responds "with less arousal" to high arousing pictures, without individual calibration, this would lead to rather flat arousal responses in reaction to all print ads. Since our focal unit of analysis is the advertisement, we believe it therefore makes sense to scale the individual responses to these ads, to the validated set of IAPS pictures. Not conducting this individual calibration would result in less clean (more crude) relationships between the EEG activity and the arousal process that it should represent across individuals.

Statistical Analysis

To test whether the neural arousal scores of the print advertisements are related to measures of ad effectiveness in the population at large, we computed the correlation between the neural arousal score of the ads, and averaged ratings of the ads by the population sample on Notability and Attitude.

To control for other features of the ads, we performed hierarchical regressions. We controlled for low-level visual features [i.e., luminance (i.e., the average pixel intensity) and contrast (i.e., the standard deviation of pixel intensity), using the "imread" function from the Image Processing Toolbox in Matlab] of the ad, brand familiarity, and dummies for product category in the first block, and tested the significance of the neural arousal scores in the second block. If one of the ad features other than the neural arousal scores appeared to be significant as a predictor, we also tested the interaction term consisting of that ad feature and the neural arousal scores in the third block.

Although we selected United States advertisements because they were new to our participants, several brands in the advertisements may have been familiar to the participants to varying extents. In order to control for the effect of brand familiarity, we collected data on "familiarity with the brand" with the brand logo presented and scale ranging from (1) *Very unfamiliar*, to (7) *Very familiar*, from a separate sample of 46 students, but with highly similar characteristics to the students in our EEG study (23 female, age range = 18–30 years, $M = 21.0$, SD = 2.6). Ratings were averaged across participants in order to arrive at one score per ad on brand familiarity ($M = 4.6$, SD = 2.0, range = 1.2–6.9).

RESULTS

Functional Localizer

In the data reduction step of the functional localizer task, the analysis (Step A in **Figure 1**) reveals a significant difference between low and high arousal IAPS pictures that was consistently represented in the EEG data across participants ($p < 0.01$, FWE corrected). The effect was widespread but mainly present at central sites of the head, and in the alpha frequency range (7–12 Hz, on electrodes F1, F3, F5, FCz, FC1, Cz, C2, C4, T8, CP2, CP3, CP4, CP6, Pz, P2, P5, P7, and POz; see **Figure 2**). Activity in the alpha frequency range was lower in the high arousal condition than in the low arousal condition. This cluster of activity will constitute the arousal F-ROI.

Relationship Between Neural Arousal and Population Sample Evaluation

EEG activity selected from the arousal F-ROI that is described above, but obtained during viewing of the print ads was then used, together with the participant specific coefficient obtained in step B, to predict the probability that each specific ad evoked arousal (Step C in **Figure 1**). The resulting neural arousal scores of the 150 print advertisements were then correlated with the measures of ad effectiveness from the population sample. We observed a significant correlation with these measures of ad effectiveness: The higher the advertisements scored on neural arousal, the higher they were rated by the population sample on Notability ($r = 0.20$, $p < 0.05$), but the lower they scored on Attitude toward the ad ($r = -0.26$, $p < 0.005$, both p-values corrected for multiple comparisons) (see **Figure 3**).

When controlling for other ad features, these direct relationships between neural arousal and its respective ad effectiveness measures remain. **Table 2** shows that neural arousal is positively associated with notability of the ad (standardized regression coefficient $\beta = 0.19$, $t = 2.31$, $p < 0.05$) when controlling for product category, brand familiarity and luminance and contrast. Adding neural arousal to the model in step 2 significantly increased the fit of the model (R^2 change = 0.03, F-change = 5.33, $p < 0.05$). The interaction term between the neural arousal score and contrast was not significant ($p > 0.10$) and therefore did not enter the model. Similarly, **Table 2** shows that adding neural arousal to the model predicting attitude toward the ad, significantly increased the fit of the model (R^2 change = 0.06, F-change = 11.27, $p < 0.005$) with neural arousal being negatively associated with attitude toward the ad ($\beta = -0.25$, $t = -3.36$, $p < 0.005$). The interaction terms between the neural arousal score, dummy product category 1, dummy product category 2, and brand familiarity were all non-significant ($p > 0.10$) and did not enter the model.

Cross-validation analyses confirmed that neural arousal also contributed significantly to the models in predicting ratings of a holdout sample, supporting the results that neural arousal positively predicts notability of the ad, but negatively predicts attitude toward the ad, controlling for product category, brand familiarity and luminance and contrast (see **Supplementary Appendix 4**).

Because of the null result for valence related activity (and the negative relationship between neural arousal and attitude), we wanted to rule out the possibility that our arousal measure is biased toward negative valence. Conducting an independent samples t-test on arousal activity in response to the IAPS pictures (i.e., activity that is averaged across the arousal F-ROI), for positively versus negatively valenced IAPS pictures, indicates that these pictures on average do not differ in arousal for all participants (no significant differences for any of the participants; range of t-values = −1.88 to 1.92, one sample t-test on t-values is n.s. $M = 0.06$, $t = 0.35$). This shows that there is no (negative) valence bias in our arousal measure.

Follow-Up Exploratory Analysis on Negative Relationship Between Arousal and Attitude

In order to shed light on why we (unexpectedly) found a negative relationship between neural arousal evoked by the print ads and ratings on attitude by the population at large, we followed up on the results with an additional exploratory analysis. Inspecting the scatterplot illustrating this relationship (**Figure 3B**) suggests that the ads in the bottom right corner contribute heavily to the negative relationship between our measure of arousal and ratings on attitude: More ads are present in this corner compared to in the other corners, and they extend more to the limits of the

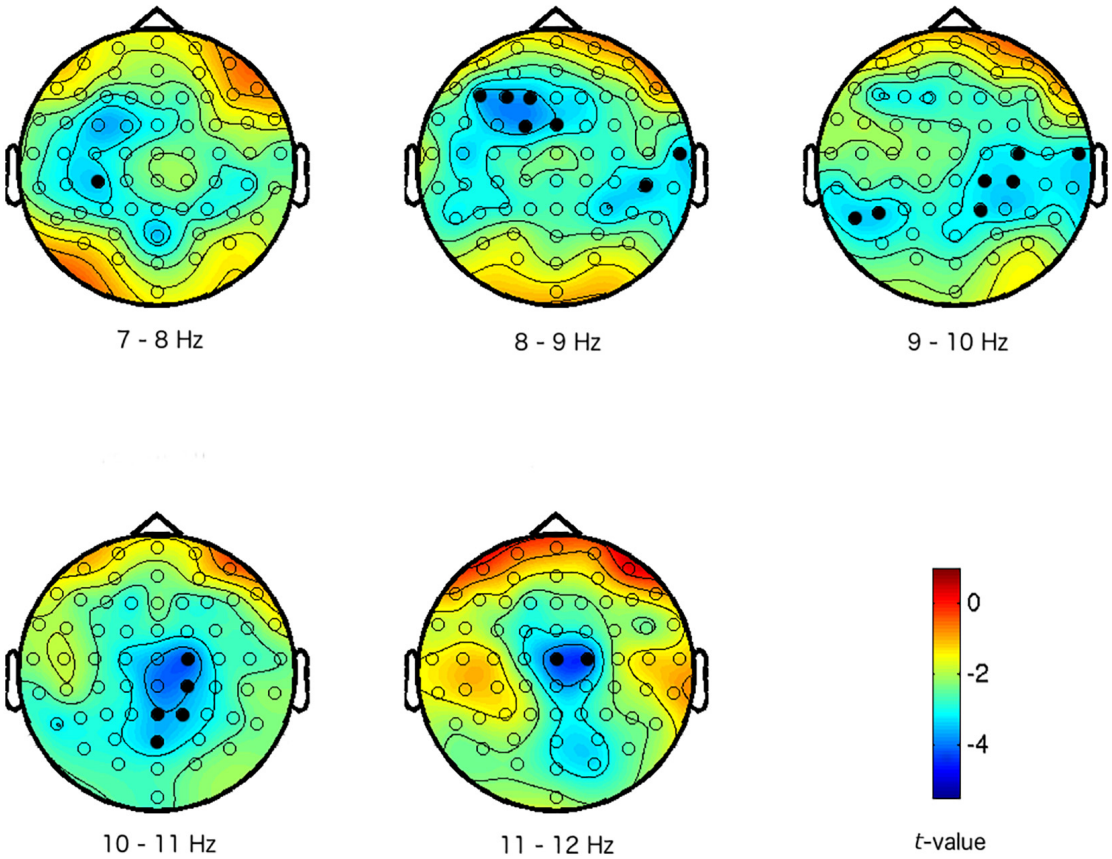


FIGURE 2 | Maps of the difference between high and low arousal IAPS pictures in activity in the alpha frequency band (7–12 Hz). The colors represent *t*-values. The different scalp maps show the contrast (expressed in *t*-values) between high and low arousal for the specific frequencies that are mentioned below the maps, and across the head for the 64 electrodes. Electrodes with activations above the threshold are marked in black (i.e., electrodes that are part of the arousal effect/cluster/F-ROI: preset cluster inclusion for data points $p < 0.005$, cluster significance $p < 0.01$ FWE).

two variables. Examining these ads for a common denominator reveals that many of those ads deal with the human body in a creative, uncommon manner or contain unusual content of a physical nature, which may not be appreciated by some of our participants and may therefore not be perceived as positive. An example of such an ad depicts one arm with hand, with a second hand pulling of the skin of the first hand, as if an invisible glove is put on, advertising for a hand sanitizer. In another such ad, the face of a person is presented with a fist appearing from the neck, punching the person in the face, referring to the (wasabi) taste of the potato chips. We hypothesize that the negative relationship between arousal and attitude in our study may exist because of these creative ads that may be perceived negatively. Searching the whole stimulus set for print ads that tick this box ($k = 22$) and excluding these from the analysis, results in a non-significant correlation between arousal and attitude of $r = -0.13$ ($p = 0.15$) for the remaining $k = 128$ print ads. Thus, these (mostly negatively evaluated) creative ads indeed contributed to the negative relationship between arousal and attitude, which is perhaps due to the nature of the creativity used here (with the use of the human body in an uncommon fashion).

DISCUSSION

Main Findings and Contributions

We presented a study in which we showed how arousal, as measured using EEG, is associated with measures of advertising effectiveness. The aim of this work was twofold. The first aim was to measure arousal evoked by advertisements using EEG, by first estimating how arousal is represented in the brain via an independent task. Our second aim was to show that this neural measure of arousal was associated with actual measures of marketing effectiveness. We specifically investigated whether the evoked arousal in a relatively small group of individuals was predictive of both the notability of the advertisements, as well as consumers' attitudes to the ads in the population at large, which are considered the primary communication objectives for advertising.

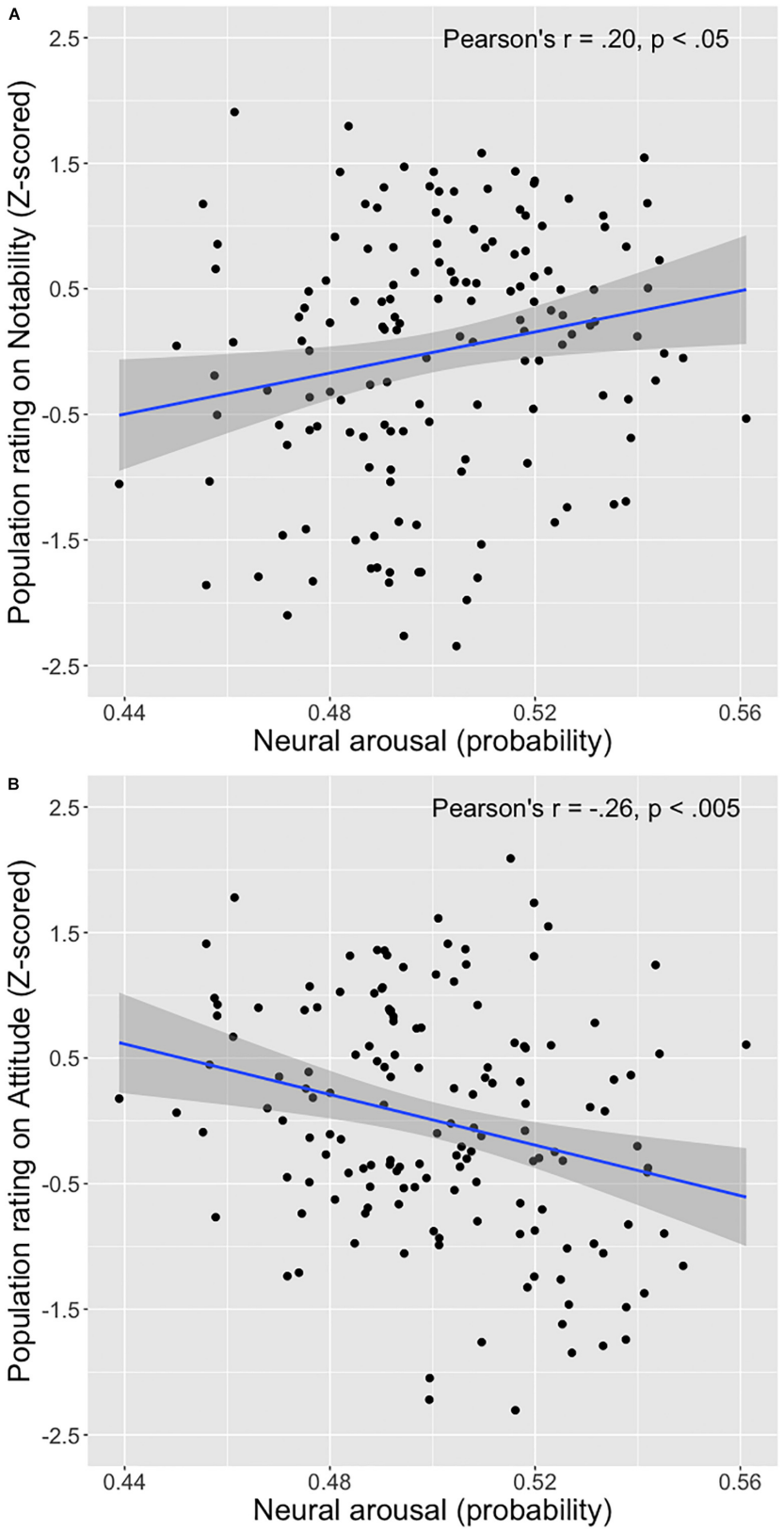


FIGURE 3 | Scatterplots of the relationship between neural arousal score of the 150 print advertisements and average population sample ratings on notability of the ad **(A)** and attitude toward the ad **(B)**.

TABLE 2 | Relationships between population sample ratings on notability of the ad, attitude toward the ad, and features of the ad.

	Notability		Attitude	
	Beta	***t***	**Beta**	***t***
Product category cars vs food	−0.16	−1.51	−0.30***	−2.97
Product category gadgets vs food	−0.17	−1.58	−0.23*	−2.32
Product category beauty vs food	−0.17	−1.66	−0.08	−0.85
Product category fashion vs food	−0.11	−1.03	−0.12	−1.29
Brand familiarity	0.12	1.30	0.42***	5.10
Luminance	−0.09	−1.06	−0.03	−0.45
Contrast	−0.24*	−2.93	−0.04	−0.51
Neural arousal	0.19*	2.31	−0.25***	−3.36
R^2 full model	0.13		0.23	
R^2 change due to neural arousal	0.03		0.06	
F change due to neural arousal	5.33*		11.27***	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.005$. Beta is the standardized regression coefficient.*

We first administered a localizer task to functionally localize arousal-related patterns of EEG activity in order to diminish the problem of reverse inference. We found that arousal-evoking IAPS pictures prompted a change in power in the alpha band in our participants, allowing us to define an EEG map of arousal. The observed representation of arousal is in agreement with previous literature on the neural correlates of arousal, showing a decrease in alpha activity when comparing high to low arousing stimuli. For example, using similar stimuli from the IAPS as we used in the current study, DeCesarei and Codispoti (2011) identified an effect of arousal that overlaps significantly with the results presented here: a decrease in alpha power (9–12 Hz), primarily over parietal electrodes. Similarly, Simons et al. (2003) found that arousing pictures, but also emotionally arousing movie clips, elicited decreased alpha power (8–13 Hz) over central and parietal electrode sites.

It should be noted, however, that such effects are not always observed. For example, Aftanas et al. (2002) presented participants with IAPS pictures inducing high, moderate and low arousal, and found that it was the *high* arousal pictures that elicited the strongest alpha increase over parietal electrodes. While participants in our study, as well as in the DeCesarei and Codispoti (2011) experiment, passively viewed pictures, they were required to rate the pictures in the study by Aftanas et al. (2002). Future research could reveal whether this difference between active and passive viewing may explain differences in associations between arousal and alpha power. Similarly, although some studies also report EEG effects of valence (e.g., Uusberg et al., 2013), these effects are also not always observed (Aftanas et al., 2002; Simons et al., 2003; DeCesarei and Codispoti, 2011), as was the case in the current study. In summary, we were able to extract a neural representation of arousal, reflected by changes in the EEG alpha band, that aligns well with previous findings.

After defining EEG activity that is representative of arousal using the localizer task, we sampled this EEG response obtained during viewing of advertisements (i.e., from the arousal F-ROI), which allowed us to estimate the level of arousal experienced for each of the print advertisements (calibrated to the participants' EEG response to the standardized and validated levels of arousal of the IAPS pictures).

The results showed that the neural measure of evoked arousal in response to the ads was positively associated with notability of the print ads, but that attitude toward the ads was negatively associated with neural measures of evoked arousal in response to the ads. The negative relationships between neural arousal and attitude may be explained by creative executions of the ads that seem not to be perceived positively. Our exploratory analysis suggested that the use of the human body in an unusual fashion may have contributed to the negative relationship between neural arousal and attitude.

Theoretical and Managerial Implications

The results of the present study showed that the neural measure of arousal evoked in response to the ads as measured using EEG was associated with two communication objectives of advertising, even after controlling for other ad features such as contrast, luminance, product category, and brand familiarity. Using this measure of arousal in response to advertisements may provide advertisers with more concrete and actionable insights on the mental state of the consumer. Equally as important, these results imply that the EEG measure reflecting arousal could provide advertisers with more guidance as to whether the ad design meets a particular communication objective, which may serve as input into decisions to optimize the ad. That is, advertisers need to consider the main objective of their campaign when designing ads since different measures of ad effectiveness may not align and may call for different ad designs. Ads that are neurally arousing may be effective in the sense that they are highly notable and thus enhance awareness, but may not necessarily be effective in terms of being positively evaluated.

The first communication objective of raising awareness was reflected by ratings on notability. As expected, the more arousing ads were found to be more notable as rated by the population sample. We conjecture that the downstream consequences of our "notability measure" are comparable to the ones of "Starch *noted* scores" as seen in older research (e.g., Lucas, 1960; Spotts et al., 1997). The Starch score indicates the extent to which an advertisement has been "noted" by viewers, so both this measure and our measure assess at least initial attention and give an indication of the extent to which advertisements can break through "the clutter" of other presented material. Whether such scores, however, actually measure recognition and thereby ad memory is debatable (Lucas, 1960; Spotts et al., 1997).

For the second communication objective however, we found somewhat surprising results: more arousing ads were evaluated less positively. In general, a clear association between arousal and attitude should not necessarily be expected, since arousal and valence are orthogonal in the circumplex model of affect. That is, both positively and negatively valanced stimuli could be associated with high arousal. However, advertisements are typically positive in valence, which is probably why previous work in advertising has associated high arousal with more positive attitudes toward ads or brands (Holbrook and Batra, 1987; Olney et al., 1991). The exploratory analysis suggested that the (mostly

negatively evaluated) creative ads contributed to the negative relationship between arousal and attitude, which is perhaps due to the nature of the creativity used (with the presentation of the human body in an uncommon fashion). Thus, an ineffective (unusual, confusing, non-fluent) execution of creativity may result in affective responses that are negative in valence, which in turn contribute to a negative relationship between neural arousal and attitude toward the ad. Future studies are necessary in order to further investigate the specific process underlying the negative relationship between arousal as measured with EEG and ad effectiveness found in the current study, before this relationship can be generalized.

Yet, research on personal theories of practitioners in advertising revealed that professionals in the field see attracting attention as the most important aspect of advertising (Kover, 1995; Nyilasy et al., 2013), and thereby assume that attention grabbing ads will be evaluated positively. Advertising agencies nevertheless realize that crafting a creative ad that cuts through the clutter involves taking a risk. In addition, they feel that their clients fear creative advertising and often resist creative advertising solutions (Nyilasy et al., 2013). The results of our study suggests that the fear of clients may perhaps be justified and thus that advertisers need to have specific communication objectives from their clients. It is important to determine in advance how crucial it is, e.g., given the current status of the brand, to stand out and create brand awareness with the advertisement while taking the risk of not getting it attitudinally right.

Limitations and Future Research Directions

We acknowledge several limitations that should be considered in the interpretation and generalization of our findings. First, while our approach of first estimating the neural substrate of arousal in an independent task mitigates the problem of reverse inference, it does not completely abolish it. Although in our opinion not very likely, it is still possible that a process other than arousal would have the exact same neural substrate as reflected in EEG recordings. Indeed, also attention, memory demands and general alertness have been found to suppress alpha oscillations (Klimesch, 2012), albeit with slightly different distributions across the scalp. Future research could try to separate these processes by using localizers not just for arousal, but also for attention and memory demands, for example.

As mentioned above, the negative relationships between arousal and attitude may be specific to the stimulus sets that were used here. It would therefore be valuable to study creativity in more depth, in order to search for patterns in executions of creativity that are perceived as positive versus negative. This knowledge will aid in the prediction of the actual tone of interest toward the ad (i.e., pleasurable or unpleasurable), in addition to the mere intensity of the interest response in the form of arousal.

While our measures of advertising effectiveness are important ones, more research is necessary to understand the specific downstream consequences of these measures. For example, even if more notable ads cause better memory of the ad, the memory for the brand or product will depend on many factors such as focus of the ad (on product or brand versus not), consistency between existing knowledge of the brand and the execution of the ad, familiarity of the brand, and possibly an interaction between these factors. In addition, the question remains how notability and attitude are weighted in determining the ultimate decision to purchase the product or not.

Finally, although we showed that our neural measure was associated with measures of advertising effectiveness at the population level, we did not examine if its contribution is above and beyond that of self-reports. This was not the aim of the current study, but it is important to emphasize because the question remains whether applying neuroimaging is more beneficial in predicting commercial success than other measurements such as questionnaires and to what extent this may be the case. Relatedly, it could be that neuroimaging methods other than EEG (such as fMRI) may be more strongly associated with effectiveness of advertisements or underlying psychological processes such as arousal (Chan et al., 2019, 2020); Venkatraman et al., 2015). Nevertheless, as we have shown here, neural measures may reveal important insight into the underlying processes (such as arousal) that may be associated with responses toward advertising messages.

FINAL CONCLUSION

In summary, the current study demonstrates how to accurately measure arousal evoked in response to advertisements using EEG. Additionally, we show that this neural measure of evoked arousal as obtained in a relatively small group of individuals and estimated via an independent task in one and the same study is useful for marketing purposes. While controlling for other ad features, it contributes uniquely to explaining different measures of advertising effectiveness in the population at large that cover the main communication objectives of advertising. This evidence is important because of the increasing implementation of small so called "neural focus groups" in marketing practice, aimed at providing indices of advertising effectiveness at the population level. The findings suggest that different levels of alpha activity evoked in response to ads cannot automatically assumed to be associated with ad effectiveness in general. Although advertisements that evoke more arousal, or less alpha activity, will likely be more noted, they are not necessarily perceived positively. Nevertheless, using this EEG measure and taking the discussion points into consideration allows advertisers to improve on assessing the effectiveness of an ad design at an early stage, and even apply this measure on a moment-to-moment basis (Eijlers et al., 2019). Because of the relative inexpensiveness of EEG, the benefits of more and concrete improvements on ad designs, and the unique insights into the underlying psychological processes may indeed outweigh the costs.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The study involving human participants was reviewed and approved by ERIM Internal Review Board (ERIM IRB), Rotterdam School of Management, Erasmus University. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

EE, MB, and AS formulated the research question, designed the studies, and wrote the manuscript. EE collected and analyzed the data. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2020.00736/full#supplementary-material

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Item Features Interact With Item Category in Their Influence on Preferences

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Low-level visual features are known to play a role in value-based decision-making. However, most previous studies focused on the role of only a single low-level feature or only for one type of item. These studies also used only one method of measurement and provided a theory accounting for those specific findings. We aimed to utilize a different more robust approach. We tested the contribution of low-level visual features to value-based decision-making of three item types: fractal-art images, faces, and snack food items. We used two techniques to estimate values: subjective ratings and actual choices. We found that low-level visual features contribute to value-based decision-making even after controlling for higher level features relevant for each item category (for faces, features like eye distance and for food snacks, features like price and calories). Importantly, we show that, overall, while low-level visual features consistently contribute to value-based decision-making as was previously shown, different features distinctively contribute to preferences of specific item types, as was evident when we estimated values using both techniques. We claim that theories relying on the role of single features for individual item types do not capture the complexity of the contribution of low-level visual features to value-based decision-making. Our conclusions call for future studies using multiple item types and various measurement methods for estimating value in order to modify current theories and construct a unifying framework regarding the relationship between low-level visual features and choice.

Keywords: visual-features, preference, decision-making, fractal-art, snacks, faces, replications

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INTRODUCTION

People make value-based choices between different items on a daily basis. In this process, we need to construct a representation of each of the items, assign a value to it, and choose the item we prefer (Rangel et al., 2008). In order to do so, we putatively dissect the item to its low-level characteristics, such as colors (Margaret and Hubel, 1988) and spatial frequency (De Valois et al., 1982; De Valois et al., 2000). The combination of these visual features lead to higher-level representations of the objects, allowing us to identify and assign value to the item (Riesenhuber and Poggio, 1999). Several studies showed the contribution of low-level visual features to preferences of simple visual items. For color patches, more saturated and cooler colors were found to be preferred (e.g., blue was

preferred over red) both in a choice task (McManus et al., 1981; Hurlbert and Ling, 2007) and in a scale rating task (Palmer and Schloss, 2010). In another choice study, subjects preferred Gabor patterns that were more symmetric (Rentschler et al., 1999).

For complex images, an important visual feature that affect preferences is the statistical property of spectral slope. Spectral slopes of nature and art images were shown to differ from slopes of other categories, such as objects or scientific charts, and this was hypothesized to relate to the aesthetic quality that one experiences when viewing art and nature (Redies, 2008; Redies et al., 2008). In addition, un-proportional enhanced energy at mid-range frequencies was found to be related to ratings of discomfort (Fernandez and Wilkins, 2008). Other visual features were also shown to influence preferences of complex images. In a study that examined natural and man-made scenes, scale-rating preferences were higher for images with higher sharpness, saturation, and contrast (Tinio and Leder, 2009). For images of snacks, items with higher luminance (Milosavljevic et al., 2012) or higher saliency (Towal et al., 2013) were more likely to be chosen in forced choice tasks. The saturation of snacks was also related to their perceived healthfulness on a scale rating task (James and Richerson, 2018). Although these studies showed the contribution of basic visual features for preferences of common objects, they each examined objects from only one category (i.e., snacks). Thus, it is difficult to depict a clear picture of the relations between basic visual features and preferences for different types of objects taken from different categories.

For complex items such as faces, the configurations between facial features are known to play an important role in face processing (for review see, Maurer et al., 2002) and face preferences (Cunningham et al., 1995; Geldart et al., 1999). The facial width to height ratio (*fWHR*) was originally proposed as an evolutionary sexual marker (being greater for males; Weston et al., 2007) and was associated with aggressive and unethical behavior (Carre and McCormick, 2008; Haselhuhn and Wong, 2011; Geniole et al., 2014, but see Kosinski, 2017). Two other studies showed that changing the distance between local face elements (between the eyes and between the eyes and nose) had a substantial effect on preferences (Searcy and Bartlett, 1996; Pallett et al., 2010). The distance between the eyes was also positively correlated with preference ratings (Cunningham, 1986). An important role for higher-level features was also shown for food items preferences. For example, the knowledge of wine prices (Plassmann et al., 2008) and of beer ingredients (Leonard et al., 2006) changed the items' taste pleasantness ratings. It had been shown that flavors associated with high caloric foods induce greater preferences in adults, measured using a scale rating (Booth et al., 1982), and induced both greater preference ratings and actual consumption in children (Johnson et al., 1991). The literature thus holds a range of features influencing preferences, from low-level features such as luminance (Milosavljevic et al., 2012) to higher-level features such as price (Plassmann et al., 2008).

Still, it remains unclear whether the effect of low-level visual features on preferences for complex items such as faces and snacks is the same as was found for simple abstract stimuli such as patches of color. Despite ample research, the interplay between low-level visual features, item category, and methods of preference elicitation has only been discussed in reviews or meta-analyses. For example, Palmer et al. (2013) reviewed the literature that relate visual aesthetics with preferences and pointed out that different behavioral techniques, such as two-alternative forced-choice, rank order, subjective rating, and other tasks, have been used to study how visual features such as colors and spatial proprieties may contribute to the formation of preferences. Most previous studies used only one method of measurement and hence provide a limited theoretical account based on specific findings. Thus, there is a need for a unifying theory that will be able to take into account the diversity of visual features, item categories, and experimental procedures across the different studies. For instance, Palmer et al. (2013) point out that the "mere exposure" effect (Zajonc, 1968) can be used in order to explain preferences for inward over outward facing objects given that viewing inward-facing objects is much more frequent (Gardner et al., 2008). The same logic can also be applied in order to understand, for instance, why people may prefer curved visual objects (Bar and Neta, 2006). This explanation can also apply for preferences in value based tasks (e.g., Shimojo et al., 2003; Atalay et al., 2013). However, it is important to note that the "mere exposure" effect can only provide a tautological explanation to such findings and cannot offer a clear theoretical prediction for the role of low-level visual features in preference formation.

One general account that may explain preference formation is the fluency theory (Reber et al., 2004). According to this theory, the ease in which information is being processed may promote valuation. This was hypothesized to stem from the demand that object processing impose on the perceptual or cognitive system, which, in turn, translates into preferences (Palmer et al., 2013). Recently, it was proposed that fluency promotes the intensity of an existing preference, making liked items more preferred whilst disliked items even less preferred (Albrecht and Claus, 2014). Although this theory explains well how low-level features may shape preferences (Oppenheimer and Frank, 2008; Palmer et al., 2013), it is not clear if it is possible to generalize the prediction of this theory across categories. Specifically, it is not clear if low-level visual features would have any effect on preferences for faces and food items after controlling for the contribution of higher-level features, such as *Calories*, *Product weight*, and the *Price* for food items or fWHR, eye distance, and nose–eyes distance for faces. According to Fluency theory, we would expect to find relatively stable and similar relations between low-level visual features and preferences for different categories of items (assuming similar ease of processing after controlling for higher-level features), considering possible effects of other high-order, visual, and non-visual attributes, that play a role in preference formation. That is, after controlling for the influence of higher-order attributes, visual complexity alone extracts its influence on processing valuation. According to fluency theory, the way low-level visual features may promote valuation should be similar across categories. On the other hand, if different association between low-level visual features and valuation would take place as a function of stimuli

category, it would be difficult to reconcile this finding based on fluency theory.

Therefore, the current study is aimed to test whether a unifying framework can account for the role of different low-level visual features of multiple item types using two measurement methods on the value-based decision-making process. Paraphrasing the well-known phrase "Beauty is in the mind of the beholder," we ask whether beauty and valuation interact in the mind of the beholder across categories and measurement methods. Examining the role that low-level visual features play in value computations is crucial to a variety of fields, from marketing to public health, as it will increase our understanding on how subtle changes in low-level visual features may affect people's preferences. In order to test this hypothesis, we systematically explored the influence of several low-level visual features such as color attributes (*Hue*, *Saturation*, and *Color-value*), *Sharpness*, and *Spectral-slope* on preferences for three categories of items and examined preferences using both preference ratings and binary choices. We used images of fractal-art, faces, and snack-food items as stimuli that contain different levels of higher-order complexity. Importantly, we examined the contribution of low-level features to preferences of these stimuli, while controlling for the influence of the category-specific attributes that may play a role in preference formation. Specifically, for fractal-art images, we assumed there were no higher-order attributes that affect preferences and examined only low-level visual features. However, for snacks, we added three market features (*Calories*, *Product weight*, and *Price*), and, for faces, we added three configural features (*fWHR*, *Eye distance,* and *Nose–eyes distance*). We chose this handful of features and categories as an example set of common features examined in the literature. Though many other features may be included as well, we will focus on these ones to explore the stability of effects and interplay between different features in their influence of preferences. All in all, in the present study we addressed our main research question from two perspectives: (1) the contribution of low-level visual features to preferences (measured by preference ratings) adjusted for higher-level features of different stimuli types and (2) how visual properties influence choices in a binary choice task, adjusted for the item's preference ratings. Importantly, for robustness and generalizability, we used a large sample size collected across multiple studies in the laboratory and online and report findings after a successful pre-registered replication of the online samples. We share all our data as well as the analysis codes.

MATERIALS AND METHODS

Participants

A total of 1,014 participants took part in the experiment (see **Table 1** for sample details). All participants gave their written informed consent in accordance with the Tel Aviv University ethics committee and were paid for their participation.

Stimuli

We used items from three different categories. The first category was 60 fractal artwork images obtained from the internet ("Fantastic Fractals", 2013). The second category was 60 common Israeli food snacks, all available in stores in Israel and cost up to 10 NIS (equal to ∼$2.7). All the snacks images were obtained in our lab by a professional photographer. Snacks were presented as an open package with a small portion of the snack besides the package. The third and final category was 60 faces (30 females) obtained from the sibling database (Vieira et al., 2013).

Procedure

All experimental protocols were approved by the Tel Aviv University ethics committee. All experiments were performed in accordance with relevant guidelines and regulations.

Laboratory Experiments (Samples 1–2)

We obtained preference ratings for fractals and snacks from 12 behavioral experiments (overall 342 participants) conducted in the lab [of which eight experiments had both fractals and snacks ratings (n = 200), one with only fractals (n = 35) and three with only snacks ratings (n = 107)]. All these experiments had a standard rating procedure before any exposure to the rated items occurred. Given that the rating task was similar across these 12 behavioral experiments, we examined the interaction between samples and the effects of interests with multiple linear regression models and found none of them to be significant (all p's > 0.05). We thus combined all preference ratings in the laboratory as if they were collected from a large joint sample, one for fractals (sample 1) and the other for snacks (sample 2; see **Table 1** for details). In the lab experiments, participants rated their preferences for the fractals using a continuous numerical scale in which they indicated how much they liked each item from 1 to 10 (see **Figure 1A**). For the snack foods, participants indicated their willingness to pay (WTP) for each food item using the incentive-compatible Becker–DeGroot–Marschak auction (Becker et al., 1964; see also Salomon et al., 2018 for detailed procedure, as explained in the section "Auction Procedure for Snack-Food Items"), with a continuous price scale of 1–10 NIS. We used the WTP task, as it is considered a task that elicits the participant's preference ratings for the food snacks. Participants used a mouse

TABLE 1 | Demographics and sample details.

	Sample	Category	Age (SD)	% Female	*n*
Lab	(1)	Fractals	24.38 (3.649)	67	235
	(2)	Snacks	24.64 (3.768)	66	307
Online	(3)	Fractals	28.06 (5.397)	50	107
	(4)	Snacks	40.01 (13.042)	50	108
	(5)	Faces	42.87 (15.817)	51	119
Replication	(6)	Fractals	38.73 (13.358)	53	114
	(7)	Snacks	39.45 (13.457)	55	109
	(8)	Faces	38.42 (13.043)	46	115
Total mean			34.57 (7.064)	54 (7.207)	151.75 (71.261)

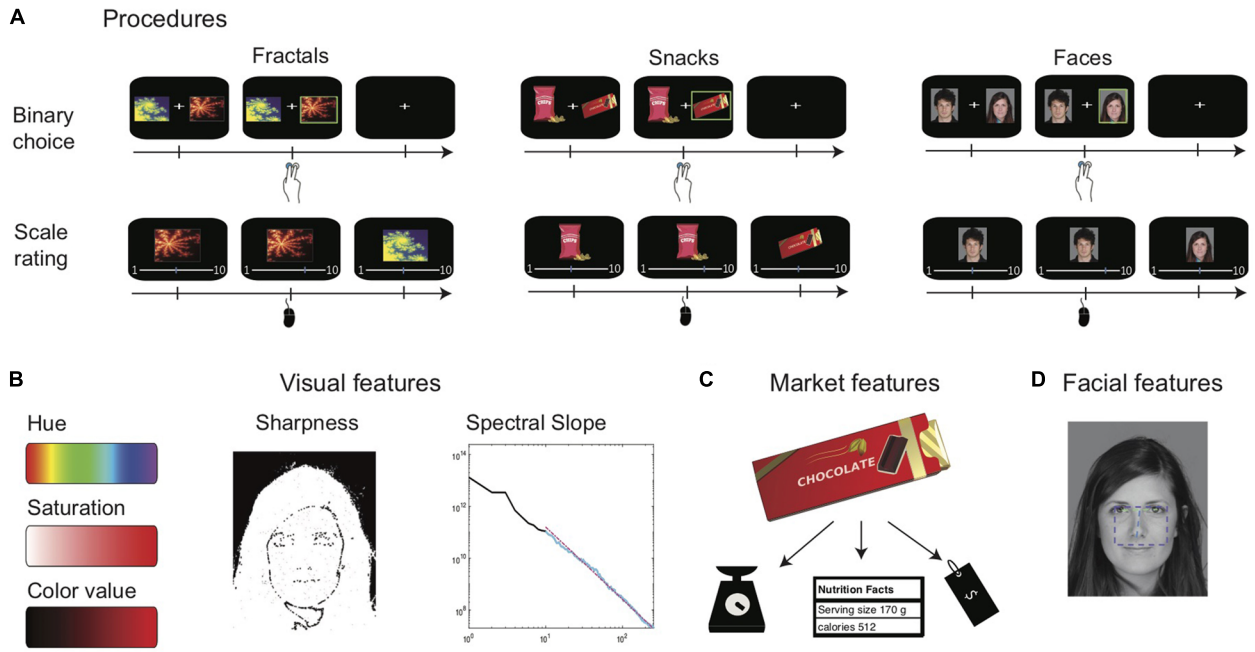


FIGURE 1 | Study design. **(A)** Trial timeline in each of the two measurement methods and for the three different item types used. **(B)** The five visual features extracted for all item types. Color attributes: the color bars range from lowest **(left)** to highest **(right)** value of the feature. Sharpness: an illustration of edges extracted from a face. The Sharpness feature is set to the average of the image's edges (without the black background). Spectral slope: the chart shows an illustration of spectral slope calculation for one item. The averages power of frequencies in black line, of it, the fitted range of 10–256 cycles is indicated in light blue, with the fitted line in dotted pink. **(C)** The three market features extracted for the food items. **(D)** The three facial features extracted for faces: *fWHR* is indicated by the purple rectangle's aspect ratio, *Eye distance* by the green line, and *Nose–eyes distance* by the blue line. Images of faces adapted from a published open access paper (Salomon et al., 2018) and originate from a database by Vieira et al. (2013). Illustrations of two snacks are presented instead of the actual commercial snacks that were presented to participants.

to indicate their preference on a continuous number scale. The procedure was self-paced, and each item was presented once, resulting in 60 trials per participant for each category. Faces were not rated in lab experiments. There were no binary choices in the lab experiments.

Online Experiments (Samples 3–5)

To replicate the lab preference ratings and explore the effects of visual features on binary choice tasks, we obtained choices and preference ratings in three online experiments (for fractals, snacks, and faces). Note that, for snacks, the procedure was a scaled preference rating and not the incentive compatible BDM since it was performed online. Overall, 334 participants took part in the online experiments, of which 107, 108, and 119 participated in the fractals, snacks, and faces experiment, respectively. All online experiments were conducted via an Israeli online website[1] that specializes in conducting online experiments. Each participant performed the binary choice task followed by the preference rating procedure (see **Figure 1A**) of one of the categories (fractals, snacks, or faces). In the binary choice task, ∼14% of all possible binary choice combinations (60 × 59/2, resulting in 240 trials per participant) were randomly selected and presented for each participant. On each trial, participants indicated which of the two items they preferred by pressing the keyboard. Each choice was presented for 2.5 s, followed by a 1 s fixation cross presented at the center of the screen. The preference rating for all categories (fractals, snacks, and faces) was obtained via the non-incentive scale rating procedure, which was identical to the lab preference rating procedure, described above.

Replication Experiments (Samples 6–8)

To obtain a full replication of our data, we pre-registered our data acquired from samples 1–5 and performed an identical replication of the above online experiments[2]. Overall, 338 participants took part in the replication online experiments, of which 114, 109, and 115 participated in the fractals, snacks, and faces experiments, respectively.

Feature Analyses

Visual Features

We extracted five visual features for each item (see **Figure 1B**) using Matlab (Mathworks, Inc. Natick, MA, United States, SCR: 001622): *Hue*, *Saturation,* and *Color value*, the color attributes according to the HSV color-map (Joblove and Greenberg, 1978), were calculated as the mean attribute of the item's image. *Sharpness* was calculated as the mean image gradient

[1]https://www.midgampanel.com/

[2]https://osf.io/zmp49/?view_only=8c65101a29f14140b771aa87bcd91106

(Ferzli and Karam, 2009) using the Sobel–Feldman operator (Sobel and Feldman, 1968). *Spectral-slope* was calculated according to Mather (2014): we converted all images to gray-scale, resized them with bicubic interpolation such that the short dimension is 512 pixels, and extracted 512 × 512 pixels from the center of the image for further analysis. We then performed Fourier transformation to convert the image to the frequency domain and calculated the rotational average of the power spectrum. Finally, we fitted a least square linear line on the rotational averages between 10 and 256 cycles (this range is used in order to avoid artifacts from extreme low or high frequencies). We defined the *Spectral slope* of the image as the slope of the least square line.

In addition, we acquired the following category specific features for faces and snacks:

Facial Features

We extracted three facial features for faces (see **Figure 1D**) using the Viola–Jones algorithm (Viola and Jones, 2001) using Matlab: (1) *Eye distance* (the distance between the two eyes normalized by face size); (2) *fWHR*; and (3) *Nose–eyes distance* (the distance between the bottom of the nose and the center of the two eyes, normalized by face size).

Market Features

We collected three market features for each of the snacks (see **Figure 1C**): (1) *Price*; (2) *Product weight* (in grams); and (3) *Calories* (per 100 g). We extracted the information from the labeling on the snack's package and from the Internet. Detailed correlation matrices of all features are reported in **Supplementary Figure S1**.

Behavioral Analyses

Both the WTP scores and the preference ratings were obtained on continuous scales with a mean of 3.48 (2.589 SDs) for fractals and 3.54 (2.531 SDs) for snacks in the lab samples, 4.64 (2.532 SDs) for fractals, 5.32 (2.760 SDs) for snacks and 4.82 (2.071 SDs) for faces in the online samples, and 4.78 (2.537 SDs) for fractals, 5.43 (2.813 SDs) for snacks, and 4.83 (2.249 SDs) for faces in the replication samples. All WTP and ratings were z-scored separately for each participant to remove variance between participants resulting from them using different ranges of the scale. All the extracted values of the features (*visual*, *market,* and *facial* features) were also z-scored to enable a direct comparison of regression coefficients. We removed from further analysis items with feature values exceeding 3 standard deviations (SDs) away from the mean (1 fractal, 2 snacks, and 1 face). We excluded trials with reaction times exceeding 3 SDs away from the mean (calculated within task and within participant) or trials with no response. Overall, we removed an average of 3.23% (1.455 SDs) of trials per participant across all samples. In addition, we removed participants with more than 30% excluded trials in either ratings or choice data and participants with extreme intransitivity in their binary choices (exceeding 3 SDs away from the mean of the sample's transitivity scores). The transitivity score was calculated as the SD of Colley Matrix algorithm (Colley, 2002), as was also performed in previous studies in our lab (Salomon et al., 2018). We removed 20 participants in the online and replication samples (between two and five participants for each sample), and we concluded with 1,014 valid participants overall in all samples. No participants were removed from the lab samples. In the binary choice task, right and left displays were randomly assigned on each trial. Proportions of choosing the left item were 0.496 for fractals, 0.472 for snacks, and 0.495 for faces in the online samples and 0.498 for fractals, 0.481 for snacks, and 0.496 for faces in the replication samples. We performed all data analyses in R (version 3.3.2. SCR: 001905).

Statistical Analyses

Is There a Linear Relationship Between Low-Level Visual Features and Category-Specific Features With Preference Ratings?

To examine the influence of low-level visual features and category-specific features (market and facial features) on preference ratings, we fitted for each category a linear mixed-effects regression model (see **Supplementary Model S1** for detailed formulas) with a random-intercept and random slopes. That is, we allowed the intercept and the slope coefficients of each of the features (visual and category-specific features) to vary across participants. Ratings served as the dependent variable and the different features as fixed and random independent variables. We fitted this model separately for each of the lab (samples 1–2), online (samples 3–5), and replication (samples 6–8) samples. For each of the samples, we entered all features together to the regression model. Thus, the results reflect the unique contribution of each feature adjusted for all other features.

Do Low-Level Visual Features and Category-Specific Features Affect Binary Choices That Have Been Adjusted for Preference Ratings?

To examine the influence of the different features on choices, adjusted for preference ratings, we first determined the preference ratings of each item for each participant using their ratings in the scale rating task. We then calculated the ratings value difference between the two items in every choice option (hereafter *delta ratings,* e.g., Milosavljevic et al., 2012). We chose to account for rating value differences in each choice option since they are expected to have a strong influence on choice. By entering *delta ratings* into the regression models, we allowed the exploration of more subtle effects of visual features on choices.

Furthermore, for each of the features (visual and category-specific features) we extracted the score difference between the two items (left item minus right item) in every choice option (hereafter *delta feature,* e.g., *delta Hue*, *delta Price,* etc.). For each of the samples, we entered the delta *ratings* feature with all delta visual and delta category-specific features together to the regression model. We fitted for each category a mixed-effects logistic regression (see **Supplementary Model S2** for detailed formulas). We fitted a random-intercept and random-slope model with choices as the dependent variable and *delta ratings* and all *delta features* (the delta of visual, market, and facial features) as fixed independent variables. We allowed for the intercept and slope of *delta ratings* to vary across participants. We fitted this model

separately for each of the online (samples 3–5) and replication (samples 6–8) samples.

Data and code sharing: all data and analyses codes are available at https://osf.io/zmp49/?view_only = 8c65101a29f14140b771aa87bcd91106.

RESULTS

The current study is composed of many samples with numerous possible effects, and we thus report below the summary of effects. Detailed description of all model results with effect sizes and confidence intervals are reported in **Supplementary Tables S1**, **S2**. As mentioned above in the methods, lab experiments consisted of only preference ratings (or BDM for snacks), whilst in the online and replication experiments, participants performed the binary choice task and then the preference rating task for one of the categories.

Is There a Linear Relationship for Low-Level Visual Features and Category-Specific Features With Preference Ratings?

In ratings data obtained from the experiments conducted in the lab, we found that each of the visual features had a different influence on preference ratings and, in some cases, an opposite effect, depending on the items' category (**Figure 2A**). Specifically, *Hue* had a positive effect on preference ratings of fractals whilst a negative effect on snacks. *Saturation* had a negative effect only on snacks, and *Color-value* had a negative effect only on fractals. *Sharpness*, however, had a positive effect for both fractals and snacks, and *Spectral-slope* had a positive effect for fractals whilst a negative effect for snacks.

In order to examine the robustness of these results we repeated the lab experiments on an online cohort of participants. This complex pattern of relations between visual features and item category and their influence on preference ratings was mostly replicated in the online experiments (**Figure 2B**). That is, *Hue* had a positive effect on fractals (*sample 3*) and a negative effect on snacks (*sample 4*). *Color value* had a negative effect on fractals (*sample 3*), *Sharpness* had a positive effect on both fractals and snacks (*samples 3 and 4*), and *Spectral slope* had a positive effect on fractals (*sample 3*). The negative effects of *Saturation* and of *Spectral slope* on snacks in the lab data were not replicated in the online samples. In addition, we found a positive effect for Saturation and a negative effect for *Color value* on snacks, which were absent in the lab samples.

In addition to the samples of fractals and snacks, in the online experiments, we collected data of preference ratings for faces. Similar to the fractals and snacks, we found that there was an effect of visual features on preference ratings for faces. However, in general, these were different features, and the direction of influence was different compared to the effects we found for fractals and snacks. That is, *Hue* and *Saturation* had a positive effect and *Color value* and *Spectral slope* a negative effect on preference ratings for faces (*sample 5*). These results further support our finding that the effect of visual features on preference ratings is category specific.

We then examined the replication results of our pre-registered samples, which served as a second replication of the effects of visual features on preference ratings for fractals and snacks (following the lab and online samples) and a replication for faces (following the online sample). Importantly, we replicated the complex pattern we obtained in the lab and online samples (**Figure 2C**). Specifically, *Hue* had a positive effect on fractals (*sample 6, similar to samples 1 and 3*) and a negative effect on snacks (*sample 7, similar in samples 2 and 4*). *Color value* had a negative effect on fractals (*sample 6, similar in samples 1 and 3*), *Sharpness* had a positive effect on fractals and on snacks (*samples 6 and 7, similar to samples 1 and 2 as well as 3 and 4*), and *Spectral slope* had a positive effect on fractals (*sample 6, similar in samples 1 and 3*). For faces, *Saturation* had a positive effect, and *Color value* and *Spectral slope* had a negative effect (*sample 8, similar to sample 5*). The negative effect for *Saturation* on snacks in the lab data (*sample 2*), which was reversed in the online sample (*sample 4*), was not significant in the replication samples (*sample 7*). The effects that were found in the online samples for *Color value* on snacks (*sample 4*) and for *Hue* on faces (*sample 5*) were not replicated in the replication samples (*samples 7 and 8*).

In order to investigate the role of basic visual features adjusted for the effects of higher-level features, we added market features for snacks and facial features for faces to the regression models, alongside the visual features. The effects of the higher-level features were examined and replicated to some extent. For snacks, we found a positive effect for *Calories, Product weight,* and *Price* in the lab sample (*sample 2*). The effect of *Calories* on ratings was replicated first in the online sample (*sample 4*) and again in the replication sample after pre-registration (*sample 7*). However, the effects of *Product weight* and *Price* were not replicated in the online sample (*sample 4*). In the replication sample (*sample 7*), the effect of *Price* was replicated, but the effect of *Product weight* was reversed. For faces, we found a negative effect for *fWHR*, a negative effect for *Eye distance* and a positive effect for *Nose–eyes distance* in the online sample (*sample 5*). These effects for faces were fully replicated in the replication sample after pre-registration (*sample 8*).

Overall, the category-dependent pattern for the influence of visual features on preference ratings was stable across independent samples and experimental settings (lab vs. online experiments). For detailed results of the regression models, see **Supplementary Table S1**.

Do Low-Level Visual Features and Category-Specific Features Affect Binary Choices Adjusted for Preference Ratings?

We next examined the influence of low-level visual features and category-specific features on actual choices after we controlled for their value, as indicated in their preference ratings. Similarly to the preference ratings results, the effect of the various features on choices was category specific. That is, each feature affected choice differently and this effect depended on the specific items'

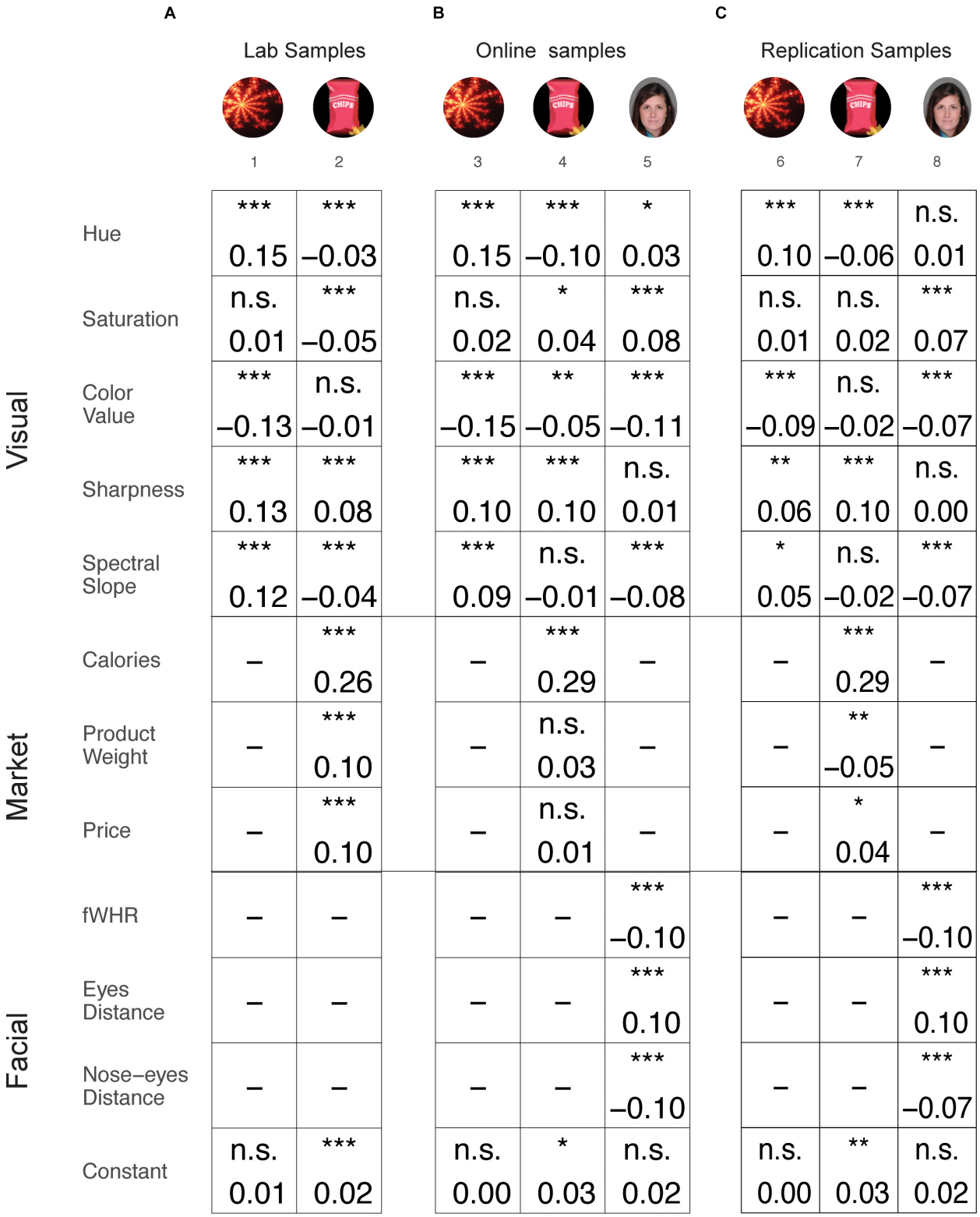


FIGURE 2 | Results summary of the mixed linear regression models for ratings. Effects presented separately for lab **(A)**, online **(B)**, and replication **(C)** samples. Each column represents a different sample and each row represents a different feature. The value in the square indicates the coefficient value for the current feature in the current samples' model. Black text indicates that the current feature was substantial across all samples in the category. Gray text indicates that one or more samples of this category were not significant, thus the effect was not stable across all samples. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Images of faces adapted from a published open access paper (Salomon et al., 2018) and originate from a database by Vieira et al. (2013).

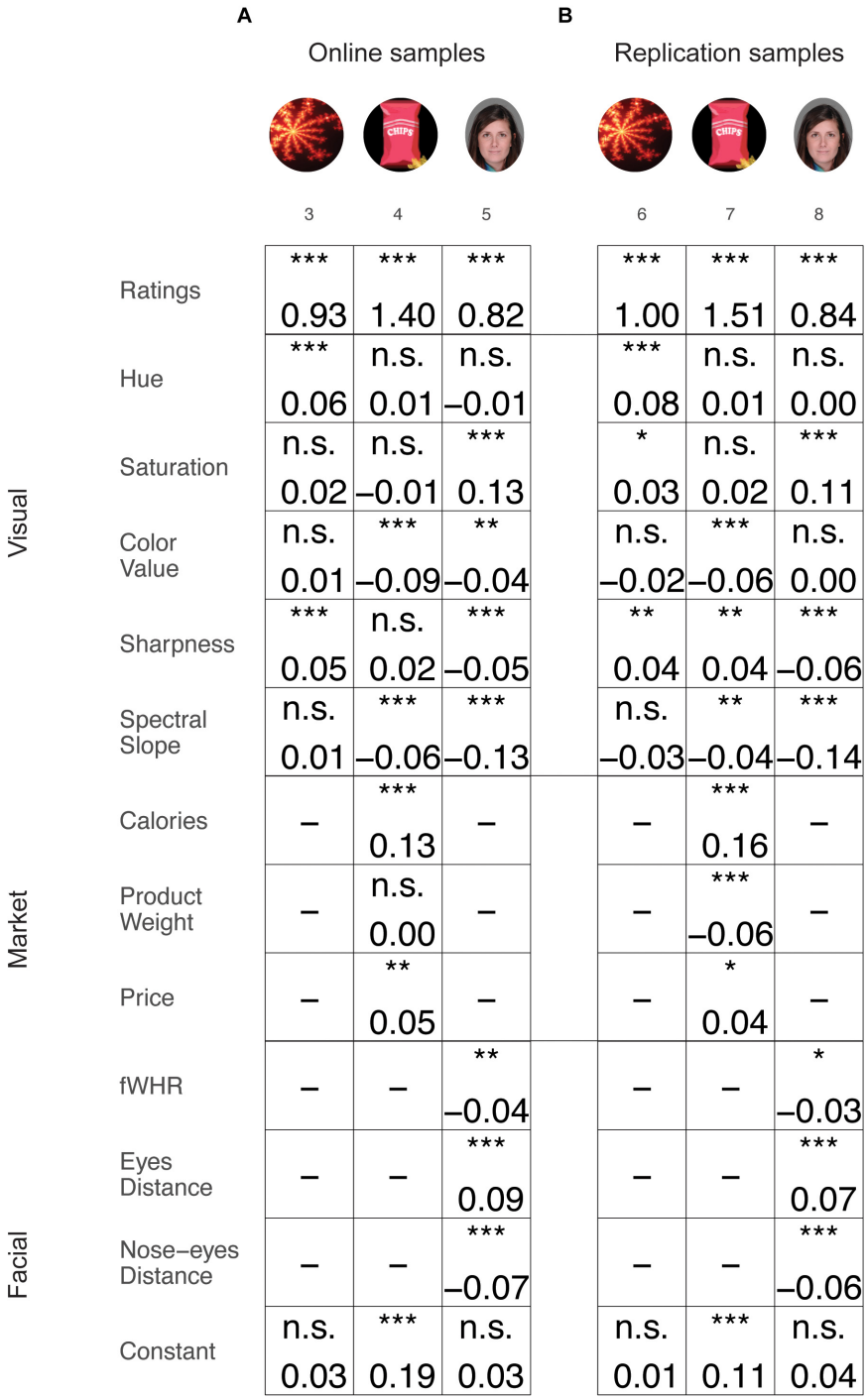


FIGURE 3 | Results of the mixed logistic regression models for choices. Effects presented separately for online **(A)** and replication **(B)** samples. Each column represents different samples and each row represent different features. The value in the square indicates the coefficient value for the current feature in the current samples' model. Black text indicates that the current feature was substantial across all samples of this category. Gray text indicates that one or more samples of this category were not significant, and the effect was thus not stable across samples. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Images of faces adapted from a published open access paper (Salomon et al., 2018) and originate from a database by Vieira et al. (2013).

category (**Figure 3**). Note, that these effects are after controlling for the higher-level features in the model (facial and market) and were mostly replicated in the independent replication samples (*samples 6, 7, and 8*). It is important to emphasize that the effects of the various features on choice (described in **Figure 3**) exist after adjusting for the items' preference ratings, as the ratings of

each item were included in the regression model. That is, visual features can impact choices, regardless of the items' ratings value.

Particularly, participants tended to choose items with higher *Hue* in fractals (*sample 3*), higher *Saturation* in faces (*sample 5*), lower *Color value* in snacks and in faces (*samples 4 and 5*), higher *Sharpness* in fractals (*sample 3*) but lower *Sharpness* in faces (*sample 5*), and lower *Spectral slope* in snacks and faces (*sample 4 and 5*). For the category-specific features, participants tended to choose items with higher *Calories* and higher *Price* in snacks (*sample 4*) and higher *Eye distance* and lower *fWHR* and *Nose–eyes distance* in faces (*sample 5*). All these effects were then replicated in the replication samples (*sample 6* for fractals, *7* for snacks, and *8* for faces), except for the effect for *Color value* in faces, which was not significant (*sample 8*). In addition, we found positive effects for *Saturation* on fractals (*sample 6*), a positive effect for *Sharpness,* and a negative effect for *Product weight* on snacks (*sample 7*), which was not found in the online sample (*samples 3 and 4*). These results indicate a pattern, by which different visual features influence choices between items, in a replicated manner within the same category but not across categories. For detailed results of the regression models, see **Supplementary Table S2**.

Effects Across Tasks

We demonstrate a complex pattern of the effects of basic visual features on preference ratings and binary choices. **Figure 4** shows a summary of the effects that were replicated, obtained only in preference rating (**Figure 4A**), only in choices (**Figure 4B**), and in both procedures (**Figure 4C**). Note that we address the latter options as exclusive, meaning an effect that was observed in both procedures will not appear in the "only ratings" or "only choices" options. There were several effects that were similar across both task procedures. For the basic visual features, *Hue* and *Sharpness* had a positive effect on fractals, *Saturation* had a positive effect on faces, and *Spectral slope* had a negative effect on faces. For the higher-level features, *Eye distance* (Facial) had a positive effect, while *fWHR* and *Nose–eyes distance* had a negative effect on faces. *Calories* (Market) had a positive effect on snacks. Hence, these effects are stable across independent samples (including a replication of pre-registered samples) and could be generalized across measurement procedures.

In contrast, there were several effects that were replicated only in one task procedure but not in the other. In the preference ratings task, *Color value* had a negative effect for fractals and faces, *Hue* had a negative effect on snacks, *Sharpness* had a positive effect on snacks, and *Spectral slope* had a positive effect on fractals.

On the other hand, in the choice task, *Sharpness* had a negative effect on faces, while *Color value* and *Spectral slope* had a negative effect on snacks. Note, that there was no clear and replicated effect on fractals in the choice task that was absent in the ratings task. For *the higher-level* features, only market features replicated solely in the choice task, as *Price* had a positive effect on choices.

These results further emphasize the uniqueness of the effects, by which different visual features influence preferences or choices between items, in a replicated manner within the same category, but not across categories or across measurement procedures. We note that when testing the role of visual features on binary choice we accounted for the subjective ratings of each item. Therefore, the influence of a feature on ratings is statistically accounted for when we examine the effect of that feature on binary choices. The differences between measurement tools thus imply that visual features influence each measurement differently.

DISCUSSION

Most studies thus far have shown the influence of isolated visual properties, such as contrast or hue, on specific aesthetic items (e.g., paintings, abstract images, etc.; Palmer et al., 2013). However, an investigation of isolated types of items does not provide the possibility to examine the contribution and interactions of different features on different types in parallel and of different measurement methods. In the current study, we tested for the first time in one study, the influence of low-level visual features on preferences of fractal art images, faces and snack-food items, using both ratings and binary choices. We show that low-level visual features contribute to preferences differently for each stimulus type and measurement method. We focused on five basic visual features that have a key role in low level visual processing: the three main color features of *Hue*, *Saturation,* and *Color value* (Margaret and Hubel, 1988), *Sharpness* (Ferzli and Karam, 2009), and *Spectral Slope* (Burton and Moorhead, 1987; Field, 1987). For colors, most studies that examined color preferences on simple color patches stimuli had shown a general preference toward cooler and brighter colors (i.e., higher *Hue*, *Saturation*, and *Color value*; McManus et al., 1981; Hurlbert and Ling, 2007; Palmer and Schloss, 2010). However, we show that for complex items, this tendency was replicated only for the *Hue* of fractals and *Saturation* of faces. Namely, participants preferred fractals with higher *Hue* (but not faces or snacks) and faces with higher *Saturation* (but not fractals or snacks) in both rankings and choices. Moreover, we found the opposite effect for *Color value*, which showed a negative effect on rankings of fractals and faces and on choices of snacks. For snacks, we also found an opposite effect for *Hue* on ratings, showing higher preferences for lower hues. This trend may corresponds with a previous study showing that snacks packaging with lower hues are being perceived as healthier (James and Richerson, 2018), but further studies are needed to support this interpretation.

For complex images, in line with a study where preference for greater *sharpness* was shown (Tinio and Leder, 2009), we found preference for greater sharpness for fractals in both ratings and choices and for snacks only in ratings. For faces, however, we found the opposite preference toward lower sharpness in choices and no effect on ratings. For the *Spectral Slope* of the images, studies had shown differences in its mean and variance between categories (Redies et al., 2008; Mather, 2014), and it was hypothesized to be related to the aesthetic perception of the images (Redies, 2008). Yet, it is not clear if and in what way would differences in the *Spectral Slope* of images within a certain category relate to preferences. Here, we found a negative

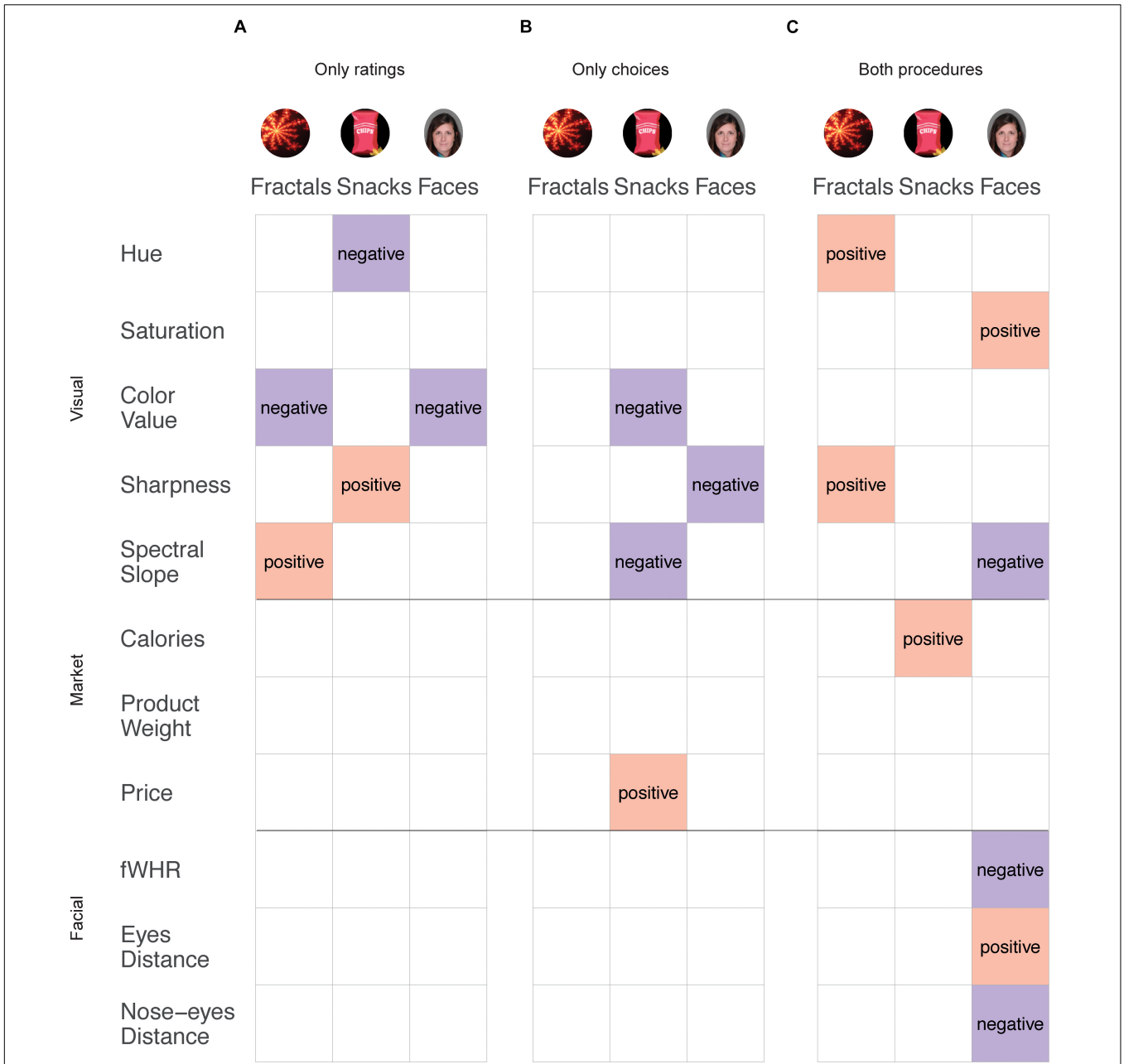


FIGURE 4 | Summary of results from both ratings and choice data. All effects shown here were stable across all samples for each category, for only ratings **(A)**, only choices **(B)**, or both ratings and choices **(C)**. Columns represent categories and rows represent features. The color indicates the direction of the effect (pink: positive, purple: negative). Images of faces adapted from a published open access paper (Salomon et al., 2018) and originate from a database by Vieira et al. (2013).

effect for *Spectral Slope* on faces in both procedures and for snacks only in choices, but a positive effect for fractals only in ratings. Based on the current literature, it is difficult to find definitive reasons for why a specific feature contributed to one category over the other. This is one of the main conclusions of our study: when testing only a certain feature using a certain methodology on a specific stimulus type (as was mostly done in previous studies), it is hard to generalize across domains and features.

Furthermore, our results provide insights regarding the effects that higher-level features have on preferences and choices. For snacks, we found that participants like items with higher *Calories*, as indicated both in their ratings and choices, which is in line with other studies that showed higher preferences for high-calorie foods (Booth et al., 1982; Johnson et al., 1991). In addition, choices were influenced by the snacks' *Price*, in accordance with studies showing the effect of price expectations on preferences (Leonard et al., 2006; Uher et al., 2006). This is in

line with imaging studies examining the neural correlates of these elements, such as choices vs. ratings (Shenhav and Karmarkar, 2019) and preferences vs. *Price* (Knutson et al., 2007). Still, the lack of effect of *Price* on preference ratings is interesting and calls for further investigation. Note, that we collected the snack's higher-level features from information detailed on the packaging or the Internet. However, there might be a substantial difference between the actual features (i.e., the number of *Calories* in a snack, the *Product weight*) to the perceived features (i.e., the number of *Calories* the participant thinks are in the snack and how big the snack is in the eye of the participant). In addition, it is not clear how such higher-level features contribute to the perception and identification of the items or contribute directly to their preferences. Future studies may wish to examine the variations of actual versus perceived levels of such features in their effects on preferences.

For faces, in line with previous work, participants preferred faces with greater distance between the eyes and nose in both ratings and choices (Cunningham, 1986). Additionally, participants preferred faces with lower nose to eyes distance and smaller *fWHR* in both procedures. The effects of these two features were inconclusive in previous studies. The nose to eyes distance was shown to correlate with preferences in an inverted U-shape (Pallett et al., 2010), whilst the Mid-face range (corresponding with this feature) had no correlation with preference (Cunningham, 1986). For *fWHR*, a recent large sample study claimed for a null effect for this feature (Kosinski, 2017). Our study thus sheds light on the interaction between facial features and preferences, however, further studies are required to determine the exact role of these features on preferences.

We chose to present only two regression models in the main results: showing the relation of features on scale ratings and showing the effects of features on binary choices, while taking into account the scale ratings (i.e., entering them into the statistical model). We chose to conduct the analysis in such a manner following a seminal paper, which examined the effects of saliency on binary choices, after entering scale rating to the model (Milosavljevic et al., 2012). Yet, there are many different analyses that could have been done with our current data to explore the relation between features and preferences. For example, we show additional models in the supplementary: one for explaining preference ratings after entering the binary choices to the model (see **Supplementary Figure S2**) and the second for explaining binary choices without entering preference rating to the model (see **Supplementary Figure S3**). It is not surprising that different analysis models lead to slightly different results (Botvinik-nezer et al., 2019). Indeed, we suggest that this strengthens our main conclusion that multiple items types and categories should be tested together. These additional analyses emphasize the need for a more robust approach, given that the kinds of "isolated" effects reported thus far should be considered with caution as they were dependent on the category, task, and analysis used in each study.

In the current study, we focused on a selected number of categories and features we found to be abundant in the literature. Future studies are needed to explore additional categories and features that were beyond the scope of this study. For instance, how would higher level features, such as *Price* and *Product weight*, influence different categories such as supply goods or restaurants meals in addition to snacks? How would the complexity of different features influence their interplay with each other and their influence on preferences?

As we suggested in the introduction, according to fluency theory (Reber et al., 2004; see also Palmer et al., 2013), the ease in which information is being processed may promote valuation. That is, people prefer displays or objects they can perceive easily and impose less demand on the perceptual or cognitive system. Contrary to the prediction of fluency theory, that is, to find relatively stable and similar relations between low-level visual features and preferences for different categories of items, we found a unique pattern per category that relates low-level visual features and preferences. Therefore, our results suggest that category type serves as a strong moderator between low-level visual features and valuation. Moreover, it is important to note that our design controlled for the influence of higher-order, category-specific attributes on valuation. One way to reconcile this finding with fluency theory is to address other low-level visual features that may extract their influence on valuation such as line orientation, complexity, and symmetry, contour curvature and compositional biases (for more details see Palmer et al., 2013) that were not considered in the current study. It is possible that such confounding variables may also influence ease of processing. Nonetheless, we choose to emphasize specific features (*Hue*, *Saturation*, *Color value*, *Sharpness,* and *Spectral Slope*) that have been widely investigated separately in previous work (Burton and Moorhead, 1987; Margaret and Hubel, 1988; Ferzli and Karam, 2009) and are taken as the corner stone of the research in aesthetics preference. Further studies are needed in order to rule out the influence of other visual factors.

Another possible explanation to our findings is that each category involves a different level of abstraction. The current design helps us to revel the unique contribution of low-level features on valuation while controlling for the contribution of higher-level features. However, it is possible that the processing of more complex stimuli, such as face and food items, require that more controlled, top-down processing would take place. Different models in cognitive and system neuroscience proposed that visual analysis start with parallel extraction of different spatial frequencies of a given image. These models suggest that the time course of visual processing follows a predominately "coarse-to-fine" processing strategy (Bullier, 2001; Hochstein and Ahissar, 2002; Bar et al., 2006; Hegdé, 2008). For example, according to Bar and colleagues, early visual magnocellular information is projected to the orbitofrontal cortex (OFC) where it triggers top-down facilitation of object recognition by generating associations that direct the predictions, which are crucial in order to constrain bottom-up processes in favor of a small set of relevant possibilities (Bar et al., 2006). It is possible that top-down processing is category specific; for example, fractals and unfamiliar faces do not convey the same information as well-known snacks. This difference

may affect how top-down processing directs and influences the way lower-level visual attributes may be manifested and influence valuation processes. Future research can explore how top-down processing is category-specific by using other types of stimuli such as artificial vs. naturalistic, curved vs. sharp (Bar and Neta, 2006), abstract shapes vs. recognizable objects (Silvia and Barona, 2009), and objects with different subjective valences.

Recent work suggests that common principles underlie both subjective valuation and sensory perception (Polanía et al., 2019). We suggest that value representation complies with this very basic feature of the brain's ability to process information mentioned above, i.e., the ability to follow a "coarse-to-fine" strategy. Our results may suggest that subjective valuation described as top-down narrowing of bottom-up processing is category dependent. That is, it is possible that during subjective valuation, the type of stimulus at hand, emphasizes the related features that are more associated and relevant for narrowing the bottom-up process. This suggestion is in line with Bar's predicted hypothesis by which top-down processing aids in generating associations that direct the predictions, which are crucial to constrain bottom-up processes in favor of a small set of relevant possibilities (Bar and Neta, 2006). These associations may be specific features of the stimuli and are category dependent. Using "coarse-to-fine" models may offer a parsimonious explanation to different observed effects of choice variability, biases, or diversions from rationality. These models have plausible assumptions regarding the limited-capacity nature of our biological system together with a clear neurobiological and cognitive basis.

Following the replication crisis in different scientific fields (Prinz et al., 2011; Nave et al., 2015; Lithgow et al., 2017), the research community has become committed to producing reproducible science, using larger sample sizes, pre-registrations, sharing open codes, and data (Nosek et al., 2012, 2015). Therefore, here we share all our data, analysis, and task codes. Furthermore, a major part of our findings has been pre-registered prior to collecting additional data, and we were able to replicate them in three new samples. This provides further robustness and generalizability to our results. We show that the effects of visual features on preferences are stable across samples and are not similar across categories. Future studies could examine the generalizability of the visual features we used on other stimuli within each category of items to examine whether the effects obtained in the current study are stimuli specific.

To conclude, we offer for the first time an elaborate testing of multiple visual features on multiple categories with several measurement tools to show that the influence of low level visual features is complex and specific to the item category tested and the way items' value was estimated (either by preference ratings or choice). Moreover, we demonstrated that low-level features affect preference ratings and also influence choices even after controlling for preference ratings, showing that these effects are sustainable and independent of items' value. Our results emphasize the importance of examining multiple features and categories, rather than deducing the influence of a certain feature on preference for a certain category. We chose these item categories and specific features as they are commonly used by us and others in value-based decision-making experiments and in perceptual visual experiments and thus, we aimed to test the commonality and differences in the effects between them. Naturally, there are many other possible features and categories that we did not examine that could have been tested. Importantly, we were able to replicate almost all effects of the low-level visual features that we found in the current study, demonstrating that these effects are stable and could be generalized across samples. This exemplifies the importance of pre-registration and testing our results using independent samples in order to obtain robust conclusions. Future studies are suggested to follow this approach of testing multiple features, on multiple items in different settings potentially on the same participants, to take into account as many features as possible to be able to shed light on the long-lasting question posed by Fechner (1871) regarding the influence of visual features on preferences.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Tel Aviv University Ethics Committee. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

SO designed the experiments, collected and analyzed the data, and wrote the manuscript. TSe assisted with design of the experiments, data analysis, and contributed to write-up of the manuscript. DL contributed to the design of the experiments, data analysis, and manuscript write-up. TSc designed the experiments, assisted with data analysis, and wrote the manuscript with SO. All authors actively contributed to the writing process of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.00988/full#supplementary-material

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Neural Substrates of Brand Love: An Activation Likelihood Estimation Meta-Analysis of Functional Neuroimaging Studies

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Brand love is a critical concept for building a relationship between brands and consumers because falling in love with a brand can lead to strong brand loyalty. Despite the importance of marketing strategies, however, the underlying neural mechanisms of brand love remain unclear. The present study used an activation likelihood estimation meta-analysis method to investigate the neural correlates of brand love and compared it with those of maternal and romantic love. In total, 47 experiments investigating brand, maternal, and romantic love were examined, and the neural systems involved for the three loves were compared and contrasted. Results revealed that the putamen and insula were commonly activated in the three loves. Moreover, activated brain regions in brand love were detected in the dorsal striatum. Activated regions for maternal love were detected in the cortical area and globus pallidus and were associated with pair bonds, empathy, and altruism. Finally, those for romantic love were detected in the hedonic, strong passionate, and intimate-related regions, such as the nucleus accumbens and ventral tegmental area. Thus, the common regions of brain activation between brand and romantic love were in the dorsal striatum. Meanwhile, no common activated regions were observed between brand and maternal love except for the regions shared among the three love types. Although brand love shared little with the two interpersonal (maternal and romantic) loves and relatively resembled aspects of romantic rather than maternal love, our results demonstrated that brand love may have intrinsically different dispositions from the two interpersonal loves.

Keywords: brand love, brand relationship, brand loyalty, meta-analysis, neuroimaging

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INTRODUCTION

In developing marketing strategies, it is crucial to establish emotional bonds between brand(s) and consumers. This relationship has been defined as brand love, brand attachment, and/or brand commitment (Fournier, 1998; Ahluwalia et al., 2000; Thomson et al., 2005; Carroll and Ahuvia, 2006; Park et al., 2006, 2009; Batra et al., 2012). These emotional relationships between consumers and brands can contribute to loyalty, corporate growth, and long-term profitability (Thomson et al., 2005; Carroll and Ahuvia, 2006; Albert et al., 2008; Khamitov et al., 2019). Consumers with strong emotional bonds to their favorite brands attribute

positive traits to them and exhibit strong intentions in protecting their beloved brand if it is maligned (Park et al., 2008). These consumers prefer to maintain proximity with their beloved brand (Fournier, 1998; Thomson et al., 2005; Park et al., 2010) and are willing to pay a premium price (Hazan and Shaver, 1994). Along with progress in studies on this area, concepts on consumer-brand relationships have been proposed and analyzed via statistical studies incorporating factor analyses (Thomson et al., 2005; Carroll and Ahuvia, 2006; Ahuvia et al., 2008; Albert et al., 2009; Sarkar, 2011; Batra et al., 2012; Bagozzi et al., 2016). Khamitov et al. (2019) classified five constructs of consumer brand relationships based on: attachment, love, self-brand connection, identification, and trust. Thus, although consumer-brand relationships can have various aspects, they also have close similarities in emphasizing both emotional relationships and strong ties between brands and consumers beyond a simple like or dislike. Carroll and Ahuvia (2006) referred to these relationships as "brand love," defined as "emotional and passionate feelings for any trademark." Ahuvia (1992, 1993) considered the feeling of love toward various objects. After that, Ahuvia (2005a,b) introduced the idea of "brand love" as concepts related to loved brands, possessions, and consumption activities, although the term was not explicitly used until that time. Subsequently, Ahuvia et al. (2008) developed the brand love theory. Moreover, Batra et al. (2012) comprehensively demonstrated that brand love comprises several constructs (passion-driven behaviors; passionate desire to use/willingness to invest resources/things done in past, self-brand integration; desired self-identity/current self-identity/life meaning/attitude strength 1: frequent thoughts, positive emotional connection; intuitive fit/emotional attachment/positive affect, long-term relationship, anticipated separation distress, overall attitude valence, attitude strength 2: certainty/confidence). Lastovicka and Sirianni (2011) considered material possession love to be a love for an irreplaceable object, unlike brand love, and investigated the root of material possession love. The results of these studies indicated that the feeling of love for objects, including brand love, are complex and varied. Therefore, in the present article, we broadly interpret the term "brand love" as a feeling of love for objects (including brands, products, possessions, activities, place, etc.) formed by emotional relationships between objects and consumers in a consumption context. Thus, practitioners and researchers have conducted marketing studies to investigate the relationships between consumers and brands by directly and prudently applying interpersonal love relationships to consumer brand relationships.

In particular, love studies typified by Sternberg (1986) have strongly influenced investigations examining brand love. He proposed a triangular theory involving three components—intimacy, passion, and commitment—that are important for forming interpersonal love relationships. Shimp and Madden (1988) proposed eight types of consumer-object relationships by adopting Sternberg's love theory. Several studies have directly applied romantic love relationships to brand love (Whang et al., 2004; Sarkar, 2011; Sarkar et al., 2012). These studies tend to claim that both strong passion and strong emotive arousal are essential concepts in the relationship between consumers and brands, similar to romantic relationships between individuals. The concept of brand attachment is based on Bowlby's work (Bowlby, 1969). In attachment studies, the realm of attachment is defined as the relationship between parents and infants. However, marketing studies have extended this concept to the relationship between a person and an object. Park et al. (2008) defined brand attachment as "the strength of the cognitive and affective bond connecting the brand with the self." Moreover, attachment style (anxiety or avoidance) to brands influences brand attitudes and can manifest as loyalty and preference (Swaminathan et al., 2009; Thomson et al., 2012; Mende et al., 2013). Based on the self-expansion theory (Aron and Aron, 1986), Ahuvia (1993, 2005a,b) has adapted it to a consumption context. Subsequently, Ahuvia et al. (2009) elaborated on Ahuvia's theory to propose the conditional integration theory. They classified the integration between self and loved objects (brands) into two types: the actual level of integration and the desired level of integration with the loved objects (brands). When a brand reaches high levels of integrations in both actual and desired types, consumers feel love for a brand. Reiman and Aron (2009) also included brand meanings in the self that can foster brand love. Escalas and Bettman (2003) proposed the concept of self-brand connections in terms of brand association.

Thus, applying interpersonal love relationships to brand love has some effectiveness; however, Batra et al. (2012) specifically criticized the idea that interpersonal love theories can be directly applied to brand love and mentioned the applicability of interpersonal love to brand love. It is important to assess the similarities and differences between interpersonal love and consumer-object relationships (Ahuvia, 1992, 1993, 2005a,b; Ahuvia et al., 2008, 2009; Albert et al., 2008, 2009, 2013; Albert and Valette-Florence, 2010; Batra et al., 2012; Albert and Merunka, 2013; Langner et al., 2015; Bagozzi et al., 2016). While the importance of self-identification was reported for both interpersonal love and brand love, altruistic concerns were not observed for brand love (Batra et al., 2012). Yoon et al. (2006) used neuroscience techniques to demonstrate that brand personality was not processed like human personality in the information system within the brains of consumers. Bagozzi et al. (2016) reported weaker intensity and passion for brand love than that for interpersonal love. Langner et al. (2015) used qualitative and quantitative approaches to verify the transferability of interpersonal love to brand love. Langner et al. (2016) observed no respondents with altruistic attitudes to brand love and that brand love was a less intense emotion than partner love. The authors proposed that brand love had a different emotional nature than that of interpersonal (romantic) love. In contrast, Carroll and Ahuvia (2006) and Albert and Valette-Florence (2010) confirmed that the concepts of interpersonal love were effective in measuring brand love.

Although significant findings on the applicability of interpersonal love have been reported, it remains unclear to what extent the properties overlap between interpersonal

Abbreviations: ALE, Activation Likelihood Estimation; GP, Globus Pallidus; MNI, Montreal Neurological Institute; PET, Positron Emission Tomography; IFG, Inferior Frontal Gyrus; MTG, Middle Temporal Gyrus.

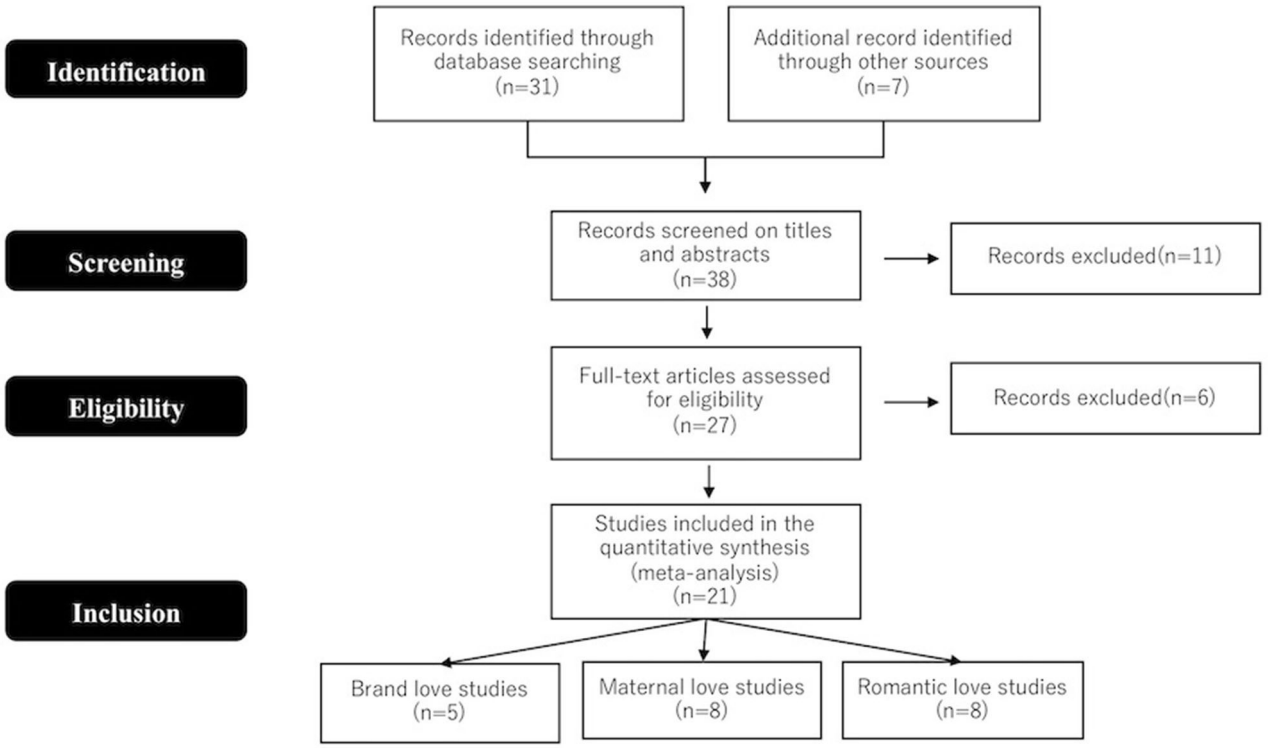


FIGURE 1 | Prisma flow diagram.

and brand love; in other words, whether the overlap is broad or narrow, and whether brand love shares intrinsic dispositions of interpersonal love. The present study considered maternal and romantic love as typical interpersonal and aimed to identify similarities and differences among the three love types (i.e., brand, maternal, and romantic) using a neuroscience approach. We performed a quantitative meta-analysis using the activation likelihood estimation (ALE) method (Turkeltaub et al., 2002) for neuroimaging studies to evaluate commonly- and uniquely-activated brain regions in the three love types across multiple studies. Meta-analyses are essential to determine the convergence of results across multiple independent studies.

MATERIALS AND METHODS

Studies included in the present meta-analysis were selected by searching the NeuroSynth database [https://neurosynth.org/ (14,372 articles)] using the following terms: "romantic" for romantic love studies, "maternal or bonding" for maternal love studies, "brand or brand loyalty or brand love or brand attachment" for brand love studies. The literature search retrieved 31 articles. However, the literature search for studies in the field of brands and marketing was not solely restricted to the NeuroSynth database. As such, additional studies were retrieved by searching the Google Scholar database. Search terms included combinations of the following neuroimaging terms: "MRI," "fMRI," and "brain," as well as marketing- and brand-related terms, such as "brand," "brand loyalty," "brand love," and "brand attachment." Seven articles were added using this search engine. After reading the titles and abstracts of these 38 articles, 11 were eliminated and the full texts of the remaining 27 were read and assessed based on the following inclusion criteria: peer-reviewed original research in an English language journal; healthy adult population; results reported Talairach or Montreal Neurological Institute (MNI) space; and reported brain activation images. For studies that reported results from more than one subject group, each group was treated separately in accordance with the approach of Turkeltaub et al. (2012). Since only one article (Reimann et al., 2011) reported images of brain activation without coordinates, they were estimated by comparing the images with coordinates in the MNI standardized brain image. Prisma flow diagram (**Figure 1**) gives details on the screening process.

Twenty-one studies were included in the present meta-analysis (**Table 1**). All Talairach coordinates were converted to MNI space using icbm2tal transform (www.brainmap.org) before the formal analysis (Lancaster et al., 2007). The ALE method, which is a coordinate-based quantitative meta-analysis method used to test for commonly-activated brain regions across different experiments, was used in the meta-analysis. In a comparison of alternative coordinate-based meta-analysis methods, such as kernel density analysis (Wager et al., 2004) and signed differential mapping (Radua and Mataix-Cols, 2009; Radua et al., 2010),

TABLE 1 | Studies included in the meta-analysis.

	Experiments	Subject	Foci	Experiment stimuli
Brand love	Schaefer and Rotte (2007)	14	5	Brand logos
	Plassmann et al. (2007)	22	1	Closing
	Reimann et al. (2011)	12	2	Songs
	Schaefer et al. (2011)	16	1	Pictures of branded product
	Reimann et al. (2012)	16	6	Brand logos
Maternal love	Bartels and Zeki (2004)	19	30	Pictures
	Lenzi et al. (2008)	16	15	Pictures of facial expression
			7	
			15	
	Noriuchi et al. (2008)	13	14	Video clips
			24	
			43	
	Musser et al. (2012)	22	6	Cry sound
	Wan et al. (2014)	20	34	Video clips
			19	
		9	14	
		20	18	
	Atzil et al. (2017)	25	22	Video clips
	Ho and Swain (2017)	29	1	Cry sound
			3	
	Kluczniok et al. (2017)	27	23	Pictures of facial expressiion
			9	
			5	
Romantic love	Bartels and Zeki (2000)	17	13	Pictures of the faces
	Zeki and Romaya (2010)	24	8	Pictures of the faces
	Xu et al. (2011)	18	8	Pictures of the faces
			7	
			2	
	Acevedo et al. (2012)	17	30	Pictures of the faces
			26	
			9	
			24	
	Cooper et al. (2012)	39	4	Pictures of the faces
			3	
			15	
			5	
			5	
			1	
			2	
			2	
	Xu et al. (2012)	12	1	Pictures of the faces
		6	3	
	Cooper et al. (2013)	38	13	Pictures of the faces
			8	
			14	
	Ebisch et al. (2014)	24	1	Partner's hands/Ball
			2	

ALE was found to produce results most comparable to image-based meta-analysis (Salimi-Khorshidi et al., 2009). In fact, ALE is the most preferred method for meta-analytical comparison of neuroimaging data because it is difficult to access full-brain activation images.

In ALE, all foci reported in the selected studies were modeled by creating three-dimensional Gaussian probability distributions centered at each focus (i.e., reported x, y, and z coordinates). These probabilities were then combined within and across experiments to produce a whole-brain map of ALE values for each voxel. This experimental ALE map compared a null hypothesis map representing the noise distribution. To determine the reliability of the ALE maps, a permutation procedure was applied to test the differentiation between true convergence of foci and random clustering (Eickhoff et al., 2009, 2012; Turkeltaub et al., 2012). ALE meta-analysis was performed using the GingerALE version 3.02 tool (http://www.brainmap.org/). The threshold was set at $p < 0.001$ uncorrected with a minimum cluster size of 100 mm^3. There are a few reasons why we adopted the statistical criteria. First, GingerALE manual recommend the criteria. Secondly, uncorrected p-value < 0.001 is widely adopted as a statistical criterion (Carp, 2012; Eickhoff et al., 2012; Garrison et al., 2013). In addition, the reason why we adopted this cluster size is that the minimum cluster size of 100 mm^3 can be thought of slightly more conservative size than recommended cluster size (Carp, 2012; Eklund et al., 2016). According to Carp (2012), 80 mm^3 is the recommended cluster size. ALE maps were generated for each of the three loves types (i.e., brand, maternal, and romantic). In this study, all ALE coordinates were reported in MNI space. All activated brain images were exported as NIfTI files and overlaid onto a canonical anatomical T1 brain template in MNI space using Mango software version 4.1 (http://ric.uthscsa.edu/mango/). Conjunction analysis is needed to statistically investigate both similarity and discrepancy among the three loves, but it is difficult to perform conjunction analysis using GingerALE version 3.02. This is because sample size does not achieve the criterion recommended by GingerALE manual. However, we computed a voxel-wise hadamard product between the two result images of ALE to extract top 5% voxels, with the view of performing an approach similar to conjunction analysis but not using hypothesis test for evaluating significance. This analysis was performed using Matlab.

RESULTS

Individual ALE maps were obtained for the three love types and ALE meta-analytical results are summarized in **Tables 2**, **3** and shown in **Figure 2**. **Table 2** presents the coordinates and levels of the maximum ALE value. **Table 3** is the brief version of **Table 2**. Results of the ALE analysis for the three love types are described below.

Brand Love

The greatest likelihood for brain activation in brand love was in the left caudate body, right putamen, and left putamen, followed by the left insula. Thus, ALE for brand love demonstrated a

TABLE 2 | Regional loci of brain activation by meta-analysis.

	Brain regions	L/R	BA	Coordinate (MNI)			ALE
				X	Y	Z	
BRAND LOVE							
	Caudate body	L	/	−8	14	4	0.0083
	Putamen	R	/	28	0	0	0.0081
	Putamen	L	/	−20	8	14	0.0079
	Insula	L	13	−34	8	16	0.0077
	Caudate body	L	/	−18	0	24	0.0077
	Caudate head	R	/	22	30	−2	0.0077
	Putamen	R	/	24	6	6	0.0077
	Caudate head	L	/	−16	30	0	0.0076
	Insula	R	13	38	2	20	0.0076
MATERNAL LOVE							
	Cuneus	R	18	6	−84	24	0.0234
	Hippocampus	L	/	−30	−30	−12	0.0230
	Inferior frontal gyrus	R	9	54	8	28	0.0213
	Insula	L	13	−44	12	−10	0.0195
	Middle temporal gyrus	R	37	58	−64	10	0.0181
	Precentral gyrus	L	6	−50	−4	4	0.0180
	Lateral globus pallidus	R	/	20	0	−10	0.0179
	Medial frontal gyrus	L	10	−2	62	4	0.0171
	Parahippocampal gyrus	R	28	26	−14	−20	0.0162
	Insula	L	13	−50	−34	22	0.0160
	Superior temporal gyrus	R	/	28	8	−32	0.0158
	Amygdala	L	/	−28	−4	−24	0.0155
	Putamen	L	/	−18	8	2	0.0150
	Anterior cingulate	L	24	−4	28	−4	0.0146
	Postcentral gyrus	R	1	66	−22	44	0.0142
	Anterior cingulate	L	25	−4	4	−10	0.0142
	Posterior cingulate	L	31	−2	−54	26	0.0141
	Superior temporal gyrus	L	39	−52	−54	8	0.0141
	Middle temporal gyrus	L	21	−58	−8	−22	0.0140
	Uncus	L	34	−22	4	−26	0.0139
	Middle temporal gyrus	R	21	60	−8	−22	0.0139
	Declive	L	/	−42	−60	−22	0.0139
	Anterior cingulate	L	32	0	44	−10	0.0139
	Middle frontal gyrus	R	6	52	10	48	0.0137
	Insula	R	13	48	−30	18	0.0137
	Inferior frontal gyrus	L	47	−28	22	−24	0.0136
	Superior temporal gyrus	L	38	−36	18	−32	0.0135

(Continued)

TABLE 2 | Continued

Brain regions	L/R	BA	Coordinate (MNI)			ALE
			X	Y	Z	
ROMANTIC LOVE						
Cingulate gyrus	R	22	4	20	42	0.0370
Hippocampus	R	/	34	−36	0	0.0337
Putamen	L	/	−22	2	6	0.0243
Substania nigra (VTA)	R	/	18	−20	−10	0.0241
Caudate head (NAcc)	L	/	−6	10	−4	0.0239
Mammillary body	L	/	2	−12	−8	0.0227
Hippocampus	L	/	−34	−32	−4	0.0224
Thalamus	L	/	0	−6	−6	0.0221
Putamen	L	/	−20	2	18	0.0198
Culmen	L	/	0	−60	2	0.0197
Claustrum	R	/	40	12	−4	0.0196
Insula	L	13	−44	6	−2	0.0183
No gray matter found		/	2	−26	−20	0.0181
Caudate head	R	/	10	4	−4	0.0181
Caudate body	R	/	18	4	22	0.0178
Caudate body	R	/	16	−12	22	0.0168
Extra-nuclear	L	13	−38	8	−14	0.0164
Hippocampus	L	/	−32	−46	2	0.0155
Medial frontal gyrus	R	10	2	58	−10	0.0151
Posterior cingulate	R	30	8	−52	16	0.0151
Caudate tail	R	/	32	−44	12	0.0145
Anterior cingulate	L	32	−6	40	−14	0.0144
Lateral globus pallidus	L	/	−20	−2	−12	0.0142
Anterior lobe	L	/	−6	−48	−28	0.0142
Inferior frontal gyrus	R	47	36	28	−8	0.0139
Cuneus	L	7	−8	−68	36	0.0138
Medial globus pallidus	R	/	22	−6	−8	0.0136
Medial dorsal nucleus	L	/	−6	−18	2	0.0131
Culmen	R	/	6	−60	−20	0.0129
Caudate head	R	/	8	12	−6	0.0129
Superior occipital gyrus	L	19	−34	−72	36	0.0126
Red nucleus	L	/	−2	−24	−10	0.0124
Anterior cingulate	R	24	12	36	−10	0.0121

BA, Brodmann area; L, left; R, right; ALE, activation likelihood estimation. The threshold was set at p 0 < 0.001 uncorrected for each ALE map.

high convergence of activation mainly in the dorsal striatum, including the putamen and caudate. These regions are related to the reward system (Balleine et al., 2007), positive effect (Phan et al., 2002), reinforcement learning (Packard and Knowlton, 2002; Samejima et al., 2005), and the narrowing of preference target size in a choice set (Kim et al., 2014). Studies using positron emission tomography (PET) have reported that dopamine release is increased in the dorsal striatum during monetary reward tasks (Koepp et al., 1998; Zald et al., 2004). Thus, the caudate and putamen play crucial roles in the reward system of the brain. Moreover, it has been recently clarified that the caudate and putamen are engaged in different functional roles in reward

TABLE 3 | Summary table for **Table 2**.

Regions		Functions	Love types		
			Brand	Maternal	Romantic
Basal ganglia	Putamen	Habitual behavior/reward/RL	Y	Y	Y
	Caudate	Valuation/reward/RL	Y		Y
	VTA	Motivation/reward/impulsive desire/RL			Y
	NAcc	Pleasure/reward/impulsive desire/RL			Y
	GP	Pair bond/empathy/altruism		Y	
Limbic	Amygdala	Emotional memory		Y	
	Hippocampus	Episodic memory		Y	Y
	Cingulate gyrus	Adjustment for emotion and cognition		Y	Y
Cortical regions	Insula	Subjective feelings/interoception/self-consciousness	Y	Y	Y
	Cuneus	Empathy/visual processing/working memory		Y	
	IFG	Empathy/executive function/working memory		Y	
	MTG	Empathy/object recognition/working memory		Y	

VTA, Ventral Tegmental Area; NAcc, nucleus accumbens; GP, globus pallidus; RL, reinforcement learning; IFG, Inferior Frontal Gyrus; MTG, Middle Temporal Gyrus. "Y" means significant activated regions in each love types.

learning. In the reward system, the caudate and anterior putamen play roles in reward expectation and the middle-posterior putamen coded values for habitual behaviors (Kawagoe et al., 1998; Gerardin et al., 2003; Haruno and Kawato, 2006; Balleine et al., 2007; Van Wouwe et al., 2012; Wunderlich et al., 2012; Lee et al., 2014). In addition, the caudate acts as an integrator in the brain valuation system that evaluates subjective values (Bartra et al., 2013; Audrin et al., 2017).

Maternal Love

Brain regions with the most significant likelihood of activation associated with maternal love were the right cuneus, left hippocampus, and right inferior frontal gyrus (IFG), followed by the left insula. The other main activated regions were in the middle temporal gyrus (MTG), left precentral gyrus, right lateral GP, left medial frontal gyrus, right parahippocampal gyrus. Thus, in maternal love studies, the most activated brain areas were the region in the cortical area. The IFG and insula are regions related to social cognition such as cognitive empathy (Gallese et al., 2004; Chakrabarti et al., 2006; Riem et al., 2011). Both MTG pathways—the anterior cingulate/insula and the posterior cingulate/insula—are related to emotional empathy and inference from others' minds on inhibiting self (Jackson et al., 2006; Singer et al., 2006; Shibata and Inui, 2011). The combination of the precentral gyrus and insula is related to the theory of mind (Keysers and Gazzola, 2007). The cuneus are also the regions related to empathy and the theory of mind (Völlm et al., 2006). The function of the GP is related to the effects of oxytocin, prompted by strong altruism, pair bonding, and favoring derived from long-term relationships (Lim and Young, 2004; Lim et al., 2004; Acevedo et al., 2019).

Romantic Love

Brain areas most associated with romantic love were the right cingulate gyrus, right hippocampus and left putamen, followed by the right substantia nigra, including the ventral tegmental area. The other main activated regions were in the left caudate head, including the nucleus accumbens, left mammillary body, left hippocampus, left thalamus, and left culmen. Thus, in romantic love studies, significantly elevated probabilities of activation in the basal ganglia area were more prominent in the midbrain. Moreover, the regions composed of Papez circuit (Papez, 1937) or related to the reward system (Phan et al., 2002) were activated. In particular, the ventral tegmental area and the nucleus accumbens are related to impulsive desire (Krämer and Gruber, 2015), pleasure (Olds and Milner, 1954), eliminating unpleasantness (Papoiu et al., 2013), financial reward (Thut et al., 1997; Delgado et al., 2000; Elliott et al., 2000; Knutson et al., 2000), and addiction (Gilpin and Koob, 2008).

Conjunction Analysis

Results are shown in **Figure 4**. There were no overlapped regions between brand love and maternal love. On the conjunction between brand love and romantic love, we identified overlap voxels in the putamen and the caudate.

DISCUSSION

To the best of our knowledge, the present study was the first to review the neural correlates of brand love using ALE meta-analysis. Our meta-analysis aimed to identify the similarities and discrepancies in activated brain regions underlying brand love, maternal love, and romantic love. Although conjunction analysis was performed with the loose criterion mentioned above, we consider that results from conjunction analysis have effectiveness as a just reference. Therefore, we mainly investigated commonalities and differences among brain regions in the three love types by comparing brain-activated regions. With these considerations, we will discuss the uniqueness and characteristics of brand love compared with typical interpersonal loves, such as maternal and romantic love.

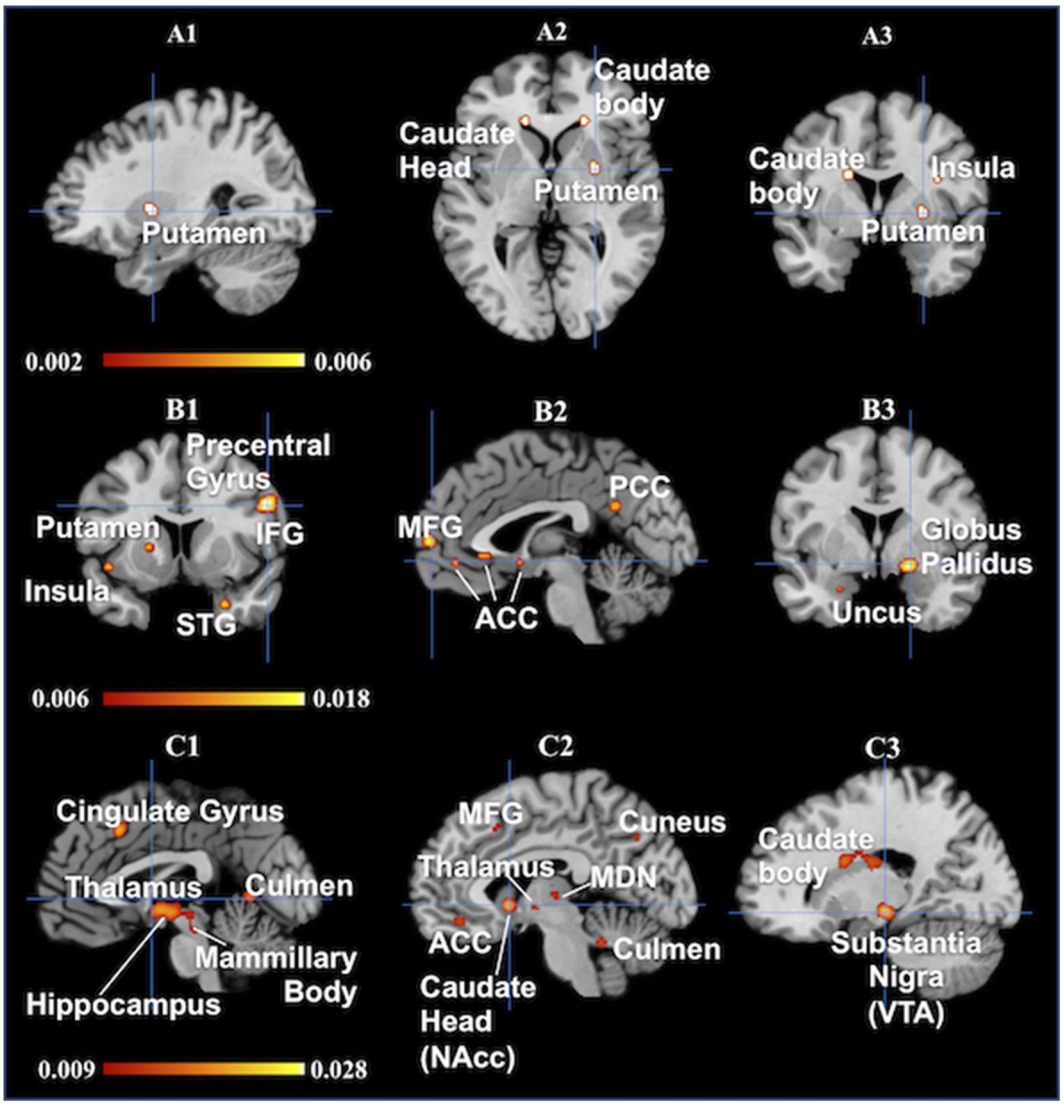


FIGURE 2 | Results are from the ALE software for meta-analyses. All activations are significant at $p < 0.001$ uncorrected/**(A1–A3)**: Brand love, each of crosshairs is (28 0 0), **(A1)** sagital, **(A2)** Axial, **(A3)** coronal/**(B1–B3)**: Maternal love, **(B1)** sagital, Crosshair is (−2 59 −8), **(B2)** coronal, Crosshair is (−2 59 −8), **(B3)** coronal, Crosshair is (20 0 −10)/**(C1–C3)**: Romantic love, All views are sagital, **(C1)** Crosshairs is (−1 0 0), **(C2)** Crosshair is (−6 10 −4), **(C3)** Crosshair is (18 −20 −10). IFG, inferior frontal gyrus; STG, superior temporal gyrus; MFG, medial frontal gyrus; ACC, anterior cingulate cortex; PCC, posterior cingulate cortex; MDN, medial dorsal nucleus; NAcc, nucleus accumbens; VTA, ventral tegmental area.

Shared Brain-Activated Regions: Brand Love and the Typical Interpersonal Loves

Activation of the insula and putamen was commonly observed among the three love types (**Tables 2**, **3**). In brand love, the activated region in the insula was the dorsal position compared with both maternal love and romantic love. However, the activated regions in maternal love and romantic love overlapped. In the putamen, activated regions among the three loves essentially overlapped (**Figure 3**).

Many studies have investigated the function of the insula. Investigations on the insula have demonstrated that the anterior insula plays an important role in interoception and subjective feelings (Caprara et al., 1985; Damasio et al., 2000; Iaria et al., 2008; Rudrauf et al., 2009; Terasawa et al., 2012, 2013; Zaki et al., 2012; Wang et al., 2019). Most studies have reported that brain-activated regions related to interoception and subjective feelings overlap (Caprara et al., 1985; Damasio et al., 2000; Iaria et al., 2008; Rudrauf et al., 2009; Terasawa et al., 2012, 2013; Zaki et al., 2012; Wang et al., 2019). In particular, Craig (2003) proposed the hypothesis that the most subjective feeling derived from interoception is engendered in the insula. Moreover, Craig and Craig (2009) further proposed that the insula is associated with self-consciousness and the accuracy of self-monitoring derived from the sense of body because Craig and Craig (2009)

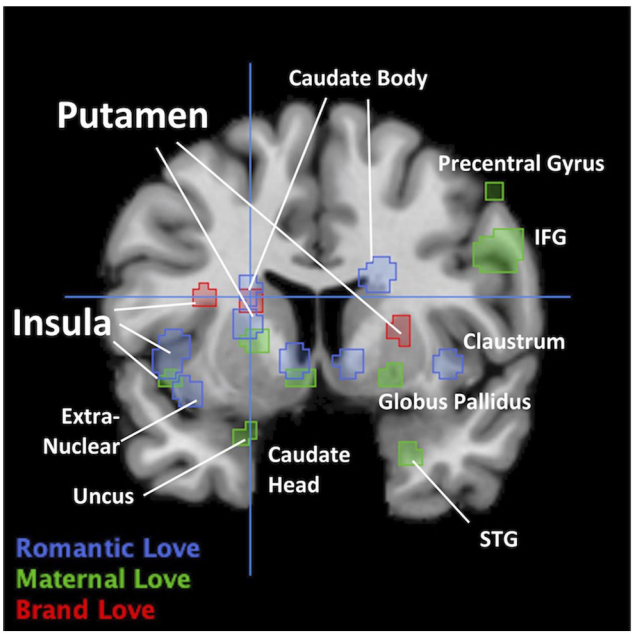


FIGURE 3 | Overlapped regions across three loves in coronal view. Crosshair is (−20 7 15). IFG, Inferior Frontal Gyrus; STG, superior temporal gyrus.

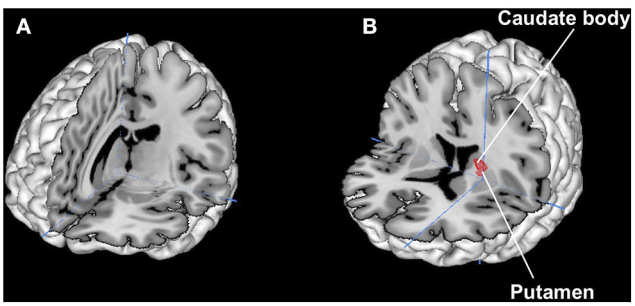


FIGURE 4 | Results of conjunction analysis. **(A)** Brand love and Maternal love. No overlapped regions, crosshair is (7 −18 10)/**(B)**: Brand love and Romantic love. Overlapped regions are the putamen (−20 6 16), (−21 5 15), and the caudate body (−19 7 16), crosshair is (−21 1 4).

insisted that the "insula contained a somatotopic representation of subjective feelings of one's current movements as part of a representation of all feelings from body." Thereby, our results indicate that the insula can be involved in self-related concepts according to marketing literature.

Previous studies have reported the importance of forming relevancy and integration between a brand and consumers' self-concept to build strong relationships and brand equity (Ahuvia, 1992, 1993, 2005a,b; Escalas and Bettman, 2003, 2015; Park et al., 2008; Ahuvia et al., 2009; Reiman and Aron, 2009; Batra et al., 2012). Ahuvia (1993, 2005a,b) and Ahuvia et al. (2009) suggested that the integration of the brand (the loved objects) into consumers' sense of identity brought out feelings of love for brands and objects in a consumption context. Escalas and Bettman (2015) argued that brands help consumers form their self-identity. According to their hypothesis, consumers can express who they want to be by possessing specific brands. These considerations are related to seeking the ideal self; moreover, achieving the ideal self produces higher self-esteem. Thus, self-identification and self-brand connections with brands play a crucial role in brand love. This result also indicates that activations in the insula are associated with "brand saliency." The concept of "brand saliency" in the consumer's mind has been pointed out as an important idea in marketing strategy. Brand saliency involves keeping consumers aware and frequently reminded of a brand in order to occupy the largest share of the consumer's mind. Our results indicate that brain activation in the insula may be involved in brand saliency. More specifically, brand saliency is presumed to be a phenomenon derived from interoception. Moreover, it has been known that the insula plays a critical role in salience network and has been clarified that the salience network is involved in the detection of a self-referential information in the default mode network (Orliac et al., 2013). This implicates that brand saliency is a consumer's mind being involved in the salience network.

As mentioned above, many studies have reported that the putamen plays an important role in the reward network in the dorsal striatum. In particular, the anterior putamen and the caudate mediate goal-directed behaviors and deliberate decision making. In particular, the anterior putamen is involved in integrating and mediating information regarding the expectation of reward. On the other hand, it has been revealed that the posterior putamen is involved in coding value on habitual behavior such as repeated training (Balleine et al., 2007; Tricomi et al., 2009; Wunderlich et al., 2012; Dolan and Dayan, 2013). These roles in the putamen do not contradict one another. The anterior putamen is activated in the early stages, while activation of the posterior putamen increases in the later stages during the reward-based decision-making task (Gerardin et al., 2003; Lee et al., 2014). Therefore, the putamen works by maintaining a balance between the anterior and posterior parts according to circumstances and as necessary. However, symptoms, such as addiction, dependence, and compulsive-obsessive behaviors occur when this balance is disrupted (Van Wouwe et al., 2012; Sjoerds et al., 2013; Marsh et al., 2014). For example, alcohol-dependent patients exhibited stronger activation in the posterior putamen than healthy controls in an instrument task (Sjoerds et al., 2013). Moreover, the weak connectivity between the ventromedial prefrontal cortex and anterior putamen was observed in alcohol-dependent subjects when they acted habitually in the tasks compared to healthy controls. This means that the imbalance derived from impairing the executive control function in the frontal brain region causes an over-reliance on habit. In addition, it has been reported that reduced connectivity in the posterior insula-putamen is involved in cocaine addiction, relapse risk, and impulsivity (McHugh et al., 2013).

Our results demonstrated that the putamen is a shared brain region among the three love types and is an important substrate region for brand love. Many marketing studies have reported that frequency is one of the most crucial indicators

of brand loyalty (Jacoby and Chestnut, 1978). Among academic marketing researchers and practitioners, it is widely known that consumers' purchasing behaviors are based on habit and have a strong tendency to persist (Pollak, 1970; Wood et al., 2002; Seetharaman, 2004; Quinn and Wood, 2005; Wood and Neal, 2009). It is difficult to make habitual consumers switch to other products they purchase habitually because a familiarity cue causes activation of associative responses (Wood and Neal, 2009; Riefer et al., 2017). Consumers have a tendency not to evaluate new products but existing products, since it is difficult and unfavorable for them to learn new usage behaviors (Murray and Häubl, 2007). Therefore, habitual behaviors without uncertainty generate fluency. Furthermore, fluency without cognitive load leads to familiarity. Ultimately, familiarity leads to positive feelings toward making decisions about choosing a brand (Wood and Rünger, 2016).

Based on the considerations above, love, including brand love, is based on certain repetitive relationships and is strongly involved in self-related emotions derived from interoception. In addition, both a motivation for goal-directed action and a habituation dependent on pleasantness derived from achieving its goals can reinforce relationships between subjects and objects.

In other words, brand love can be thought of as an information processing system based on the reinforcement learning system and related to fast and heuristic thinking involving subjective feelings in the context of dual process theories (Evans, 2008; Stanovich, 2008; Kahneman, 2011).

Different Brain-Activated Regions: Brand Love and Typical Interpersonal Loves

Characteristic brain-activated regions in maternal love compared with brand love include the cortical regions and the GP. As mentioned, cortical regions activated in maternal love are related to social cognition such as empathy, theory of mind, and caregiving (Gallese et al., 2004; Chakrabarti et al., 2006; Jackson et al., 2006; Singer et al., 2006; Keysers and Gazzola, 2007; Riem et al., 2011; Shibata and Inui, 2011). In addition, the GP is involved in pair bonding and altruism, which are kinds of social cognition (Lim and Young, 2004; Lim et al., 2004; Acevedo et al., 2019). Some studies on brand love also have considered empathy as a crucial element in brand love (Fournier and Alvarez, 2012; Kervyn et al., 2012). However, in our meta-analysis, these social cognition-related brain regions were not activated in brand love; as such, we assume that brand love has a very weak disposition toward social cognitive aspects. In particular, the deactivation in the GP showed that brand love may not have as strong an aspect of social cognition as those observed for pair bonds and altruism. Batra et al. (2012) suggested that altruism is not a part of brand love despite containing altruistic concerns that are crucial elements in interpersonal love. Langner et al. (2015) also made the same point. Moreover, Albert et al. (2013) showed that altruism had no effects on building brand love. Thus, while our results support these findings, oxytocin reportedly enhances customer-brand relationships (Fürst et al., 2015). Oxytocin is a neuropeptide that is known to modulate the formation of social relationships, such as pair bonds and emotional empathy, and behavior (Lim and Young, 2004; Lim et al., 2004; Riem et al., 2011; Geng et al., 2018; Yao et al., 2018; Acevedo et al., 2019; Kruppa et al., 2019; Xu et al., 2019). Lastovicka and Anderson (2014) reported that consumer-object relationships such as playing with and nurturing material objects may increase oxytocin levels, implying that brand love could have social cognitive dispositions with activation in brain regions associated with oxytocin such as the GP even if consumer-brand relationships (a consumer-object relationship), are one-way, unlike interpersonal love. Previous brain activation studies investigating brand love could not detect oxytocin-related regions using assessment methods such as the current respondent assessment scales. However, it is possible that future novel experimental designs and procedures could reveal activation in oxytocin-related brain regions represented by pair bonds and altruistic dispositions.

In contrast, romantic love shares more common brain-activated regions with brand love than maternal love, especially in the dorsal striatum (the putamen and the caudate, see **Tables 2**, **3**, **Figure 4**). Other brain activation in romantic love characteristically converged regions related to thalamo-cortico-thalamic circuits consisting of the cortical regions, thalamus, and ventral striatum. The brain regions activated in romantic love are involved with impulsive desire and addiction (Gilpin and Koob, 2008; Krämer and Gruber, 2015). However, activation of these brain regions was not observed in brand love. Therefore, both romantic and brand love are involved in attitudes toward certain rewards related to goal-oriented and habitual behaviors (Kawagoe et al., 1998; Gerardin et al., 2003; Haruno and Kawato, 2006; Balleine et al., 2007; Van Wouwe et al., 2012; Wunderlich et al., 2012; Lee et al., 2014). Romantic love, however, showed dispositions toward more impulsive, intimate, and passionate relationships compared to brand love. The marketing literature stresses the importance of building impulsive, intimate, and passionate relationships between brands and consumers (Shimp and Madden, 1988; Fournier, 1998, 2014; Keller, 2001; Thomson et al., 2005; Carroll and Ahuvia, 2006; Park et al., 2008; Albert et al., 2009; Albert and Valette-Florence, 2010; Lastovicka and Sirianni, 2011; Sarkar, 2011; Batra et al., 2012; Sarkar et al., 2012; Cui et al., 2018; Mrad, 2018). Thus, while these strong emotions are important elements for brand love, we did not observe activation of brain regions related to impulsive, intimate, and passionate relationships in brand love in the present study. This finding suggests that brand love is not as strong an impulsive emotion as romantic love or as asserted in other studies on brand love. From a consumption context, consumers do not expect a strong reciprocal desire and passion despite being loyal and committed customers who might expect rewards from their loved brand, although these intensive emotions have been thought of as crucial concepts for romantic love (Ahuvia, 2005b; Albert et al., 2013). Ahuvia (2005b) demonstrated that several concepts of strong emotive arousal such as sexual arousal in interpersonal love were irrelevant in a consumption context. Bagozzi et al. (2016) demonstrated that most consumers did not experience intense emotion for brands. Langner et al. (2015) also verified that brand love is a weaker intensive emotion than that for loved persons based on results of the self-assessment manikin

(SAM) arousal scale and skin conductance. Therefore, our results support these considerations (Ahuvia, 2005b; Albert et al., 2013; Langner et al., 2015; Bagozzi et al., 2016).

The results of our comparisons between brand love and two interpersonal loves (maternal and romantic love) demonstrated different dispositions for brand love from the interpersonal loves, although these loves also showed similarities. These findings suggest that the feelings of love for objects depend on the context of the relationship (Ahuvia, 1992, 2005a; Ahuvia et al., 2008; Lastovicka and Sirianni, 2011; Batra et al., 2012; Lastovicka and Anderson, 2014). In addition, Lastovicka and Sirianni (2011) proposed that material possession love was rooted in deficits in interpersonal relationships, although this is a non-interpersonal love. Thus, our results indicate that theories of interpersonal love should be prudently applied to brand love as the feelings of love for an object are complex concepts formed under the influence of various relationships (Ahuvia, 1992, 1993, 2005a,b; Albert et al., 2008, 2009, 2013; Ahuvia et al., 2009; Albert and Valette-Florence, 2010; Batra et al., 2012; Albert and Merunka, 2013; Langner et al., 2015; Bagozzi et al., 2016). The results of our study provide marketers useful views regarding the influence of love relationship styles on the formation of feelings of love for objects.

Limitations and Future Research

Our study also had several limitations, the most important of which was that we had no choice but to perform ALE meta-analysis for brand love using a smaller sample size ($n = 5$ experiments) due to the scarcity of brain activation studies addressing brand love. A sample size of least 10–15 experiments are required to reduce the likelihood that meta-analytic results are unduly affected by a single experiment (Eickhoff and Bzdok, 2013). Due to this limitation, we could not conduct an appropriate conjunction analysis among the three loves by using a statistical approach. We would like to address the same issue after accumulating more brain imaging studies on consumer brand relationships. Moreover, we think considerations were needed in terms of demographic attributes such as age and sex, and psychographic, various product categories, the kinds of loved objects, and more detailed context regarding the relationships and their interactions since there can be various ways of thinking about love concepts depending on these attributes.

The results of our study contribute to the literature because, to our knowledge, it was the first ALE meta-analysis to reveal shared and different brain-activated regions between brand love and interpersonal love relationships, such as maternal love and romantic love. This study focused on comparisons between brand love and two interpersonal loves (maternal and romantic); however, as mentioned above, the feelings of love for objects are complicated and varied concepts that depend on objects that are loved and the context of the relationships. Therefore, further research is needed to address these limitations.

CONCLUSION: WHAT IS BRAND LOVE?

Our major findings were that (1) brand love is typically less passionate and intense than interpersonal love (especially romantic love) (Ahuvia, 2005b; Albert et al., 2013; Langner et al., 2015; Bagozzi et al., 2016); (2) altruistic elements were not observed in brand love, although these are crucial elements in interpersonal love (Batra et al., 2012; Albert et al., 2013; Langner et al., 2015); (3) the core of brand love involves incorporating the loved object into the self (Ahuvia, 1992, 1993, 2005a,b; Escalas and Bettman, 2003, 2015; Thomson et al., 2005; Park et al., 2006, 2008, 2009; Ahuvia et al., 2008; Albert et al., 2008, 2009, 2013; Reiman and Aron, 2009; Lastovicka and Sirianni, 2011; Batra et al., 2012; Albert and Merunka, 2013; Bagozzi et al., 2016; Khamitov et al., 2019). Our findings support those of previous studies on brand love. Therefore, we concluded that brand love differed from the two interpersonal loves (maternal and romantic love).

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

SW: conceptualization, data curation, investigation, and writing. SW and HA: analysis, methodology, and supervision. All authors contributed to the article and approved the submitted version.

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METHODS
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Data Triangulation in Consumer Neuroscience: Integrating Functional Neuroimaging With Meta-Analyses, Psychometrics, and Behavioral Data

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This article reviews a wide range of functional magnetic resonance imaging (fMRI) studies conducted in the field of consumer neuroscience to (1) highlight common interpretative approaches of neuroimaging data (i.e., forward inference and reverse inference), (2) discuss potential interpretative issues associated with these approaches, and (3) provide a framework that employs a multi-method approach aimed to possibly raise the explanatory power and, thus, the validity of functional neuroimaging research in consumer neuroscience. Based on this framework, we argue that the validity of fMRI studies can be improved by the triangulation of (1) careful design of neuroimaging studies and analyses of data, (2) meta-analyses, and (3) the integration of psychometric and behavioral data with neuroimaging data. Guidelines on when and how to employ triangulation methods on neuroimaging data are included. Moreover, we also included discussions on practices and research directions that validate fMRI studies in consumer neuroscience beyond data triangulation.

Keywords: consumer neuroscience, fMRI, data triangulation, neuroimaging database, validity

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INTRODUCTION

Since the dawn of consumer neuroscience, researchers have employed neuroimaging techniques, especially functional magnetic resonance imaging (fMRI), to explore latent mental processes underlying consumer behavior (e.g., Yoon et al., 2006; Hedgcock and Rao, 2009; Reimann et al., 2010; Meade and Craig, 2012; Plassmann and Weber, 2015). Thanks to their collective effort through more than a decade of research, consumer neuroscientists have accumulated a wealth of insights that sheds light upon many aspects of consumer behavior. However, an unresolved challenge exists: that of reverse inference. Defined as the use of neuroimaging data to infer the presence of specific cognitive and affective processes (Poldrack, 2008), reverse inference may be tricky when interpretating neuroimaging results (Reimann et al., 2011, 2016; Plassmann et al., 2012, 2015).

In this article, we attempt to summarize potential issues associated with reverse inference, and we argue that proper data triangulation can help address these issues. Herein, we define data triangulation as the practice of utilizing multiple methods and data sources to study the same phenomenon (Patton, 1999; Carter et al., 2014). In neuroimaging research, triangulation would thus entail integrating neuroimaging data with data from meta-analyses, psychometric assessments, and consumer behavior.

Because the neuroimaging techniques employed in consumer neuroscience often consist of fMRI, we focus exclusively on fMRI research in our review of research papers, examinations of research methods, and recommendations to consumer researchers (hereinafter, we use the terms "neuroimaging" and "fMRI" synonymously). However, many of our analyses and recommendations could possibly be applied to other imaging techniques as well.

This paper is organized as follows. First, we review more than 50 empirical articles employing fMRI techniques published in consumer and marketing research journals as well as neuroscience journals, and we use this review to discusses fMRI's contributions to consumer research. Second, we discuss two major interpretative approaches of neuroimaging research—forward inference and reverse inference—and explain how these approaches contribute to understanding consumer behavior. Third, we discuss potential issues and challenges associated with reverse inference. Fourth, we argue that the utilization of data triangulation of fMRI data with meta-analytic data as well as psychometric and behavioral data can enhance the validity of fMRI studies. Fifth, we provide and discuss several recommendations for future consumer neuroscience research.

FUNCTIONAL NEUROIMAGING IN CONSUMER RESEARCH

Over the past one and a half decades, the field of consumer neuroscience has significantly contributed to consumer research. In **Table 1**, we have reviewed and attempted to summarize more than 50 empirical articles utilizing fMRI techniques. The works summarized here have been published in consumer research journals such as the *Journal of the Academy of Marketing Science*, the *Journal of Consumer Research*, the *Journal of Marketing Research*, the *Journal of Consumer Psychology*, and the *Journal of the Association for Consumer Research*, as well as journals in fields outside consumer research, including psychology, neuroscience, and the general science. For journals outside consumer research, we have focused our review on *Cortex*, *Journal of Neuroscience*, *Journal of Neuroscience, Psychology, and Economics, NeuroImage*, *Neuron*, *Psychological Science*, the *Proceedings of the National Academy of Sciences*, and *Social Cognitive and Affective Neuroscience*, in which some of the earlier work on consumer neuroscience appeared and more recent work has continued to appear. For consumer research journals, the list of included works is based on research results for methodological keywords such as "neuroimaging" and "fMRI." For journals outside consumer research, the list of included works is focused on fMRI studies generated from searching keywords such as "consumer neuroscience," "neuromarketing," "market," "marketing," "consumer," and "purchase." Given our focus on specific journals and keywords, we acknowledge that some works related to consumer neuroscience may not be included in this review. Additionally, since our article's focus is on fMRI, we would like to note that important work has been done using other imaging techniques such as electroencephalography (EEG). Nevertheless, the works included in **Table 1** cover a broad range of topics relevant to consumer researchers, including theoretical domains such as information processing (Craig et al., 2012; Esch et al., 2012), judgment and decision making (Hedgcock and Rao, 2009; Karmarkar et al., 2015), and goals and motivation (Hedgcock et al., 2012; Wiggin et al., 2019), as well as substantive domains such as advertising (Craig et al., 2012; Venkatraman et al., 2012; Falk et al., 2016), pricing (Plassmann et al., 2008; Plassmann and Weber, 2015), branding (Reimann et al., 2012, 2018; Chan et al., 2018), and packaging design (Reimann et al., 2010). The table also examines the papers' usage of meta-analyses as well as psychometrics/behavioral data, two major data source that we recommend triangulating with the fMRI data. Taken together, **Table 1** provides a summary of the status of the consumer neuroscience literature and the type of data being used, showing that over the past one and a half decades researchers have started to integrate different data forms in their investigations.

APPROACHES FOR THE INTERPRETATION OF CONSUMER NEUROSCIENCE DATA: FORWARD VERSUS REVERSE INFERENCE

According to Wixted and Mickes (2013), neuroimaging studies take at least two major interpretative approaches. The first approach examines the neuroanatomical localization of behaviors and mental tasks, a process often referred to as *forward inference* (Henson, 2005; Poldrack, 2011). Forward inference has been adopted in consumer neuroscience to investigate the neurophysiological substrates of a wide range of consumer research concepts including, but not limited to, valuation (De Martino et al., 2009), social influence of buying decisions (Yokoyama et al., 2014), perception of money (Huang and Yu, 2019), and consumer curiosity (Wiggin et al., 2019). A typical forward inference question is this: While the concept of consumers' willingness to pay (WTP) for a product is not unfamiliar to consumer researchers, where is WTP encoded in the brain? Plassmann et al. (2007) attempted to answer this interesting question by having hungry participants bid for the right to eat food. The authors pinpointed the medial prefrontal cortex and the dorsolateral prefrontal cortex as encoding locations of WTP. While the forward inference approach is laudable, it does not come without limitations. One such limitation is that while forward inference may highlight that a particular consumer research concept is correlated with activation of a certain brain area, forward inference often leaves open the psychological interpretation of possible underlying processes at play. This limitation may be less problematic in research that is largely interested in brain mapping but becomes more challenging in research that also cares about underlying psychological processes.

The second major approach of neuroimaging research involves using brain activation patterns to infer psychological processes. Specifically, by building on previously established functions and/or connectivity of specific brain regions, consumer researchers can make educated guesses as to which cognitive

TABLE 1 | Consumer neuroscience research in marketing, consumer research, and neuroscience journals (chronological order).

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
McClure et al. (2004), *Neuron*	What are the neural correlates of the consumer preference for Coke and Pepsi two similar drinks, and how can brand knowledge influence the behavioral preference and brain responses.	When the brands are delivered anonymously, brain activity in the ventromedial prefrontal cortex correlates with participant's behavioral preferences for the drinks. However, when participants know that it is Coke that they are drinking, behavioral preferences are drastically influenced and activity in the hippocampus, dorsolateral prefrontal cortex, and midbrain are also found.	• Ventromedial prefrontal cortex (reward). • Dorsolateral prefrontal cortex, hippocampus, and midbrain (recall of cultural influences).	Investigate neural correlates		Yes
Yoon et al. (2006) *JCR*	Whether semantic judgments about products and persons are processed similarly.	Mental judgments about persons and products are processed differently.	• Medial prefrontal cortex (semantic judgments about persons). • Left inferior prefrontal cortex (semantic judgments about products).	Distinguish multiple processes		
Knutson et al. (2007), *Neuron*	How product preference and price are captured in consumer brain and how their neural correlates predict purchase.	Product preference activates the nucleus accumbens. Excessive price, on the other hand, activates the insula and deactivates the medial prefrontal cortex. Activities in each of these regions can independently predict purchase.	• Nucleus accumbens (gain prediction). • Insula (loss prediction). • Medial prefrontal cortex (gain prediction errors).	Investigate neural correlates and predict behaviors		
Plassmann et al. (2007), *JN*	How willingness to pay is encoded in the brain.	Willingness to pay is encoded in the medial orbitofrontal cortex and in the dorsolateral prefrontal cortex.	Medial orbitofrontal cortex (reward and valuation)	Investigate neural correlates		
Weber et al. (2007), *NI*	What are the neural correlates of reference-dependence of utility evaluation (i.e., the endowment effect), before and after the buying/selling decision in real market contexts.	Fear-related processes are observed when a product is being sold but not when it is being bought. After the decision is made, reward related processes are observed if a high external reference price of the product is provided.	• Left amygdala (fear and loss). • Caudate nucleus (action planning and monetary rewards expectation). • Orbitofrontal cortex (reward). • Anterior cingulate (mental conflicts, reward, and valuation).	Investigate neural correlates		

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Bray et al. (2008), *JN*	What are the neural correlates of the outcome-specific transfer (the consumer tendency to choose the option with a particular outcome when a Pavlovian cue is present, if the Pavlovian cue has previously been associated with that outcome).	A region in the ventral caudolateral putamen is associated with outcome-specific transfer.	Ventral putamen (reward outcome and reward learning)	Investigate neural correlates		
Klucharev et al. (2008), *SCAN*	What are the neural correlates of the persuasive effect of high expertise of the communicator (i.e., the "expert power")	Expert content is associated with brain regions associated with active semantic elaboration, memory formation, and trustful behavior, reward processing, and learning	• Left dorsomedial prefrontal cortex, anterior cingulate, superior temporal sulcus (semantic processing). • Hippocampus and parahippocampal gyrus (memory). • Caudate nucleus (trust, reward, learning).	Investigate neural correlates		
Plassmann et al. (2008), *PNAS*	How the price of a product influences the neural computations with its experienced pleasantness.	Increase of the price of a wine increases both the activation in the medial orbitofrontal cortex and the subjective report of pleasantness.	• Medial orbitofrontal cortex (encoding of experienced pleasantness).	Identify psychological processes		
De Martino et al. (2009), *JN*	Whether reference-independent and -dependent value computations are reflected in the same region of the brain.	The computation of reference-independent value is associated with the activity in the orbitofrontal cortex and dorsal striatum. On the other hand, the computation of reference-dependent value is associated with the activity in the ventral striatum.	• Orbitofrontal cortex. • Dorsal striatum. • Ventral striatum.	Investigate neural correlates		
Dietvorst et al. (2009), *JMR*	How to judge salespersons' ability of interpersonal-mentalizing (i.e., inferring the viewpoints of customers).	Interpersonal mentalizing process ("read" others' minds, process subtle interpersonal cues, and then adjust volitions accordingly).	Medial prefrontal cortex and bilateral temporo-parietal junctions (interpersonal-mentalizing skills)	Predict behaviors		Yes
Hedgcock and Rao (2009), *JMR*	Why the introduction of a decoy option (i.e., an option that is dominated and thus should not the influence preference for other options) into the choice set makes one of the original options more attractive (the "attraction effect").	The decoy option produces the attraction effect by reducing negative emotions experienced by the decision maker.	• Amygdala (negative emotions). • Medial prefrontal cortex (self-referential evaluation of preferences). • Dorsal lateral prefrontal cortex (use of decision rules). • Anterior cingulate cortex (conflict monitoring). • Right inferior parietal lobule (numerical magnitude processing).	Identify psychological processes		Yes

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Berns et al. (2010), *NI*	How the popularity of music influences individual rating thereof.	Popularity rating influences individual rating by creating anxiety due to a mismatch between one's own and others' preferences. This anxiety in turn drives choice switch in the direction of popularity rating. Popularity does not seem to change the individual preferences for music *per se*.	• Caudate nucleus (reward and likability). • Anterior insula and anterior cingulate (physiological arousal and negative affective states). • Middle temporal gyrus (semantic processing).	Identify psychological processes, and test competing theories		
Linder et al. (2010), *NI*	How consumers evaluate food with (vs. without) organic labels.	Organic food label is associated with increased activity in the ventral striatum. The difference in such activity can predict the real-world consumption behavior of organic food.	Ventral striatum (reward)	Identify psychological processes and predict behavior		
Rademacher et al. (2010), *NI*	Whether the anticipation and consumption of rewards (monetary and social) involves the same or different neural networks.	Anticipation and consumption of rewards involve dissociable neural networks. Anticipation of both monetary and social reward involves the reward system including the ventral striatum. On the other hand, the consumption of monetary reward involves the thalamus, whereas the consumption of social reward involves the amygdala.	• Brain reward system including ventral striatum (reward anticipation). • Amygdala (social reward consumption). • Thalamus (monetary reward consumption).	Investigate neural correlates		
Reimann et al. (2010), *JCP*	How consumers process aesthetic package design.	The reward system in the brain plays a role in processing aesthetic package design.	• Striatum (anticipated reward). • Ventromedial prefrontal cortex (reward outcome).	Identify neural correlates and psychological processes		Yes
Schaefer and Rotte (2010), *SCAN*	How brands are represented in the brain.	Brands rated higher on "social competence" is associated with greater activation in the medial prefrontal cortex, whereas brands rated higher on "potency" is associated with greater activation in the superior frontal gyri.	• Medial prefrontal cortex (social cognition). • Superior frontal gyri (working memory).	Investigate neural correlates		

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Smith et al. (2010), *JN*	Whether expected and experienced value are reflected in the same part of the brain.	Experienced value is reflected in the anterior ventromedial prefrontal cortex, whereas expected value is reflected in the posterior ventromedial prefrontal cortex.	Ventromedial prefrontal cortex (reward).	Investigate neural correlates		
Tusche et al. (2010), *JN*	What brain regions can predict consumer choice, and how product attention influences such predictions.	Insula and medial prefrontal cortex activation patterns can predict consumer choice, both under high and low product attention.	Insula and medial prefrontal cortex (reward).	Predict behavior		
Kang et al. (2011), *JN*	Whether hypothetical and real decision-making processes undergo the same type of valuation and choice computations or not.	Common areas in the orbitofrontal cortex and the ventral striatum are related to both hypothetical and real evaluation of goods. The difference found between the two types of decision-making are quantitative instead of qualitative.	Orbitofrontal cortex and ventral striatum, anterior cingulate cortex, caudate, inferior frontal gyrus (reward).	Identify psychological processes, and test competing theories		
Levy et al. (2011), *JN*	Does a single neural mechanism capture the reward values of options and thus predict consumer preferences, both when a decision requires subsequent choice and when the choice is absent.	The striatum and medial prefrontal cortex represent values whether choice is required or not.	Striatum and medial prefrontal cortex (reward).	Identify psychological processes and predict behavior		
Bagozzi et al. (2012), *JAMS*	What is the neural basis of customer orientation (as opposed to sales orientation) in salespersons.	Customer oriented, but not sales oriented, salespersons features greater activity in their mirror neuron systems, as well as empathy-related neural process.	• Posterior inferior frontal cortex, Broca's area, and anterior inferior parietal lobule (mirror neuron system). • Medial prefrontal cortex, precuneus, and right inferior parietal cortex (empathy). • Insula and amygdala (empathic concern). • Inferior parietal lobule (self-other monitoring).	Investigate neural correlates		Yes
Berns and Moore (2012), *JCP*	Whether brain activation acquired from a small sample can predict product acceptance in a broader population.	Although subjective likability of the songs was not predictive of sales, activity within the ventral striatum was significantly correlated with the number of units sold.	Precuneus, orbitofrontal cortex, and ventral striatum/nucleus accumbens (reward).	Predict behavior		Yes

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Craig et al. (2012), *JMR*	How consumers process deceptive advertisement claims.	Consumers process deceptive claims in two distinct stages: First, greater attention may be allocated to more deceptive information; second, more attention and belief reasoning may then be directed toward believable and moderately information.	• Amygdala, precuneus (expectation violation observed in person-to-person cheater detection). • Superior temporal and inferior parietal areas (including superior temporal sulcus and temporo-parietal junctions) (verification and assessment of claims).	Identify psychological processes and distinguish multiple processes		Yes
Esch et al. (2012), *JCP*	What are the consumer linguistic encoding/retrieval processes and how do they use declarative/experiential information in the evaluation of unfamiliar vs. familiar (strong and weak) brands.	The evaluation of unfamiliar brands is associated with linguistic encoding, whereas the evaluation of strong brands is associated with information retrieval. Moreover, consumers use experienced emotions rather than declarative information to evaluate brands.	• Broca's area (linguistic processing). • Wernicke's area (brand retrieval). • Pallidum (positive emotions).	Investigate neural correlates and identify psychological processes		
Falk et al. (2012), *PS*	Can neural responses collected from a small group of people predict the effectiveness of an anti-smoking television campaign.	Activations in the medial prefrontal cortex predicts the population-level effectiveness of the campaign.	Medial prefrontal cortex (individual behavior change).	Predict behavior		Yes
Hedgcock et al. (2012), *JCP*	How depletion causes self-control failure in a two-stage model (stage 1: recognizing the need for self-control; stage 2: implementing controlled responses). Specifically, whether depletion undermines stage 1 only, stage 2 only, or both.	Depletion affects the implementation stage only and leaves intact the ability to recognize the need for self-control.	• Anterior cingulate cortex (goal conflict identification). • Dorsolateral prefrontal cortex (controlled actions implementation).	Identify psychological processes, and test competing theories		Yes
Lawrence et al. (2012), *NI*	How the nucleus accumbens is associated with food cue and predicts subsequent food consumption and body mass index.	Food cue related activations in the nucleus accumbens predicts subsequent snack food consumption (but not subjective hunger) in female participants. Nucleus accumbens activities also predict body mass index but only in participants with lowered self-control.	• Left nucleus accumbens (food motivation, reward, wanting). • Ventromedial prefrontal cortex (subject hunger/appetite).	Investigate neural correlates and predict behavior		

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Reimann et al. (2012), *JCP*	• How consumers relate to their beloved brands.	Emotional arousal decreases over the brand relationship span, while inclusion of the brand into the self increases over time.	Insula (urging, addiction, loss aversion, and interpersonal love)	Identify neural correlates and psychological processes		Yes
Grabenhorst et al. (2013), *NI*	How sample food labels influence consumer healthy food choice.	Food labels can bias food evaluations in the amygdala, and the strength of such biases can predict behaviors toward healthier food choices.	Amygdala (emotion).	Identify psychological processes		
Bruce et al. (2014a), *SCAN*	How children's brains react to food brand logos in children.	Food logos (vs. baseline) are associated with activity in the orbitofrontal cortex and inferior prefrontal cortex. Food logos (vs. non-food logos) are associated with activity in the posterior cingulate cortex.	• Orbitofrontal cortex (motivation). • Inferior prefrontal cortex (cognitive control). • Posterior cingulate cortex (visual engagement).	Investigate neural correlates		
Bruce et al. (2014b), *JNPE*	How consumers react to food attributes presented to them, especially the food's price and technology used to produce it.	Increased number of presented attributes is associated with increased activity in the dorsolateral prefrontal cortex	Dorsolateral prefrontal cortex (working memory and uncertainty).	Investigate neural correlates		
Gearhardt et al. (2014), *SCAN*	What the neural responses of food-related (vs. non-food-related) commercials, and how weight influences such neural responses.	Adolescents exhibit overall greater activation in brain regions associated with visual processing, attention, cognitive processing, movement, somatosensory responses, and reward, when they process food-related (vs. non-food-related) commercials. Moreover, during food relative to non-food commercials, obese participants feature less activation in brain regions associated with visual processing, attention, reward, and salience detection. Obese participants also feature more activation in brain regions associated with semantic control.	• Occipital gyrus, cuneus (visual processing). • Parietal lobes, posterior cerebellar lobe, temporal gyrus (attention and cognition). • Anterior cerebellar cortex (movement). • Postcentral gyrus (somatosensory response). • Orbitofrontal cortex, anterior cingulate cortex, ventromedial prefrontal cortex (reward). • Precuneus (salience detection). • Medial temporal gyrus (semantic control).	Investigate neural correlates		
Kanayet et al. (2014), *PS*	Whether numeric magnitude and monetary value are processed by distinct regions in the neural network involved in the valuation of monetary reward.	Changes in numeric magnitude is associated with activities in intraparietal sulcus, whereas monetary value is associated in the activity in orbitofrontal cortex.	• Intraparietal sulcus (numeric information). • Orbitofrontal cortex (reward, valuation).	Investigate neural correlates and distinguish multiple processes		

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Lighthall et al. (2014), *JN*	How older adults compensate their age-related memory decline during memory-dependent decision-making in consumption.	Medial prefrontal cortex provides functional compensation for aging adults in memory-dependent decision-making tasks.	Medial prefrontal cortex and its connectivity with dorsolateral prefrontal cortex.	Identify psychological processes		
Tang et al. (2014), *PS*	How actual and perceived foods' caloric content influences the neural predictors of food choice.	Actual, but not perceived, food caloric content is associated with activations in the ventromedial prefrontal cortex, which is known as a predictor of food choice. The ventromedial prefrontal cortex demonstrates a functional connectivity with an appetitive brain network, which is modulated by the willingness to pay.	• Ventromedial prefrontal cortex (reward). • Functional connectivity to ventromedial prefrontal cortex, including amygdala, hippocampus, ventral stratum (computation of subject value). • Insula (sensory characteristics of food).	Identify psychological processes, investigate neural correlates, and predict behavior		
Yokoyama et al. (2014), *NI*	What are the brain regions associated with the perception of social risk when purchase decisions are being made.	In a purchase intention task, ratings of social risk during purchase decision are associated with activity in the left anterior insula. In a social risk task, ratings of social risk are associated with activity in the left temporal parietal junction and medial prefrontal cortex.	• Left anterior insula (emotion-related network). • Left temporal parietal junction and medial prefrontal cortex (theory of mind).	Investigate neural correlates		
Cascio et al. (2015), *JMR*	How consumers make recommendation decisions in light of the preferences and opinions of others.	Decisions to update other-directed recommendations in response to peer opinions may unite brain systems associated with social influence and the concept of being a "successful idea salesperson."	• Precuneus/posterior cingulate cortex, dorsal, dorsal anterior cingulate cortex, ventral striatum, anterior insula, orbitofrontal cortex/dorsomedial prefrontal cortex (social influence). • bilateral temporo-parietal junctions, medial prefrontal cortex (successful recommendations).	Identify psychological processes	Yes	
Chen et al. (2015), *JMR*	Whether consumers have an *a priori* network in their minds that reflects personality traits associated with brands and, if so, what cognitive processes are captured by such a network.	An *a priori* neural network is distributed widely across the brain and reflects personality traits associated with brands.	A wide range of brain areas including the anterior cingulate, middle cingulate, dorsomedial prefrontal, medial prefrontal, premotor, dorsolateral prefrontal, posterior cingulate, primary visual, lateral prefrontal, and inferior frontal cortices; the insula; and the hippocampus.	Investigate neural correlates	Yes	

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Genevsky and Knutson (2015), *PS*	What factors influence the outcomes of online microlending, and whether a neural activity may forecast this outcome.	Positive affect, both self-reported and captured by the activity in the nucleus accumbens can promote the success of loan requests.	Nucleus accumbens (positive arousal)	Identify psychological processes and predict behavior		Yes
Karmarkar et al. (2015), *JMR*	Whether seeing the price of a product before or after seeing the product influences the way the product is processed.	Price primacy (i.e., seeing the product price before seeing the product) makes consumers evaluate the product based on its monetary worth, whereas product primacy (i.e., seeing the product before seeing the product price) makes consumers evaluate the product based on its attractiveness and likability.	• Medial prefrontal cortex (perceived monetary value). • Nucleus accumbens (attractiveness or expressed preference).	Identify psychological processes		Yes
Plassmann and Weber (2015), *JMR*	What individual differences can predict the consumer responsiveness to the "marketing placebo effects" (i.e., the effect by which consumption experience and subsequent behavior are influenced by marketing-based expectations such as price, quality beliefs, etc.).	Reward seeking, somatosensory awareness, and need for cognition can predict marketing placebo effects.	• Gray matter volume of the striatum (reward responsiveness/learning). • Gray matter volume of prefrontal structures (i.e., lateral orbitofrontal, lateral prefrontal, and dorsomedial prefrontal cortex) (cognitive top-down processing). • Gray matter volume of the posterior insula and somatosensory cortices (Somatosensory bottom-up processing).	Identify psychological processes	Yes	Yes
Venkatraman et al. (2015), *JMR*	How to predict ads' effectiveness using fMRI.	Product desirability measured at the brain level is associated with real-world, market-level response to advertising.	• Amygdala (affective processing). • Dorsolateral prefrontal cortex (cognitive processing). • Ventromedial prefrontal cortex, striatum (desirability).	Predict behavior		Yes
Falk et al. (2016), *SCAN*	Whether and the brain activation acquired in a small group of smokers react to an anti-smoking email campaign can predict the effectiveness of the campaign on a population-level. If yes, via what mechanism.	Neural activity in the medial prefrontal cortex acquired in a small group of smokers is predictive of population-level responses to the campaign. Self-related processing is the neurocognitive mechanism that links neural and behavioral responses.	Medial prefrontal cortex (self-related processing).	Identify psychological processes and predict behavior	Yes	Yes

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Kühn et al. (2016), *NI*	How to predict product sales in the real market using fMRI.	fMRI signal acquired in a small sample in eight brain regions that are associated with product decision-making predicts the real-world sales of products shown in the scanner.	• Nucleus accumbens, medial orbitofrontal cortex, amygdala, hippocampus, inferior frontal gyrus, and dorsomedial prefrontal cortex (a range of mental processes associated positively with sales). • Dorsolateral prefrontal cortex and insula (a range of mental processes associated negatively with sales).	Predict behavior		Yes
Reimann et al. (2016), *JACR*	Why offering consumers the choice between a full-sized food portion alone and a half-sized food portion paired with a small non-food premium (e.g., a small toy or the mere possibility of winning frequent flyer miles) can motivate smaller portion choice.	Food and the expectation of receiving a non-food premium activate a common area of the brain (the striatum), which is associated with reward, desire, and motivation.	Striatum (reward processing).	Identify neural correlates and psychological processes	Yes	Yes
Chung et al. (2017), *JN*	What is the underlying mental process of decoy effect.	Underlying decoy effect seems to be context-dependent valuation. Moreover, deliberate control that monitors and corrects decision-making errors and biases is associated with the successful overcome of decoy effect.	• Left ventral striatum (reward value). • Right inferior frontal gyrus (response inhibition).	Identify psychological processes		
Genevsky et al. (2017), *JN*	Whether and, if yes, what neural activities can predict real crowdfunding outcomes weeks later from the time of fMRI scan.	The nucleus accumbens and medial prefrontal cortex both predict individual choices to fund in crowdfunding. However, only the nucleus accumbens predicts the market-level funding outcome.	• Nucleus accumbens (positive arousal). • Medial prefrontal cortex (value integration).	Predict behavior	Yes	Yes

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Dal Mas and Wittmann (2017), *Cortex*	How consumers react to boredom and what are the neural systems underlying these reactions.	Consumer accept higher prices to avoid expected boredom, a behavioral bias modulated by caudate nucleus. During the actual performance of a boring task, insula is activated and is associated with individual differences in boredom-related decision making	• Caudate nucleus (reward). • Insula (experiencing boredom).	Investigate neural correlates		
Chan et al. (2018), *JMR*	How to profile brand image using neuroimaging methods.	Perceived cobranding suitability, brand image strength can be used to profile brand image.	Occipital cortex, precuneus, posterior cingulate cortex, parahippocampal gyrus, and temporoparietal junction (areas associated with visual processing, episodic memory, self-awareness, and the default network)	Predict behavior		Yes
Reimann et al. (2018), *JACR*	Whether brand betrayal is an extreme form of brand dissatisfaction.	Brand dissatisfaction can be distinguished from brand betrayal.	Dorsolateral prefrontal cortex, angular gyrus, caudate tail (betrayal experience)	Identify psychological processes and distinguish multiple processes	Yes	Yes
Schmidt et al. (2018), *JN*	What underlies the individual differences in making healthy food choices.	The gray matter volume in the ventromedial prefrontal cortex and the dorsolateral prefrontal cortex predict individual differences in shifting to healthier food.	Ventromedial prefrontal cortex and dorsolateral prefrontal cortex (reward and valuation)	Predict behavior		
Chan et al. (2019), *NI*	Whether the predictive power of neural similarity distributes across the whole brain or only in specific regions ("neural similarity" here refers to the similar neural responses to stimuli across individuals). Whether similarity acquired in a small group of individuals is known to predict preference for the stimuli in a larger population.	Neural similarity of temporal lobe and cerebellum across a small group of individuals can predict the preference and recall of stimuli (e.g., commercials or products) in a larger sample.	Temporal lobe and cerebellum (level of engagement with video stimuli, sensory integration, emotional processing).	Investigate neural correlates and predict behavior	Yes	Yes

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Doré et al. (2019), *JN*	How affective reactivity, valuation, and emotion regulation interact to deliver the impact of emotionally evocative messages (e.g., ads).	Increased activation in the amygdala predicts the effectiveness of emotionally evocative message both on individual and population levels. This effect is mediated by activity in the ventromedial prefrontal cortex and moderated by an emotion regulation pattern in the brain.	• Amygdala (affective reactivity). • Ventromedial prefrontal cortex (integrative valuation). • Whole-brain pattern of emotion regulation.	Identify psychological processes and predict behavior		
Huang and Yu (2019), *NI*	What are the neural substrates of the money illusion (the phenomenon wherein consumers evaluate money based on its face value instead of its true purchasing power), in both win and loss domains.	Posterior insula encodes the true value of money in the win domain but not in the loss domain. The ventral striatum, ventromedial prefrontal cortex, and amygdala process money illusion in both win and loss domains. Functional connectivity is also associated with money illusion, such that individuals with greater money illusion exhibit stronger functional connectivity between the ventral striatum and ventral anterior cingulate cortex in the win domain, but stronger functional connectivity between the ventral striatum and amygdala in the loss domain.	• Posterior insula (emotional and somatosensory arousal). • Ventral striatum, ventromedial prefrontal cortex, ventral anterior cingulate cortex (reward). • Amygdala (emotion).	Investigate neural correlates		

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TABLE 1 | Continued

Author(s) and Journal*	fMRI-related research question	Major findings	Identified brain areas	Role of fMRI in study	Meta-analysis	Triangulation with psychometric and/or behavioral data
Huijsmans et al. (2019), *PNAS*	How the "scarcity mindset" created by insufficient resources (e.g., state of poverty) influences consumer decision-making.	A scarcity mindset is associated with increased activity in the orbitofrontal cortex and decreased activity in the dorsolateral prefrontal cortex	• Orbitofrontal cortex (valuation). • Dorsolateral prefrontal cortex (goal-directed choice).	Identify psychological processes		
Warren and Reimann (2019), *JACR*	What distinguishes products that look cool from those that look funny.	Cool [humorous] products diverge from the norm in a way that does [does not] make sense. Thus, cool (vs. humorous) products are processed differently in the brain.	Anterior cingulate cortex (resolution of conflict in the environment, error detection, and problem resolution).	Identify psychological processes and distinguish multiple processes	Yes	Yes
Wiggin et al. (2019), *JCR*	How curiosity influences indulgence behavior.	Curiosity gives rise to desire for rewards, which in turn encourages indulgent behavior.	Insula (desire for rewards)	Identify neural correlates and psychological processes		Yes
Tong et al. (2020), *PNAS*	What are the neural mechanism underlying online video watching.	Video viewing engagement (duration, frequency, etc.) can be predicted by increased activity in the nucleus accumbens and medial prefrontal cortex, and decreased activity in the anterior insula.	• Nucleus accumbens (positive arousal). • Medial prefrontal cortex (value integration of affect with other considerations). • Anterior insula (negative or general arousal).	Investigate neural correlates and predict behavior		

**JACR, Journal of Association for Consumer Research; JAMS, Journal of the Academy of Marketing Science; JCR, Journal of Consumer Research; JMR, Journal of Marketing Research; JN, Journal of Neuroscience; JNPE, Journal of Neuroscience, Psychology, and Economics; NI, NeruoImage; PNAS, Proceedings of the National Academy of Sciences of the United States of America; PS, Psychological Science; SCAN, Social Cognitive and Affective Neuroscience.*

and emotional processes may be taking place as consumers process information or make decisions. This process is known as *reverse inference* (Poldrack, 2006, 2011). For instance, if a researcher posits that visual processing is taking place in an fMRI study because of increased activation in the occipital lobe, the researcher is reverse inferencing.

Reverse inference is important for consumer research (and for neuroscience in general) because it allows consumer researchers to access implicit or latent physiological processes (Reimann et al., 2011; Karmarkar and Plassmann, 2019). Specifically, the reverse inference approach can contribute to consumer research in at least three ways, as discussed below.

The first and most direct application of this research approach is that it allows consumer researchers to allude to underlying implicit psychological processes by observing activities of specific brain regions. This application requires a previously established link between brain regions and their functions. For instance, in studying how consumers process aesthetic package design, Reimann et al. (2010) recorded participants' brain activity as they viewed aesthetic (vs. standardized) product package designs using fMRI. The authors observed that when processing aesthetic (vs. standardized) package designs, participants' brains featured greater activation in the striatum, a brain area that has been associated with reward evaluations and processing (Delgado et al., 2003; Balleine et al., 2007; Kable and Glimcher, 2007; Báez-Mendoza and Schultz, 2013), among other activations. Following a similar interpretative logic, Plassmann et al. (2008) found that increasing the price of wine increases both reports of pleasantness as well as activity of the medial orbitofrontal cortex, a brain area that has widely been thought to encode pleasantness.

Second, neuroimaging can aid consumer researchers when competing theories exist to explain an observed phenomenon. Specifically, researchers have relied on established theories of brain regions' functions to determine which theory is (or theories are) supported by actual brain activation. One such paper is Hedgcock et al. (2012) seminal examination of self-control depletion. Building on a two-stage model of self-control (i.e., recognizing the need for self-control → implementing self-control), the authors examined three completing models of depletion: (1) depletion only impairs the ability to recognize the need for self-control, (2) depletion only impairs the ability to implement self-control, and (3) depletion impairs both abilities. An fMRI study demonstrated that under depletion, a brain region associated with the implementation of controlled action (i.e., the right middle frontal gyrus located in the dorsolateral prefrontal cortex) features reduced activation, but such patterns were not found in the brain region associated with the detection of goal conflict (i.e., the anterior cingulate cortex). Therefore, the authors were able to conclude that only the implementation stage was likely to be affected by depletion (Hedgcock et al., 2012).

Third, the reverse inference approach is also useful in distinguishing different processes, networks, or stages of processing (i.e., neurophysiological dissociation). Such studies usually involve the observation of activations in different brain functional regions and/or networks (and occasionally also at different times) when participants undertake different cognitive tasks. For instance, Yoon et al. (2006) investigated whether semantic judgments of brands and humans are processed similarly. It has long been observed that consumers, marketers, and researchers alike tend to use similar if not identical words to describe both brands and people (Fournier, 1998; Fournier and Alvarez, 2012; MacInnis and Folkes, 2017). For instance, a brand can be "reliable" like a person and can form relationships with humans as other humans do. This tendency naturally raises the question of whether brands and humans are processed identically or at least similarly in the human brain. Yoon et al. (2006) work, however, showed that this may not be the case: Processing humans was associated with the medial prefrontal cortex, whereas processing brands was associated with the left inferior prefrontal cortex, which has been found to be involved in object processing.

In summary, neuroimaging studies often take two major interpretative approaches: Using both behaviors and mental tasks to explore neurophysiological correlates and to map the brain (i.e., forward inference) and using brain activations to infer certain psychological processes (i.e., reverse inference). With reverse inference, we have further identified three ways in which reverse inference contributes to consumer research: (1) determining underlying, implicit, and unknown psychological processes; (2) determining the plausibility of enhancing and/or completing theories; and (3) distinguishing multiple processes, networks, or stages of processing. Both approaches are of great value and are widely employed in consumer neuroscience and neuroscience in general. In the present paper, we focus on reverse inference due to its theoretical and methodological intricacies and highlight its potential issues when employed.

POTENTIAL ISSUES ASSOCIATED WITH REVERSE INFERENCE

Although reverse inference is by no means an incorrect research approach *per se* (Hutzler, 2014), neuroscientists have noticed interpretational issues associated with it (Poldrack, 2006; Del Pinal and Nathan, 2017). More specifically, when activation in a brain region of interest is not particularly selective for a specific cognitive process (i.e., when multiple cognitive processes can activate the same brain region), the validity of reverse inference can be undermined (Poldrack, 2006, 2011).

For instance, it has long been known that the anterior cingulate cortex is heavily involved in the processing of conflicting information from the environment (Botvinick et al., 2001; Van Veen et al., 2001; Carter and van Veen, 2007), so it is tempting to assume that the consumer brain is processing conflicting information when activation in this brain region is observed. However, prior literature shows that the anterior cingulate cortex is also sensitive to the gain and loss of rewards (e.g., Taylor et al., 2006; Seo and Lee, 2007). As a result, researchers cannot, without committing a logical fallacy, argue for the involvement of conflicting information based on the activation observed in the anterior cingulate cortex alone.[1]

[1]Note, however, that this issue related to reverse inference may not be present in studies in which researchers try to predict behaviors (e.g., choice and purchase)

Unfortunately, multi-functional brain regions are quite common (e.g., Miller and Cohen, 2001; Postuma and Dagher, 2006). As a result, issues associated with reverse inference are neither foreign to consumer neuroscience nor foreign to neuroscience in general. Indeed, in the recent consumer neuroscience literature, the medial prefrontal cortex has been associated with reward processing (Reimann et al., 2010; Karmarkar et al., 2015), pleasantness (Plassmann et al., 2008), self-referential evaluation of preferences (Hedgcock and Rao, 2009), and social processes (Dietvorst et al., 2009; Cascio et al., 2015). While the exact three-dimensional locations of the medial prefrontal cortex may slightly vary across these investigations, they generally belong to the same anatomical brain area. Similarly, activation in the insula has been claimed to indicate negative affect status (Berns et al., 2010), social influence (Cascio et al., 2015), and desire for rewards (Wiggin et al., 2019).

What, then, can and should consumer researchers do to address this issue? Below, we will focus on three major strategies that can mitigate potential issues inherent in reverse inference: (1) reducing false alarms via refined study design and analysis, (2) employing neuroimaging meta-analyses to estimate the extent of reverse inference, and (3) integrating neuroimaging data with psychometric assessments and data from behavioral studies to provide additional confidence in the findings. We also posit that data triangulation employing these methods may greatly enhance the validity of neuroimaging research.

ADDRESSING POTENTIAL ISSUES ASSOCIATED WITH REVERSE INFERENCE

To address the potential issues associated with reverse inference, we first explain its logic. Let *COG* be the cognitive process of interest, and let *ACT* be the activation in the brain region purportedly associated with this process. The validity of reverse inference is thus given by the probability that *COG* takes place given that *ACT* is present, or, formally, $P(COG|ACT)$. According to Bayes' theorem:

$$P(COG|ACT) = \frac{P(ACT|COG)\,P(COG)}{P(ACT)}$$

It should be noted that the term *COG* here is always conditioned on the specific task used in the studies. In other words, the prior probability of $P(COG)$ in this equation should in fact be $P(COG|TASK)$, where *TASK* stands for the task setting and design. We have omitted this term in the equation for the sake of succinctness, but we will revisit this task-relevant nature of reverse inference in later discussions.

based on brain activation (i.e., "neuroforecasting"; for a review, see Knutson and Genevsky, 2018). This is because, in such prediction studies, the focus is to establish whether certain brain regions are predictive of actual behavior rather than to investigate the mental processes associated with such regions. For instance, if activations in the ventral striatum of the small number of individuals listening to music in a scanner are predictive of the market-scale sales of the music (Berns and Moore, 2012), then this prediction is valid in and of itself, and whether or not one can infer certain mental processes (e.g., reward processing) based on ventral striatum activation is irrelevant in such predictions.

The equation above translates the question of reverse inference into "When the activation of specific brain regions is observed, how likely is it that the cognitive process of interest indeed took place?" To be able to make any meaningful argument based on such reverse inference, consumer researchers need to estimate and, if possible, systematically increase the value of $P(COG|ACT)$. This can be done in multiple ways, as summarized below.

Reducing False Alarms in Reverse Inference via Careful Design and Analysis

Activations in a brain region that (1) is purportedly associated with a cognitive process of interest but (2) does not actually reflect the proposed cognitive are called *false alarms*, which is a major culprit of reverse inference's validity issues (Hutzler, 2014). Mathematically, the denominator in the above equation, $P(ACT)$, is the prior probability that indicates the tendency of this brain region to become activated *by default*. If a brain region can easily become activated (i.e., if the false alarm rate is high) – because, for instance, it is involved in many different cognitive processes – then $P(COG|ACT)$ will be relevantly small because $P(ACT)$ is large, rendering reverse inference invalid.

Although how easily a brain region can become active and in how many different functions a brain region can get involved are questions largely beyond consumer researchers' control, methods exist to control the level of $P(ACT)$.

First, consumer researchers could design studies in such a way that the chances of false alarms are reduced. To illustrate, the term $P(ACT)$ in the equation of Bayes' Theorem can be further broken down to $P(ACT|COG)\,P(COG) + P(ACT|\neg COG)\,P(\neg COG)$; thus,

$$P(COG|ACT) = \frac{P(ACT|COG)\,P(COG)}{P(ACT|COG)\,P(COG) + P(ACT|\neg COG)\,P(\neg COG)}$$

where $\neg COG$ indicates that the cognitive process of interest is not present.

According to this equation, if a brain region can be activated by a mental process different from the one of interest (i.e., the false alarm, the probability of which is captured by $P[ACT|\neg COG]$), then the validity of reverse inference $P(COG|ACT)$ will decrease as a result (all else being equal). Conversely, if, based on the systematic review of prior literature and study design, consumer researchers can lessen the possibility that such alternative cognitive processes take place, then the term $P(ACT|\neg COG)\,P(\neg COG)]$ should shrink in value, and, as a result, the validity of reverse inference will increase. For instance, in a thought experiment, Hutzler (2014) discusses an experiment that infers the recognition of visual words from activation of the fusiform gyrus. Because the imagery study only involves the presentation of words, consumer researchers can reasonably rule out the competing cognitive theory of facial recognition. In this way, although the fusiform gyrus is multifunctional, the study design creates functional specificity by eliminating an alternative theory and, thus, controlling the baseline level of $P(ACT)$, which

is in fact $P(ACT|TASK)$. Needless to say, ruling out alternative cognitive processes via design requires a good understanding of the literature on the brain region(s) of interest and depends heavily upon how much is known about the functionality of the brain region (cf. Agis and Hillis, 2017).

Another way to reduce false alarms is to use finer (i.e., smaller and/or better-defined) structures for reverse inference. Smaller ROIs are more selective and, thus, more predictive of cognitive processes than larger regions (Poldrack, 2006). In addition, instead of relying on the activation of individual brain regions, consumer researchers could use patterns of such activations to decode underlying cognitive processes, a method called multi-voxel pattern analysis (MVPA). This method utilizes pattern recognition to identify connections between cognitive processes and neuroimaging activation patterns. Such connections can then be used to reduce false alarms, as holistic activation patterns are much more selective for specific cognitive processes than individual brain regions are (Norman et al., 2006; Poldrack, 2008, 2011; Mahmoudi et al., 2012; Del Pinal and Nathan, 2017).

Integrating Information From Neuroimaging Meta-Analyses

Why can meta-analyses help validate reverse inference? To answer this question, we must first discuss two important notions that are pertinent to reverse inference: consistency and specificity (Wager et al., 2009). *Consistency* is the extent to which brain activations replicate across studies, scanners, and labs, when certain cognitive processes are engaged. For instance, when participants see fear-inducing stimuli in a scanner, do their amygdalae tend to become activated regardless of where and in which labs they are scanned, who is scanning them, and how fear is induced in these scans? If the answer is "yes," then the amygdala can be assumed to be consistently associated with fear. In the equation above, consistency is captured by $P(ACT|COG)$, which is in proportion to $P(COG|ACT)$. In other words, if consistency is inflated, then the evaluation of reverse inference will also be inflated, causing a validity issue. Unfortunately, in neuroimaging studies, $P(ACT|COG)$ does tend to be inflated, because the usually small sample sizes and large numbers of tests give rise to underpowered studies and high false positive rates (Wager et al., 2009; Yarkoni et al., 2011). As a result, to evaluate the validity of reverse inference, consistency must be accounted for. On the other hand, *specificity* captures whether a brain region is selective for a mental process, which is directly associated with the validity of reverse inference as discussed in section "Reducing False Alarms in Reverse Inference via Careful Design and Analysis."

Therefore, to estimate $P(COG|ACT)$ and assess the validity of reverse inference, it is crucial to estimate consistency and specificity. However, neither feature can be acquired from a single study. Rather, one must consult a substantial number of studies to make a good estimation of consistency and specificity and, in turn, the validity of reverse inference.

Neuroimaging databases, such as neurosynth.org (Yarkoni et al., 2011), attempt to provide a means to account for consistency and specificity based on prior neuroimaging literature and meta-analyses generated using the database. Such databases thus attempt to quantify the extent of reverse inference by estimating the posterior probability $P(COG|ACT)$. Neurosynth.org claims to be an open-source, large-scale, automated synthesis of functional neuroimaging data, utilizing text-mining and meta-analytic techniques to synthesize more than 14,000 published research papers (as of June 2020) and providing probabilistic mappings between brain regions and terms. These terms describe cognitive states (e.g., "pain," "working memory," or "fear") and are used in the abstract of a paper, so they serve as a proxy of the mental process of interest. Based on this database and the meta-analysis provided therein, consumer researchers are able to tell whether there tends to be a non-zero association between the usages of certain terms (e.g., "emotion") and the activation of a given brain region (e.g., the amygdala) in the extant literature. More importantly, the database also provides the posterior probability of a term, if the activation of a specific brain region is found (i.e., an estimated $P(COG|ACT)$ based on extant literature).

To illustrate the usefulness and usage of meta-analysis, imagine that a consumer researcher is interested in how product evaluation can be influenced by the physical attractiveness of photos of human models that appear on product packages. Let us further assume after a literature review, the researcher hypothesizes that highly attractive models are more rewarding than average-looking models and thus lead to more favorable product evaluation. Since the reward valuation of physical attractiveness is associated with activity in the ventromedial prefrontal cortex (O'Doherty et al., 2003; Pegors et al., 2015), the researcher chooses the ventromedial prefrontal cortex as the ROI that reflects reward processing in this hypothesis. [Note, however, that in this scenario we focus on a single brain region only to make the example as simple as possible. In reality, it is always advisable to expect more than one ROI to be activated and, as a result, to (1) always include a whole brain analyses under the proper family-wise error rate (FWER)/false discovery rate (FDR) threshold (i.e., techniques to control false positives in fMRI data analysis, see Bennett et al., 2009) and/or (2) investigate brain regions in their activation patterns rather than in isolation, for instance employing MVPA as discussed in Section "Reducing False Alarms in Reverse Inference via Careful Design and Analysis"].

The researcher then sets out to test the hypothesis with fMRI, in which participants are shown a battery of product packages with images of either highly attractive models or average-looking models on them. Consistent with the hypothesis, when viewing packages with highly attractive (vs. average-looking) models, participants exhibit a brain activation in the ventromedial prefrontal cortex, in a region of interest with the center being the MNI coordinates $x = -4$, $y = 38$, $z = -16$. Also consistent with the hypothesis, the BOLD signal in the ventromedial prefrontal cortex mediates the liking of the product reported by in-scanner button pressing.

Based on these results, it would seem that the hypothesis is supported by the fMRI result. However, is this truly the case? Can the researcher reasonably infer reward processing from this brain activation, understanding the risks of reverse inference,

especially regarding such notoriously multifunctional regions as the ventromedial prefrontal cortex?

To answer this question, the researcher needs to estimate *P*(*Reward Processing*|*vmPFC activation in and around* [−4, 38, −16]), which indicates how much confidence the researcher can put in this reverse inference. Neurosynth.org is designed precisely to quantify such reverse inferences. After inputting the coordinates of the peak voxel activation in neurosynth.org, it generates a table under the "Associations" tab (see **Figure 1**) based on its meta-analytical data corpus. Clearly, some terms in the table are brain regions (e.g., "ventromedial," "vmpfc"), while others are cognitive processes (e.g., "terms," "decision," "choice").

Not surprisingly, the term "reward" (highlighted in **Figure 1**) appears in the association table. For this term of interest, the meta-analysis first returns a *z*-score of 5.39. This z-score shows whether there exists a non-zero relationship between the term ("reward" in this case) and the location (i.e., $x = -4$, $y = 38$, $z = -16$). The larger the z-score, the more confidence the researcher can have in claiming that this brain location is indeed associated with reward in the extant literature. Note that this z-score, however, *cannot* be used to determine the validity of the reverse inference being employed, *nor* can it be used to infer the strength of the association between the mental process (i.e., the term) and the location of the activation in the brain (Yarkoni, 2015b).

More informative is the number under the "posterior prob." column. This number is the estimation of $P(COG|ACT)$ and, thus, of the validity of the reverse inference. In our case, the posterior probability is 0.7 (see **Figure 1**). However, what does this number mean? Note that Bayes' Theorem dictates that posterior probabilities must be calculated based on prior probabilities. In the case of neurosynth.org, its creators arbitrarily impose a uniform 50% prior probability on *all* terms [$P(COG) = 0.5$ for any *COG*]. In other words, neurosynth.org assumes that if we take a random paper in the database, the prior probability of that paper using *any* term is exactly 50%. This is, of course, not true in reality; however, by making this assumption, neurosynth.org provides a threshold that applies to *all* terms, such that if the posterior probability is greater than 0.5, then the researcher can reasonably assume that the reverse inference he or she is examining has some merit at an above-chance level (Yarkoni et al., 2011; Yarkoni, 2015b). In addition, this uniform, arbitrary 0.5 prior probability allows researchers to make quantitative comparisons across all terms, such that if a location has a greater posterior probability for a term, then this region is more preferentially associated with that term than are the terms with lower posterior probabilities. It should be noted, however, that if the arbitrary prior probability is changed to other values from 0.5, the posterior probability will also vary as a result. Therefore, the absolute value of the posterior probability does not carry much meaning *per se*, and interpretations thereof should be made only in relation to other probabilities, such as the default 0.5, or the posterior probability for a different term associated with the same voxel.

Therefore, in our case, the 0.7 posterior probability means that if there is a 50–50 chance that a study uses the term "reward" *a priori*, then the estimated posterior probability for the term "reward" to be used increases to 70% after we observe the activation of the ventromedial prefrontal cortex in and around MNI coordinates $x = -4$, $y = 38$, $z = -16$. Thus, it seems that there is an above-chance likelihood that reward process is present in this hypothetical study. Please note again that one can only interpret change (i.e., 0.7 vs. the baseline 0.5) and not the absolute value.

However, we should take care here to avoid jumping to conclusions. It is very important to note that the fact that there is a decent chance of reward processing having taken place given the observed activation does not necessarily mean that this region is *selective* for reward. Rather, other terms may also have comparable or even higher levels of posterior probability in this reported region. Indeed, if we pay close attention to other terms in **Figure 1**, terms such as "autobiographical memory" and "mentalizing" (both highlighted) will arise, each having a posterior probability even greater than that of "reward" (0.84 and 0.79, respectively). Admittedly, many terms with the highest posterior probabilities in this table are reward-related (e.g., "reward," "value," "money"). However, even after taking all these terms into consideration, the conclusion the researcher can draw from this meta-analysis is still inconclusive; that is, the ventromedial prefrontal cortex in and around ($x = -4$, $y = 38$, $z = -16$) is preferentially (but not selectively) associated with reward. In other words, at this point in the analysis, we are still not sure if reward processing is truly happening.

Thus far, we have discussed what the neurosynth.org database tells us and, equally importantly, what it does *not* tell us (also cf. Yarkoni, 2015a,b for a discussion). The most important question, however, still remains. The researcher in our hypothetical example theorizes that reward is underlying the processing of product packages with images of highly attractive (vs. average-looking) human models on them. The fMRI result seems to support this argument, and the meta-analysis suggests that there is a good chance that the researcher is on the right track. However, the researcher still cannot draw decisive conclusions, due to the existence of alternative, equally viable (at least judging from the meta-analysis) mental processes (in this case, autobiographical memory and mentalizing). So, what should the researcher do now?

This question can be partially addressed by the meta-analysis that brings up this very question. Indeed, a valuable function of meta-analysis is to identify a (limited) set of competing theories so the proposed hypothesis can be supported by eliminating other (at least major) alternatives. Needless to say, the easiest alternatives to exclude are those that are unlikely to occur under the particular study design being employed. For instance, in the design of the hypothetical study described above, autobiographical memory is very unlikely to have been involved (since there is not a memory-related task involved) and thus can be reasonably excluded.

However, mentalizing – the process by which individuals make sense of the mental state of others or oneself – may well survive this "exclusion by study design." After all, when consumers see other human beings (i.e., human models used in our hypothetical fMRI experiment), especially if they show

Data for coordinates: -4 38 -16

Maps Studies Associations FAQs

Associations with meta-analysis maps

Show 25 entries Search:

Name	z-score	Posterior prob.	Func. conn. (r)	Meta-analytic coact. (r)
ventromedial	9.86	0.82	0.45	0.46
ventromedial prefrontal	9.83	0.83	0.42	0.47
medial	8.27	0.72	0.5	0.5
vmpfc	8.19	0.84	0.38	0.45
medial prefrontal	7.89	0.75	0.49	0.49
cortex vmpfc	6.6	0.83	0.31	0.36
social	6.16	0.7	0.38	0.32
value	6.07	0.75	0.21	0.3
prefrontal	5.94	0.66	0.15	0.28
orbitofrontal	5.73	0.71	0.38	0.3
decision	5.42	0.71	0.04	0.14
prefrontal cortex	5.42	0.65	0.19	0.3
autobiographical memory	5.4	0.84	0.25	0.24
reward	5.39	0.7	0.19	0.24
orbitofrontal cortex	5.08	0.71	0.36	0.3
choice	4.98	0.75	0.07	0.13
ventral medial	4.93	0.83	0.21	0.31
mentalizing	4.91	0.79	0.29	0.24
decision making	4.65	0.71	0.08	0.12
money	4.65	0.82	0.08	0.15
asd	4.63	4.63	0.03	0.12
medial lateral	4.63	0.8	0.13	0.12
medial orbitofrontal	4.63	0.8	0.32	0.29
autobiographical	4.57	0.78	0.38	0.31
positive negative	4.49	0.74	0.13	0.16

FIGURE 1 | Meta-analysis results generated by neurosynth.org (retrieved on June 26, 2020).

emotions, consumers may well engage in mentalizing and, in turn, feature the well-documented activation in the ventromedial prefrontal cortex (Lombardo et al., 2010; Atique et al., 2011; Schnell et al., 2011). At this point, the researcher needs to think above and beyond the meta-analysis. One possible solution, for example, is to acquire the activation pattern of mentalizing; if this pattern is inconsistent with the actual results, then it is very likely that mentalizing may not have taken place. In this case, mentalizing involves not only the activation of the ventromedial prefrontal cortex but also activity in the precuneus and/or the temporoparietal junction, which often accompany ventromedial activations. Thus, if the researcher fails to find meaningful activations in these additional regions, mentalizing may not have been engaged in the study. Needless to say, the researcher should turn to extant literature to identify such patterns; however, another newly launched meta-analysis database, neuroquery.org, may also greatly assist in this process, in that it helps researchers predict which brain regions are likely to become activated given designated cognitive processes. Moreover, pattern-based activation can prove useful even if mentalizing does take place. For instance, if reward processing indeed occurs, it may not only involve the ventromedial prefrontal cortex but also trigger the orbitofrontal cortex and the ventral striatum. If the researcher can find activity in these regions that are also involved in reward processing, it becomes more evident that reward is taking place, even in the presence of mentalizing.

Although meta-analyses can shed important light upon the validity of reverse inference, it is not without limitations.

Other than the information meta-analysis cannot yield, which we already discussed in Section "Integrating Information from Neuroimaging Meta-Analyses," there exist other factors that limit the usefulness of meta-analyses.

First, when the term related to the cognitive process of interest has been rarely examined in the literature, the database will provide little information to the researcher. For instance, consumer researchers interested in personal control may recognize the scantiness of neuroimaging studies investigating perceived control and loss thereof, despite the richness of non-imaging work, which has been conducted mostly on non-human animals (e.g., Maier and Watkins, 2005; Amat et al., 2010, 2014).

Second, when a term is used inconsistently in the literature, the usefulness of meta-analysis is also limited. For instance, in the literature, the term "control" not only is used to refer to "personal control" but also is found in works involving self-control, motor control, executive control, and even the control condition in experimental studies. These terms are not distinguishable in the database due to the limitation of text-recognition tools, thus rendering meta-analyses on such terms virtually uninformative.

Third, meta-analysis databases like neurosynth.org cannot capture nuances across studies and designs. Such situations may introduce noise to meta-analyses and thus undermine the usefulness of their results, except in the case of well-defined and consistently-used cognitive processes and experimental procedures (Dockès et al., 2020).

For instance, meta-analysis databases may not be able to distinguish between "perceptual curiosity" and "epistemic curiosity," as the terms tend to be aggregated together, despite their conceptual and neurophysiological distinctions in the literature on curiosity (Loewenstein, 1994; Jepma et al., 2012; Kidd and Hayden, 2015; Wiggin et al., 2019). To make matters worse, there are too few neuroimaging studies on curiosity to provide sufficient statistical power for the meta-analysis, if such terms exist in the database at all. Moreover, the inconsistent study procedures introduce noise to the database. Thus, if a researcher hypothesizes perceptual (but not epistemic) curiosity as the cognitive process underlying a certain consumer behavior, meta-analysis might not be able to provide much useful insight. In the following section, we argue that behavioral data can prove useful in addressing these concerns.

In addition, another database, NeuroQuery.org (Dockès et al., 2020), has recently been made publicly available.[2] This new database complements the previously discussed databases in important ways, which we discuss below. An issue with the traditional databases is that the results they generate are largely based on decontextualized, aggregated data and arbitrary thresholding. Specifically, such databases rely on automated text-analysis algorithms and scripts to analyze and document the neuroscience concepts (in the form of "terms") included in a sizable corpus of literature with considerable statistic power. However, to investigate these neuroscience concepts, the original research papers included in the corpus may take different approaches, employ different designs, and use different terms. Due to current limitations of text-mining techniques, traditional databases are unable to capture such task-related information, nuances across studies and designs, and idiosyncratic usages of the same terms. This situation can prove problematic, because the output of such analysis can suffer from a low signal-to-noise ratio and thus can be difficult to control and interpret, except in the case of well-defined concepts and/or highly standardized procedures (Dockès et al., 2020). Neuroquery.org, on the other hand, attempts to employ a different approach. Specifically, NeuroQuery.org begins with keywords (e.g., psychological processes, neuropsychological conditions, and anatomy) and uses these terms to predict what brain regions are likely to become activated if proposed psychological processes are engaged. The model this database utilizes can produce accurate and usable predictions of ROIs even for less common terms, terms that are named inconsistently in neuroscience vocabulary, or sets of terms that have not been studied together previously.

Integrating Psychometric and Behavioral Data

Although many researchers turn to neuroimaging techniques to discover mental processes precisely because of behavioral studies' limitations, psychometric and behavioral data are useful in neuroimaging studies in many ways. To begin with, in relation to our discussions on meta-analyses, psychometric and behavioral data can prove helpful in compensating the shortcomings of meta-analyses, as they can provide a better-calibrated, task-relevant environment to investigate psychological processes of interest. In the aforementioned case of curiosity, for instance, extant literature provides rich behavioral manipulations to introduce perceptual vs. epistemic curiosity (e.g., Loewenstein, 1994), and the researcher can thus conduct behavioral experiments to observe whether perceptual (but not epistemic) curiosity produces the consumer behavior in question. If so, such studies can provide more evidence to complement the fMRI data.

Even when meta-analyses can be employed without the issues discussed in the previous section, psychometric and behavioral data can still prove helpful to reverse inference studies by provide additional evidence that the proposed cognitive process is indeed implicated in the phenomenon being studied. Mathematically, doing so increases $P(COG)$ and in turn $P(COG|ACT)$. For instance, Plassmann and Weber (2015) investigate the consumer responsiveness to the "marketing placebo effects" (MPE; the effect by which consumption experience and subsequent behavior are influenced by marketing-based expectancy such price, quality beliefs, etc.). The authors provide a comprehensive account of the cognitive processes that can influence MPE: reward responsiveness, cognitive top-down processing, and somatosensory bottom-up processing. In an MRI study, the gray matter volume of brain regions associated with these cognitive processes is found to be predictive of the MPE effect. To provide further support for this theoretical account, the authors further conducted a study demonstrating that personality traits related to these cognitive processes are also predictive of MPE, as are gray matter volume measures, thus fostering extra confidence in the proposed processes.

[2]The authors also thank an reviewer for bringing this new development to our attention during the review process.

Note that for triangulation purposes, the behavioral data do not need to be "purely behavioral" (i.e., collected from separate studies that do not feature neuroimaging elements at all). Rather, the collection of psychometric and behavioral data can either be part of the original fMRI study and/or collected in separate studies.

For instance, imagine a study investigating how food print ads drive consumers' willingness to purchase. To explore the cognitive process underlying food ads, suppose the researcher shows hungry participants multiple food ad images in the scanner as they report how much they want to purchase the food advertised. Let us further assume that the researcher finds that more successful ads are associated with (1) a neural network associated with reward and impulse (which might include, say, the nucleus accumbens, orbital prefrontal cortex, ventromedial prefrontal cortex, anterior insula, etc.) and (2) importantly, reduced activation in the medial prefrontal gyrus, a region associated with inhibition behavior (e.g., Batterink et al., 2010). Based on this pattern, our hypothetical researcher speculates that more successful food ads might be associated with greater inhibition/control failure and, in turn, higher willingness to purchase. (Here again, we caution our readers that the theorization and selection of ROIs herein are overly simplified for the sake of clarity and succinctness).

This theorizing is clearly an example of potentially problematic reverse inferences. How, then, can behavioral data help the researcher with this proposed process? Of course, the aforementioned "purely behavioral" studies can be conducted, wherein the researcher shows that depleted participants exhibit greater willingness to purchase to the same food ad than non-depleted participants do, thus demonstrating the involvement of control process. Alternatively, the researcher could show that people's acceptance of the same food ad is a function of their trait self-control. However, the researchers can also collect behavioral data and combine them with neuroimaging data collected in either the existing or a new study to provide support for the proposed hypothesis.

For instance, if inhibition/control indeed plays a role in the acceptance of food ads, the aggregated activation in related brain regions acquired from a group as small as the participants scanned may be predictive of the effectiveness of the ads in the real world on a market or population level (i.e., neuroforecasting, Genevsky et al., 2017). Such "related brain regions" may be the medial prefrontal gyrus found in the existing hypothetical study or may involve a more extensive inhibitory network established by the literature. Similarly, the researcher could also run a structural scan to see whether the cortical thickness of these brain regions is predictive of individual participants' acceptance of the ads (e.g., rating, choice, etc.). Furthermore, the researcher can even use transcranial magnetic stimulation (TMS) to temporarily disrupt the function in these brain regions (if they are relative shallow) or recruit participants with lesions in these areas and obverse how these participants react to the ads in comparison to control participants. In all these approaches, behavioral data are combined with brain data to shed light upon the underlying cognitive processes – in this case, inhibition and control.

As shown above, psychometric and behavioral data can be triangulated with brain data in a very flexible manner and can provide interesting and useful insights to researchers in many ways. Based on the specific issues they are investigating, the nature of the existing design and data, and the technology and resources available to them, researchers can select approaches to behavioral data to fit their needs.

Summary: The Importance of Triangulation

In summary, in consumer neuroscience, researchers can address the validity issue of reverse inference by (1) refining the neuroimaging study design and analysis to reduce false alarms, (2) utilizing neuroimaging databases and the meta-analysis data therein to quantify the extent of reverse inference, and (3) using psychometric and behavioral data to provide additional process evidence.

In this paper, we advocate not the isolated employment but the triangulation of these methods. Such triangulation can enable each method to compensate for the others' shortcomings and disadvantages, thus providing synergy toward improved overall validity. As discussed earlier, notwithstanding their unique advantages, each of these methods suffers from certain shortcomings: fMRI studies can investigate hidden mental processes but are potentially vulnerable to reverse inference issues; neuroimaging meta-analysis can assist researchers in quantifying reverse inference, but its usability can be limited and its analysis may not necessarily be conclusive; and behavioral data are flexible and can be well calibrated to the stimuli and procedures but may not be able to address the mental process of interest in a direct manner (the very reason researchers turn to neuroimaging in the first place).

Understanding the pros and cons of each method is important, as the cons serve as a starting point to identify the potential validity issues with one's data, while the pros help researchers understand what data triangulations should be employed to address these issues. Indeed, this is precisely what the literature on Multitrait-Multimethod Matrices (MTMM, Campbell and Fiske, 1959; Bagozzi and Yi, 1993) suggests: that is, a single method may not be enough to distinguish the cognitive process of interest from unsubstantial, random-method variance and noise and, instead, multiple methods taking different angles can possibly redress single-method concern effectively.

Therefore, despite the increased time, effort, and expertise needed to adopt a multi-method approach, we still believe that the triangulation approach we have proposed herein should be considered by consumer neuroscience researchers. Specifically, for neuroimaging studies in consumer neuroscience, we believe the researcher should always (1) carefully refine the design of the fMRI study and (2) utilize meta-analyses (of course, sometimes the database is not usable for certain keywords and designs, but this is not known to the researcher until they have utilized the database). On the other hand, we believe that the researcher should base their decision of whether to include (3) psychometric and behavioral data, as well as what to include, on the specific issue they are facing. If, for example, the researcher makes a

claim about certain mental cognitive processes based on brain activation, but the subsequent study design and meta-analysis cannot rule out competing theories and provide conclusive judgments, we would then recommend that psychometric and behavioral data be included. However, if it is already well-established in the behavioral literature that treatment X (e.g., seeing a picture of a snake) will cause mental activity M (e.g., fear) in the population of interest, and if, with due caution and prudence, the researcher can reasonably believe there is no good reason why this causal link would disappear in the scanner, then perhaps in such a case the researcher does not need to reinvent the wheel. Therefore, much as we applaud the merit of psychometric and behavioral data in general and believe they are beneficial most of the time, as a general principle we encourage researchers to include meaningful psychometric and behavioral data that address existing issues stemming from their particular research question and design, instead of triangulating for the sake of triangulating.

In addition to the hypothetical examples we used in previous sections, real-world examples of triangulation can also be found in the extant literature in consumer neuroscience. Regarding the works we summarized in **Table 1**, in Section "Integrating Psychometric and Behavioral Data," we already discussed how Plassmann and Weber (2015) triangulated anatomical neuroimaging data with psychometric measures to explore the marketing placebo effect, and we would like to note that in this work the authors also utilize the NeuroSynth meta-analytical tool in support of their conclusions. Similarly, in Reimann et al. (2018), an fMRI study demonstrates that brand betrayal and brand satisfaction involve different brain areas. This result is triangulated with both psychometric measures and the NeuroSynth database. The authors were able to pinpoint a number of aspects on which brand dissatisfaction is differentiated from brand betrayal, including prior relationship with the brand, anger, and rumination. Furthermore, by combining fMRI, individual-level data and marketing-level behavioral data, Genevsky et al. (2017) found that nucleus accumbens activity not only predicts individual choices to fund in crowdfunding but also market-level funding outcome. The authors also examined the role sensory processes play in the identified pattern, and NeuroSynth was employed to predefine the volumes of interest (VOIs).

FUTURE DIRECTIONS IN CONSUMER NEUROSCIENCE

In addition to data triangulation, other practices can also improve the validity of individual studies and consumer neuroscience. Although a thorough discussion of these practices would be outside the scope of this paper, we would still like to take this opportunity to briefly advocate some of these practices for future studies in the field.

Toward a Quantification of Triangulation

As discussed in Section "Summary: The Importance of Triangulation," the notion of data triangulation proposed in this paper is consistent with that of the Multitrait-Multimethod Matrix (MTMM, Campbell and Fiske, 1959). The MTMM provides useful information that can benefit fMRI studies in three ways. First, the MTMM provides estimations of reliability of each measure, which could potentially help address the issue that fMRI measures tend to suffer from poor overall reliability (Elliott et al., 2020). Second, the MTMM provides assessment of convergent validity: if a concept (e.g., a mental process) is measured through multiple methods, the measures should be strongly correlated. Third, the MTMM also helps researchers to establish discriminant (or divergent) of measures, such that measures for different constructs should not be correlated (Campbell and Fiske, 1959).

Therefore, the MTMM would be a good tool to evaluate how well the triangulation improves the validity. The challenge is, however, how to directly compare the vastly different methods (e.g., behavioral data of distinct nature and neuroimaging data) on the MTMM. Although the analysis above already lays out the means in which triangulation can help improve the validity of fMRI studies, quantifying such improvement would provide the proposed triangulation with even more solid footing. Thus, we advocate the quantification of the proposed triangulation as a direction for future research.

Toward an Interpretable Consumer Neuroscience

Recent years have witnessed an increase in the important discussion regarding how to promote openness and transparency of research in the fields of psychology and neuroscience (e.g., Aarts et al., 2015; Gorgolewski and Poldrack, 2016; Kidwell et al., 2016; Nichols et al., 2016; Gilmore et al., 2017; Klein et al., 2018; Shrout and Rodgers, 2018). In solidarity with the fields' joint effort toward a more precise and interpretable discipline, we also take the opportunity to advocate these practices in consumer neuroscience. For example, we suggest that consumer researchers could report information regarding experimental design, image acquisition, preprocessing, statistical modeling and statistical inferences, as well as result tables, which could be provided in a web appendix alongside the main paper. Some guidelines and checklists are provided, for instance, by Nichols et al. (2016) and in the appendix to Reimann et al. (2018). These practices may be helpful to make research reports more interpretable.

Another laudable practice is data sharing. This practice is more than just academic integrity, but also improves the validity of data analysis. In a recent paper published in *Nature* (Botvinik-Nezer et al., 2020), 70 independent teams of researchers were asked to analyze the same dataset. Since no two teams employed the same workflow of analysis, this flexibility in data analysis creates a considerable variation in the results of hypotheses testing. When the results from teams are aggregated, however, they show a significant convergence on activated regions. Thus, for better cross-validation, consumer neuroscientists may want to consider sharing data, which can be done with dedicated online repositories such as OpenfMRI.org (Poldrack et al., 2013), NeuroVault.org (Gorgolewski et al., 2015), and OpenVoxel.org. Furthermore, we encourage consumer researchers to share the

workflow by which the data were analyzed, and report (if applicable) the code they used to analyze scan data on online platforms such as GitHub.com to further promote transparency, openness, and cross-validation.

CONCLUSION

Consumer neuroscience may hold valuable insights for the advancement of consumer research, with perhaps the most intriguing of these being its potential to (1) reveal hidden cognitive and emotional processes that have been inaccessible to traditional research methods and (2) to confirm physiological and psychological processes underlying consumer behavior. Indeed, over the years, consumer researchers have been employing fMRI, along with other neuroimaging techniques, in an attempt to open the black boxes of consumer experience, motivation, decision-making, and so on. Needless to say, fMRI has shed new light upon our understanding of consumer behavior, and we fully acknowledge the important contributions made by the field. That being said, as we pointed out earlier, many studies' reliance on reverse inference may render them vulnerable to validity issues. To promote the validity of individual neuroimaging studies as well as consumer neuroscience as a field, in this paper we advocate for the triangulation of neuroimaging data with meta-analyses as well as psychometric and behavioral data. We believe these research practices may substantially increase the conclusions we can draw from fMRI data. Therefore, we encourage the employment of data triangulation in consumer neuroscience research. Lastly, we take this opportunity to offer our special acknowledgment to the intensive methodological discussions and disputes taking place in our parent disciplines, such as cognitive neuroscience and functional neuroimaging, as this paper draws largely upon their lessons and wisdom.

DATA AVAILABILITY STATEMENT

The original contributions generated for this study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

CC conducted the review on extant literature and the analysis on reverse inference in the frontend with the consent of MR. Both CC and MR drafted the frontend. Both authors contributed to the article and approved the submitted version.

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Measuring dlPFC Signals to Predict the Success of Merchandising Elements at the Point-of-Sale – A fNIRS Approach

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The (re-)launch of products is frequently accompanied by point-of-sale (PoS) marketing campaigns in order to foster sales. Predicting the success of these merchandising elements at the PoS on sales is of interest to research and practice, as the misinvestments that are based on the fragmented PoS literature are tremendous. Likewise, the predictive power of neuropsychological methods has been demonstrated in various research work. Nevertheless, the practical application of these neuropsychological methods is still limited. In order to foster the application of neuropsychological methods in research and practice, the current research work aims to explore, whether mobile functional near-infrared spectroscopy (fNIRS) – as a portable neuroimaging method – has the potential to predict the success of PoS merchandising elements by rendering significant neural signatures of brain regions of the dorsolateral prefrontal cortex (dlPFC), highlighting its potential to forecast shoppers' behaviour aka sales at the PoS. Building on previous research findings, the results of the given research work indicate that the neural signal of brain regions of the dlPFC, measured with mobile fNIRS, is able to predict actual sales associated with PoS merchandising elements, relying on the *cortical relief effect*. More precisely, the research findings support the hypothesis that the reduced neural activity of brain regions associated with the dlPFC can predict sales at the PoS, emphasising another crucial neural signature to predict shoppers' purchase behaviour, next to the frequently cited *reward association system*. The research findings offer an innovative perspective on how to design and evaluate PoS merchandising elements, indicating fruitful theoretical and practical implications.

Keywords: consumer neuroscience, fNIRS, merchandising elements, point-of-sale, DLPFC, cortical relief effect

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INTRODUCTION

The (re-)launch of products is frequently accompanied by point-of-sale (PoS) marketing campaigns, given that effective PoS merchandising elements have been shown to significantly increase sales of advertised products (Sinha and Verma, 2017). Predicting the success of these PoS marketing campaigns in terms of the company's objectives, for example forecasting the sales before

its launch, is of substantial economic importance. An aspect that is reflected in the multibillion-dollar investments companies spend on advertising and merchandising each year (Guttman, 2019). Consequently, a significant amount of research investigated the PoS and its effective design. In this regard, previous PoS research examined in particular the assortment size, the in-store design and the PoS atmosphere. The assortment size and the associated choice overload effects have been investigated most frequently, identifying the circumstances and operating principles in form of an inverted U-shape function between variety and purchase probability (Chernev, 2006; Heitmann et al., 2007; Grant and Schwartz, 2011; Chernev et al., 2012; Beneke et al., 2013). Other research examined PoS in-store demonstrations, product presentations and consumer inspiration, which showed positive effects on attention and evaluation processes of consumers (Nordfält and Lange, 2013; Townsend and Kahn, 2014; Huddleston et al., 2015; Phillips et al., 2015; Bottger et al., 2017). Considering the sensory complexity of the PoS, previous research investigated also the store environments and the PoS atmosphere, exploring how multisensory aspects like music, scent and touch influence shopping behaviour in combined fashion. The results indicate that congruent and matching modalities seem to be most favourable by consumers (Mattila and Wirtz, 2001; Spence and Gallace, 2011; Quartier et al., 2014; Spence et al., 2014; Michel et al., 2017). Although it has been shown that investments in PoS atmospherics and product arrangements can pay off, most merchandising activities are still associated with high costs (Spence et al., 2014). Moreover, many operating stimuli at the PoS that have been shown to greatly influence shoppers are only analysed in isolation without considering the complexity of the entire PoS and its various influencing factors. Consequently, the efficient and effective prediction of the success of PoS marketing campaigns on market level is of great interest for research and practice, given that it might provide a holistic picture of the marketing activities at the PoS that may reduce misinvestments. It is, thus, not surprising that retailers and producers, who launch and promote a myriad of new product variations every year, try to implement marketing campaigns that have been effectively tested before.

The selection of merchandising elements is frequently grounded on insights that are received from exploring the consumers' perceptions of the – advertised – product or service-associated attributes. In order to measure the consumers' perceptions of these attributes, self-report measurements are often used, asking consumers directly about their subjective opinions in regard to a product or service. Although self-report measurements have been indicated to be beneficial in some marketing studies, social psychology suggests that self-reports, when used in isolation, are unreliable to accurately predict the consumers' preferences (Nisbett and Wilson, 1977; De Cremer et al., 2008; Petit and Bon, 2010; Baldo et al., 2015b). This is mostly because the consumers' expressed intentions do not always translate into actual (purchase) behaviour or even sales (Ajzen, 1991; Padel and Foster, 2005; Frank and Brock, 2018). Against this background, other measurements might be more expedient to solve the indicated matter (Ariely and Berns, 2010; Plassmann et al., 2015; Karmarkar and Yoon, 2016).

The application of neuropsychological methods, using neural brain activity data to forecast products and marketing campaigns success, has been indicated to offer a promising approach to gain further knowledge about the consumers' perception processes (Ariely and Berns, 2010; Berns and Moore, 2012; Falk et al., 2012, 2015; Plassmann et al., 2015; Venkatraman et al., 2015; Daugherty et al., 2016; Karmarkar and Yoon, 2016; Kühn et al., 2016; Motoki et al., 2020; Tong et al., 2020). Plassmann et al. (2007) explored, for example, how neuropsychological methods could be used to investigate brand equity as a determining factor that influences the perception and, consequently, the behaviour of consumers. Subsequently, multiple studies demonstrated the predictive power of neuropsychological data, displaying the capability of forecasting music and movie success or advertising elasticities of television ads (Baldo et al., 2015a; Boksem and Smidts, 2015; Venkatraman et al., 2015; Cha et al., 2019; Tong et al., 2020). Although the predictive power of neuropsychological methods has been demonstrated to outperform 'traditional' marketing methods (Venkatraman et al., 2015), neuropsychological methods and the generated neuropsychological insights are only partially adapted in practice. One reason for this might be that previous research often emphasised *reward associations* in order to predict sales with the utilisation of neuropsychological methods (Ariely and Berns, 2010; Plassmann et al., 2015). Thereby the predictions rely on medially and subcortical located brain regions of the *reward evaluation system*, such as the nucleus accumbens (NAcc), the ventral striatum, the orbitofrontal cortex (OFC) and the ventromedial prefrontal cortex (vmPFC). These brain areas can only be measured with stationary neuroimaging methods, such as functional magnetic resonance imaging (fMRI), whose application is quite costly and time-consuming. However, although just recently a study conducted by Cha et al. (2019) indicated that the application of functional near-infrared spectroscopy (fNIRS) allows to correlate medial prefrontal cortex (mPFC) neural activity to popularity of music on YouTube, another – in previous research often neglected – neural signature might as well be decisive to predicting PoS sales, namely the deactivation of the dorsolateral prefrontal cortex (dlPFC). The dlPFC is known to play a major role in decision-making by integrating cognitive evaluations whilst modulating affective reward responses (Hare et al., 2009). Frequently, increased dlPFC activity is associated with cognitive (self-)control in decision-making and other cognitive processes such as working memory, abstract problem solving and exertion of control in order to favour long-term goals (Miller and Cohen, 2001; Hare et al., 2009; Carlén, 2017). For example, in food-related value-based decision-making increased neural activity in brain areas of the dlPFC have been identified for participants that execute a greater self-control on their food choice (Hare et al., 2009). Simultaneously, a reduced neural activity of the dlPFC has been associated for brand-related decisions that require less strategy-based reasoning (Deppe et al., 2005; Schaefer and Rotte, 2007; Koenigs and Tranel, 2008; Krampe et al., 2018a). First shown in the study by Deppe et al. (2005), decision sets that include the participants

favoured brand, emotionalise the choice, which allows a quicker, straightforward and less complex decision-making process in favour of the preferred product, a replicated and robust effect called *cortical relief effect*.

In conclusion, preferred choice options seem to be easier to process, which makes it easier to choose for the favoured product during a decision-making process that seem to be less cognitively controlled and assumed to elicit a reduced activity in brain regions of the dlPFC (Deppe et al., 2005; Schaefer and Rotte, 2007; Koenigs and Tranel, 2008; Krampe et al., 2018a). Less self-controlled decisions might, therefore, result in more impulsive decision-making, choosing the option that is preferentially presented in a choice situation (Boettiger et al., 2007; Kable and Glimcher, 2007; Hare et al., 2009). Consequently, merchandising elements that are about to expose a reduced neural activity in brain regions ascribed to the dlPFC might be less cognitively engaging, resulting in more impulsive decisions, which might rescale in increased sales at the PoS. Hence, while earlier neuropsychological studies that aimed to predict consumer behaviour on population level with neuropsychological methods focussed mainly on medial and subcortical located brain regions of the *reward evaluation system*; only a few studies considered the dlPFC in their prediction models. Consequently, this research work is one of the first to evaluate whether the reduced neural dlPFC activity, as a neural signature, can predict PoS sales, building on insights of the *cortical relief effect*.

Having this in mind, the current research work aims to explore the predictive power of the cortical brain regions of the dlPFC to forecast the success of PoS merchandising elements. By doing so, the given research work overcomes the limitations of stationary neuroimaging methods by utilising mobile fNIRS as a portable applicable neuropsychological method for the research field of shopper neuroscience, demonstrating its potential application in ecological valid setting, such as the PoS (Kopton and Kenning, 2014; Çakir et al., 2018; Krampe et al., 2018b). Against this background, the given research work aims to explore whether mobile fNIRS – as a mobile applicable neuroimaging method – has the potential to predict the success of PoS merchandising elements by rendering significant neural *cortical relief* signatures of the dlPFC.

PREDICTING SUCCESS OF POS MERCHANDISING ELEMENTS – THE 'DUPLO' CASE

A special case in the analyses of PoS merchandising elements is the product 'duplo' by Ferrero (Ferrero Deutschland GmbH, n.d.). 'Duplo' constitutes a special case for research, since its effects on shoppers' processing and behaviour were not only explored in prior studies with neuropsychological and traditional marketing methods (Kühn et al., 2016; Strelow and Scheier, 2018; Strelow et al., 2020), allowing comparisons between different data types, but also provide unique, real-market stimuli materials for research, that are, in contrast to research stimuli specifically designed for a study, highly ecologically valid. The product 'duplo' was introduced to the German market in 1964 and is currently the market leader of chocolate bars in Germany, with a turnover of 200 million Euro (VuMA, 2019b). There, more than 50% of the turnover is achieved by secondary (out of shelf) displays, which are displayed with PoS merchandising elements (Briesemeister and Selmer, 2020). Over the past 40 years, many PoS merchandising elements have been used to promote the chocolate bar. Six merchandising elements were explored by prior research, representing a typical choice set for marketing campaigns, including past and recent PoS and TV campaigns as well as similar but unknown merchandising elements (**Figure 1**).

An fMRI study conducted by Kühn et al. (2016) investigated the different PoS 'duplo' merchandising elements on neural level. In particular, two fMRI-derived sales prediction values were extracted based on the neural BOLD signals measured (1) during the perception of the merchandising elements contrasted to the implicit baseline and (2) for the signal change from the baseline contrast of (the advertised) package 'duplo' product seen before and after the merchandising element. The fMRI-derived sales prediction values summarised the signal of multiple neural regions, whereby the prediction was mainly driven by the neural activity of the *reward system* (NAcc and medial OFC) and the *deactivation of the dlPFC* (Brodmann area 9 and 46). Furthermore, explicit subjective ratings of the 'duplo' merchandising elements were evaluated. In order to measure the actual sales – defined as the revenue generated by the different merchandising elements – the merchandising elements were tested at the PoS in a field experiment in parallel to the fMRI study (for detailed information, please see Kühn et al., 2016) (**Figure 2D**). Results demonstrated that the fMRI-derived sales prediction value based on the merchandising element presentation was the best predictor for the sales numbers (**Figure 2A**). While the first two and last two ranking positions were equivalent between fMRI-derived sales prediction value of merchandising elements and actual sales, only one match at the third position was found for the subjective rankings (**Figure 2C**) and no match for the fMRI-derived sales prediction value of the product contrast (**Figure 2B**). Inspecting the integrated neural brain areas *ad hoc* in detail, Kühn et al. (2016) identified the medial OFC as most predictive for actual market sales.

In order to explore the shoppers' associations with the different PoS merchandising elements and to understand the shopper response to the merchandising elements, following the fMRI study, the merchandising elements were examined in a second study conducted by Strelow and Scheier (2018), utilising an implicit reward association test (IAT). During the IAT, each PoS merchandising element as well as the brand itself were assessed on different reward values that were spontaneously associated with the brand and the merchandising element. From the results of the IAT for the merchandising elements, Strelow and Scheier were able to discriminate the lower three merchandising from the top three merchandising elements, although the ranking order was not congruent with the actual sales numbers identified by Kühn et al. (2016) (**Figure 2E**). Subsequently, the fit between the merchandising elements and the brand's reward associations was analysed, indicating that the first and last two ranks of the actual PoS sale performance



FIGURE 1 | Merchandising elements of the product 'duplo'. The six merchandising elements were used in prior studies (Kühn et al., 2016; Strelow and Scheier, 2018) and the current study, including: **(A)** a *woman* eating a 'duplo' bar, used at the PoS from 1995 to 2015; **(B)** *hands* holding a 'duplo' bar, representing a TV campaign that had been on air for 6 months from 2011 to 2012; **(C)** a *group* of people and three 'duplo' bars, which represented a TV campaign that had been on air for nearly 20 years between 1991 and 2010; **(D)** a *couple* with a 'duplo' bar and **(E)** *hands* holding a 'duplo' bar *with text*, which were not used in advertising previously, as well as **(F)** a *toothbrush* with a 'duplo' bar used as control merchandising element. Figure adapted from Kühn et al. (2016). Permission to reuse has been obtained.



FIGURE 2 | Ranking of the six merchandising elements based on prior research. Ranking order of the merchandising elements derived from: **(A)** fMRI-derived sales prediction value of merchandising elements from Kühn et al. (2016); **(B)** fMRI-derived sales prediction value of product contrasts from Kühn et al. (2016); **(C)** the explicit rating of participants of the study by Kühn et al. (2016); **(D)** actual product sales of the field study of Kühn et al. (2016); **(E)** mean average reward association strength by Strelow and Scheier (2018); **(F)** brand-fit score of reward association by Strelow and Scheier (2018). Figure adapted from Kühn et al. (2016) and Strelow and Scheier (2018). Permission to reuse has been obtained.

can be determined by the data (**Figure 2F**). The fit of the brand associations with the merchandising element associations can be interpreted either as an *enhancement* or at least as a confirmation of the brand reward associations representing the degree of congruence between the expected associations elicited by the brand and the associations evoked by the brands merchandising elements.

In conclusion, data from both (neuro)psychological methods, the fMRI data and the IAT data, seem to outperform self-report shoppers' ratings of the merchandising elements. A high brand-fit score as indicated by Strelow and Scheier (2018) between the merchandising element and the brand seems to be predictive for the success of a merchandising element, since the shoppers' expected and experienced brand associations are congruent with the merchandising element, potentially resulting in a *cortical relief effect*, reducing the experienced cognitive dissonance. In the study conducted by Kühn et al. (2016) the fMRI-derived sales prediction value based on the merchandising element presentation were most predictive for actual sales data. Although, the brain regions of *reward evaluation system*, especially medial OFC, were again highlighted as the driving force for the prediction, a decreased neural activity in the dlPFC was integrated in the formula to predict sales, an aspect that represents reduced cognitive effort and greater *cortical relief*

(MacPherson et al., 2002; Carter and van Veen, 2007; Cho et al., 2010; Izuma et al., 2010; Bartra et al., 2013). Building on previous research, which demonstrated that mobile fNIRS is particularly capable of measuring neural cortical activity, especially lateral areas of the prefrontal cortex (Krampe et al., 2018a; Liu et al., 2018), the investigation of the neural signatures of the dlPFC's deactivation might be a fruitful avenue to predict the success of merchandising elements. While doing so, this research work opens up the potential application of mobile fNIRS in a realistic shopping environment, namely the PoS, to predict success on market level. Hence, the given research work aims to explore, whether the dlPFC can act as a predictive neural signature for actual market sales by utilising and validating mobile fNIRS as a mobile neuropsychological method for the research field of shopper neuroscience, leading to the following hypothesis:

The neural signatures of the dlPFC during the perception of merchandising elements measured with mobile fNIRS are able to predict the sales associated with the PoS merchandising elements.

MATERIALS AND METHODS

Participants

In line with previous research (Rampl et al., 2012; Kühn et al., 2016; Krampe et al., 2018a,b; Strelow and Scheier, 2018) only healthy, female participants (N = 45), who indicated that they were mainly responsible for the grocery shopping in their household, were recruited to participate in this study. Female participants were recruited because women are more frequently responsible for the household's grocery shopping (VuMA, 2019a,c,d,e; BVE, 2020). Due to bad signal quality, 12 participants had to be excluded from the data analysis, resulting in a final sample size of n = 34 (M_{age} = 41.06, SD_{age} = 8.41; Age_{min} = 23, Age_{max} = 54). All participants were right-handed and had no history of major psychological or neurological disorders.

Experimental Task Procedure

After participants were welcomed, they were informed verbally and in written form about the aim of the study, the task and the utilised mobile fNIRS device. Once participants fully understood the task, a written informed consent was signed in accordance with the Declaration of Helsinki. Thereafter, participants were seated in front of a computer screen and the mobile fNIRS headband was attached on the participants forehead. In order to increase consistency between the participants measured brain regions, the mobile fNIRS headband was locally standardised on the vertical axis using the craniometric point of the nasion as an orientation point and the middle of the two preauricular points for positioning on the horizontal axis, covering the prefrontal cortex. Before starting the experimental task, data quality was checked and, if necessary, signal quality was improved by shifting the hair away from the detectors, making direct skin contact. In addition, the fNIRS headband was covered with an light-protecting cap to control for external light sources. Once the preparation was finished, participants were instructed to look at the computer screen while the task was performed.

The task was designed analogous to the paradigm developed by Kühn et al. (2016) (**Figure 3**), applying an event-related experimental design. During the task, a merchandising element was displayed for 3 s, followed by a randomised jitter of 4–6 s. Before and after the merchandising element, the advertised product was shown for 2 s, again followed by a randomised jitter of 4–6 s. In total, every merchandising element was shown six times, whereby the order of the merchandising elements was totally randomised. The task was performed twice, resulting in a total number of 72 trials, with 12 trials for every of the six merchandising elements. After completing the task, the mobile fNIRS device was removed and participants were asked to complete a final questionnaire, assessing demographics as well as their explicit subjective ranking of the merchandising elements. At the end of the study and a verbal disclosure, participants received a monetary incentive for their participation and were free to leave.

fNIRS Data Collection

The continuous-wave fNIRSport-System (NIRx Medical Technologies, Berlin, Germany) was used for data collection (Boas et al., 2014; Scholkmann et al., 2014). In general, fNIRS measures cerebral haemodynamic responses through near-infrared light sources (Ferrari and Quaresima, 2012). The mobile fNIRS system recorded optical signals on two-wavelengths (760 and 850 nm) at a sampling rate of 7.81 Hz. As imaging depth increases with emitter-detector distance, but signal quality is suggested to be best at a separation of 3 cm, the optodes and diodes are set to the distance of 3 cm (McCormick et al., 1992; Gratton et al., 2006; Ferrari and Quaresima, 2012; Gagnon et al., 2012; Naseer and Hong, 2015). The system consists of 22 channels, comprising eight light sources and seven detectors (**Figure 4**). In order to identify the equivalent brain areas of Brodmann area 9 (**Figure 4C1**) and 46 (**Figure 4C2**), the dlPFC definition had to be transferred to the mobile fNIRS optode montage setup (**Figure 4A**). Channels classified as relevant to cover Brodmann area 9 are Ch2, Ch5, Ch7, Ch8, Ch9, Ch10, Ch12, Ch13, and Ch14, and for Brodmann area 46 are Ch16 and Ch21 (**Figure 4B**). The NIRS-Star software package (version 14.2) was used for checking signal quality and data collection.

The valid application of mobile fNIRS in the field of consumer and shopper neuroscience has been demonstrated in several studies (Kopton and Kenning, 2014; Çakir et al., 2018; Krampe et al., 2018a,b). Most of the consumer neuroscience research using fNIRS focussed on the identification of neural correlates associated with merchandising in virtual in-store settings (Krampe et al., 2018b; Liu et al., 2018) or used fNIRS measurements to predict individual food-choice behaviour (Çakir et al., 2018). A recent fNIRS study conducted by Cha et al. (2019) correlated neural activation patterns of the mPFC to online popularity of pop music on YouTube, presenting an extension of earlier studies that predicted music popularity in the field of consumer neuroscience applying fMRI (Berns and Moore, 2012). Overall, prior fNIRS research suggested that especially cortical regions are measurable, whilst brain regions located

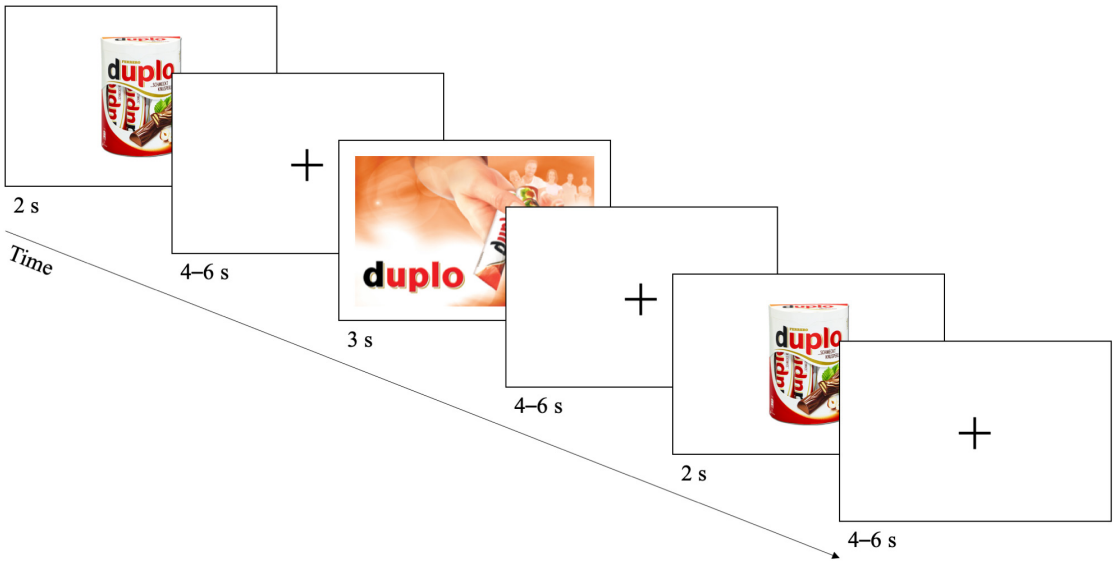


FIGURE 3 | Schematic representation of a trial in the experimental task. The task design is adapted from Kühn et al. (2016). During each trial, one merchandising element was displayed randomly for 3 s. Before and after the merchandising element, the advertised product was shown for 2 s. All stimuli were separated by a randomized jitter of 4–6 s. Figure adapted from Kühn et al. (2016). Permission to reuse had been obtained.

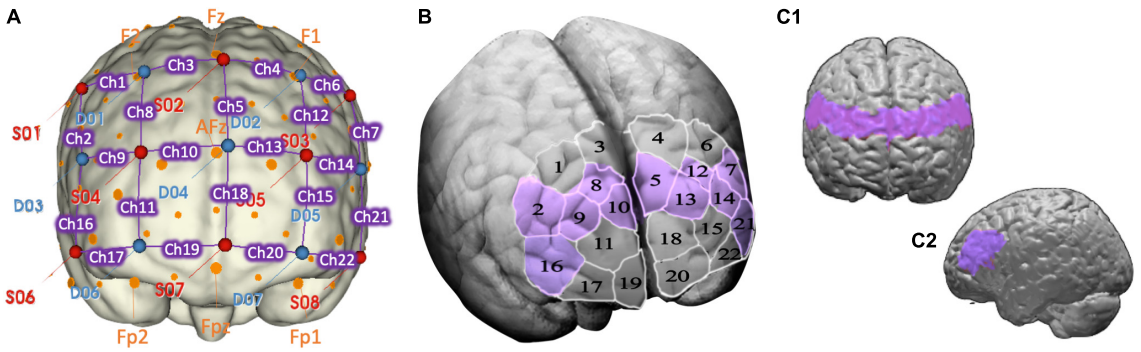


FIGURE 4 | fNIRS optode montage setup (topolayout) with marked regions representing Brodmann area 9 and 46. **(A)** fNIRS optode montage setup of the sources (S; red) and detectors (D; blue) with the associated fNIRS channels (Ch; purple) and the coordinates of the EEG 10-20 system (orange dots) (modified graphic from Nissen et al., 2019), **(B)** fNIRS channel areas plotted on a standardised brain with channels constituting Brodmann area 9 and 46 marked in purple (modified graphic from Krampe et al., 2018b), **(C1)** Brodmann area 9 and **(C2)** Brodmann area 46 marked in purple.

medially within in the brain or subcortically are not assessable with mobile fNIRS (Krampe et al., 2018a). Furthermore, most of previous fNIRS studies focussed on the medial brain regions, with only one study correlating neural activity pattern to behaviour on population level. As a result, the predictive value of lateral brain areas has not yet been addressed and mobile fNIRS as an innovative neuropsychological method in the field of consumer and shopper neuroscience, requiring further profound and robust validation.

fNIRS Data Analysis

In order to analyse the collected data, data was pre-processed using the NIRx Software Package (NIRx Medical Technologies, Berlin, Germany). In order to increase signal quality, channels exhibiting discontinuous shifts during the measurement were removed. Furthermore, fNIRS data time series were smoothed, applying a band-pass filter (high and low frequency filter) (Naseer and Hong, 2015; Pinti et al., 2019) with the frequently applied low cut-off frequency of 0.01 Hz and high cut-off frequency of 0.2 Hz (Franceschini et al., 2003; Hu et al., 2012; Spichtig et al., 2012; Krampe et al., 2018a; Nissen et al., 2019) in order to control for physiological noises and artefacts such as heartbeat and Mayer waves (Scholkmann et al., 2014; Naseer and Hong, 2015; Pinti et al., 2019). The modified Beer-Lambert law was used to convert raw light absorption rates into haemoglobin concentrations (Kocsis et al., 2006; Kopton and Kenning, 2014; Scholkmann et al., 2014). Haemodynamic states were computed in accordance with commonly used pathlength factors (for 750 nm set to 7.25 and for 850 set to 6.38) (Essenpreis et al., 1993; Kohl et al., 1998; Zhao et al., 2002). For the further analysis only

oxygenated haemoglobin signals were interpreted, as they seem to better correlate with cerebral blood flow (Hoshi et al., 2001). Information on the oxygenated haemoglobin concentrations are available in the **Supplementary Material**.

A general linear model (GLM) was set up for every participant and convolved with the haemodynamic response function, including six regressors with one for each merchandising element and an additional 12 regressors for the product stimuli (six before and six after each merchandising element). The GLM was first calculated on a single subject individual level (within-subjects level), and subsequently, a second-level group contrasts analysis was carried out to calculate neural activations across subjects (between-subjects level). In order to extract standardised activation values, a *t*-contrast was executed for each merchandising element against the implicit baseline, using the *t*-values in the further analysis. Given that significant activation differences are not of interest, the contrast analysis was used as a procedure to standardise the neural activations, which made a multiple comparison correction redundant. To test the hypothesis, fNIRS-derived sales prediction values were calculated from the standardised activation values of the *t*-contrasts for every merchandising element, respectively (**Equation 1**). The resulting fNIRS-derived sales prediction values can be interpreted according to their degree of reduced dlPFC neural activity. Hence, the fNIRS-derived sales prediction values for Brodmann area 9 and 46 were used to rank the order of the merchandising elements from lowest to greatest values, whereby a greater neural deactivation (more negative value) corresponds to a higher rank. Thus, the ranking is a result of the least neural activity, displaying less cognitive interfered processing (*cortical relief effect*) that is hypothesised to translate to sales at the PoS. Consequently, the resulting rank order based on the reduced dlPFC signal values should coincides with the rank order of the actual sales data. In order to evaluate the predictive success of the fNIRS-derived sales prediction values rankings with the original sales data, the results were compared qualitatively and based on Spearman rho correlation coefficients for the ordinal rank orders as well as on Pearson correlation for the quantifiable sales prediction values and actual sales data at a significance threshold of $p < 0.05$.

$$\textit{Let } Ch_x \textit{ be defined as the signal value of fNIRS channel } x \textit{ on the contrast of a merchandising element against the implicit baseline :}$$

$$\textit{fNIRS derived sales prediction value} = \sum_{x_i=x_1}^{x_n} Ch_{x_i}$$

$$\textit{for Brodmann area } 9\ D_x = \{2; 5; 7; 8; 9; 10; 12; 13; 14\} \textit{ and for Brodmann area } 46\ D_x = \{16; 21\}.$$

Equation 1 | Formula for fNIRS-derived sales prediction value. The *t*-values of channel Ch2, Ch5, Ch7, Ch8, Ch9, Ch10, Ch12, Ch13, and Ch14 were allocated to represent Brodmann area 9, while for Brodmann area 46 the channel Ch16 and Ch21 were defined. This calculation was performed for each merchandising element, resulting in six fNIRS-derived sales prediction values per Brodmann area (9 and 49).

Conclusively, based on the neural data analysis two different types of dlPFC fNIRS-derived sales prediction values were extracted and rank ordered, according to their degree of the reduced dlPFC activity. First, the fNIRS-derived sales prediction values of Brodmann area 9; and second of Brodmann area 46, calculated from the contrasts of each merchandising element against the implicit baseline, have been evaluated. The participants' explicit subjective rating of the merchandising elements was also evaluated, whereby the total number of 1st rank positions for each merchandising element was taken as an indicator. Finally, and in order to estimate the predictive power of the different data types, the actual sales associated with the merchandising elements – defined as the revenue generated by the different merchandising elements – were adopted from Kühn et al. (2016), who explored the revenues generated by the merchandising elements on a quarter display at the PoS in a supermarket (for detailed information on data, data collection and analysis, please see Kühn et al., 2016).

RESULTS

Supporting the hypothesis, the results suggest that the neural sales prediction values of brain regions of the dlPFC calculated from the merchandising contrasts (**Figure 5**) are able to predict the actual sales associated with PoS merchandising elements. The best predictor is the fNIRS-derived sales prediction values of Brodmann area 46. This finding was confirmed by the correlation analyses that revealed a positive significant Spearman rho correlation on the rank order data ($r_s = 0.943$, $n = 6$, $p = 0.005$) and a positive significant Pearson correlation on the sales prediction values and actual sales ($r_p = 0.868$, $n = 6$, $p = 0.025$) (**Figure 6**). For the qualitatively comparisons with the actual sales data ranking (**Figure 7i**), this rank order has all rank positions matched with the exception of the last 4th and 5th positions, which are reversed (**Figure 7A**).

Similarly, the neural results reveal that the first rank position based on the calculated Brodmann area 9 fNIRS-derived sales prediction value of the merchandising contrast (**Figure 7B**) corresponds to the rank positions of the actual sales data. However, the associated correlations on rank order and sales prediction value with the actual sales data failed to reach significance threshold of $p < 0.05$ ($r_s = 0.771$, $n = 6$, $p = 0.072$; $r_p = 0.648$, $n = 6$, $p = 0.164$). For the explicit subjective ranking no matched rank positions could be identified qualitatively (**Figure 7C**), confirmed by small, non-significant correlations with the actual sales data ($r_s = -0.29$, $n = 6$, $p = 0.577$; $r_p = 0.309$, $n = 6$, $p = 0.551$). The *t*-values on each channel and scatterplots on the non-significant predictors are available in the **Supplementary Material**. Thus, fNIRS-derived sales prediction values aggregating the channels constituting Brodmann area 46 could resample the actual sales data best.

DISCUSSION

The current research work aims to explore the predictive power of brain regions ascribed to the dlPFC to forecast

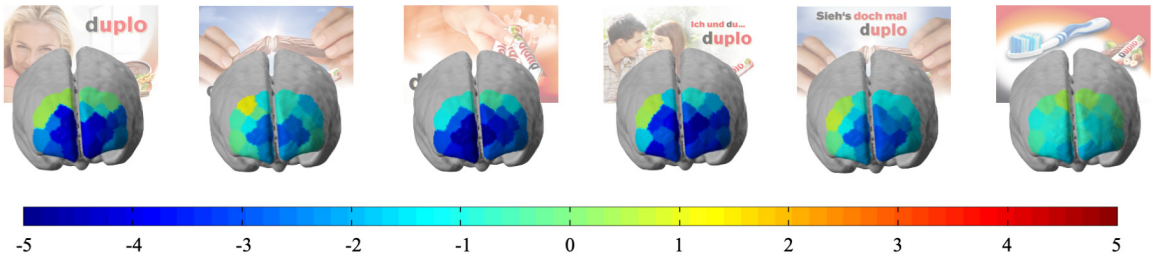


FIGURE 5 | *T*-value coloured activation maps for the contrast of merchandising element against the implicit baseline. The associated merchandising element is displayed behind the brain map. Channel allocation can be found in **Figure 4B**. Colour bar indicates the *t*-values of the contrasts.

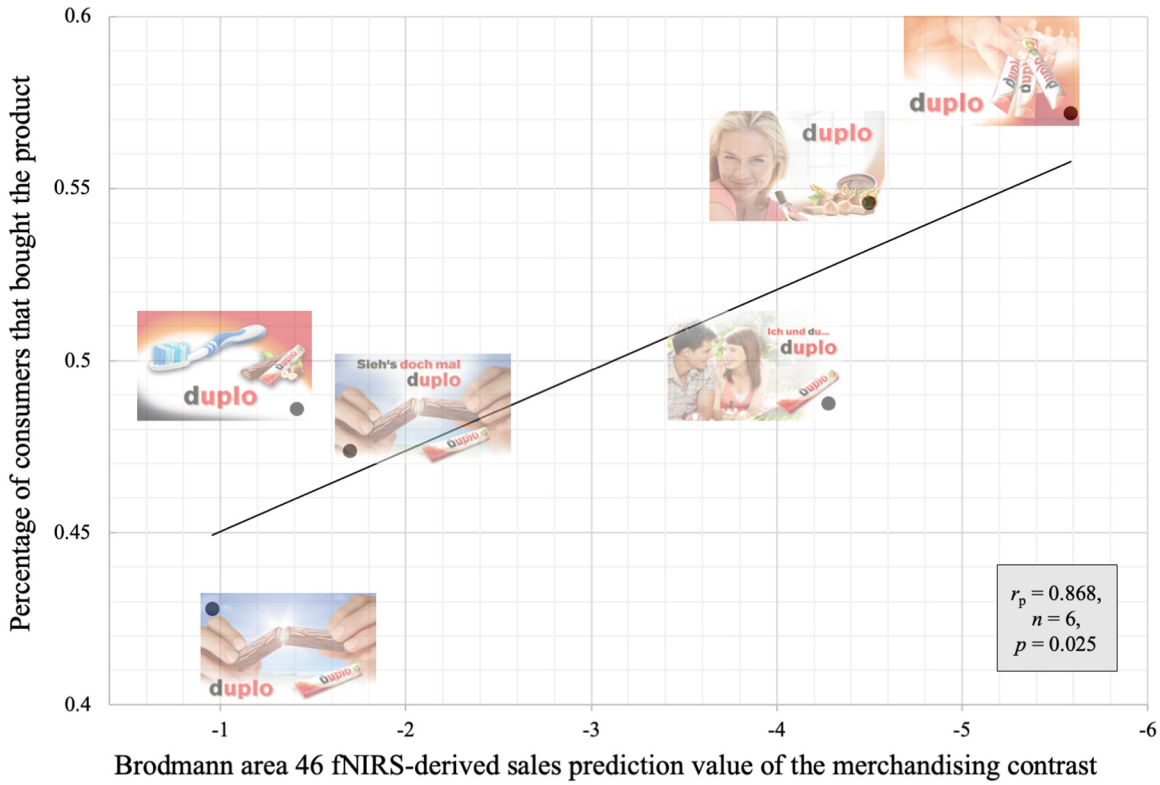


FIGURE 6 | Scatterplot depicting the association between the Brodmann area 46 fNIRS-derived sales prediction value of the merchandising contrast, and actual product sales (Kühn et al., 2016) expressed in percentage of the customers that bought the product on the display with the merchandising element. Pearson correlation presented in the grey box.

the success of PoS merchandising elements, thereby validating mobile fNIRS – as a portable applicable neuropsychological method – and opening up its potential application in realistic shopping environments, such as at the PoS. As one of the first studies, this research work evaluates the neural signatures of the dlPFC deactivation in isolation to predict market sales success with mobile fNIRS, building on the *cortical relief effect*. More precisely, the integration of mobile fNIRS in the field of shopper neuroscience has been used to investigate six PoS merchandising elements, which have been examined with marketing methods in earlier studies, while overcoming the limitations associated with stationary neuroimaging methods (Kühn et al., 2016; Strelow and Scheier, 2018). The research findings support the hypothesis that the deactivation of the dlPFC is predictive for the shopper behaviour aka sales at the PoS, highlighting an additional crucial neural signature measurable with mobile fNIRS. The results show that fNIRS-derived sales prediction values of Brodmann area 9 and 46 are capable of predicting the actual sales of PoS merchandising elements, whereby Brodmann area 46 (consisting of channels 16 and 21) seem to be the most predictive brain area of the dlPFC.

In the context of prior studies on the 'duplo' case, the current research findings suggest that merchandising elements promoting a brand are processed in two neural signatures of

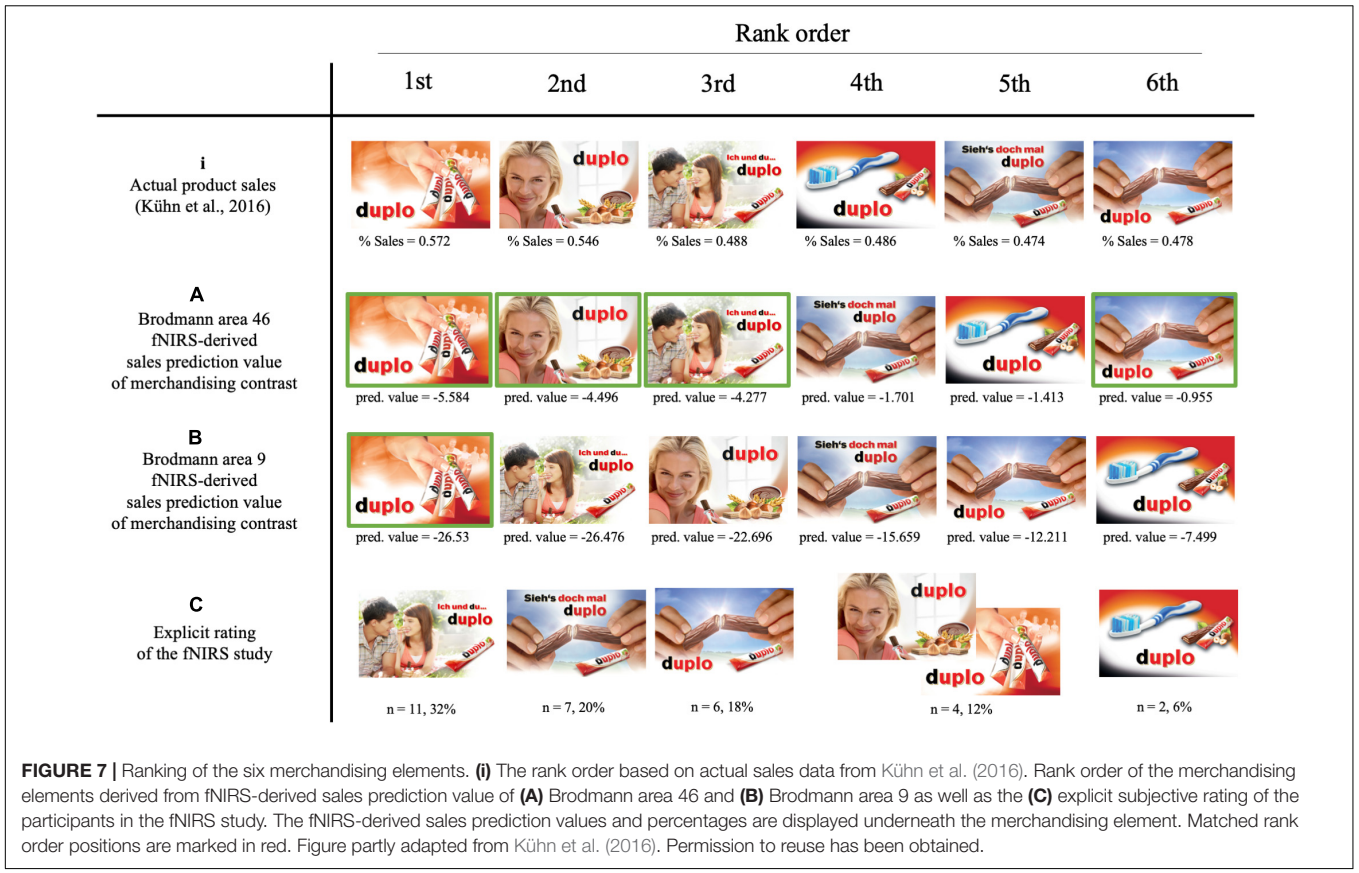


FIGURE 7 | Ranking of the six merchandising elements. **(i)** The rank order based on actual sales data from Kühn et al. (2016). Rank order of the merchandising elements derived from fNIRS-derived sales prediction value of **(A)** Brodmann area 46 and **(B)** Brodmann area 9 as well as the **(C)** explicit subjective rating of the participants in the fNIRS study. The fNIRS-derived sales prediction values and percentages are displayed underneath the merchandising element. Matched rank order positions are marked in red. Figure partly adapted from Kühn et al. (2016). Permission to reuse has been obtained.

the (prefrontal) cortex, leading to different cognitive processes. Whereas in the past the neural activity of the *reward evaluation system* has been used to predict marketing, advertising and sales effects at the PoS, the role of *cortical relief effects* and reduced cognitive controlled processes have been neglected. Although occasionally studies integrated the dlPFC besides other brain regions in their prediction models, cortical relief processes have – to the best of the authors' knowledge – not yet been used to predict and explain purchase behaviour at the PoS.

Supposing that 70% of the purchases at the PoS are spontaneous and given that an act of purchase takes approximately about 60 s (Hertle and Graf, 2009; Valizade-Funder and Heil, 2010), it is suggested that an habituative, less self-controlled process takes place in most of the purchases (Rook and Fisher, 1995). Consequently, any kind of irritation that disrupts the state of cortical relief by incongruency or aspects that require more cognitive effort could potentially interrupt the act of impulsive purchase, resulting in a termination or, at least, a delay in the cognitive or affective purchase process of shoppers. This effect seems to be particularly relevant when shoppers experienced a conflict between their perceived brand image and the triggered reward associations elicited by the PoS merchandising element – a neuropsychological process, which seem to result in an increased neural cortical dlPFC activity (Deppe et al., 2005; Plassmann et al., 2007; Koenigs and Tranel, 2008; Kato et al., 2009; Krampe et al., 2018b) and which could be measured with mobile fNIRS. Likewise, the congruency of the brand image and the associated PoS merchandising element might result in a neuropsychological *(cortical) relief effect* for congruent brand-merchandising PoS elements or vice versa result in an increased neural activity effect in the dlPFC, when the product and merchandising element are perceived as incongruent. Both effects can, consequently, be measured in brain regions of the dlPFC, indicating its specificity to predict sales at the PoS. Consequently, next to the *reward association system*, brain regions of the dlPFC might also function as a process variable to predict sales in a PoS setting. The utilisation of mobile fNIRS with its technical capabilities to measure cortical brain regions might, therefore, provide an innovative and fruitful method for future research.

Implications

The research findings provide several implications for marketing theory and practice. First, from a theoretical perspective, the research findings suggest that the shopper behaviour at the PoS is not only driven by reward associations offered by brands, but is also influenced by the perceived (in-)congruency and the level of conflicts or cortical relief experienced between the shoppers' brand image and the experienced PoS merchandising element. While earlier neuropsychological studies investigated mainly medial and subcortical located brain regions of the reward evaluation system to forecast population success; only a few studies considered the dlPFC to predict shoppers' behaviour. Consequently, this research work is one of the first that evaluates

the predictive power of brain regions ascribed to the dlPFC neural deactivation, providing an innovative approach to interpret consumer responses to merchandising elements at the PoS.

Second, as a methodological contribution, the validation of a mobile and in its application fast-growing methodology of mobile fNIRS demonstrates its potential to predict success in real-world settings such as the PoS. Due to its mobile application it provides a great variety of application options for research and practice to measure shoppers' neural responses directly in complex settings such as the PoS, increasing the ecological validity of research results.

From a practical point of view, the research results offer an innovative perspective on how to design, evaluate or forecast the success of PoS merchandising elements in combination with the to-be-advertised products – including all kind of merchandising elements such as lighting, furnishing, display screens, price tags and information displays. Cortical relief disrupting conflicts can arise on all levels of the customer journey, beginning with the perception of a stimulus and ending in cognitive overload effects elicited by, for example, the overwhelming assortment in the shelves. To carefully match the shoppers' brand image with PoS merchandising elements in order to reduce conflicts and cognitive dissonance might, consequently, be of high value for producers and retailers. The integration of the idea to investigate the (in-)congruency and potential conflicts as well as its repercussions enables the analysis of the shoppers' PoS journey by evaluating different merchandising elements, with its aim to reduce or at best avoid conflicts in the perception of the product specific attributes (e.g., the brand image) and the PoS merchandising elements to be used. A comprehensive investigation of all cues that appear at the PoS during a customer journey, to explore all potential reactions of the shoppers' brain during a shopping trip, to identify cues that potentially reduce the overall net-incongruence at the PoS, might be beneficial. The neuropsychological neuroimaging method of fNIRS may, therefore, be of particular interest as it enables the investigation of the hypothesised effect directly at the PoS because of its mobile, ecological valid usability. Following from this, the research results might be used to explore different PoS merchandising elements to quantify the cognitive engagement represented by the neural activity of the dlPFC evoked by a shopping trip, measured with the use of mobile fNIRS. The ultimate goal would be a measurement of all rewarding and conflicting cues during an average shopping trip, possibly enhanced by the identification of additional motivating cues, to generate a deeper understanding of the shoppers' behaviour at the PoS.

Limitation and Future Research Suggestions

One aim of the research work is to indicate the usefulness of mobile fNIRS to predict shopper behaviour at the PoS. The current study provides a first step to actually measure shoppers' neural activity, when confronted with PoS merchandising elements and products at the PoS, using mobile fNIRS. Nevertheless, this research work investigates the neural signatures on basis of a laboratory setting with an experimental paradigm performed in front of a computer screen. The next logical step for future studies should be to explore whether the research findings received under laboratory settings remain also valid in a naturalistic environment measurement at the PoS, utilising mobile fNIRS in realistic PoS settings. Furthermore, mobile fNIRS is a relative innovative neuroimaging method, at least for the research field of shopper neuroscience, indicating the need to consider the continuous development of its technical capabilities. Future research might, thus, use other more advanced mobile fNIRS devices to improve data quality and reduce the application costs. Finally, whilst interpreting the neural activity and the neural reactions associated with PoS merchandising elements, it is implicitly assumed that the *cortical relief effect* is measured. However, it might be that the merchandising elements have been seen in a TV or PoS campaign before, leading to the measurement of a familiarity effect. This effect might be evoked because the familiar merchandising element might require less cognitive effort to be processed, resulting in a reduced neural activity of the dlPFC. In order to cope with this potential limitation, future studies might replicate the given study with only novel PoS merchandising elements that vary in the degree of their brand fit.

CONCLUSION

Whereas previous research work mainly focused on the *reward association system* and its associated subcortical brain regions to predict sales, utilising stationary neuroscientific methods (e.g., Berns and Moore, 2012; Venkatraman et al., 2015; Tong et al., 2020), the research findings of the current study not only suggest that the shoppers' reward associations seem to be predictive for sales at the PoS, but indicate the importance of the conflicts perceived by the shopper and the congruency between the perceived brand image and the displayed PoS merchandising elements. In other words, the research results signify that the brand 'duplo' activates expectation of rewards, which either fits with the associations triggered by the merchandising PoS element or do not fit with the brand's image perceived by shoppers, leading to either conflicting or supporting, cortical relief effects, displayed by an increase neural activity or a decreased neural activity of the dlPFC, respectively. These neuropsychological processes can, therefore, be quantified with the measurement of the neural activity of the dlPFC, using mobile fNIRS. Consequently, the quantified neural activity of the dlPFC, indicating the congruence between the brand's image and the triggered reward associations of the PoS merchandising element, might, next to the reward association system, be decisive for the prediction of sales at the PoS, acting as an additional process variable, measurable with mobile fNIRS.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because it was ensured to the participants that their data is not available for third parties and it was guaranteed that participants can request the complete deletion of their datasets at any

time. Requests to access the datasets should be directed to nadine.gier@hhu.de.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

NG conducted the study, performed the data analysis and wrote the manuscript. NG and CK contributed to the conception and design of the study. NG, ES, and CK were involved in the data collection. ES and CK substantiated sections of the manuscript. All the authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2020.575494/full#supplementary-material

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The Impact of Visual Art and High Affective Arousal on Heuristic Decision-Making in Consumers

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In marketing, the use of visual-art-based designs on products or packaging crucially impacts consumers' decision-making when purchasing. While visual art in product packaging should be designed to induce consumer's favorable evaluations, it should not evoke excessive affective arousal, because this may lead to the depletion of consumer's cognitive resources. Thus, consumers may use heuristic decision-making and commit an inadvertent mistake while purchasing. Most existing studies on visual arts in marketing have focused on preference (i.e., affective valence) using subjective evaluations. To address this, we applied a neuroscientific measure, electroencephalogram (EEG) to increase experimental validity. Two successive tasks were designed to examine the effects of affective arousal and affective valence, evoked by visual artwork, on the consecutive cognitive decision-making. In task 1, to evaluate the effect of visual art, EEG of two independent groups of people was measured when they viewed abstract artwork. The abstract art of neoplasticism (AbNP) group ($n = 20$) was showing Mondrian's artwork, while the abstract art of expressionism (AbEX) group ($n = 18$) viewed Kandinsky's artwork. The neoplasticism movement strove to eliminate emotion in art and expressionism to express the feelings of the artist. Building on Gallese's embodied simulation theory, AbNP and AbEX artworks were expected to induce lower and higher affect, respectively. In task 2, we investigated how the induced affect differentially influenced a succeeding cognitive Stroop task. We anticipated that the AbEX group would deplete more cognitive resources than AbNP group, based on capacity limitation theory. Significantly stronger affect was induced in the AbEX group in task 1 than in the AbNP group, especially in affective arousal. In task 2, the AbEX group showed a faster reaction time and higher error rate in the Stroop task. According to our hypotheses, the higher affective arousal state of the AbEX group might deplete more cognitive resources during task 1 and result in poorer performance in task 2 because affect impacted their cognitive resources. This is the first study using neuroscientific measures to prove that high affective arousal induced by visual arts on packaging may induce heuristic decision-making in consumers, thereby advancing our understanding of neuromarketing.

Keywords: visual arts, affective arousal, consumer, decision-making, EEG, Stroop task

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INTRODUCTION

The application of visual art-based designs to products or their packaging greatly impacts the purchase-related decision-making of consumers. The phenomenon of "art infusion" (Hagtvedt and Patrick, 2008, 2011), whereby perceptions of visual art spill over onto an object with which the art is associated, has a favorable effect on the consumer product evaluation. For example, art image (vs. non-art image) printed on the packaging caused a spillover of luxury perceptions and resulted in favorable evaluations of the product by the consumers (Hagtvedt and Patrick, 2008).

When we appreciate a work of figurative art, besides deriving meaning, we may also feel the affect expressed by the artist through the artwork (Uusitalo et al., 2012). This affective influence is grounded in embodied simulation theory, which posits that the emotions and sensations of the artist can be simulated within the visceromotor and somatosensory systems of the viewer (Gallese and Sinigaglia, 2011). Interestingly, an artwork may elicit affect among viewers even in the absence of clear figurative content, as in the case of abstract art (Freedberg and Gallese, 2007). There are two opposing art movements in abstract art: neoplasticism and expressionism. Although subsumed under the same label of abstract art, the neoplasticism movement, led by Mondrian, tried to eliminate emotion from art, whereas the expressionism movement, led by Kandinsky, insisted that art should express the feelings of the artist (Strickland and Boswell, 1992; Melcher and Bacci, 2013; van Paasschen et al., 2015).

To evaluate the affect induced in viewer, a two-dimensional model of affect including independent measures of affective valence and affective arousal has widely been adopted by psychologists (Russell and Barrett, 1999; Schmidtke and Heller, 2004). According to the lateralization of emotional processes in the frontal lobes (Ahern and Schwartz, 1985; Davidson and Irwin, 1999; Grimm et al., 2006; Cheung et al., 2019), positive valence activates the left dorsolateral prefrontal cortex (DLPFC), while negative valence activates the right DLPFC. Affective arousal activates the right parietotemporal (PT) region (Heller et al., 1997). This two-dimensional affect can be measured using EEG based on a negative correlation between regional cortical activation and EEG alpha power (Coan and Allen, 2004; Oakes et al., 2004). Due to the limited spatial resolution of EEG, researchers have started using functional magnetic resonance imaging (fMRI) to precisely localize the cortical sources of valence-related activation. The results of their studies are consistent with the lateralization of emotional processes in the prefrontal cortex, i.e., the left DLPFC is activated for positive valence and the right ventrolateral prefrontal cortex (VLPFC) is activated for negative valence. Additionally, within the prefrontal cortical region, the dorsomedial prefrontal cortex (DMPFC) is activated during affective arousal (Dolcos et al., 2004; Grimm et al., 2006). To evaluate the affect induced by a visual art stimulus, positive frontal alpha asymmetry using EEG (i.e., positive valence responses) was observed, regardless of whether it was perceived as beautiful. However, when evaluating commercial stimuli, this positive asymmetry was elicited only when the stimulus was considered beautiful (Cheung et al., 2019). This can be explained by self-rewarding characteristics of aesthetic experiences that may impact the beholder's affective state (Mastandrea et al., 2019). The frontal alpha asymmetry is also associated with several brain functions such as personality (Schmidtke and Heller, 2004) and working memory (Bacher et al., 2017).

The Heuristic-Systematic dual-processing model (Chaiken, 1980) states that consumers tend to process information systematically when there is motivation and ability to process the information. Such processing includes an analytic orientation in which consumers carefully examine all task-relevant information. However, if there is a low motivation or the capacity to process information is constrained or the available time is less, irrespective of the motivation, the heuristic processing (characterized by effort-reduction and limited consideration of information) is executed. That is, the available time is similar to the cognitive capacity or the ability to process information (Suri and Monroe, 2003). In the study of the influence of affect on decision-making, a considerable number of studies have shown that a positive mood tends to trigger heuristic processing when making judgments, while a negative mood leads to systematic processing (Bless et al., 1996; Elsbach and Barr, 1999; Park and Banaji, 2000; Mitchell and Phillips, 2007). Furthermore, according to capacity limitation theory (CLT), which posits cognition and affect share the same cognitive resources (Mackie and Worth, 1989; Seibert and Ellis, 1991; Mitchell and Phillips, 2007), heuristic processing is appropriate when fast decisions are required, i.e., under time constraint, and when there is a shortage of processing capacity. Thus, it tends to result in poorer decision-making performance (Suri and Monroe, 2003; Shah and Oppenheimer, 2008). As affect consists of affective valence and affective arousal, visual artwork inducing either high affective valence or high affective arousal may deplete the viewer's cognitive resources while processing, thereby resulting in poorer performance in the subsequent cognitive task. To impact consumer's purchase-related decision-making, visual art should be designed to facilitate systematic decision-making as well as evoke aesthetic preference. Heuristic decision-making may lead to errors in purchasing resulting in regret. Most existing studies have focused on the effect of art associated with a product from a viewpoint of aesthetic preference or favorable evaluation (Hagtvedt and Patrick, 2008, 2011). Moreover, the literature exploring the influence of the affect induced by visual stimuli on the cognitive bases of decision-making has primarily focused on mood or affective valence while neglecting affective arousal (Hagtvedt and Patrick, 2008; Mastandrea et al., 2019). Therefore, this study aims to examine whether opposing styles of visual art (expressing vs. suppressing) on product packaging impact the consumers' affect differently. If this proves to be the case, we intended to investigate

Abbreviations: AbEX, abstract art of expressionism; AbNP, abstract art of neoplasticism; *Aff(Ar.c)*, conventional affective arousal index; *Aff(Ar.n)*, novel affective arousal index; *Aff(Va.c)*, conventional affective valence index; *Aff(Va.n)*, novel affective valence index; DLPFC, dorsolateral prefrontal cortex; DMPFC, dorsomedial prefrontal cortex; P_n (*r*), mean power ratio at electrode *n;* PT, parietotemporal; VLPFC, ventrolateral prefrontal cortex.

how the differential changes in consumers' affect induced by the two styles of visual art, influence the way information is processed in purchase decision-making. We chose abstract art instead of figurative art, because the latter may drive some meaning which will impact the viewers' affect. We measured the affect induced by abstract art by using 128-channel EEG as well as subjective evaluation. Color word Stroop task was used as the cognitive task, since it has been widely used to evaluate the effects produced after affect has been induced (Brand et al., 1997).

We hypothesized that the affect induced in consumers who viewed abstract art of expressionism (AbEX) is greater than who viewed abstract art of neoplasticism (AbNP) based on embodied simulation theory, because the expressionism artists poured affect much more to their artworks as opposed to neoplasticism artists. Thus, the consumers who view AbEX (vs. AbNP) can imagine the artist's emotional and gestural movement more strongly. This greater affect induced in consumers who viewed AbEX (vs. AbNP) could cause a depletion of cognitive resources by the CLT and compel them to adopt heuristic information processing, grounding on Heuristic-Systematic dual-processing model, thereby resulting in poorer performance in the subsequent cognitive task.

MATERIALS AND METHODS

Participants

To verify our hypotheses, we recruited 50 healthy, right-handed participants. Even though there are sex differences in behavior and cognition based on sexual dimorphism (e.g., Kandel, 1999, 2012), only male participants with short hair were recruited so as to maintain homogeneity and since short hair takes lesser time to adjust each of the 128 electrodes perpendicular to the scalp in the 128-channel HydroCel Geodesic Sensor Net (see Section "EEG recording"). All participants had normal or corrected-to-normal vision and were undergraduate students from the South Korea. The participants were not artists since the cortical reaction of artists is different from the non-artists when exposed to artworks (Bhattacharya and Petsche, 2005; Seeley and Kozbelt, 2008; Kottlow et al., 2011).

They were randomly divided into two experimental groups: one group was showing Mondrian's abstract artwork (AbNP group), and the other, Kandinsky's abstract artwork (AbEX group) (see Section "Viewing the abstract artwork (task 1)"). We excluded data from 12 of the participants due to excessive EEG artifact, potential sleepiness, malfunctions of the EEG system, and extreme outliers as estimated by box plots. After these exclusions, data from 20 AbNP group participants (age: $M = 24.45$, $SD = 2.24$) and 18 AbEX group participants (age: $M = 23.72$, $SD = 2.45$) were used in further analysis. No significant difference was found in age ($F < 1$) between the two groups. Informed consent was obtained from all participants, and they were compensated (₩30,000; approximately $30) for completing the study. This study was approved by the Institutional Review Board at the Korea Research Institute of Standards and Science (KRISS-I-15-1) and was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki.

Procedure and Experimental Setup

Procedure

The experiment consisted of two consecutive tasks, i.e., viewing the abstract artwork (task 1) and performing the Stroop task (task 2). It was conducted in a dimly lit, acoustically and electromagnetically shielded room. Participants were made to sit on comfortable armchairs in front of a 23-in. computer monitor placed at a distance of approximately 67 cm from their eyes. Prior to the experiment, the participants were familiarized with the Stroop task. Next, a 128-channel Hydrocel Geodesic Sensor Net (HCGSN) (see Section "EEG recording") in one of three sizes (small: 54–66 cm, medium: 56–58 cm, large: 58–61 cm) depending on each participant's head circumference, was applied and the impedance was checked. In task 1, we measured the differences in affect induced by contrasting artworks, i.e., AbNP vs. AbEX, using EEG. In task 2, we measured the participants' reaction time (*RT*) and error rate (*ErR*) while they were performing the Stroop task but did not measure EEG because there was severe motion artifact. Additionally, since we used the 128-channel dense HCGSN, which uses a saline solution to reduce the impedance between the electrode and the scalp, the electrical noise between these substances increased as the saline dried out (see Section "EEG recording"). Between tasks 1 and 2, it was impractical to check the impedance or refill the saline solution since the difference of affect induced by the two opposing styles of abstract art would then be diminished. Therefore, task 2 was designed to follow task 1 immediately without checking the impedance between tasks 1 and 2, and thus, without measuring EEG.

Visual stimuli, both the abstract art and the Stroop task, were programmed and presented via E-Prime® 2.0 (Psychology Software Tools Inc., Pittsburgh, Pennsylvania), a stimulus software compatible with the EEG data acquisition software Net Station 5.2 (EGI, Eugene, OR, United States). To assess the subjective evaluation of visual stimuli more objectively, two manipulation check groups were recruited (Perdue and Summers, 1986), consisting of male participants for AbNP group ($n = 33$; age: $M = 27.91$, $SD = 4.11$) and AbEX group ($n = 33$; age: $M = 28.45$, $SD = 4.22$). While observing each piece of abstract art, the participants responded to a series of questions on a 9-point Likert scale ranging from strongly disagree to strongly agree, including questions around affective valence ("This artwork makes me feel positive"), affective arousal ("This artwork makes me feel aroused"), dynamicity ("This artwork makes me feel dynamic"), complexity ("This artwork is highly complex"), and emotional infusion ("I can feel great amount of emotional properties"). The average duration of the experiment per participant was 1 h (see **Figure 1**).

Experimental Setup

Viewing the abstract artwork (task 1)

Task 1 lasted for approximately 8 min, including a baseline session and an ArtView session. After completing the 3-min baseline session, the participants moved on to the 5-min ArtView

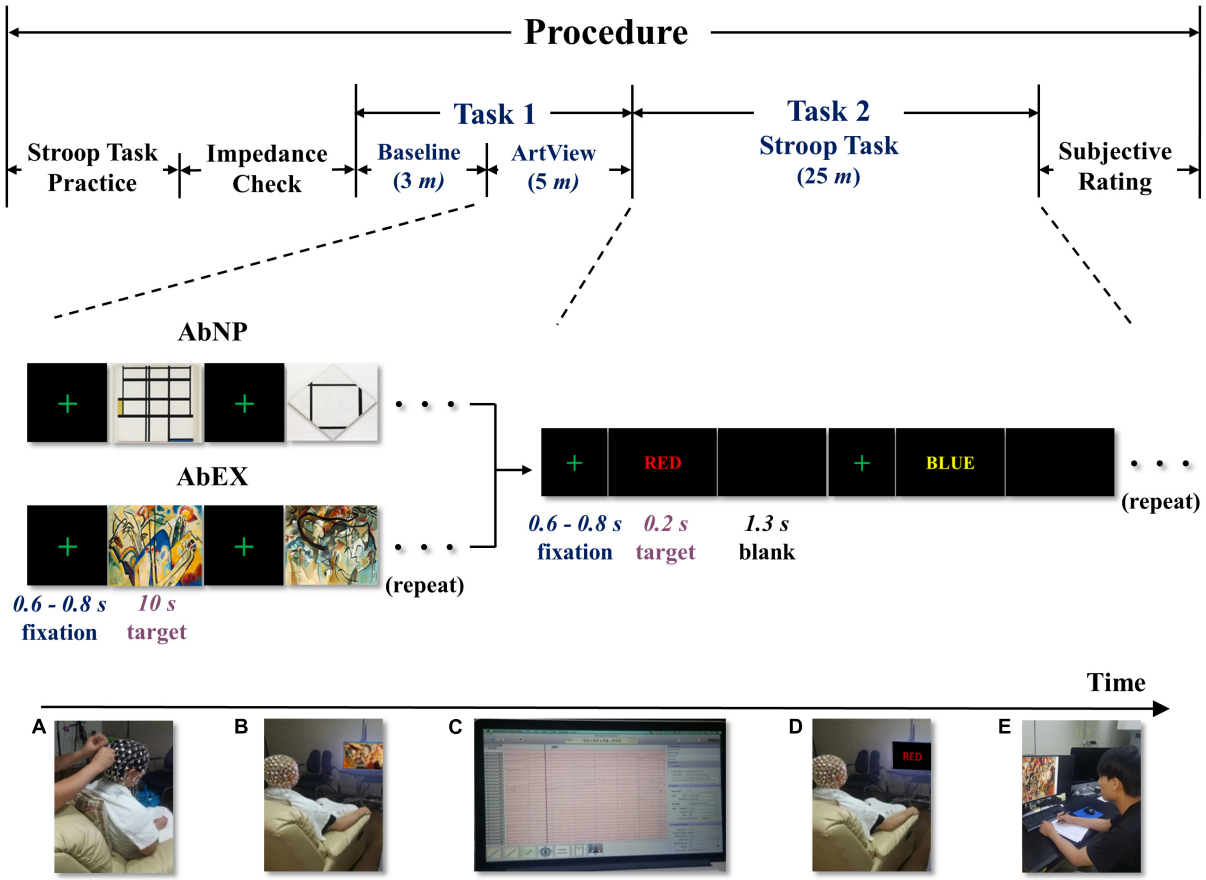


FIGURE 1 | The experimental procedure including tasks 1 and 2: bottom left to right, **(A)** applying sensor net and checking impedance, **(B)** viewing abstract artwork, **(C)** acquiring EEG signals, **(D)** performing the Stroop task, and **(E)** subjective ratings for abstract artwork. ArtView, artwork-viewing session; AbNP, artwork of Mondrian in the style of neoplasticism; AbEX, artwork of Kandinsky in the style of expressionism.

session. For the purpose of experimentally inducing affect, we used abstract artwork from the Website of the Museum of Modern Art (MOMA[1]). Even though the international affective picture system (IAPS) is a highly replicated data set associated with known stimuli valence-rated set of images, it was not used in the current study since it consists of pictures and not artworks. In this study, we want to examine how visual art (not picture), used in product packaging design influences the viewer's decision-making. We chose abstract art instead of figurative art, because the latter may drive some meaning that can modulate the viewer's affect. Specifically, artworks of two leading abstract artists, Mondrian and Kandinsky, were selected because the former exemplifies AbNP and the latter AbEX (Brandabur, 1973; Strickland and Boswell, 1992; Simon, 2013). Before starting task 1, the saline solution was reduced to avoid excess saline solution from dripping down the participants' foreheads causing annoyance, and thus influencing sensible human affect. Thus, to prevent the drying out of the saline solution, we designed task 1 to be 10 min in duration (see Sections "Procedure" and "EEG recording"). We decided to select five abstract artworks for each group—AbNP and AbEX, which were *1937 Composition I in Yellow, Blue, and White*, *1926 Tableau I, Lozenge with Four Lines and Gray*, *1936 Composition in White, Black, and Red*, *1937–42 Composition in Red, Blue, and Yellow*, and *1929 Composition No. II, with Red and Blue* for AbNP (see **Figure 2A**) and *1911 Composition IV*, *1911 Composition V*, *1913 Composition VI*, *1913 Composition VII*, and *1913 Fragment 2 for Composition VII* for AbEX (see **Figure 2B**). These five consecutive sets, in which a fixation screen was followed by an image, were presented four times to each participant, i.e., 20 stimuli per participant (see **Figure 1**). This study focused on how the opposing styles of artwork influence the cognitive task, i.e., cognitive decision-making. Participants were asked to rest their forearms on the armrest of the chair. In addition, during the baseline session, the participants were asked to relax both their mind and body and avoid ideas and thoughts as much as possible. During the ArtView session, participants were expected to first fixate on a cross at the center of the monitor, and then observe a series of abstract paintings belonging to either AbNP or AbEX, depending on their assigned group. Throughout the observation process, participants were asked to focus on the images as much as possible. Each block in the experimental trials consisted of

[1]http://www.moma.org/collection/artists/2981

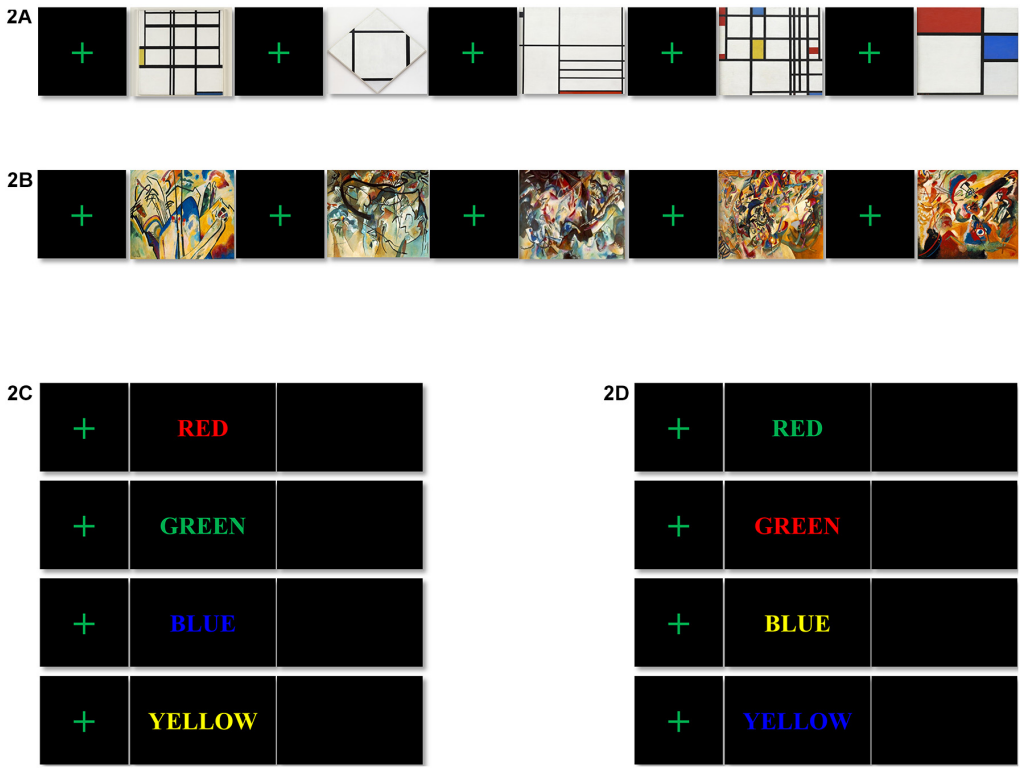


FIGURE 2 | Stimuli for tasks 1 and 2: the visual stimuli for task 1, **(A)** artwork of Mondrian in the style of neoplasticism (AbNP); from left to right, 1937 *Composition I in Yellow, Blue, and White*, 1926 *Tableau I, Lozenge with Four Lines and Gray*, 1936 *Composition in White, Black, and Red*, 1937–42 *Composition in Red, Blue, and Yellow*, and 1929 *Composition No. II, with Red and Blue*, and **(B)** artwork of Kandinsky in the style of expressionism (AbEX); from left to right, 1911 *Composition IV*, 1911 *Composition V*, 1913 *Composition VI*, 1913 *Composition VII*, and 1913 *Fragment 2 for Composition VII*. The color-word stimuli for task 2: **(C)** congruent color-word stimuli; **(D)** incongruent color-word stimuli.

five consecutive sets. Each image was shown for 10 s, while the duration of the fixation cross varied from 0.6 to 0.8 s to reduce the predictability of the task and maintain the participants' attention. Completing one block took approximately 53.5 s (i.e., $\simeq(0.7 + 10.0\text{ s}) \times 5$). Participants completed the same block four times, separated by 5-s intervals. Thus, the ArtView session took approximately 5 min total (i.e., $\simeq(53.5 + 5\text{ s}) \times 4 - 5\text{ s}$) (see **Figures 1**, **2**).

Performing the stroop task (task 2)

For task 2, a color-word Stroop task was employed because it has been considered the golden standard for attentional measure (MacLeod, 1992). Furthermore, the Stroop task has widely been used to evaluate the effects produced after affect has been induced (Brand et al., 1997). Task 2 lasted approximately 25 min (see **Figure 1**). Eight different color words were used as stimuli and were written in four colors (red, green, blue, and yellow) on a black background. Four of the color words were used for congruent stimuli (e.g., the word "RED" written in red), and the other four for incongruent stimuli (e.g., the word "RED" written in green). Participants were asked to look at the color words and press the button marked "1" for congruent or "2" for incongruent as accurately and as quickly as possible, i.e., under time constraint. Each stimulus in task 2 was again preceded by a fixation cross at the center of a black screen. Each small block consisted of eight consecutive trials in which a fixation cross was followed by a congruent or incongruent color word, presented in a random order, followed by a blank screen. While the duration of the fixation cross varied in the same way as was done for task 1 (i.e., it was presented for 0.6–0.8 s), the duration of each color word and the blank screen was set for 0.2 and 1.3 s, respectively. Therefore, one small block took approximately 17.6 s (i.e., $\simeq(0.7\text{ s} + 0.2 + 1.3\text{ s}) \times 8$). A large block of 20 small blocks was repeated four times with 15-s intervals. It took almost 25 min (i.e., $\simeq(17.6 \times 20 + 15\text{ s}) \times 4 - 15\text{ s}$) to complete task 2. Each participant saw 640 color words ($(8 \times 20) \times 4 = 640$), where the congruent and incongruent words were equally distributed (320 times each) and presented in a random order (see **Figures 1**, **2**).

Data Recording and Analyses

EEG Recording and Analyses

EEG recording

During task 1, EEG data was recorded using a 128-channel Hydrocel Geodesic Sensor Net (HydroCel GSN (HCGSN) 130, Electrical Geodesics, Inc. [EGI], Eugene, OR, United States) and amplified by Geodesic EEG System 400 (Net Amps 400, EGI, Eugene, OR, United States). Before applying the 128-channel

dense HCGSN to participant's head, the HCGSN was soaked in electrolyte for at least 5 min to improve conductance and ensure adequate wetting of the sponges attached to electrodes. Generally, with enough electrolytes in the sponge, the HCGSN can be used for a 2-h recording. However, trickling of excessive electrolyte on participants' forehead will have a serious influence on sensible human affect. Therefore, the electrolyte in the sponge was reduced in this study, thus increasing the impedance between the electrode and scalp dramatically as the solution dries out. To reduce the impedance, the 128 electrodes were adjusted perpendicular to the participant's scalp. To save time, male participants with short hair were recruited as opposed to female participants with long hair. All electrodes were referenced to Cz and the impedances were checked to ensure that they were less than 50 kΩ. The EEG data were digitized using a 24-bit A/D converter at a 1-kHz sampling rate with an online band-pass filter set at 0–400 Hz, and analyzed using EGI acquisition software (Net Station version 5.2, EGI, Eugene, OR, United States) on an Apple Mac Pro computer running on OS 10.5.5. To minimize EEG artifact associated with eye movements such as blinking, we asked the participants to keep their eyes open, stay alert, and not move their body unless necessary during both the baseline and ArtView sessions.

EEG analysis

The data were filtered offline by a 0.5–50-Hz band-pass filter using Net Station S/W and down-sampled to 250 Hz. Next, 30 stimulus-locked segments (each 10-s long), consisting of 10 from the baseline session and 20 from the ArtView session, were extracted per participant, since sample sizes equal to or greater than 30 have normal distribution as per the central limit theorem (Moen and Powell, 2005). If we increase the length of the EEG segment, i.e., the bin size, the number of specific waves in the segment will increase along with the probability of including noise. We want a large enough number to capture the specific wave, while excluding noise. To decide the optimal bin size, we made a trade-off between the sample size balancing signal and noise. In this study, we were interested in the theta, alpha, and beta bands. Therefore, the frequency of interest of EEG ranges from 4 to 32 Hz. For the lowest frequency in this (4 Hz), almost 40 cycles of the wave are included in a 10-s segment of EEG. For frequencies above 4 Hz, the sample size will be larger. Therefore, we set the bin size as 10 s. Below 10 s, the reliability of theta band power measurements would be severely degraded and above 10 s, the reliability of power measurements of the three frequency bands would reduce due to noise. In task 1, the time to show one abstract art was also 10 s (see **Figure 1**). To reject artifacts resulting from eye blinks or movements from the EEG, a validated method based on an independent component analysis algorithm from the EEGLAB toolbox (Delorme and Makeig, 2004; Gabard-Durnam et al., 2018) was used. We analyzed the artifact-free EEG traces by applying a fast Fourier transform (FFT) with a Hamming window using MATLAB R2014a (MathWorks, Natick, MA, United States). When we inspected the frequency characteristics of a specific EEG segment, we transformed the EEG from the time domain to the frequency domain with the FFT. Since the EEG returns non-stationary signals, the frequency characteristics will vary during the 10-s interval. If we apply the FFT to the full length of the EEG segment, we will not know how the frequency characteristics change over the 10-s interval. Therefore, we apply the FFT over short intervals. The width of the window is the length of the short time interval to which the FFT is applied. In this study, we assumed it as 1 s. There are different windows used to reduce spectral leakage when performing a FFT on time data to convert it into the frequency domain. The Hamming window is a taper formed with a raised cosine with non-zero endpoints, optimized to minimize the nearest side lobe. The purpose of overlapping is to reduce the effects of windowing. Most windowing functions (e.g., Blackman, Hamming) are taper-shaped, which means that they drop to 0 (or close to 0) near the frame edges. This of course affects the FFT results and can lead to the loss of some important information (e.g., transients). Thus, overlapping is used to reduce the negative effect of windowing. In this study, we chose a 50% overlapping, i.e., a 0.5-s overlapping for a 1-s window. Finally, 19 windows were left with 1-s width in a 10-s segment, because the width of the 20th window is only 0.5 s.

To inspect the regional cortical activity around each electrode on the scalp, we calculated the mean powers in the theta ($P(\theta)$, 4–8 Hz), alpha ($P(\alpha)$, 8–14 Hz), and beta bands ($P(\beta)$, 14–32 Hz) for each window and averaged these over the 19 windows. We averaged the mean powers over the artifact-free 10-s segments for each of the 128 electrodes. We defined the average mean power at each electrode n in the theta, alpha, and beta bands as, $P_n(\theta)$, $P_n(\alpha)$, and $P_n(\beta)$, respectively. Next, to evaluate regional cortical activity around each scalp electrode, we defined the mean power ratio at electrode n as $P_n(r)$ (see Eq. (1) below for reference). In Eq. (1), $P_n(\alpha)$ is the alpha-band power and $P_n(t)$, which equals $\{P_n(\theta) + P_n(\alpha) + P_n(\beta)\}$, is the total power at electrode n. Instead of calculating the reciprocal of alpha-band power, $1/P_n(\alpha)$, based on a negative correlation between cortical activity and alpha-band power (Coan and Allen, 2004; Oakes et al., 2004; Pizzagalli et al., 2005; Koslov et al., 2011), we calculated the reciprocal of the alpha-band power normalized to the total power of each participant, $1/\{P_n(\alpha) / P_n(t)\}$, to reduce inter-individual variation arising from differences in skull thickness (Eshel et al., 1995; Allen et al., 2004; Hagemann et al., 2008). We excluded mean power in the delta band ($P_n(\delta)$, 0.5–4 Hz) when calculating total power of the $P_n(t)$, because the experiment was carried out during daytime when participants do not sleep. In real life, the delta wave of EEG can be observed only in the deep-sleep state. Thus, the delta band of EEG measured during daytime can be regarded as noise and filtered. Using this method, $P_n(r)$ is proportional to the cortical activity around electrode number n.

To investigate affect, we defined a conventional index of affect grounding on the limbic system including amygdala, which has been the focus of majority of studies (Ahern and Schwartz, 1985; Heller et al., 1997; Phelps and Anderson, 1997; Davidson and Irwin, 1999). Specifically, we defined the conventional index for affective valence as *Aff(Va.c)*, based on differential lateralization for positive and negative emotions (Ahern and Schwartz, 1985; Heller et al., 1997). This was calculated by subtracting the

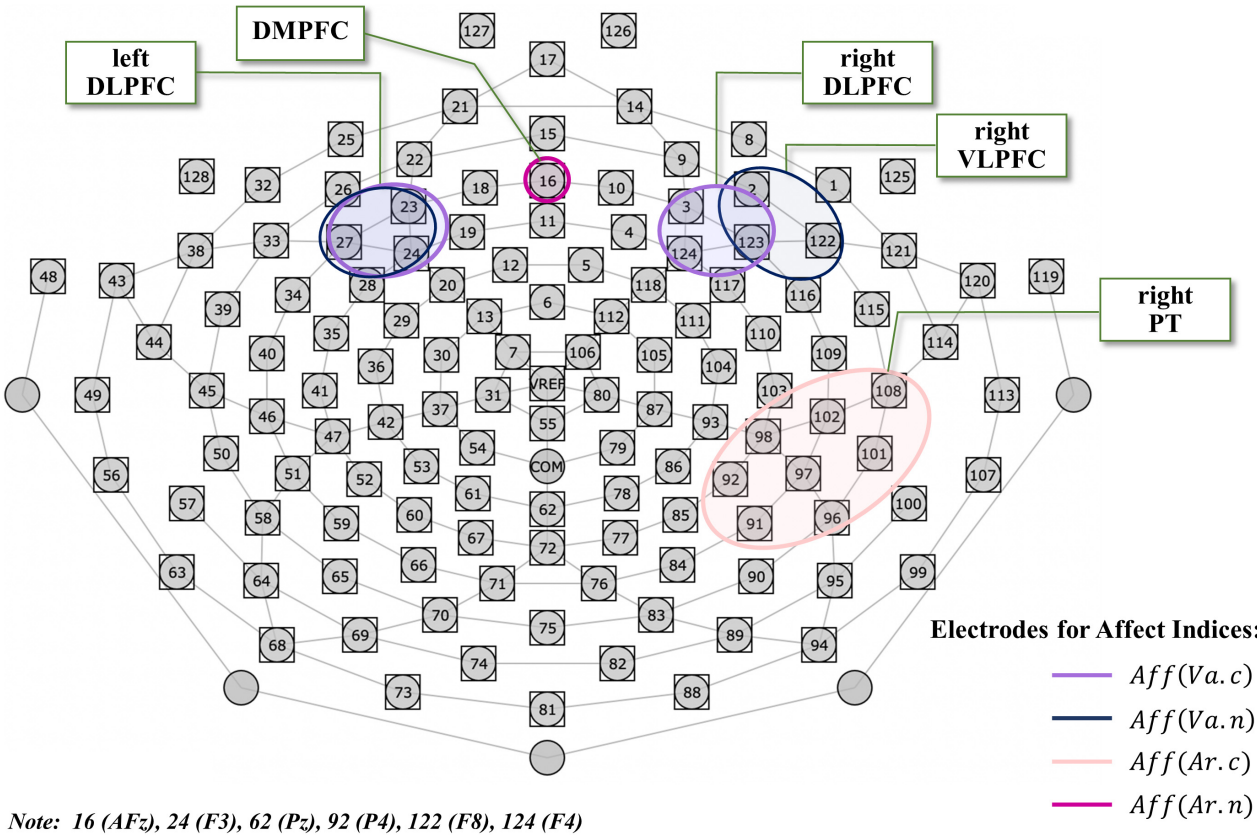


FIGURE 3 | The HydroCel GSN 128-channel map used in this experiment. The electrodes used for EEG analysis are surrounded by colored lines corresponding to each of the specific affect indices, where light violet represents the conventional valence index comprising left DLPFC (23-24-27) and right DLPFC (3-123-124); dark blue represents the novel valence index comprising left DLPFC (23-24-27) and right VLPFC (2-122-123); light pink represents the conventional arousal index comprising right PT (91-92-96-97-98-101-102-108); and purple represents the novel arousal index comprising DMPFC (16). The electrode on vertex Cz (REF) was used as reference, and the electrode at COM between Cz and Pz as the ground. DLPFC, dorsolateral prefrontal cortex; VLPFC, ventrolateral prefrontal cortex; PT, parietotemporal; DMPFC, dorsomedial prefrontal cortex.

natural-log-transformed $P_n\,(r)$ on the scalp near the right DLPFC from that near the left DLPFC. We clustered three electrodes (23-24-27) including F3 on the scalp near the left DLPFC, and three electrodes (3-123-124) including F4 on the scalp near the right DLPFC, according to the reference system of the HydroCel GSN 128-channel map and the international 10-10 system (see **Figure 3** and Equation (2)). We also defined a novel index of affect, focusing on the role of the prefrontal cortex (PFC) regions in emotion processing (Anderson et al., 2003). We defined the novel index for affective valence as *Aff(Va.n)*, based on a fMRI study (Dolcos et al., 2004), which was calculated by subtracting the natural-log-transformed $P_n\,(r)$ on the scalp near the right VLPFC from that near the left DLPFC. We clustered three electrodes (2-122-123) including F8 on the scalp near the right VLPFC. The clustering of the scalp near the left DLPFC was the same as that of the conventional index (see **Figure 3** and Equation (3)). A more positive value of *Aff(Va.c)* or *Aff(Va.n)* reflects a positive affective valence state (in other words, a more pleasant state), whereas a more negative value represents the opposite. To examine affective arousal, we defined a conventional index as *Aff(Ar.c)*, which was calculated from the $P_n\,(r)$ in the region of the right PT since the PT is responsible for affective arousal (Heller et al., 1997). We clustered eight electrodes (91-92-96-97-98-101-102-108) including P4 and T8 for right PT (see **Figure 3** and Equation (4)). We also defined a novel index for affective arousal as *Aff(Ar.n)*, which was calculated from the $P_n\,(r)$ on electrode number 16 near the DMPFC based on previous fMRI studies (Dolcos et al., 2004; Grimm et al., 2006) (see Section "Introduction," **Figure 3**, and Equation (5)). Thus, a greater value of *Aff(Ar.c)* or *Aff(Ar.n)* represents a higher affective arousal state. As shown in **Figure 3**, we measured and analyzed the EEG for frontal and right parietotemporal regions together.

$$P_n\,(r) \equiv \frac{1}{P_n\,(\alpha)\,/\{P_n\,(\theta) + P_n\,(\alpha) + P_n(\beta)\}} \equiv \frac{1}{P_n\,(\alpha)\,/p_n\,(t)} = \frac{p_n\,(t)}{p_n\,(\alpha)} \quad (1)$$

$$Aff\,(Va.c) \equiv [ln^{(P_{23}(r))} - ln^{(P_3(r))} + ln^{(P_{24}(r))} - ln^{(P_{124}(r))} + ln^{(P_{27}(r))} - ln^{(P_{123}(r))}]/3 \quad (2)$$

$$Aff(Va.n) \equiv [ln^{(P_{23}(r))} - ln^{(P_2(r))} + ln^{(P_{24}(r))} - ln^{(P_{123}(r))} + ln^{(P_{27}(r))} - ln^{(P_{122}(r))}]/3 = \frac{\left[ln\left\{\frac{P_{23}(r)}{P_2(r)}\right\} + ln\left\{\frac{P_{24}(r)}{P_{123}(r)}\right\} + ln\left\{\frac{P_{27}(r)}{P_{122}(r)}\right\}\right]}{3} \quad (3)$$

$$Aff(Ar.c) \equiv \frac{\left\{\begin{array}{l} P_{91}(r) + P_{92}(r) + P_{96}(r) + P_{97}(r) \\ +P_{98}(r) + P_{101}(r) + P_{102}(r) + P_{108}(r) \end{array}\right\}}{8} \quad (4)$$

$$Aff(Ar.n) \equiv P_{16}(r) \quad (5)$$

Stroop Task Analyses

The *RTs* for correct responses were labeled as *RT_correct*, while those for incorrect responses were labeled as *RT_incorrect*. Similarly, the *RTs* for congruent stimuli were labeled as *RT_cong*, while those for incongruent stimuli were labeled as *RT_incong*. *ErR* was defined as the number of incorrect responses for the congruent (incongruent) stimuli divided by 320 and labeled as *ErR_cong* (*ErR_incong*). Trials with no response were excluded when calculating the *RT*. However, such trials were also considered incorrect when computing the *ErR*. The six indices defined above were calculated for each participant by taking the averages of their corresponding responses to the 640 stimuli.

Statistical Analysis

Based on an experimental design using repeated-measures analysis of variance (ANOVA) for within-between interaction with a medium effect size (Cohen's *d* of 0.5), using G*Power 3.1.9.2 (Faul et al., 2007), we calculated a minimum sample size of 17 per group to achieve 80% power ($\alpha = 0.05$). This sample size is comparable with that of previous similar experimental studies (e.g., Inzlicht and Gutsell, 2007). Even though the within-subject design requires more small minimum sample sizes compared with the between-subject design, we employed the between-subject design because the performance of color-word Stroop task depends on the order, i.e., the performance of second trial will be better than the first under same cognitive capacity conditions.

As the indices for both groups that evaluated affect in Task 1 and cognitive performance in task 2 were normally distributed according to the Kolmogorov–Smirnov tests (all $p > .05$), we employed a 2 × 2 (session × group) repeated-measures ANOVA to test our hypotheses while excluding the influence of different baseline levels for each participant in task 1. We explored the interaction effects between sessions (baseline vs. ArtView) and groups (AbNP vs. AbEX) on affective valence and affective arousal in task 1. This approach is used to test whether there was a difference in affect between the baseline and ArtView sessions as a function of viewing the two kinds of abstract art. In Task 2, we investigated the main effects of the responses (correct vs. incorrect), stimuli (congruent vs. incongruent), and groups (AbNP vs. AbEX) on *RT*and *ErR* to test the impact of the differential affect induced in the two groups during task 1 on *RT* and *ErR* when performing the Stroop task. In addition, correlations between the two performance indices, *RT* and *ErR*, in task 2 were analyzed. Effect sizes were estimated as partial eta-squared (η_p^2). Levels of significance and marginal significance were set at $\alpha = 0.05$ and $\alpha = 0.07$, respectively. SPSS 24 (IBM, Armonk, NY, United States) was used to perform the statistical analyses.

RESULTS

Task 1: Influence of Visual Art on Affect

A 2 (baseline vs. ArtView) × 2 (AbNP vs. AbEX) repeated-measures ANOVA showed no interaction for the conventional affective valence index *Aff(Va.c)* ($F(1, 36) = 1.11$, $p = 0.300$, $\eta_p^2 = 0.03$), or for the novel affective valence index *Aff(Va.n)* ($F(1, 36) = 1.38$, $p = 0.248$, $\eta_p^2 = 0.04$). However, for conventional affective arousal index *Aff(Ar.c)*, the session × group interaction was marginally significant ($F(1, 36) = 3.77$, $p = 0.060$, $\eta_p^2 = 0.10$). This indicated that the increase in affective arousal from the baseline to the ArtView session was larger for the AbEX group ($M_{\text{baseline}} = 2.73$, 95% CI = [2.57, 2.88] vs. $M_{\text{ArtView}} = 3.19$, 95% CI = [3.03, 3.35]) when compared with the AbNP group ($M_{\text{baseline}} = 2.83$, 95% CI = [2.68, 2.98] vs. $M_{\text{ArtView}} = 3.09$, 95% CI = [2.94, 3.24]) (see **Figure 4A**). For *Aff(Ar.n)*, the interaction was also significant ($F(1, 36) = 6.41$, $p = 0.016$, $\eta_p^2 = 0.15$), indicating that the same pattern held true for the novel affective arousal index (AbEX: $M_{\text{baseline}} = 3.05$, 95% CI = [2.92, 3.17] vs. $M_{\text{ArtView}} = 3.45$, 95% CI = [3.35, 3.56]; AbNP: $M_{\text{baseline}} = 3.13$, 95% CI = [3.02, 3.25] vs. $M_{\text{ArtView}} = 3.30$, 95% CI = [3.20, 3.39]) (see **Figure 4B**). This means that the affective arousal was induced to a higher degree in participants who viewed abstract art of expressionism as opposed to those who viewed neoplasticism.

To inspect the influence of the two opposing styles of abstract art (i.e., expression vs. suppression) on the viewers' affect, we analyzed the EEG power in time-frequency domain, i.e., short-time Fourier transform (STFT) of EEG, by using EEGLAB and MATLAB. We plotted the individual spectrograms belonging to four sites (left DLPFC and right DLPFC for affective valence and right PT and DMPFC for affective arousal) for baseline and ArtView sessions and for both AbNP and AbEX groups. The number of individual spectrograms was 304 (i.e., 38 participants × 2 sessions [baseline and ArtView] × 4 sites [left DLPFC, right DLPFC, right PT, and DMPFC]). These spectrograms are available in the following URL[2].

To enhance the discrimination of alpha power reduction, i.e., to increase the frequency resolution of the spectrogram, the FFT was applied to 4-s windows with a 2-s overlap, instead of 1-s window with a 0.5-s overlap as described in Section "EEG analysis." Since the present study does not intend to examine event-related potential (ERP), where the ensemble average will improve the signal-to-noise ratio as the number of trials increase, we chose one segment each corresponding to the baseline and ArtView sessions of the two groups, instead of 10 segments from the baseline session and 20 from the ArtView session (see Section "EEG analysis"). The reason is that the spectrogram of

[2]https://drive.google.com/open?id=1ag4CUi9vOHT39q95ob7XCAQbhWP51vkI

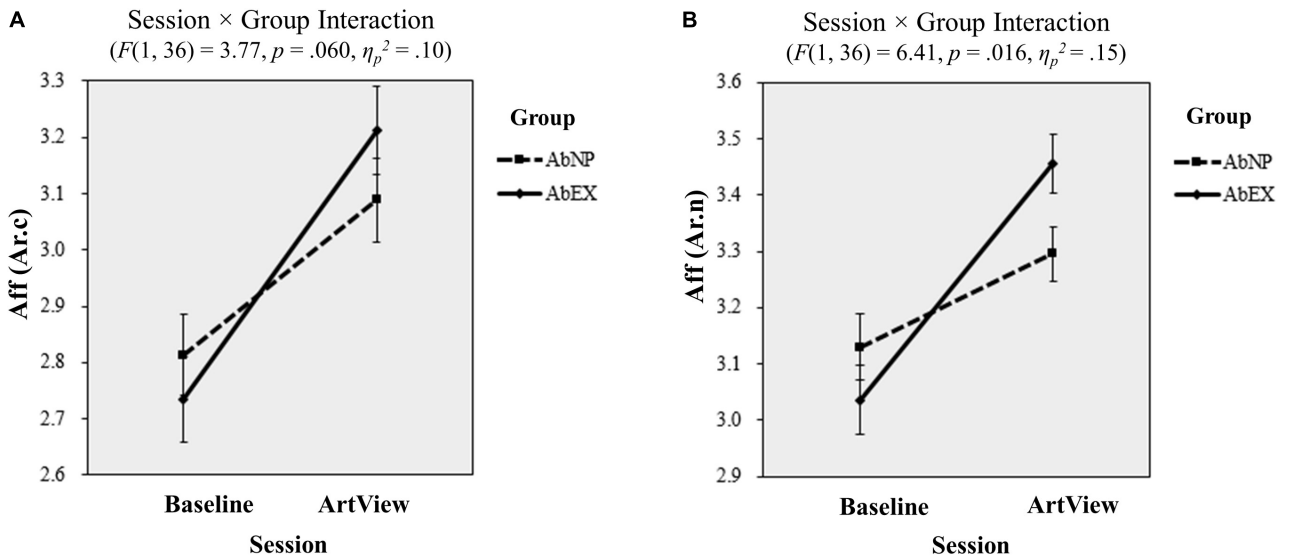


FIGURE 4 | Results of the EEG analyses from task 1 for affective arousal: the effect of viewing abstract artwork (vs. baseline) on **(A)** *Aff*(*Ar.c*) and **(B)** *Aff*(*Ar.n*) is shown for the AbNP (dashed line) and AbEX groups (solid line), respectively. Error bars show standard errors of the mean. The terms *Aff*(*Ar.c*) and *Aff*(*Ar.n*) represent the conventional and novel indices for arousal respectively used in the EEG analyses. ArtView, artwork-viewing session; AbNP group, abstract neoplastic artwork-viewing group; AbEX group, abstract expressionist artwork-viewing group.

the spontaneous EEG in the present study will tend to be white noise as the number of segments increase, because the EEG in these segments are not synchronized. Moreover, to ensure the fairness of EEG power comparison, the time range of each segment was set to be the same in each spectrogram. In this study, we restricted the time range of the 304 spectrograms to 10–40 s because some of the individual spectrograms had severe noise when the range exceeded 40 s.

As an illustrative example, a typical participant was selected for each group. At first, three participants for each group were selected randomly. After then, the participant whose difference of *Aff(Ar.n)* between baseline and ArtView sessions was the largest among the three was chosen from each group, because the effect of abstract artwork on this index was significant as described in **Figure 4**. As a result, the 11th participant was selected for AbNP group and the 5th participant for AbEX group. To evaluate the effect of the artwork on the conventional index of affective arousal, i.e., *Aff(Ar.c)*, we analyzed the spectrogram for the typical participant from the AbNP and AbEX groups and represented the results in **Figure 5A** for right PT. We also evaluated for the novel index, i.e., *Aff(Ar.n)*, and represented the spectrogram in **Figure 5B** for DMPFC. Each title of the individual spectrogram comprises the participant ID, the session, and the site corresponding to when and where the spectrogram was evaluated. For example, the title "AbNP011B right PT SPECTROGRAM" in **Figure 5A** represents that the spectrogram was evaluated at the site of the right PT during the baseline session for the 11th participant of the AbNP group. The title "AbEX005E DMPFC SPECTROGRAM" represents that the spectrogram evaluated at DMPFC during the experiment, i.e., ArtView, session for the 5th participant of the AbEX group. The pink dotted line in each spectrogram represents the boundary of alpha band EEG, which is 8–13 Hz. The color bar represents the strength of EEG in decibels (dB). Each spectrogram represents EEG power (color in dB) depending on time (10–40 s) and frequency (4–32 Hz). Results show that the alpha power suppression in ArtView session is evident when compared with the baseline session, especially in the AbEX group for *Aff(Ar.c)* as shown in **Figure 5A** and for *Aff(Ar.n)* as shown in **Figure 5B**. These results also support the results of the statistical analysis, which was based on the alpha power, as described in **Figure 4A** for *Aff(Ar.c)* and in **Figure 4B** for *Aff(Ar.n)*, i.e., the session × group interaction was significant for novel as well as conventional indices of affective arousal.

Next, we calculated the mean spectrogram for baseline and ArtView sessions for each group. We defined these as "group spectrograms" as described in **Figure 6** for affective arousal. Even though the difference of alpha power reduction in group spectrograms of **Figure 6** was not as apparent as in typical spectrograms shown in **Figure 5**, the trend was similar.

Task 2: Performance in the Stroop Task

Reaction Time

A 2 (correct vs. incorrect) × 2 (AbNP vs. AbEX) repeated-measures ANOVA was conducted to analyze *RT*. The main effect of response was significant ($F(1, 36) = 300.63$, $p < 0.001$, $\eta_p^2 = 0.89$), with *RT_incorrect* ($M = 436.38$ ms, 95% CI = [418.71, 454.04]) being faster than *RT_correct* ($M = 510.49$ ms, 95% CI = [494.38, 526.60]). This means that when participants make quick decisions, they run the risk of committing mistakes regardless of how much cognitive resources they have remaining. The main effect of group was also significant ($F(1, 36) = 18.42$, $p < 0.001$, $\eta_p^2 = 0.34$), with the *RT* of the AbEX group ($M = 438.86$ ms, 95% CI = [415.14, 462.57])

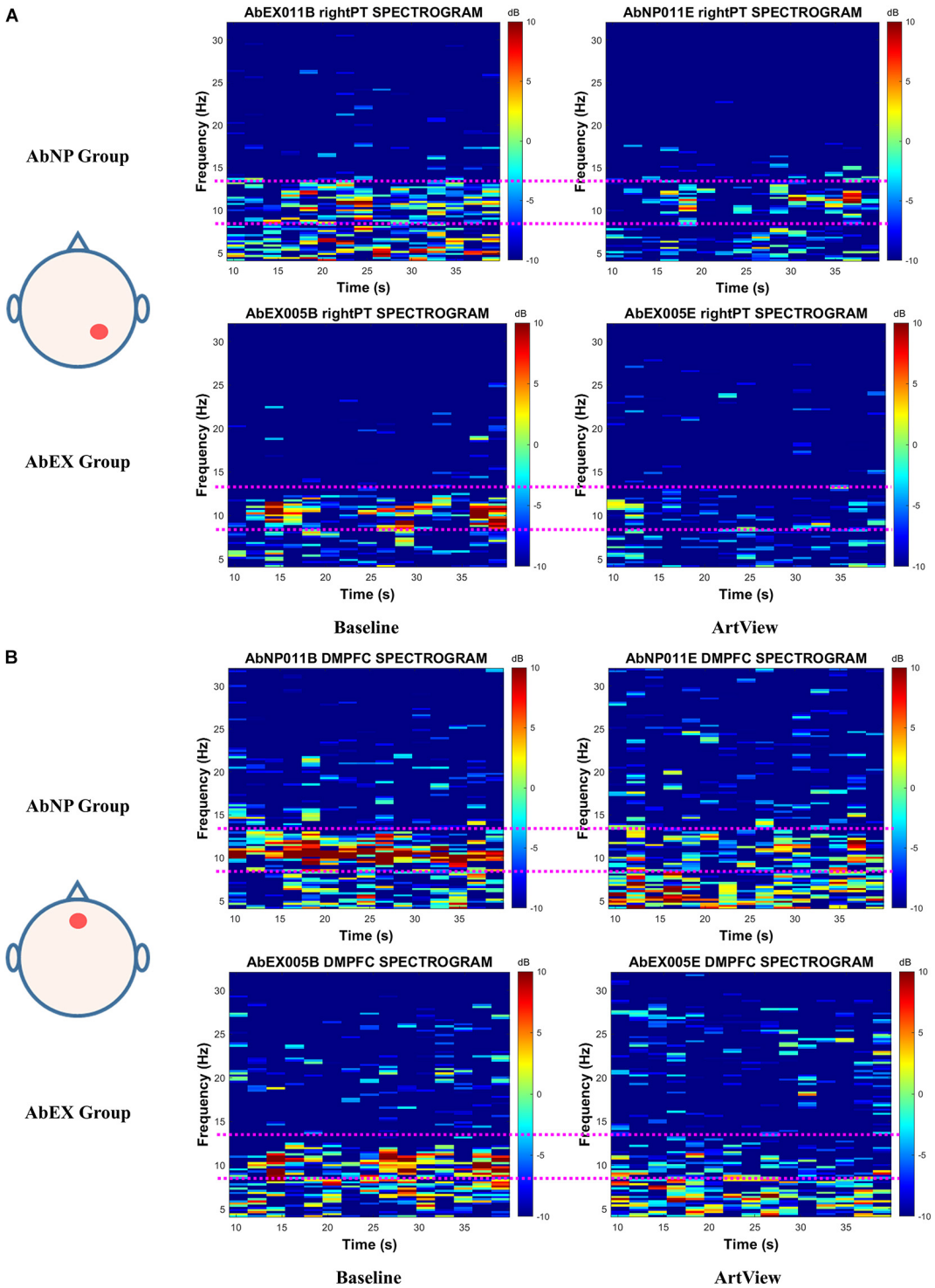


FIGURE 5 | The EEG spectrogram for a typical participant of the AbNP group and that of the AbEX group for **(A)** *Aff(Ar.c)* represents the effect of viewing abstract artwork (vs. baseline) on right parietotemporal cortex (PT). For **(B)** *Aff(Ar.n)* represents the effect of viewing abstract artwork (vs. baseline) on the dorsomedial prefrontal cortex (DMPFC). The alpha power suppression in ArtView (vs. baseline) session is visually obvious, especially in AbEX group for *Aff(Ar.c)* and for *Aff(Ar.n)*. This result is consistent with the results of statistical analysis in **Figure 4A** for *Aff(Ar.c)* and in **Figure 4B** for *Aff(Ar.n)*, i.e., the session × group interaction was significant for novel as well as conventional indices of affective arousal. The terms *Aff* (*Ar.c*) and *Aff* (*Ar.n*) represent the conventional and the novel indices for arousal, respectively. ArtView, AbNP group, and AbEX group have the same meanings described in the legend of **Figure 4**. The pink dotted line in each spectrogram represents the boundary of alpha band EEG, i.e., 8–13 Hz. The color bar represents the strength of EEG power in dB. Each spectrogram represents EEG power, which depends on time and frequency.

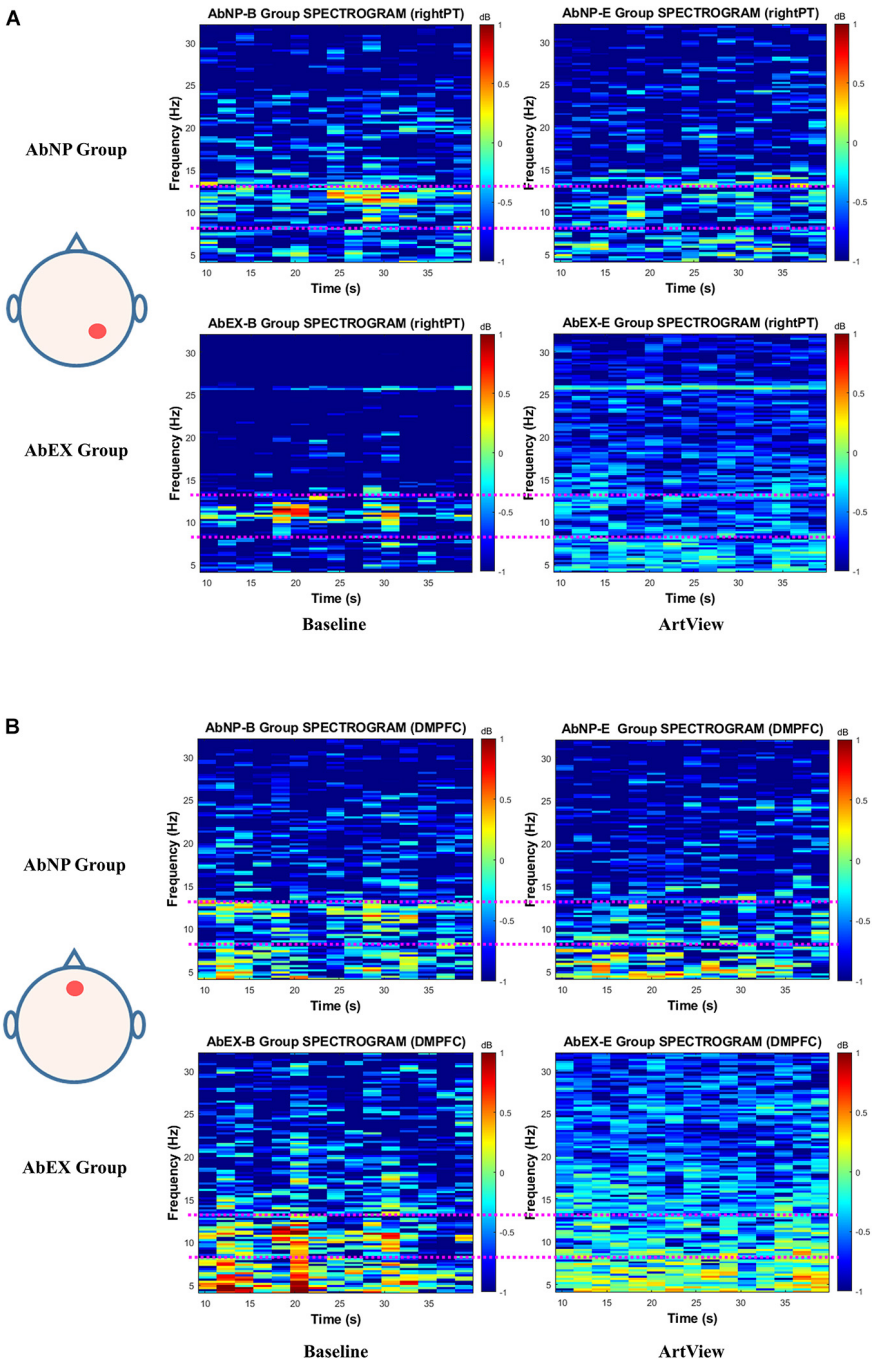


FIGURE 6 | The EEG spectrogram for a mean of the AbNP group and that of the AbEX group, depending on baseline and ArtView sessions, for **(A)** *Aff(Ar.c)* represents the effect of viewing abstract artwork (vs. baseline) on right parietotemporal cortex (PT). For **(B)**, *Aff(Ar.n)* represents the effect of viewing abstract artwork (vs. baseline) on the dorsomedial prefrontal cortex (DMPFC). The trend of the difference of alpha power reduction in group spectrograms is similar to that of the typical spectrograms in **Figure 5**. This result is consistent with the results of statistical analysis in **Figure 4A** for *Aff(Ar.c)* and in **Figure 4B** for *Aff(Ar.n)*. The terms*Aff*(*Ar.c*), *Aff*(*Ar.n*), ArtView, AbNP group, and AbEX group, the pink dotted line, and the color bar in each spectrogram have the same meanings described in the legend of **Figure 5**.

being faster than that of the AbNP group (M = 508.01 ms, 95% CI = [485.52, 530.51]). This means that if participants' cognitive resources are depleted, they are more likely to make quick decisions regardless of their mistake. Consistent with these two results, the response × group interaction was not significant ($F(1, 36) = 0.53$, $p = 0.472$, $\eta_p^2 = 0.01$) (see **Figure 7A**).

A 2 (congruent vs. incongruent) × 2 (AbNP vs. AbEX) repeated-measures ANOVA was conducted on *RT*. The main

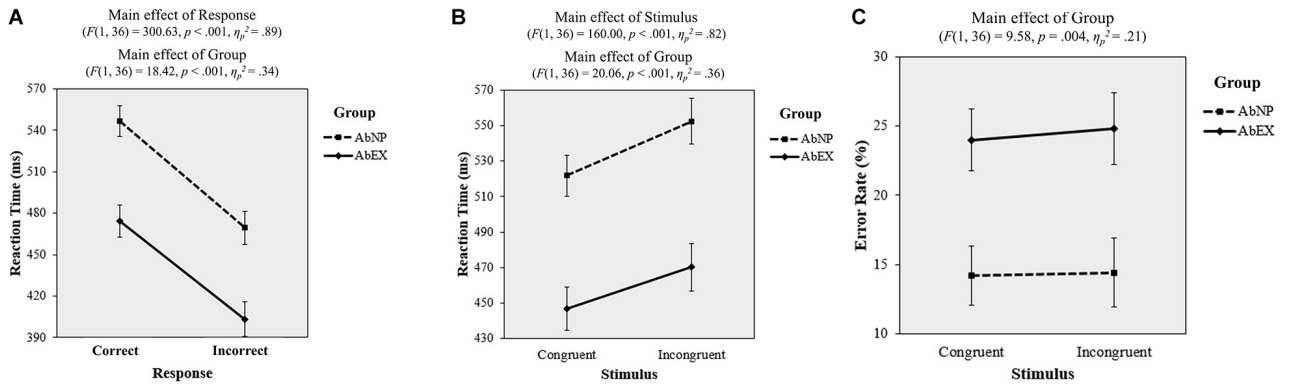


FIGURE 7 | Plots of the results of task 2 for both the AbNP and AbEX groups, including reaction time, by **(A)** response type or **(B)** stimulus type, and **(C)** error rate by stimulus type. Error bars indicate standard errors of the mean. AbNP group and AbEX group have the same meanings described in the legend of **Figure 4**.

effect of the stimulus ($F(1, 36) = 160.00$, $p < 0.001$, $\eta_p^2 = 0.82$) was significant, with *RT_incong* ($M = 511.35$ ms, 95% CI = [492.55, 530.15]) being slower than *RT_cong* ($M = 484.36$ ms, 95% CI = [467.31, 501.41]). This means that as the cognitive task become difficult, participants tend to take longer to make decisions regardless of the amount of their cognitive resources remaining. The main effect of group was also significant ($F(1, 36) = 20.06$, $p < 0.001$, $\eta_p^2 = 0.36$), with the *RT* of the AbEX group ($M = 458.51$ ms, 95% CI = [432.65, 484.36]) being faster than that of the AbNP group ($M = 537.20$ ms, 95% CI = [512.68, 561.73]). This means that if participants' cognitive resources are depleted, they are more likely to make quicker decisions regardless of the difficulty of cognitive task. Consistent with these two results, the stimulus × group interaction was not significant ($F(1, 36) = 2.98$, $p = 0.093$, $\eta_p^2 = 0.08$) (see **Figure 7B**).

Error Rate

A 2 (congruent vs. incongruent) × 2 (AbNP vs. AbEX) repeated-measures ANOVA was conducted on *ErR*. The result indicated a significant main effect ($F(1, 36) = 9.58$, $p = 0.004$, $\eta_p^2 = 0.21$), with the effect of *ErR* on the AbEX group ($M = 24.40\%$, 95% CI = [19.60, 29.20]) being higher than that of the AbNP group ($M = 14.31\%$, 95% CI = [9.75, 18.86]). However, neither the main effect of the stimulus type ($F(1, 36) = 0.48$, $p = 0.495$, $\eta_p^2 = 0.01$) nor the interaction were significant ($F(1, 36) = 0.15$, $p = 0.705$, $\eta_p^2 < 0.01$) (see **Figure 7C**). This means that if participants deplete their cognitive resources, then they tend to make mistakes regardless of the difficulty of cognitive task.

Correlations Between *RT* and *ErR*

There were significant negative correlations between *RT* and *ErR* in both the AbNP group (congruent: $r = -0.46$, $p = 0.041$; incongruent: $r = -0.47$, $p = 0.037$) and the AbEX group (congruent: $r = -0.88$, $p < 0.001$; incongruent: $r = -0.90$, $p < 0.001$). This means that if participants make quick decisions, they are more likely to commit mistake. This trend is more evident as their cognitive resources deplete more.

Subjective Ratings for Abstract Artwork

A one-way ANOVA was conducted on the subjective ratings provided by participants from the manipulation check groups. Participants who viewed AbEX rated the four items, i.e., "affective arousal," "dynamicity," "complexity," and "emotional infusion" significantly higher than those who viewed AbNP. However, there was no significant difference between the two groups for affective valence. **Table 1** details the means, 95% confidence intervals, and statistical tests for these comparisons.

DISCUSSION

The primary aim of this study was to examine whether changes in consumer's affect induced by opposing styles of visual art (expressing vs. suppressing) on product packaging differ, if so, to investigate how the differential changes in consumer's affect induced by the two styles of visual art influence the way information is processed in purchase decision-making.

Proving our first hypothesis, the results showed that observing AbEX increased affective arousal when compared with observing AbNP. This finding was apparent in both the conventional and novel affective arousal indices, i.e., *Aff(Ar.c)* and *Aff(Ar.n)* (see these definitions in Section "EEG analysis"), based on EEG analyses of task 1, which included baseline and ArtView sessions. This implies that affective arousal is induced more in consumers who view abstract art of expressionism as opposed to neoplasticism.

Our results are in line with previous findings. Both the right PT cortex (Heller et al., 1997) and DMPFC (Dolcos et al., 2004; Grimm et al., 2006) were involved in the induction of affective arousal. We hypothesized that abstract artwork expressing the emotion and gestural movement of the artist, represented by dynamic elements in the artwork of Kandinsky, would evoke higher affective arousal. Our EEG data, as well as the subjective ratings of the participants, provide empirical evidence to support this hypothesis. Our results are also consistent with studies showing that the abstract artwork by Kandinsky ranks high in both complexity (Wohlwill, 1968) and affective arousal

TABLE 1 | Means and confidence intervals for the subjective ratings of the abstract artwork.

	AbNP group ($n = 33$)		AbEX group ($n = 33$)		Comparison	
	M	95% CI	*M*	95% CI	*F*(1, 64)	*p*
Arousal	3.60	[3.00, 4.20]	4.72	[4.24, 5.20]	8.91	0.004
Dynamicity	3.27	[2.79, 3.75]	5.38	[4.94, 5.81]	43.81	<0.001
Complexity	3.74	[3.25, 4.23]	6.85	[6.51, 7.18]	114.08	<0.001
Emotional infusion	3.88	[3.21, 4.54]	5.19	[4.63, 5.76]	9.43	0.003
Valence	3.83	[3.21, 4.45]	3.85	[3.42, 4.28]	<1.00	0.961

AbNP, artwork of Mondrian in the style of neoplasticism; AbEX, artwork of Kandinsky in the style of expressionism; CI, confidence interval; M, mean.

(Hagtvedt et al., 2008). Furthermore, it has been demonstrated that viewing pictures which induced affective arousal increased motor cortex excitability (Hajcak et al., 2007), and that dynamic elements in the abstract artwork by Franz Kline activated the motor cortex (Sbriscia-Fioretti et al., 2013). Thus, higher levels of dynamic properties in Kandinsky's artwork compared with Mondrian's artwork might have facilitated embodied simulation of the gestural movements of the artist (Gallese and Sinigaglia, 2011). The results of this study showed an elevated affective arousal state of the AbEX group compared with that of the AbNP group and can be explained by the embodied simulation theory, i.e., Kandinsky's emotion was simulated within the somatosensory systems of the AbEX group. This means that affective arousal will be induced more in consumers who view visual art that is expressing as opposed to suppressing its artist's affect.

Consistent with our second hypothesis, we found that participants who viewed artwork by Kandinsky but not Mondrian performed poorly in the subsequent Stroop task. We confirmed that affective arousal as well as affective valence may play a grand claim in determining the impact of affect on cognition (Mitchell and Phillips, 2007). The higher affective arousal induced by AbEX compared with AbNP might deplete the necessary cognitive resources needed for performing the Stroop task (Pallak et al., 1975). We infer that the lower performance associated with viewing AbEX than AbNP is due to the unavoidable use of a heuristic, rather than a systematic, strategy for decision-making due to a deficiency in cognitive resources caused by the enhanced affective arousal (Paulhus and Lim, 1994; Pham, 1996; Fedorikhin and Patrick, 2010). Significant evidence exists to support this conjecture. First, the reaction time (*RT*) indices in our data (see **Figure 7A**) indicate that the AbEX group responded faster than the AbNP group regardless of response type (correct vs. incorrect), and the *RT* for the incorrect answers is shorter than that of the correct answers regardless of group type (AbNP vs. AbEX). This means that if consumers' cognitive resources are depleted, they are likely to make quick decisions regardless of their mistake and while making quick decisions, they tend to commit mistakes regardless of the amount of their cognitive resources remaining. Second, the *RT* indices in our data (see **Figure 7B**) indicate that the AbEX group responded faster than the AbNP group regardless of stimulus type (congruent vs. incongruent) and the *RT* for the incongruent stimuli is longer than that of the congruent stimuli regardless of group type (AbNP vs. AbEX). This implies that if consumers' cognitive resources are depleted, they are likely to make quick decisions regardless of the difficulty of cognitive task and as the cognitive task becomes more difficult, they tend to take longer time to make decisions regardless of the amount of their cognitive resources remaining. Third, the error rate (*ErR*) was found to be higher in the AbEX group than in the AbNP group for both congruent and incongruent stimuli (see **Figure 7C**). This suggests that if consumers deplete their cognitive resources, then they tend to make mistakes regardless of the difficulty of cognitive task. It is important to note that faster *RT* may be the cause of higher *ErR*, a phenomenon that is typical of heuristic decision-making. This result is consistent with the negative correlations between *RT* and *ErR* in both the AbNP and AbEX groups. This supports previous studies where it is seen that the available time is analogous to cognitive capacity or the ability to process information (Suri and Monroe, 2003).

The question then becomes how and why affective arousal reduces the consumers' cognitive capacity and leads to heuristic processing. Earlier research suggests various reasons for the depletion of cognitive resources (Fedorikhin and Patrick, 2010). Consistent with the results of this study (i.e., higher affective arousal group, AbEX, performed poorly in the subsequent Stroop task), individuals in a high-arousal state are more likely to be persuaded by peripheral cues than those in a low-arousal state (Sanbonmatsu and Kardes, 1988). In addition, they are more likely to suppress reliance on cues that are cognitive-capacity demanding (Pham, 1996; Fedorikhin and Patrick, 2010). According to the dynamic complexity model, highly aroused individuals also tend to reduce the cognitive complexity of judgments by focusing on the primary dimension and discarding the secondary dimension (Paulhus and Lim, 1994).

This research has a potential limitation. Only male participants with relatively short hair were recruited to reduce the time required to adjust the 128 electrodes and to maintain homogeneity. For future research, the study can include female participants. To evaluate cognitive task performance, other measures could also be considered such as n-back task, digit span task, digit symbol test, and word fluency test, which have been widely used as psychometric tests in cognitive psychology studies (Gajewski et al., 2018).

In summary, the current study proves that viewing abstract expressionist artwork (by Kandinsky) induces a far stronger affect in the viewer than viewing neoplastic artwork (by Mondrian),

particularly in terms of affective arousal. This results in a downstream effect that diminishes performance in subsequent cognitive tasks, as demonstrated by the Stroop task. One possible reason for worse performance is the depletion of cognitive resources. Such depletion occurs as a result of a heightened affective arousal caused by the greater complexity and dynamicity of abstract artwork that attempt to express, rather than suppress, the emotions of the artist. This paper is the first known attempt to demonstrate how the changes in consumer's affect induced by visual art with different styles designed on product or product packaging influence their decision-making under time constraint (e.g., while purchasing). Our findings indicate that if an art-based design on product or product packaging expresses (vs. suppress) the artist's emotion (e.g., includes dynamic components), then the design may deplete consumer's cognitive resources, thereby leading to heuristic decision-making and resulting in inadvertent mistakes while purchasing. This research provides a foundation to build a solid theory on the relationship between abstract art inducing high affective arousal and leading to heuristic decision-making. The findings are especially relevant in the field of neuromarketing when the abstract art is used in the packaging of products (Breiter et al., 2015; Ramsøy et al., 2018).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/ **Supplementary Material**.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Korea Research Institute of Standards and Science. The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

YRK and YEK designed the study under the supervision of KP and conducted the experiments under the supervision of W-SK. YRK and WY drafted the manuscript under the supervision of KP and W-SK. KP supervised statistical analyses, interpreted the data, and provided critical revisions with respect to research in marketing. DH analyzed the EEG data under the supervision of W-SK. W-SK supervised the measurement and analysis of the EEG and provided critical revisions regarding research in neuroscience. All the authors involved approved the final manuscript prior to submission.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.565829/full#supplementary-material

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REVIEW
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Picking Your Brains: Where and How Neuroscience Tools Can Enhance Marketing Research

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The use of neuroscience tools to study consumer behavior and the decision making process in marketing has improved our understanding of cognitive, neuronal, and emotional mechanisms related to marketing-relevant behavior. However, knowledge about neuroscience tools that are used in consumer neuroscience research is scattered. In this article, we present the results of a literature review that aims to provide an overview of the available consumer neuroscience tools and classifies them according to their characteristics. We analyse a total of 219 full-texts in the area of consumer neuroscience. Our findings suggest that there are seven tools that are currently used in consumer neuroscience research. In particular, electroencephalography (EEG) and eye tracking (ET) are the most commonly used tools in the field. We also find that consumer neuroscience tools are used to study consumer preferences and behaviors in different marketing domains such as advertising, branding, online experience, pricing, product development and product experience. Finally, we identify two ready-to-use platforms, namely iMotions and GRAIL that can help in integrating the measurements of different consumer neuroscience tools simultaneously. Measuring brain activity and physiological responses on a common platform could help by (1) reducing time and costs for experiments and (2) linking cognitive and emotional aspects with neuronal processes. Overall, this article provides relevant input in setting directions for future research and for business applications in consumer neuroscience. We hope that this study will provide help to researchers and practitioners in identifying available, non-invasive and useful tools to study consumer behavior.

Keywords: neuromarketing, consumer neuroscience, review, iMotion, GRAIL, marketing, neurophysiological tools, physiological tools

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1. INTRODUCTION

Concepts, methodologies and tools in marketing have remained unchanged for a relatively long period. However, changing market structures (e.g., offline to online, globalization, hyper-competitive environment, increasing demand) demand new marketing methodologies and tools that are able to adapt to this new situation (Hackley, 2009; Armstrong et al., 2018). Thus, academics and practitioners have investigated how marketing research could benefit from the integration of methods and tools from other disciplines. In the early 2000s, a novel approach for studying

consumer behavior emerged. This new approach is now known as Consumer Neuroscience (a.k.a. Neuromarketing) and lies at the intersection of three disciplines: marketing, psychology, and neuroscience (Plassmann et al., 2012).

The goal of consumer neuroscience is the study of neuropsychological mechanisms that support and lead consumer decision making and behavior. Consumer neuroscience uses both psychological and neuroscience methods to investigate marketing related issues concerning buying behavior, thus offering scientific explanation on consumer's preferences and behaviors (Levallois et al., 2012; Russo et al., 2015). There are multiple consumer neuroscience tools that are used to study consumer decision-making and behavior. Usually, consumer neuroscience tools include devices that can measure vital physiological functions (e.g., heartbeat, respiration rate, blood pressure) and reflexes (e.g., gaze fixation, pupil dilatation, face expression) (Global Harmonization Task Force, 2012). These tools reveal information about impressions, reactions (e.g., positive, negative) and emotional responses (e.g., positive, negative) when exposed to marketing stimuli (Hamelin et al., 2017). Consumer neuroscience tools also allow real-time measurements of brain activity, such as functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG). These tools measure the neural activity of consumers while they perform consumption-related behavior (e.g., buying or testing a product), or in the periods directly preceding and following such behaviors (Plassmann et al., 2015; Montazeribarforoushi et al., 2017).

Many studies have focussed on the benefits of neuroscience tools in marketing (Vecchiato et al., 2011; Bercea, 2013; Hsu and Yoon, 2015; Ramsøy, 2015; Boz et al., 2017; Lee et al., 2017; Alvino, 2019; Songsamoe et al., 2019). Several studies also provide an overview of the most common neuroscience tools that could be used in consumer neuroscience tools, for instance EEG and fMRI. However, there is lack of literature that surveys these tools to provide guidance for practitioners and researchers. The aim of this article is *to provide an overview of the use and characteristics of neuroscience tools employed for studying consumer behavior*.

In order to achieve our aim we make use of a literature review as explained in section 2. After selecting relevant publications we first study the classification criteria used to categorize consumer neuroscience tools and propose criteria to classify those practically used tools in section 3. We then discuss the various characteristics of the consumer neuroscience tools in section 4. Thereafter, in section 5, we study the various applications of consumer neuroscience tools in marketing. Section 6 describes the benefits and potential of two novel ready-to-use platforms that integrate different consumer neuroscience tools together. Finally, we present the conclusions of our study in section 7.

2. METHOD

We use a literature review methodology (Webster and Watson, 2002) to survey the scientific contributions and construct an overview of the use and characteristics of neuroscience tools used to study consumer behavior. For the literature review, we have considered academic articles indexed by Scopus published between 2004 and 2019, as the first "neuromarketing" article was published in 2004 (Brammer, 2004). The first paper that uses the term "consumer neuroscience" was published in 2008 (Hubert and Kenning, 2008).

As shown in **Figure 1**, we follow a three-step process to select the studies for this review. First, we search academic records on Scopus, using the following query, *("neuromarketing" OR ("consumer" AND "neuroscience"))*. This query returns all the records that mention "neuromarketing" or "consumer neuroscience" as a keyword. Due to a high number of records (412 records) found, we decide to screen the studies by evaluating their abstract and conclusions. We screen the records based on the following parameters:

1. We remove the records that did not focus on neuromarketing or consumer neuroscience as a research topic.
2. We only consider records in the English language.
3. We exclude the studies that were not marketing related.

Post screening a total of 211 studies were found eligible for this survey. Finally, we add 8 more records to the eligible studies based on suitable studies (including books and reports) found as a result of backward reference search. We select 219 studies that belong to several domains where consumer neuroscience is a research topic, for example, neuroscience, marketing, psychology, economics and engineering in this survey. We further evaluate the studies and group them according to the following three categories: review, empirical (based on experiments) and conceptual (based on interviews). In the selected corpus we find 137 empirical research, 69 review, 9 conceptual papers, and 4 reports.

Figure 2 shows the year of publication of the selected studies. We recorded the tools discussed by each study and the tools employed for data collection in each empirical study. We recorded the various characteristics (e.g., advantages, disadvantages, cost of procurement, etc.) of the tools mentioned in the studies. In addition, we recorded the classification criteria used by the studies to categorize the tools, the marketing domain of application and the type of product or service tested. Based on the review of selected studies, we develop insights in order to achieve the objective of this review.

3. AN OVERVIEW OF CONSUMER NEUROSCIENCE TOOLS

Consumer neuroscience uses neuroscience tools to study behavior of consumers and their decision-making processes. Traditional marketing techniques such as self-reports or interviews mainly allow the measurement of conscious reactions to marketing-related stimuli (e.g., advertisements, brands). Conversely, neuroscience tools enable researchers to measure physiological signals aroused by marketing stimuli such as music, videos, brand logo, or websites (Schneider and Woolgar, 2015; Alvino et al., 2018; Alvino, 2019; Muñoz-Leiva et al., 2019).

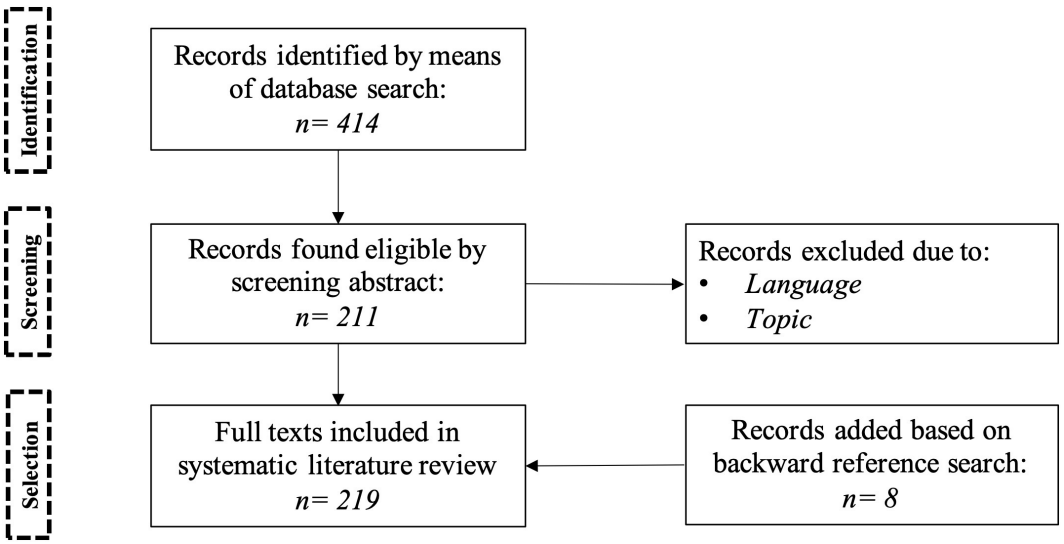


FIGURE 1 | Overview of review methodology.

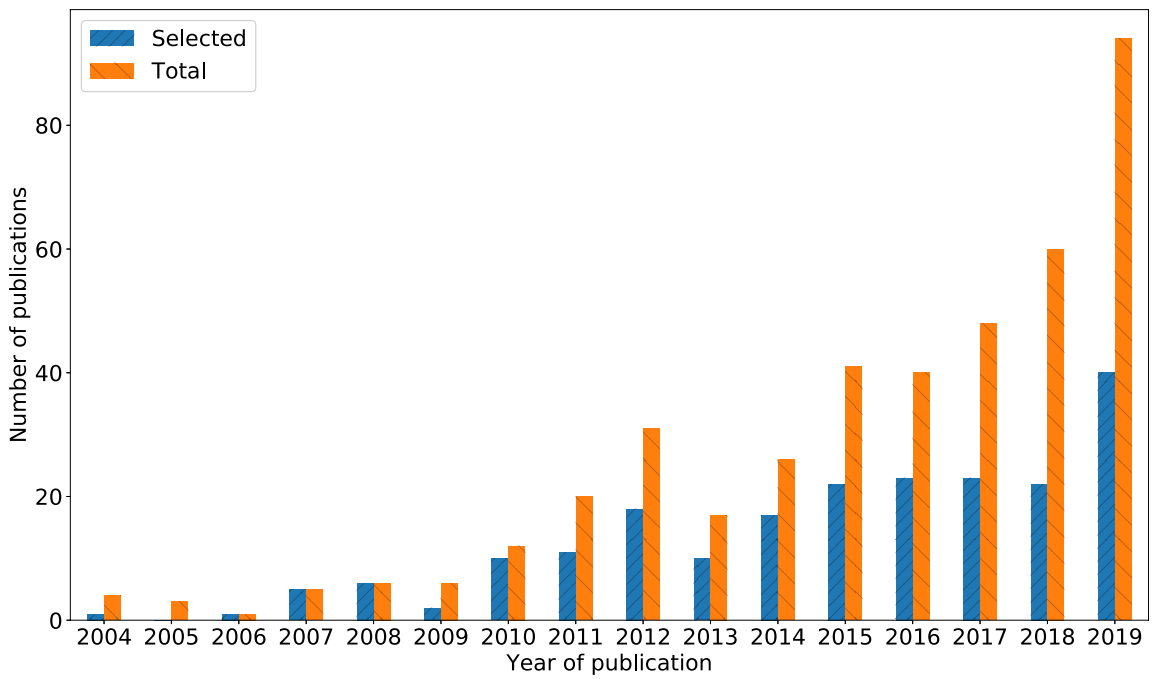


FIGURE 2 | Number of publications selected for this study.

These tools also help to understand how a consumer experiences marketing stimuli and to identify the factors that influence and modify consumers' preferences. There are several definitions and descriptions of consumer neuroscience tools (Fugate, 2008; Fisher et al., 2010; Morin, 2011; Gang et al., 2012; Venkatraman et al., 2015; Chapman et al., 2019; Lajante and Ladhari, 2019; Tobon et al., 2020). In this section, we focus on classifications of neuroscience tools as classification criteria that identify, group, and properly name tools via a standardized system.

3.1. Classification of Tools

Consumer Neuroscience tools are usually categorized based on the type of measurements. Studies (Kenning et al., 2007a; Boz et al., 2017; Stasi et al., 2018) have broadly divided these tools into two categories namely *physiological tools and neurophysiological*

tools. Physiological tools can measure voluntary and involuntary reflexes such as fixating and tracking visual stimuli or movements of the mimetic musculature of the face (facial expressions) (Global Harmonization Task Force, 2012). Physiological tools (or methods) include electrocardiogram (ECG), electrodermal activity (EDA), participants' facial muscles fEMG, eye-tracker (ET) and voice pitch analysis (VOPAN) (Isabella et al., 2015; Boz et al., 2017; Stasi et al., 2018). Neurophysiological tools (or methods) measure and record brain activity to study consumer behavior (Boz et al., 2017). Examples of neurophysiological tools are electroencephalography (EEG), positron emission tomography (PET), magnetoencephalogaphy (MEG), functional magnetic resonance imaging (fMRI) and transcranial magnetic stimulation (TMS) (Kenning et al., 2007a,b).

Literature (Wang and Minor, 2008; Bercea, 2013; Fortunato et al., 2014; Harris et al., 2018; Lim, 2018) shows that these tools can also be classified based on the *type of brain activity* they measure; i.e., tools that:

1. Measure the metabolic activity in the brain
2. Measure electrical activity in the brain
3. Do not measure brain activity.

Wang and Minor (2008) identifies three tools that measure changes in chemical composition or changes in the flow of fluids in the brain (brain imaging analysis), namely functional magnetic resonance imaging (fMRI), positron emission tomography (PET), transcranial magnetic stimulation (TMS) or magnetoencephalogaphy (MEG). In contrast, electroencephalography (EEG) and steady-state topography (SST) measure non-hemispheric brain wave analysis and hemispheric lateralization (brain wave analysis). Bercea (2013) states that PET and fMRI can record metabolic brain activity and that EEG, SST, TMS, MEG and functional near-infrared spectroscopy (fNIRS) can record electrical brain activity. According to Harris et al. (2018), changes in metabolic brain processes are measured by fMRI, PET and functional transcranial Doppler sonography (fTCS). In contrast, changes in electrical activity are measured by various techniques including EEG, MEG, SST, and TMS. The tools that do not record brain activity can be considered physiological tools such as galvanic skin response (GSR), electrocardiogram (ECG), eye tracking (ET), facial expression recognition software (fERS), voice pitch analysis, and implicit association tests (IAT) (Wang and Minor, 2008; Bercea, 2013; Fortunato et al., 2014; Harris et al., 2018).
Similarly, Lim (2018) classifies consumer neuroscience tools into three categories, i.e., tools that:

1. Record outside brain activity
2. Record inside brain activity
3. Manipulate neural activity.

In the first category, we find tools such as GSR, ECG, ET, and fERS. The second category (tools that record neural activity) is then divided into two categories: electromagnetic and metabolic. PET and fMRI can record metabolic brain activity, and EEG, MEG, SST can record electrical brain activity (Lim, 2018). In the last category (manipulate neural activity), we find transcranial magnetic stimulation (TMS) and neurotransmitters (NTs). Neurotransmitters are chemical substances that enable the transmission of neurological signals from one neuron to another target neuron (Lim, 2018).
Finally, Ramsøy (2015) identifies four different types of consumer neuroscience tools, namely:

1. Self-reports
2. Behavioral measurement
3. Physiological measurement
4. Neuroimaging.

Self-report is one of the most widely used methods of collecting information regarding individual health status, feelings, attitudes, and beliefs. For example, it might be important to know how participants feel while shopping in a store or while performing a task (Paulhus and Vazire, 2007). Behavioral measurements reveal information about consumer behaviors, impressions, and concern particular mental states or responses (Ramsøy, 2015). In behavioral measurements, people are observed and recorded when they perform a task, for instance, reaction time (RT), which is the opposite of self-report. Physiological measurements are useful to evaluate people's biological responses to stimuli. Physiological measurements are usually not under a consumer's voluntary control, therefore they cannot be easily influenced, in contrast to self-reports and behavioral measurements (Ramsøy, 2015). Examples of physiological measurements are body language, facial expression, eye movement and pupil dilatation, palm sweating, respiration and pulse. Finally, neuroimaging refers to different tools that are used to identify and analyse brain activity. Ramsøy (2015) classifies as neuroimaging tools EEG, fMRI, MRI, PET MEG, and single photon emission tomography (SPECT).

We identify three classification criteria used in the literature for categorizing neuroscience tools. There are some similarities between some of the classifications, for instance, (Isabella et al., 2015) with (Boz et al., 2017) or (Wang and Minor, 2008) with (Bercea, 2013) and (Harris et al., 2018); we observe that those authors chose different criteria to group consumer neuroscience tools. As shown in **Table 1**, previous studies group consumer neuroscience tools in different number of levels (2, 3, or 4) on the base of (1) type of measurements (e.g., behavioral, physiological, neurophysiological), (2) type of neuronal activity (neuronal activity outside or inside the brain), (3) brain activity recorded (e.g., metabolic or electric), (4) no brain activity, or (5) manipulate neuronal activity. Surprisingly, some of these classifications also describe these tools erroneously. While some authors classify them as data collection methods (and not tools), some other authors mistake the tools for measurements. E.g., some authors describe eye tracking, heart rate and electrodermal activity (skin conductance) as tools, instead of properties of the human body or, more precisely, changes in eye movements, muscle contraction of the heart and electrical properties of the skin (Wiles and Cornwell, 1991; Braithwaite et al., 2013; Ramsøy, 2015). Some authors also refer to the Implicit Association Test as a tool, however, the IAT is a test that can be used to measure the strength of differential association of two or more target

TABLE 1 | Classification of consumer neuroscience tools.

Number of levels	(Wang and Minor, 2008)	(Bercea, 2013)	(Isabella et al., 2015)	(Ramsøy, 2015)	(Harris et al., 2018)	(Boz et al., 2017)	(Lim, 2018)	
	3	3	2	4	2	3	3	
Electroencephalography	BWA	EBAc	NPy	NIm	NPy	EBAc	NAc (Inside)	
Functional magnetic resonance imaging	BIA	MBAc	NPy	NIm	NPy	MBAc	NAc (Inside)	
Functional near-infrared spectroscopy	-	EBAc	-	NIm	-	-	-	
Functional transcranial Doppler sonography	-	-	-	-	-	MBAc	-	
Magnetoencephalography	BIA	EBAc	NPy	NIm	NPy	EBAc	NAc (Inside)	
Positron emission tomography	BIA	MBAc	NPy	NIm	NPy	MBAc	NAc (Inside)	
Steady-state topography	BWA	EBAc	-	NIm	-	EBAc	NAc (Inside)	
Single photon emission tomography	-	-	-	NIm	-	-	-	
Transcranial magnetic stimulation	-	EBAc	NPy	-	-	EBAc	MNAc	
Neurotransmitters	-	-	-	-	-	-	MNAc	
Eye Tracker	NBAc	NBAc	Py	Py	Py	Py	NAc (Outside)	
Electrocardiogram	NBAc	NBAc	Py	Py	Py	Py	NAc (Outside)	
Facial expression recognition	NBAc	NBAc	Py	Py	Py	Py	NAc (Outside)	
Galvanic skin response	NBAc	NBAc	Py	Py	Py	Py	NAc (Outside)	
Voice pitch analysis	NBAc	-	Py	-	-	-	-	
Implicit association test	-	NBAc	-	-	-	Py	-	
Self-reports	-	-	-	SR	-	-	-	
Reaction time	-	-	-	BM	-	-	-	

BWA, Brain Wave Analysis; BIA, Brain Imaging Analysis; NBAc, No Brain Activity; NPy, Neurophysiological; Py, Physiological; NIm, Neuroimaging; SR, Self-reports; BM, Behavioral Measurements; NAc, Neuronal Activity; MNAc, Manipulate Neuronal Activity.

concepts with an attribute (Greenwald et al., 1998; Ramsøy, 2015). Finally, Lim (2018) consider neurotransmitters (NT) as consumer neuroscience methods. However, NTs are chemical substances in our brain and cannot be considered a method or a tool.

There is a difference in the number and type of tools that authors include in each classification (see **Table 1**). All authors included tools such as EEG, fMRI, MEG, PET, fERS, ET, ECG, and GSR as consumer neuroscience tools (Wang and Minor, 2008; Bercea, 2013; Ramsøy, 2015; Boz et al., 2017; Harris et al., 2018; Lim, 2018). However, other tools such as fNIRS, TMS, SST, and VPA have not been mentioned in all classifications. Self-reports and reaction time are only discussed by Ramsøy (2015). This observation suggests that some authors identify as consumer neuroscience tools only those most commonly employed in neuroscience studies.

3.2. Popularity of Tools

Even though a large number of tools are proposed for consumer neuroscience research, it might be possible that the number of tools that are practically used for research is much lower. In our analysis, we did not find evidence of practical use for some of the proposed tools. In total, we analyzed 137 empirical research papers in consumer neuroscience research and we find that only seven tools are used in these studies. In particular, we see that some studies use tools that measure brain activity such as EEG (both traditional and wearable), fMRI and fNIRS. In addition, other studies use tools that measure physiological responses such as ECG, ET, GSR, and fERS. Surprisingly, tools such as MEG, SST, SPECT, PET, TMS, and VPA are not used in the studies in our search. However, it is noteworthy that many of these studies also use self-reports, questionnaires and/or reaction times to measure behavioral measurements. In addition, we found that approximately 18% of the total number of studies (25 studies) use a combination of two or more tools simultaneously.

Another important aspect to consider is the popularity of these tools in consumer neuroscience research. The literature suggests that several tools are in demand in the field. Some studies claim that the majority of consumer neuroscience research has predominantly used fMRI to measure brain activation in response to marketing stimuli (Smidts et al., 2014; Ramsøy, 2015; Harris et al., 2018). Other studies maintain that the most widely applied consumer neuroscience tool is eye-tracking followed by galvanic skin response (16%), facial recognition (11%), heart rate variability (9%), electroencephalography (6%), and electromyography (EMG) (4%) (dos Santos et al., 2015; Boz et al., 2017). A review of 34 neuroscience studies from 2001 to 2012 finds that fewer than 25% of the studies applied EEG, while almost 70% applied fMRI (Solnais et al., 2013; Sung et al., 2019). Similarly, Lim (2018) outlines that neuroimaging is the most popular category of tools for consumer neuroscience research (33 articles; 42.3%), followed by non-neuroimaging tools (16 articles; 20.5%). In particular, (Lim, 2018) outlines that the most popular brain recording method is fMRI and EEG is the second most popular tool.

In the literature review we found that most consumer neuroscience studies use EEG (both traditional and wearable). In total, EEG was used in 83 studies (approx. 60.5%), alone or in combination with other tools (see **Figure 3**). In 19 of these studies, researchers used wearable EEG. Eye tracking is the second-most used tool, appearing in 24 studies (approx. 17.5% of the studies). Interestingly, fMRI was used only in 20 studies

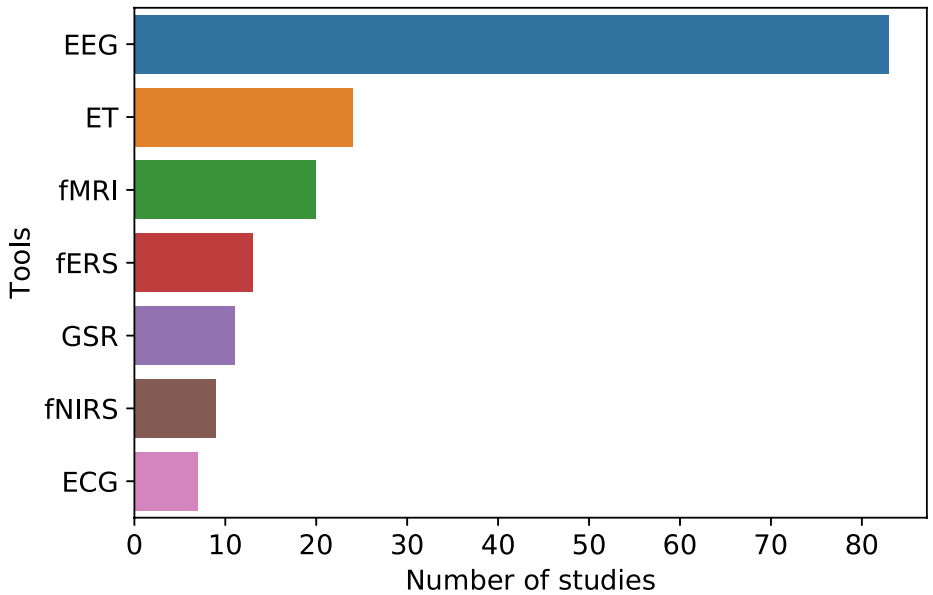


FIGURE 3 | An overview of neuroscience tools used in *consumer neuroscience* studies.

(approx. 14.5%). As shown in **Figure 3**, fERS was found in 13 studies (almost 9.5%), followed by GSR (8%), fNIRS (almost 6.6%), and ECG (approx. 5%). These results are in line with a survey conducted by the Neuromarketing Science and Business Association (NMSBA) in 2018. The survey provides a ranking of the most to the least offered tools offered by neuromarketing vendors, namely EEG, ET, fERS and GSR. fMRI shows a small decline during the period 2014–2018 (Cherubino et al., 2019).

Overall, we identify seven tools that are used to measure consumer brain activity or physiological responses to marketing stimuli. Additionally, we find that many consumer neuroscience studies also employ traditional marketing tools such as surveys, questionnaires and self-reports. It might be possible that some tools are listed as consumer neuroscience tools but they have never been used before (e.g., MEG, PET, TMS, SST, SPET, VPA). We also believe that some of these tools such as PET and TMS should not be used in consumer neuroscience research. Whilst these tools are very helpful for medical diagnosis and treatment of mental diseases, they may be too invasive or have adverse effects (e.g., pain, fainting, seizures) that could be too high to be used in consumer neuroscience studies, thus exposing participants to unnecessary risks (Rossi et al., 2009; Dobek et al., 2015). Similarly, we believe that SPET and SST are not useful for consumer neuroscience research. SPET is very similar to PET and has the same disadvantages such as costs and high risk for the subject. In fact, SPET requires an injection of radiopharmaceuticals which is risky and arguably unethical. Finally, SST could not be considered as a neuroscience tool because it is a particular application of EEG. The available literature seems to support the view that fMRI and eye-tracking are the most used tools in consumer neuroscience studies. On the contrary, we find that EEG is the most popular tool used in consumer neuroscience studies by far, followed by eye-tracking. fMRI is only the third-most used tool in the field. There could be several reasons why fMRI is considered the most popular tool. Many papers were published 4–5 years ago, and might not reflect the current situation. Perhaps the fact that fMRI is broadly discussed in popular studies such as (McClure et al., 2004; Plassmann and Karmarkar, 2015; Venkatraman et al., 2015) gives the false impression that this tool is widely used in consumer neuroscience research.

3.3. Proposed Classification of Tools

Based on the above considerations, we propose a new classification following Isabella et al. (2015) and Ramsøy (2015) classifications. **Figure 4** shows that consumer neuroscience tools can be divided in three categories, namely:

1. Behavioral,
2. Physiological,
3. Neurophysiological.

Behavioral tools (e.g., survey, observations, and RT) are part of our classification as they provide important information on behavior of consumers. These tools are also presently used in consumer neuroscience studies. We also do not differentiate between self-report and survey, as we believe self-report has a different purpose in this field than in psychology. In consumer neuroscience, self-reports are not used to assess personality but purchasing behavior and attitude of consumers (Paulhus and Vazire, 2007).

For both physiological and neurophysiological tools, we only include tools that are currently used in consumer neuroscience research. In our classification, physiological tools such as ECG, ET, fERS, and GSR can measure the autonomous functions of the body for which there is no direct or conscious control, such as blood circulation, blood pressure, heart rate and sweating (Kenning and Linzmajer, 2011). These tools allow researchers to

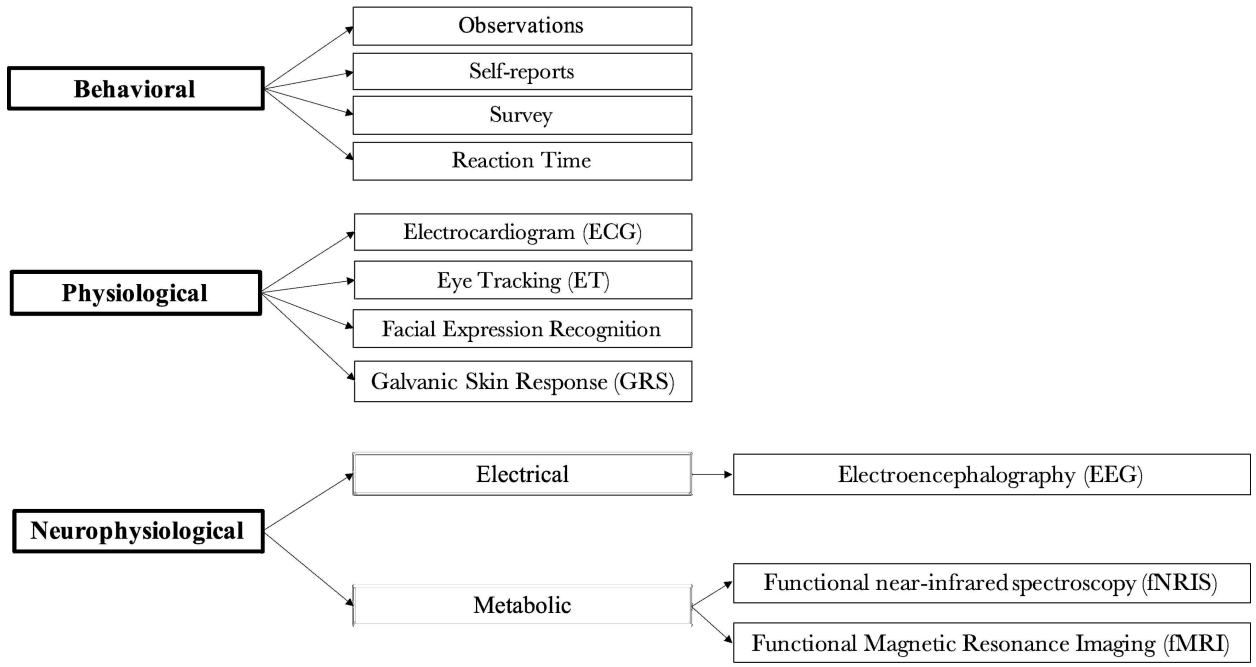


FIGURE 4 | Proposed classification of consumer neuroscience tools.

measure the autonomous functions of the body (e.g., voluntary and involuntary body reflexes). Neurophysiological tools can directly measure consumers' brain activity and can be further divided into two categories: those that measure electrical activity (EEG), and those that measure metabolic brain activity (fMRI and fNRIS). The characteristics of physiological and neurophysiological tools are discussed in the next section.

4. CHARACTERISTICS OF CONSUMER NEUROSCIENCE TOOLS

In this section, we discuss the details of the seven tools currently used in consumer neuroscience research (identified in section 3). We illustrate the cognitive processes which these tools can be used to investigate, and the main advantages and disadvantages for each tool. Secondly, we provide an estimate of average costs of procuring the tools and the average time it takes to perform an experiment. We also discuss the ease with which a tool can be used in tandem with another tool; we represent this as the *integration level* of a tool. **Table 2** provides an aggregate view of all the above-mentioned characteristics for each of the neuroscience tools.

4.1. Electroencephalogram

EEG can be considered the oldest neurophysiological tools, dating back almost a century (1924) (Murray and Antonakis, 2019). EEG is a non-invasive brain imaging method that detects brain electrical activity using different electrodes placed on the scalp (Berger, 1929). The electrodes measure small electrical potentials that reflect the activity of neurons within the brain. These potentials, whose amplitude is tiny, are then amplified, digitized and then transmitted to a personal computer for processing and storage. EEG measures the potential difference (i.e., the voltage) between two electrodes (Kane et al., 2017).

Electrodes can be made of various materials. Usually, EEG electrodes are made of metal plates and they are applied to the scalp using a conducting electrode gel. However, there has been an increase in the use of dry electrodes (no gel needed) in recent years (see next subsection). The positioning of the electrodes on the scalp has been standardized worldwide in the so called 10–20 international system (Klem et al., 1999).

Electrophysiological techniques usually have an excellent temporal resolution but poor spatial resolution (Burle et al., 2015). In general, EEG allows the detecting of the activity generated in the cortex only, and not in deeper brain structures because of the presence of the scalp's bones, the cerebrospinal fluid and the dura mater which act as filters for high frequencies. However, EEG spatial resolution (about 1 cm) can be increased using high-density EEG caps (128 electrodes or more).

In the temporal domain, EEG can measure Event Related Potentials (ERPs). ERPs are very small voltages generated in the brain in response to sensory, motor or cognitive events or stimuli (Blackwood and Muir, 1990). In the frequency domain, an EEG signal can be analyzed in different frequency bands, namely delta, theta, alpha, beta and gamma (Rahman et al., 2015). This analysis can be used in consumer neuroscience research to investigate cognitive processes such as attention, arousal, emotion, engagement, excitement, memory, reward, sensory perception and valence (see section 5) (Vecchiato and Babiloni,

TABLE 2 | Characteristics of Consumer neuroscience tools.

Tool	Measurement	Advantages	Disadvantages	Equipment price	Time	Integration level
EEG	Brain activity	Temporal resolution	Spatial resolution	€35K	1 hr	Medium
Wearable EEG	Brain Activity	Temporal resolution Portable Low cost	Spatial resolution	€500 to €25K	30 min.	Medium
fMRI	Brain Activity	Spatial resolution[a]	Temporal resolution[b] Expensive Non-portable Ethical concerns	€1M	1 hr.	Low
fNIRS	Brain Activity	Low sensitivity to motion artifacts Portable	Spatial resolution Temporal resolution	€50K	1 h.	Medium
ET	Visual attention Pupil dilatation Fixations[c]	Portable Low cost	Low flexibility Glasses/Contact lenses	€100 to €30K	15 min.	High
ECG	Heartbeat Blood flow	Portable Low cost	Slow signal Sensitivity to motion Low individual usefulness	€10K	15 min.	Medium
fERS	Facial expressions	High flexibility Portable	Low individual usefulness	€10K	15 min.	High
GSR	Skin moisture level	Portable	Low individual usefulness	€100 to €2K	15 min.	High

[a] *Spatial resolution refers to how accurately the measured activity is localized within the brain.*
[b] *Temporal resolution refers to how closely the measured activity corresponds to the timing of the actual neuronal activity.*
[c] *Amount and duration of fixations can be a metric for attention.*

2011; Ohme and Matukin, 2012; Di Flumeri et al., 2016; Rakshit and Lahiri, 2016; Dulabh et al., 2018).

EEG carries a relatively low cost for the equipment and tests. Depending on how many electrodes are used (and the technology employed), the estimated average cost is between ten and thirty five thousands euros per study (Lystad and Pollard, 2009). However, EEG also requires human resources for acquisition and analysis, as well as consumables. For setting up a consumer neuroscience experiment, an EEG technician and/or a data analyst to analyse data are required. A neurologist might also be required to check the quality and the reliability of the EEG signals. The average time for the preparation of a single experiment is between 30 min and 1 h, depending on the caps and the number of electrodes. The the time to set-up the experiment and the time to execute the experiment need to be added. EEG is characterized by a medium level of integration with the other neuroscience tools because it can be used in combination with various other tools, depending on the specific EEG hardware. Compared to other neurophysiological tools, EEG is more tolerant toward small physical movements made by the participant during an experiment.

4.2. Wearable Electroencephalogram

Electrophysiological techniques also include wearable EEG devices. A wearable EEG device consists of a portable cap, a base station and a pre-amplifier. The signal collected from electrodes is pre-amplified and transmitted wirelessly to the EEG amplifier through the base station.

Wearable EEG allows researchers to measure the same cognitive phenomena detectable with classical EEG. Wearable EEG is very popular in consumer neuroscience research due to increased subject mobility. We find that wearable EEG was used to investigate consumer behavior for e-commerce products and to measure users' emotional responses while watching products prior to purchase or product placement effectiveness (Murugappan et al., 2014; Yadava et al., 2017; Guo et al., 2018).

There are many different types of wearable EEG devices available on the market. Compared to traditional EEG, wearable EEG systems or headset devices are usually less expensive, because they have a low number of EEG channels. EEG headsets like Emotiv, OpenBCI, NeuroSky range from €500 up to a maximum of a few thousand euros (Lystad and Pollard, 2009). However, there are other more expensive wearable EEG devices (e.g., Nautilus from g.tec medical engineering) that have a higher number of electrodes and a higher performance. These devices can cost up to tens of thousands euros. Wearable EEG systems measure similar brain phenomena as the traditional EEG system. Compared to classical EEG systems, wearable EEG devices allow more liberty of movement for the subject. In addition, the average time for the preparation of the subject is less compared to traditional EEG (setup time of less than 5–6 min for Emotiv, Muse, and openBCI) (Qiu et al., 2019). Wearable EEG devices

also have a higher level of integration compared to classical EEG devices because they are portable. Recent studies suggest that wearable EEG systems are capable of collecting neural signals, the quality of which is comparable with those collected by the traditional EEG systems in a controlled laboratory environment (Schiff et al., 2016; Kam et al., 2019; Qiu et al., 2019). However, studies show that wearable EEG systems are more prone to artifacts from muscle movements (Badcock et al., 2013; Ratti et al., 2017; Qiu et al., 2019). Some studies also suggest that the signal of wearable EEG might be delayed in comparison to traditional EEG systems (Qiu et al., 2019). For academic purposes, the use of more complex (thus, more expensive) EEG systems, together with expert personnel, is highly recommended, since it provides a higher quality and a more reliable signal.

4.3. Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging (fMRI) is a metabolic brain imaging method used to analyse regional, time-varying changes in brain metabolism (Ogawa et al., 1990; Bandettini et al., 1992; Kwong et al., 1992). fMRI measures the BOLD (Blood Oxygenation Level Dependent) response by tracking the changes in the blood flow indicated by the relative amounts of different forms of haemoglobin. fMRI was introduced by Ogawa in 1990, so it is can be considered a "younger" tool compared to EEG (Murray and Antonakis, 2019).

fMRI can be used to produce activation maps showing which parts of the brain are involved in a certain process. These metabolic changes can (1) be induced by the execution of a specific motor or cognitive task or as a result of a stimulus (task-related fMRI), or (2) be the result of uncontrolled processes in the brain at rest, in absence of a stimulus or a task (resting-state fMRI) (Ogawa et al., 1990; Bandettini et al., 1992; Kwong et al., 1992). The fMRI modality used in consumer neuroscience research is the task-related fMRI. Thus, activation maps are produced by comparing BOLD level contrast between active periods (e.g., performing a task or exposed to a stimulus) and rest periods.

fMRI is widely used due to its widespread availability, its non-invasive nature (does not require injection of a radioisotope or other pharmacologic agent), and good spatial resolution (about 1 mm). In contrast, it has a poor temporal resolution (Burle et al., 2015). fMRI allows for analysis of hemodynamic activity in small structures and even those brain structures that are deep in the brain, which are usually involved in emotional responses (e.g., amygdala and accumbens). fMRI is very expensive. In a hospital or research center setting, the typical cost of a fMRI scan is between €500 and 800, while a fMRI scanner costs not less than €1 million (Lystad and Pollard, 2009). To have valuable and reliable data, an fMRI experiment requires a psychologist or neuroscientist who sets up the fMRI task, an MRI technician who performs the experiment, a physicist who set ups the hardware to acquire the right brain responses and a biomedical engineer (or the same physicist) who analyses the data. The average time for the execution of an fMRI scan is about 30 min, which includes the time for the preparation of the subject and the time to acquire the images.

In the literature, we find that fMRI is the second most used neuroimaging tool in consumer neuroscience experiments. In fact, fMRI scanners are easily available compared to other neuroimaging tools. Several fMRI studies investigate many cognitive phenomena, such as sensory perception, attention, arousal, emotion, engagement, memory, reward and valence (McClure et al., 2004; Deppe et al., 2005; Esmaeili et al., 2011; Santos et al., 2012; Ruanguttamanun, 2014; Sebastian, 2014; Koestner et al., 2016; Shen and Morris, 2016). fMRI is a suitable tool to study consumer preferences for visual stimuli (e.g., videos, images). However, fMRI might not be suitable if researchers want to replicate exact "real-world circumstances," for example touching the product or drinking from a glass. In fact, fMRI restricts participants' movements considerably, as they lie in a narrow tube (Alvino et al., 2019). Overall, fMRI may have a restricted external validity compared to other tools (e.g., EEG). There are some safety concerns on the use of this tool. Although fMRI can not be not considered an invasive tool, many subjects can suffer due to the noise of the machine (especially for fMRI sequences), the small space (claustrophobia, vertigo, nausea) and potential movement or heating of ferromagnetic objects in the body (e.g., pacemakers, surgical clip). For these reasons, subjects might not be able to complete the scan (Lystad and Pollard, 2009). Finally, fMRI has a low level of integration with other tools, due to the presence of magnetic fields. Thus, it can be integrated only with devices compatible with magnetic fields.

4.4. Functional Near-Infrared Spectroscopy

Functional near-infrared spectroscopy (fNIRS) is a non-invasive, metabolism-based brain imaging technique. It measures change in the blood's color when oxygen is delivered to brain tissue (only the top few mm of cortex) (Villringer et al., 1993; Boas et al., 2004; Burle et al., 2015). fNIRS, similarly to fMRI, is a BOLD-response technology that measures the changes in the relative levels of oxyhemoglobine (oxy-Hb) and deoxyhemoglobine (deoxy-Hb) during brain activity. When a subject performs a task, brain activity increases in those brain areas relevant to the task due to changes in oxy- and deoxy-Hb (Ernst et al., 2013).

fNIRS is relatively easy to use as its technology supports fast data acquisition from numerous positions (Ehlis et al., 2005; Sitaram et al., 2009). Its temporal resolution is relatively good (few seconds), but it seems to be lower in comparison to EEG. In addition, fNIRS cannot be applied when the focus of the research is the investigation of cognitive processes which rely on deeper structures of the brain. In fact, fNRIS's spatial resolution is very low, making it difficult to distinguish between cortical areas that are positioned close to each other.

We find that the use of fNIRS in consumer neuroscience research is very recent. fNIRS is used to investigate consumer attention, arousal, emotions, sensory perception, and valence, especially for mobile technologies (Plichta et al., 2011; Ernst et al., 2013; Cakir et al., 2018; Krampe et al., 2018). In general, fNIRS is easily available for economic researchers (Shimokawa et al., 2009; Weiskopf, 2012; Kober et al., 2014). fNIRS is a noise-free neuroimaging tool, and thus it can be very useful in studies in

which auditory stimuli play an important role (unlike fMRI) (Plichta et al., 2011). The low sensitivity of motion artifacts also creates strong potential for fNIRS and its application in real world scenarios (Nambu et al., 2009; Lloyd-Fox et al., 2010; Kober et al., 2014).

fNIRS equipment is portable and inexpensive compared to other blood-flow measurement technologies, such as fMRI. fNRIS's price is around €10.000, but it can go up to €200.000 (depending on the technique and associated electronics). An fNIRS experiment needs at least an expert technician to perform the experiment and a data analyst. The average time needed to perform an fNIRS session is about 1 h, which includes the time for the preparation of the subject (measurements of anatomical landmarks, positioning of the cap, digitization of the positions of the sensors) and the time to perform the experiment, which usually takes place in a block-design paradigm experiment, alternating active periods with rest periods. fNIRS, particularly the portable version, is characterized by a good level of integration with other consumer neuroscience tools.

4.5. Eye Tracking

An eye tracker (ET) is a device that allows the measurements of eye positions, eye movement and pupil dilatation. Researchers can use ET to measure how information on the screen is related to behavioral and emotional responses (Wang, 2011). ET measurements are fixation (looking at a specific place), length of fixation (how long a person looks), saccades (fast eye movement) and pupil dilation responses (changes in pupil size) (Wang, 2011). ET technologies usually measure eye gaze and movements at specific (and fixed) points on images or videos. However, there are more advanced devices that allow the automatic tracking of the user's head position and movement (Zurawicki, 2010). Such enhancements make the measurement process more subtle, with very little or no interaction between the researchers and their subjects. In the market, there are two types of ET devices available, namely fixed ones, which are integrated in another device (i.e., a computer monitor) and wearable ones, which consist of spectacles with integrated cameras.

ET has been widely used in consumer neuroscience research to study visual behavior (e.g., fixation, gaze, pupil dilatation), customers' visual attention mechanisms and consumers' engagement (Zamani et al., 2016; Ungureanu et al., 2017). ET has several advantages: it is portable, non-invasive, simple to use and relatively inexpensive. ET has a cost ranging between €100,000 and 300,000, depending on the level of the technology and whether the software to acquire and analyse data is included[1]. An ET experiment needs only a technician and, eventually, a data analyst. The average time needed to perform an ET experiment is about 15 min since the subject set-up is very fast. This time covers only the time needed to perform the experiment by the subject. Not all the ET has a high flexibility as some ET models might not work efficiently with glasses and contact lenses. ET is also characterized by a high level of integration with other tools due to its portability and because it is a "ready-to-use" device. To have more reliable results, ET should be used in combination with other tools.

4.6. Facial Expression Recognition Software

Facial expressions are important metrics of subjects' emotions. They are usually divided into two main categories: observable and unobservable (Fortunato et al., 2014). The analysis of facial expression is divided into two main classes, namely facial electromyography (fEMG) and facial expression recognition software. The former category measures voluntary and involuntary facial muscle movements reflecting emotional reactions toward a marketing stimulus (Bercea, 2013; Cherubino et al., 2019). The latter category is based on the use of specific software to record and analyse facial expressions based on decision classifiers, and is able to predict a purchase substantially above the chance level.

Facial expression recognition software (fERS) can be used to measure positive or negative reactions to marketing stimuli (e.g., videos). fERS is a valuable tool to investigate consumers' excitement, engagement, emotions and valence (Ângelo et al., 2013; Hamelin et al., 2017; Hernández-Fernández et al., 2019).

There are many facial recognition software platforms in the market. For example, Software iMotions Neuromarketing combines different sensors and is able to detect a subject's attention, valence and emotions (iMotions, 2020). In contrast, the Facial Action Coding System is an online platform to measure emotions and understand human behavior through face analysis[2].

The costs of an fERS are highly variable and depend mainly on how many integrated sensors the platform is able to manage. If we consider only the platform (excluding the sensors), the cost of such software can be around a few thousand euros. Conducting an experiment using facial recognition expression requires one technician to acquire face data and a technical expert for data analysis. The average time needed to perform such an experiment is 15–20 min. No subject preparation is required. Finally, this tool is characterized by a high level of integration with other consumer neuroscience tools. fERS is portable, very easy to use and can manage the data of various sensors. Using only fERS has a limited application for consumer neuroscience research, as it does not measure important cognitive processes such as attention, memory and sensory perception.

4.7. Electrocardiogram

Electrocardiogram, also called ECG or EKG, is a tool used to measure the electrical activity of the heart (Stern et al., 2001). Heart rate variability (HRV) is the physiological phenomenon of variation in the time interval between heartbeats and it reflects the activation of the sympathetic and parasympathetic parts of the autonomic nervous system. Several studies reported that changes in the hearth rate (HR) might be correlated with changes

[1](2020). *Marketing and Consumer Research*. Available online at: https://www.tobiipro.com. Emotion Research Lab.

[2](2020). *Facial Action Coding System*. Available online at: https://emotionresearchlab.com. Emotion Research Lab.

in the emotional state of a subject (arousal and valence) (Ha-Brookshire and Bhaduri, 2014; Valenza et al., 2014; Baraybar-Fernández et al., 2017).

ECG is a very simple, portable, non-invasive, widely used and accessible tool that has a good temporal resolution. To use ECG, researchers need only the device, a monitor and a computer to synchronize the ECG signal (electrophysiological response) with the stimulus. ECG has quite low costs (around tens of thousands euros). The average time needed to perform an experiment using ECG is about 15 min, because subject preparation is very fast. It does require specialized personnel to acquire and analyse the signal. However, ECG has limited applications because it should be used in combination with other consumer neuroscience tools.

4.8. Galvanic Skin Response

Galvanic Skin Response (GSR) is a physiological tool that measures the electrical conductance of the skin through one or two sensor(s), usually attached to some part of the hand or foot (Nourbakhsh et al., 2012). The physiological basis of the galvanic skin response is a change in autonomic tone (skin and subcutaneous tissue) in accordance with the emotional state of the subject. It is used to measure skin resistance, conductance, and stress level in the body.

GSR is also considered a sensitive tool for measuring changes in subject's arousal and valence (Ravaja, 2004; Ayata et al., 2016). Skin conductivity (SC) can reveal an activation in the autonomic nervous system (ANS) (Nourbakhsh et al., 2012). Because an increase in the activation of the ANS is an indicator of arousal and valence, SC can be used as a measure of arousal and valence (Vecchiato et al., 2014; Ayata et al., 2016).

GSR equipment is easy to set up and transport, making it ideal for work in the field, for example, for assessing levels of emotional arousal during in-store shopping experiences. However, GSR has a low temporal resolution. In fact, different skin types can create variability in responses across subjects, thus making results difficult to aggregate. In addition, GSR is very sensitive to artifacts. In fact, test subjects can freely move their hands and body which may result in artifacts or false readings in the GSR. During data analysis, artifacts can be detected and removed by applying post-processing tools. The major limitation of GSR is that it can only measure changes in subject's arousal and valence but it cannot determine the direction or the valence of an emotional reaction. GSR requires at least a computer to correlate the stimulus with GSR software to have reliable results.

The average cost of a GSR amplifier is in the order of a few thousand euros. A GSR experiment requires one technician to acquire GSR data and a technical expert for data analysis. The average time needed to perform a GSR experiment is about 15 min because subject preparation is very fast. Finally, GSR is characterized by a high level of integration with other consumer neuroscience tools as it is portable and very easy to use (Ozkul et al., 2019).

5. MAIN APPLICATIONS IN MARKETING

Consumer neuroscience has the potential to support marketing research on how cognitive processes (e.g., perception, memory, attention) originate in the brain and identify the brain areas involved in the explication of cognitive functions underlying marketing-relevant behavior. This section focusses on how consumer neuroscience tools are used to study consumer behavior. On the basis of the literature survey we identify the following marketing-related topics where these tools are used: advertising, branding, product experience, online experience, product development and product pricing.

5.1. Advertising

We find that almost 45% of the studies (61 studies) investigate the impact of advertising on consumer behavior (e.g., preferences, satisfaction), emotions (e.g., positive, negative), and cognitive processes (e.g., attention, memory, engagement). Consumer neuroscience research analyses how consumers experience, process and assess advertisements (Astolfi et al., 2008; Ohme et al., 2010; Treleaven-Hassard et al., 2010; Morillo et al., 2015; Soria Morillo et al., 2016; Cha et al., 2019; Golnar-Nik et al., 2019; Kaklauskas et al., 2019; Kumar et al., 2019; Mahamad et al., 2019; Shaari et al., 2019). Studies focus on all types of advertising, i.e., brochure, billboard advertising, endorsements by spokespersons, movie trailers, television advertisement, social advertisement, Youtube videos and websites (Ohme and Matukin, 2012; Vecchiato et al., 2012a,b; Randolph and Pierquet, 2015; Hamelin et al., 2017; Jin et al., 2017; Missaglia et al., 2017; Kong et al., 2019).

Depending on the tool used, we can get information on how consumers process advertising stimuli. For instance, EEG can be used to evaluate the effectiveness of advertising by measuring the brain activity within milliseconds (Vecchiato et al., 2011; Kong et al., 2013; Pileliene and Grigaliunaite, 2017b). In particular, EEG oscillations, measured through the changes in spectral power of EEG for some certain frequency bands, and in specific brain regions, while investigating in the frequency domain, or, while investigating in the time domain by looking at the derivation of particular event-related potential (ERPs), can indicate a higher or lower level of attention/memory/engagement of participants for a different type of advertisements (e.g., movie trailers, anti-binge-drinking campaigns, Boksem and Smidts, 2015; Gountas et al., 2019, see **Table 3**).

Another important tool used to investigate consumers' responses to advertisement is eye tracking. ET allows researchers to determine consumers' visual attention though heat maps, scan path and eye fixations (see **Table 4**). Measuring where and for how long a person is looking at a specific advertisement could provide important information on the level of attractiveness (e.g., high number of fixations vs. low number of fixations) and visibility (e.g., right size of product in the advertisement) of an advertisement (e.g., Youtube video, product image) (Venkatraman et al., 2015; Zamani et al., 2016).

fMRI is used to test advertisement effectiveness for product images. In particular, fMRI can be used to investigate the hemodynamics response (brain activations) in brain regions responsible of these phenomena (Morris et al., 2009; Kühn et al., 2016; Shen and Morris, 2016; Jung et al., 2018; Casado-Aranda et al., 2019). As it has a low temporal resolution, fMRI might not always be suitable for measuring brain activity during the view

TABLE 3 | Neurophysiological tools: applications in marketing, products, and services.

Tool	Cognitive processes	Behavioral measurements	Marketing application	Product or service
EEG	Attention Arousal Emotion Engagement Excitement Memory Reward Sensory perception Valence	Age difference Consumer preferences Consumer satisfaction Gender difference Intention to purchase Sentiment score Purchase behavior	Advertisement Brand In-store experience Online experience Price Product characteristics Product experience Product quality Promotion	App Brand names Car Clothes Coupon Drink Food House Mobile phone Movie trailers Music Shoes Perfume Text-to-speech Television commercial Video Wine
Wearable EEG	Attention Arousal Emotion Engagement Excitement Memory Sensory perception Valence	Age difference Consumer preferences Consumer satisfaction Gender differences Sentiment score Purchase behavior	Advertisement Brand In-store environment Online experience Price Product characteristics Product experience Promotion	Accessories and Bags Car Celebrity Clothes Coffee mug Food Shoes Sport activities Spoken-person Television commercial Video
fMRI	Attention Arousal Emotion Engagement Memory Sensory perception Reward Valence	Consumer preferences Consumer satisfaction Gender difference Sentiment score Purchase behavior	Advertisement Brand Price Product characteristics Product experience Product quality Promotion	Book Brand logo Car Food Wine
fNIRS	Attention Arousal Emotion Sensory perception Valence	Consumer preferences Purchase behavior	Advertisement Brand Price Product characteristics Product experience Product quality	Drink Lipstick Paper and display media Music player Music

of audio-visual stimuli, due to the quick changes in the scenes (Zurawicki, 2010).

Finally, tools such as GSR, ECG and facial expression recognition software can be used to measure emotional responses (e.g., sadness, joy, fear) to advertisement (Guixeres et al., 2017; Missaglia et al., 2017; Goyal and Singh, 2018). For instance, these tools can be used to test how the effects of high emotional and low emotional advertising in social advertisement (e.g., safe driving video) or YouTube videos (e.g., professional bank speakers) can affect consumer behavior (e.g., safe driving attitude) and preferences (e.g., video's popularity) (Lewinski, 2015; Hamelin et al., 2017).

TABLE 4 | Physiological tools: applications in marketing, products and services.

Tool	Cognitive processes	Behavioral measurements	Marketing application	Product or service
Eye Tracker	Attention Excitement Engagement	Age difference Consumer preferences Gender difference	Advertisement Brand In-store environment Destination marketing Online experience Product characteristics	Brand logo Car Clothes Drink Food Household products Spoken-person Video Website Wine
Galvanic Skin Response	Arousal Emotion Valence	Age difference Consumer preferences Gender difference	Advertisement Brand In-store environment Online experience Product characteristics Product experience	Brand logo Car Clothes Food Store color and light Perfume Television commercial Video
Electrocardiogram	Arousal Emotion Valence	Age difference Consumer preferences Gender difference	Advertisement Brand Online experience	Advertisement spot Perfume Television commercial Video
Facial Expression Recognition Software	Emotion Engagement Excitement Valence	Age difference Consumer preferences Gender difference Sentiment score	Advertisement Brand In-store environment Online experience Price Product characteristics Product experience Product quality	Brand logo Food Google glass Music Store color and light Spoken-person Television commercial Video

Overall, we find that there are three different areas that could benefit from the application of consumer neuroscience tools in advertising. In particular, we can use these tools to test:

- Advertising effectiveness
- Target audience
- Salient features.

Advertising effectiveness measures how well a company's advertising (or advertising campaign) reaches and generates interest among customers or potential customers. Advertising effectiveness is usually measured in relations to sales (Wells, 2014). However, consumer neuroscience research can provide researchers and companies with measurements that give a better understanding of how consumers respond to an advertisement (e.g., positive or negative). It helps to study how customers acquire and process advertisement information and how behavioral measurements can be linked to cognitive and neuronal processes. In particular, consumer neuroscience tools can help to study those behavioral measurements (e.g., preference, satisfaction) and cognitive processes (e.g., attention, engagement and memory) that are useful to investigate when determining how an advertisement can catch consumers' attention, or is encoded in their memory. Many studies focus on post-design application. However, consumer neuroscience tools can also be very useful in pre-testing an advertisement—selecting spokespersons (e.g., female), the right color temperature and type of music to use in advertisement campaigns, for example (Wang et al., 2016; Pileliene and Grigaliunaite, 2017a; Avinash et al., 2018; Daugherty et al., 2018).

Another important aspect to consider in advertising is selecting a company's target audience; the group of customers or potential customers to whom a company addresses its product or service. Finding the right target audience is crucial to improve a campaign's efficiency. Consumer neuroscience tools can be used to test the impact of advertisements on different target audiences (e.g., male, female, young, adult, user, no user). For instance,

Añaños (2015) used ET to measure differences in the level of attention in elderly adults, compared with young people during TV commercials. The results show that elderly people show a lower level of attention for integrated content compared to young people (Añaños, 2015). This finding suggests that advertising formats (low, medium, high level of disruption) can have a different impact on recognition between different target groups.

Finally, consumer neuroscience tools can be used to test an advertisement's salient features. An advertisement with good salient features is capable of holding a consumer's attention and it has great memorizing value. Consumer neuroscience tools measure how different versions of an advertisement or changes in a TV commercial or video (e.g., length, speed, complexity of the scene) can affect consumers' preferences, attention or recall for the advertisement (Zurawicki, 2010). A good example of salient features testing is the study of Ohme et al. (2009). The study measured the impact of two versions of a skin care product advertisement using EEG, EMG, and GSR. Results show that people were unable to identify any differences between the two advertisements at a conscious level (when asked). However, the neurophysiological measurements show that there was an increase in alpha bands (detected using EEG) and arousal level (detected using GSR) during the extra scene (model's gesture) in one version. EMG also revealed a significant difference in the facial muscle activity while watching the alternative scenes of the ad, specifically the additional scene provoked a higher level of corrugation muscle activity. This finding suggests that consumer neuroscience tools can add useful and important information to study an advertisement's salient features.

5.2. Branding

In today's economy, consumers buy emotional experiences rather than products and services (Hultén, 2011). The emotional linkage and experience associated with a brand is extremely important in building strong brands. Consumers' expectations on how much enjoyment they will derive from consuming a certain brand does not depend on the real value of the brand. Consumer expectations derived from consuming a brand are a mix of emotional and cognitive factors, and these expectations are usually formed on an unconscious level (Plassmann et al., 2012). Thus, consumers often find it difficult to describe why they enjoy a specific brand and/or why they are able to remember a brand. Consumer neuroscience tools can help companies to study emotional and neuronal processes while consumers choose, experience and remember brand's name or logos.

We identify two ways in which consumer neuroscience can contribute to a better understanding of the psychology of branding.

- Brand choice
- Brand loyalty.

People often choose products based on their perceived value, thus what the brand represents rather than the brand's actual value (Airey, 2009). Consumer neuroscience tools can be used to investigate the emotional component underling brand evaluation and choice, for example, differences between two similar brands (e.g., Pepsi vs. Coke) (Ma et al., 2007, 2008; Lucchiari and Pravettoni, 2012; Reimann et al., 2012a,b; Pop et al., 2013; Al-Kwifi, 2016; Guo et al., 2018). Bosshard et al. (2016) used EEG to test whether or not liked and disliked brands are further associated with different motivational aspects. The findings of this study suggest that liked brands elicited significantly more positive going waveforms (late positive potentials) than disliked brands over right parietal cortical areas. This result might infer that liking a brand influences consumers' electrical brain activity. In addition, consumer neuroscience tools can help to investigate how different brands are encoded, consolidated, and retrieved from the consumer's memory (McClure et al., 2004; Wang et al., 2012; Kačániová and Vargová, 2017; Levrini et al., 2019; Sung et al., 2019). For instance, remembered value refers to how different brand associations are encoded, consolidated, and retrieved from the consumer's memory (Plassmann et al., 2012). Using consumer neuroscience tools can help companies create and design strong brands that are easy to remember and have a strong emotional appeal.

Brand loyalty can be defined as the positive attitude toward a brand (Ferrell and Hartline, 2012). Customers that are loyal to a brand have a consistent preference for that brand, despite other situational and marketing factors that have the potential to induce switching behavior (Oliver, 1999). Consumer neuroscience tools can help researchers to study the neuronal and cognitive processes underlying brand loyalty (McClure et al., 2004; Schaefer and Rotte, 2007; Lin et al., 2010; Plassmann et al., 2012). For instance, Plassmann et al. (2007) investigated the differences in neural activation between loyal and disloyal customers of a store during purchasing decisions. Based on psychological theories, the authors assumed that for loyal customers the exposure to the store brand would modulate their decision via an emotion-based path. The authors found that customers who are loyal to a brand show more activation in the striatum compared to customers who are less loyal, even if they are buying identical clothes. The finding of this study also suggests that loyal customers usually establish an emotional bond with the physical brand stores, which might be the underlying psychological driver of their repurchases.

5.3. Online Experience and Website Optimization

Living in the digital era offers new opportunities for both consumers and companies. Consumers usually have a very wide offer of products and services worldwide, which is accessible 24/7. Similarly, companies have easier access to customers' information (e.g., location, age). Companies can also now reach their customers more easily by automating customer services (e.g., chatbot) and creating personalized messages for customers (e.g., personalized emails). Thus, the use of digital channels in business contributes to creating a very dynamic and competitive environment. Understanding the psychology behind online consumer behavior is key to compete in today's markets.

Consumer neuroscience tools can improve the online customer experience by testing the effectiveness of digital marketing campaigns for:

- Online rating and electronic word-of-mouth (eWOM) and

- Website and app optimization.

The increasing use of the Internet affects how people gather information. Nowadays, consumers can receive information on product and services more easily and faster compared to 20 years ago. In particular, online reviews, and eWOM (e.g., blogs) have become a significant and common way to acquire information about a company or a brand. Since online reviews and eWOM can influence other customers or potential customers, companies try to adopt strategies that can affect customers' rating behavior (Wang et al., 2018). Consumer neuroscience tools can be used to assess the effectiveness of online strategies by analyzing the emotional responses of consumers to online ratings and reviews (Wang et al., 2018; Hernández-Fernández et al., 2019). Measuring physiological and emotional responses associated to different strategies (e.g., a discount coupon for a five-star rating) may help to determine (1) how consumers perceive digital marketing strategies (e.g., aggressive, invasive) and (2) determine the emotional responses (positive, negative, surprise) to specific reviews or discussion topics (e.g., environment, service).

Website and App optimization is another important aspect of digital marketing strategies. Designing a good website or App is critical to improve the quality of the user experience (e.g., customization, online appointments, orders). An effective website or App should take into account different factors such as visual design and layout, usability, speed, content and search. Consumer neuroscience can be useful to test consumers' emotional responses to these factors (e.g., layout) and optimize websites and Apps (Chai et al., 2014; Jin et al., 2017; Yadava et al., 2017; Casado-Aranda et al., 2019). For instance, ET is an effective tool to test how users interact with a website (e.g., Mercedes-Benz) (Etzold et al., 2019). In fact, ET heat maps help identify shortcomings and hidden information (e.g., search button) when customers navigate on a website.

5.4. Pricing

One important element of the marketing mix that may influence consumer behavior is price. In the literature, only a few studies investigate how price influences cognitive and neural mechanisms. In particular, consumer neuroscience tools are used to study the effect of price on experienced quality by consumers (e.g., positive or negative expectations).

Consumer Neuroscience tools can be used to study three important aspects in pricing strategy:

- Price fairness
- Premium pricing
- Promotion.

Price fairness refers to the process that leads consumers to define if a price is reasonable or not, compared to one or more prices (Xia et al., 2010). Usually, people want to pay less for products, however, prices below a lower price-threshold may signal poor product quality. Instead, prices above an upper threshold may be considered as too high (price deception) (Fu et al., 2019). The biggest challenge for companies is to set a "fair" price for customers without altering their perception of quality (Cakir et al., 2018; Wang et al., 2018). Consumer neuroscience tools can be used to assess how consumers experience price and the effect of price based on their brain activity (e.g., positive, negative). For instance, consumer neuroscience tools can be used to study the difference in brain activity when consumers are exposed to low, optimal, and upper price-thresholds (Linzmajer et al., 2011).

Premium pricing, also known as prestige pricing, is used to influence consumers' expectations of the product and ultimately shape product experience (Almenberg and Dreber, 2011). Premium price is the marketing practice of selling a product for a higher price than competitors. Consumers usually associate the high price with higher quality. Thus, premium price creates an illusion of higher quality. Many marketing studies examine how knowledge about the price of a good affects how the good is experienced (Steenkamp et al., 2010; Almenberg and Dreber, 2011; Sellers Rubio et al., 2016). Consumer neuroscience studies also investigate how people enjoy consuming identical products (e.g., wines, underwear) more when they have a higher price. For instance, Plassmann et al. (2008) used fMRI to examine how tasting the same wine with different price (low and high) can effect consumers' preferences and brain activity. Their findings suggest that drinking wine with a higher price increase consumers' consumption enjoyment. In fact, the study found an increase in the medial orbitofrontal cortex (mOFC) due to changes in the price of a wine. mOFC is correlated with behavioral pleasantness for odors, tastes and music. The results suggest that increased activity in the mOFC leads to a change in the actual experienced pleasantness derived from its consumption (Plassmann et al., 2008).

Finally, consumer neuroscience tools can be used to assess the effect of promotion on buying behavior for coupons, promoted and non-promoted products, and unstructured or structured sales techniques (Jones et al., 2012; Muñoz-Leiva et al., 2019). Using EEG, Jones et al. (2012) measured consumers' brain activity during buying decisions for promoted (e.g., 15%) and non-promoted products. The author investigated how consumers (both male and female) with different characteristics (high and low math anxiety) respond to different buy/no buy decisions for promoted and non-promoted products. Using ERPs, Jones et al. (2012) tested if high math anxiety leads to a risk-reduction buying mentality (buy/no-buy decisions) compared to low math anxiety and if this difference was influenced by gender. The results showed a difference in the brain activity of High MA consumers (process price information relatively less fluently) compared to Low MA consumers (process price information more fluently) during buying decisions (e.g., larger LPC was detected for Low MA females under no promotions for non-buys compared to High MA females). This may be due to the adoption of a decision style which seeks to reject offer prices whereas High MA females may assess prices via attempting to confirm them (Jones et al., 2012). In addition, larger FN400 amplitudes associated with enhanced conceptual processing) were linked to purchases under promotions among High MA females and Low MA males (Jones et al., 2012). The reverse effect occurred for High MA females under no promotions (larger FN400 were4 found for non-buys than buys) (Jones et al., 2012). Overall, the results suggest that math anxiety, promotion format, and gender influence

both consumer behavior and brain activity during consumer buying decisions.

5.5. Product Development

Consumer neuroscience research can help companies to design and develop desirable products by studying consumers' preferences for a product's internal and external characteristics. External characteristics (or aesthetics) refer to the visual, tactile and formal attributes of a product, such as color, shape and materials (Rindova and Petkova, 2007). The literature suggests that external characteristics can strongly influence consumers' perception and preference of products. For instance, colors can influence moods and feelings (positively or negatively), and consequently a consumer's attitude toward certain products (Singh, 2006). Internal characteristics refer to those specific and physical properties (e.g., ingredients, durability, taste) that cannot be changed without altering the nature of the product itself (Olson, 1976). However, consumers' perceptions of internal characteristics may be modulated by external characteristics. Consumer Neuroscience tools can be used to investigate how product characteristics influence consumers' sensory perceptions and preferences (Milosavljevic et al., 2012; Touchette and Lee, 2017; Muñoz-Leiva and Gómez-Carmona, 2019; Ploom et al., 2019). In particular, studies investigated how design, visual and tactile attributes influence consumers' brain activity. Consumer neuroscience tools also allow researchers to study how consumers assess product quality. Research on product characteristics mostly focussed on post-design applications. In the future, consumer neuroscience tools might be used to help companies developing new products in terms of:

- Product characteristics
- Product quality.

Consumer neuroscience research also focusses on the impact of external characteristics (e.g., packaging, color) on consumers' physiological and neuronal responses. For instance, (Reimann et al., 2010) used fMRI to examine the effect of different packaging designs (decorated vs. standard) on consumers' engagement and affective processing (reward). The results of that study show that intense emotional responses, such as the view of decorated packages, elicited strong affective processing. In fact, brain areas related to the reward system (nucleus accumbens and the ventromedial prefrontal cortex) were active during the view of decorated packaging. These results suggest that decorated packaging triggers reward mechanisms and choice compared to plain and simple packaging design.

Understanding how consumers assess product quality is important to study as it may influence consumer buying behaviors. Product characteristics can affect how consumers perceive product quality (Olson, 1976). The evaluation of product characteristics is a cognitive process that modulates attention, thus, consumer neuroscience tools can be used to analyse neural processes that occur during product evaluation. For instance, EEG can be used to test attentional mechanisms during consumers' evaluation of product quality for different products (e.g., shoes, music, wine) due to its high temporal resolution (Yilmaz et al., 2014; Gkaintatzis et al., 2019). Instead, fMRI can also be used to measure how consumer expectations of product quality are assessed based on product characteristics and individual preferences (Muñoz-Leiva and Gómez-Carmona, 2019).

5.6. Product Experience

Product experience occurs through interaction between the consumer and the product, physically or visually (Brakus et al., 2009). During the product experience, consumers are typically asked to reflect on the physical and emotional reactions induced by product experience. Another important contribution of consumer neuroscience research is the study of sensation or perception during product experience. Sensation is the activation of sensory receptor cells at the level of the stimulus (e.g., taste receptors). Perception is the processing of sensory stimuli into a meaningful pattern (BCcampus, 2018). The process of sensory perception begins when a product (e.g., perfume) stimulates our sense organs (e.g., tongue, nose, skin). Consumer neuroscience studies how people process, recognize and characterize sensory information through the five major senses, sight, smell, taste, touch and hearing. Several consumer neuroscience studies investigated how appearance, odor, flavor, taste and texture attributes can influence sensory perception and preferences of different products (e.g., food, lipsticks, music, water, wine) (Nittono and Watari, 2017; Tanida et al., 2017; Avinash et al., 2018; Hsu and Chen, 2019; Meyerding and Mehlhose, 2020). For instance, (Alvino et al., 2019) used EEG to measure brain activity and individual preferences for red wines during two tasting sessions (blind and normal). The findings of that study suggest that EEG is a useful tool to study brain activity during product experience due to its high temporal resolution and superior manoeuvrability compared to other consumer neuroscience tools.

Overall, consumer neuroscience tools can be used to study different types of product experience:

- In-store experience
- Destination marketing and Tourism.

In-store experiences occur when a consumer interacts with a store's physical environment (Kerin et al., 1992; Brakus et al., 2009). In-store experience does not necessarily lead to sales but it can encourage visitors to the store. Thus, improving in-store experience can help companies to be more competitive by offering experiences that are not available online. The effect of in-store experience can be tested by measuring how in-store variables, such as color, light, or music on consumers influence consumer buying behavior (Berčík et al., 2016; Ozkul et al., 2019). For instance, consumer neuroscience tools can be used to study the effect of light intensity and color temperature on purchasing decisions for fresh food (e.g., meat, dairy products) and beverages (wine, alcohol) (Horská and Berčík, 2014). Those studies used portable devices, like wearable EEG and ET, to measure consumers' physiological responses.

Finally, consumer neuroscience tools are used to test tourism satisfaction and measure physiological reactions during tourism experiences (Ma et al., 2014; Muñoz-Leiva et al., 2019). Consumers usually choose a travel destination not only based on

the style of vacation they want but also considering the time, price and accommodation. However, emotional reactions to tourist destinations play a big role in their choices. Thus, travel agencies usually try to create campaigns that emotionally resonate with consumers, to create a deep emotional bond between the destination (e.g., city, hotel) and the customer. Consumer neuroscience tools can be used to assess which elements of the destination marketing campaign can trigger positive or negative emotions. For example, (Bastiaansen et al., 2018) using EEG to evaluate the effectiveness of tourist destination marketing content in movies on Bruges and Kyoto. We find that the number of studies on tourism experience is limited. However, consumer neuroscience tools might be used in the future to assess how consumers experience tourism and hospitality services, for instance, room and spa services.

6. NEW METHODS IN CONSUMER NEUROSCIENCE RESEARCH

We find two ready-to-use platforms that allow the use of several consumer neuroscience tools (e.g., ET, GSR) simultaneously. Several studies have already used a combination of different consumer neuroscience tools (e.g., ET, ECG). Using ready-to-use platforms may facilitate researchers to measure behavioral, physiological, and neurophysiological responses in a single experiment. Measuring brain activity and physiological responses simultaneously could help researchers to link cognitive and emotional aspects with neuronal processes during product experience (e.g. beverage tasting), online and offline purchase decisions, product quality assessment and brand exposure. Furthermore, ready-to-use platforms might also ensure a more reliable timing of signal acquisition, and direct synchronization between stimuli and responses (iMotions, 2012). Thus, these advantages could contribute to creating more realistic theories and models in consumer neuroscience research. In this section, we compare two platforms and identify potential benefits and limitations of these methods.

The first method is iMotions Platform (iMotions platform iMotions A/S, Kobenhavn V, Denmark). iMotions is an integrated analysis platform that measures consumer behavior and monitors different aspects of human responses to marketing stimuli using different sensors. iMotions platform provides full integration and synchronization support for more than 50 biosensors. iMotions can integrate up to six consumer neuroscience tools such as ET, facial expression analysis software, GSR, ECG and EEG headsets. iMotions also uses Application Programming Interface (API) and Lab Streaming Layerand for additional sensor integration. Most importantly, iMotions has a built-in survey tool that triangulates respondents' behavioral data (e.g., answers to survey) with neurophysiological responses, providing higher validity to consumer neuroscience experiments. iMotions allows users to perform studies in different environments such as laboratory, shops. This platform can be used to study consumer behavior and neurophysiological responses by exposing subjects to images, videos, games, apps, or software and allowing them to test real-like objects in product design studies and media/ad/website testing. It enables the easy set-up of participant groups, randomizations, and block designs as needed, and the data can be viewed both in real time and replay. iMotions software platform has been recently used in consumer neuroscience research. This was used to (1) measure willingness to pay, (2) the effect of music in advertisements, and (3) to evaluate the efficiency of online appointment booking platforms (Cuesta et al., 2018; Kulke et al., 2018; Ramsøy et al., 2018; Etzold et al., 2019). The main advantages of iMotion are that it can be adjusted to the needs of customers. There are different versions and the number of integrated tools can be changed. Another advantage of iMotions is that it can be used both in real-life or lab settings.

The second method is GRAIL (Gait Real-time Analysis Interactive Lab) system. The GRAIL system (Motek Medical BV, the Netherlands) is a new medical device that uses an instrumented dual-belt treadmill placed in a speed-matched and synchronized virtual reality (VR) environment and a motion-capture system (VICON system, Vicon Motion Systems Ltd UK). GRAIL allows users to perform clinical gait analysis, which consists of the computation of various gait parameters such as posture, muscle activation and ground reaction forces in real-time (Van den Bogert et al., 2013). The core element of the system is represented by the D-Flow software platform, which integrates both motion capture technology and a motion platform, allowing the subject to interact in real time with the system and receive feedback from it. D-Flow controls all the hardware connected to the system and also includes a 3D game engine to provide interactive VR environments to mimic real-life situations that engage subjects. In fact, it makes the subject part of a real-time feedback loop, in which multi-sensory input devices measure behavioral and physiological responses, while output devices return motor sensory, visual and auditory feedback to the subject. A semi-cylindrical 180°projection screen immerses the subject in a virtual reality environment that mimics real-life situations (i.e., a market). In addition to this, thanks to D-Flow software, it is possible to integrate other tools such as electromyography, electroencephalography, electrocardiography, galvanic skin response, eye tracking and head motions detection technology.

To our knowledge, GRAIL has been never used in consumer neuroscience research. However, it could represent a useful and complete tool for consumer neuroscience research for several reasons. D-Flow software has an intuitive interface that allows operators to easily control hardware, tailor applications or define their own applications. In addition, the D-Flow interface does not require programming skills, therefore, less training is required compared to other consumer neuroscience tools for researchers and practitioners who do not have technical skills (e.g., coding, programming). Using GRAIL would facilitate companies and universities to carry out consumer neuroscience experiments by reducing the time and expenses of training (e.g., fewer training sessions, in-house training). Finally, the use of fully customisable VR environments could increase the efficacy and the accuracy of consumer neuroscience research. Consumer neuroscience experiments too often simplify the complexity of the decision process because experiments are carried out in a laboratory

TABLE 5 | Advantages and disadvantages of modern platforms.

Platform	Tools	Advantages	Disadvantages
GRAIL	Wearable EEG Facial EMG ET Head motion ECG GSR	Gait analysis Custom. virtual env. VR to improve user exp.	High cost Not portable
iMOTION	Wearable EEG ET ECG GSR Head motion Facial EMG	Portable Relatively low cost	No gait analysis No custom. virtual env.

setting (Lee et al., 2018; Alvino et al., 2019). Participants are subjected to a standardized procedure and there is no interaction with the external environment. The synchronized virtual reality (VR) environment of GRAIL immerses participants in a virtual scenario that reproduces real-life situations, while researchers can monitor participants' cognitive and behavioral phenomena using different types of tools. VR has been demonstrated to contribute to enhancing consumer experience and customer interactivity by directly impacting the users' sensory elements (Vrechopoulos et al., 2009; Bigne et al., 2016; Vickers, 2017).

GRAIL allows the recreation of real-life purchase situations, for instance, walking in a supermarket, mall or hotel while participants are still in a controlled environment. Additionally, GRAIL enables researchers to study brain activity and physiological responses while participants perform complex tasks (e.g., look at advertisement while walking) or make complex choices (e.g., choosing between several products on a shelf). VR offers the opportunity to develop completely new situations, impossible to create in the real world, and the development of contexts that will never be experienced by most people in real life.

Despite all the described advantages, it should be noted that the GRAIL system also has disadvantages. The first one is the costs of the system, which is around €400,000. These costs do not include other hardware to be integrated (e.g., EEG, EMG). The complete system needs a total space of at least 25 m^2. The average time required for a experiment is about 45 min, including subject preparation, which is the phase that requires the most time, especially if the experimenter needs to compute gait parameters.

Compared to GRAIL, iMotions is less expensive. In fact, GRAIL consists of expensive integrated devices (treadmill, motion capture system, software, computers), while iMotions includes only the software platform and does not integrate by default any hardware. In addition, iMotions is highly portable, highly flexible and it allows also facial expression recognition. If used in a real world environment, iMotions could provide a higher user experience and interactivity than GRAIL. However, iMotions does not allow the measurement of gait parameters and it provides a limited user experience when used in a lab setting. In addition, it is not always possible to use iMotion in real-world situations due to logistic and economic reasons. In contrast, the GRAIL system can provide a consistent level of user experience and interactivity because of its ability to provide highly customisable VR environments.

GRAIL allows researchers to have a permanent lab in a small space mimicking real-life scenarios. Finally, the safe environment of GRAIL can help reduce motion artifacts that can be generated by moving in a wider environment. **Table 5** summarizes the number of neuroscience tools that can be integrated and the advantages and disadvantages of both platforms.

7. DISCUSSION AND CONCLUSION

The application of physiological theories and neuroscience tools to marketing has rapidly grown in the last two decades. While the interest in consumer neuroscience is increasing, researchers in the field are facing new and complex challenges. Hence, it is important to have a clear overview of current (and potential) tools used in consumer neuroscience research. Thus, researchers (especially newcomers) might find it useful to identify or choose which tools are suitable to be applied in specific aspects of consumer neuroscience research. In this article, we examine present neuromarketing and consumer neuroscience literature with an aim to provide an overview of the use and characteristics of neuroscience tools used for studying consumer behavior.

We follow a literature review methodology as proposed by Webster and Watson (2002) in order to select relevant literature for our study. We evaluate a total of 219 publications to record details about the use and characteristics of consumer neuroscience tools. In section 2, we identify a wide range of neuroscience tools described as consumer neuroscience research (i.e., 15 tools). However, the findings of our study highlighted that the number of tools used in consumer neuroscience research might be lower. We identify seven tools that have been practically used in the field, namely EEG, fMRI, fNIRS, ECG, ET, GSR, and facial expression recognition software. We do not find any empirical evidence for the use of the other tools. We propose a criterion to classify the practically used consumer neuroscience tools as shown in **Figure 4**. We believe that classifications including self-reports and questionnaires, like Ramsøy (2015) give a more accurate and realistic idea of the variety of tools that can be used in consumer neuroscience research. In our classification, we divided consumer neuroscience tools into three categories, namely (1) behavioral (self-reports, observations, survey), (2) physiological (ECG, ET, ECG, fERS), and (3) neurophysiological (electrical: EEG and metabolic: fMRI, fNRIS).

We also evaluate the popularity of the consumer neuroscience tools based on how often they were used by researchers. Studies have argued that fMRI is the most used neuroimaging tool in consumer neuroscience research (Smidts et al., 2014; Ramsøy, 2015; Harris et al., 2018). However, we find that EEG, both traditional and wearable, is the most popular tool, followed by Eye Tracking. These results are also in line with a survey conducted by the Neuromarketing Science and Business Association (NMSBA) on consumer neuroscience vendors in

2018 (Cherubino et al., 2019). This suggests that there has been a change in the use and applications of consumer neuroscience tools in the last 5 years. It is possible that researchers no longer use fMRI because there are other tools that are available for consumer neuroscience research. It might also be possible that researchers are opting for more portable, less invasive and low-cost tools. Although fMRI is not considered an invasive tool, subjects might suffer inconvenience due to being in a small space, an inability to move and excessive noise during the scan. Also, fMRI applications in consumer neuroscience are also limited due to disturbing environmental factors (e.g., lightning conditions, auditory noise). Wearable EEG, fNIRS, ET, GSR, ECG, and Facial Expression recognition software allow higher flexibility to the subjects (e.g., sit, walk). Thus, wearable tools allow the designing of field experiments and not only laboratory experiments. Thus, these tools can help recreate a natural setting for consumer neuroscience experiments compared to fMRI. Additionally, some studies have implied that all neuroscience tools can be used in consumer neuroscience research. We argue that some neuroscience tools are not suitable for marketing research due to moral and ethical implications. In particular, we suggest that tools such as PET, TMS, and SPET should not be used in consumer neuroscience research. In fact, PET, TMS, and SPET may be too invasive or harmful to be used in consumer neuroscience studies. These tools expose participants to unnecessary risks, such as pain, fainting, seizures, and injection of radiopharmaceuticals.

In section 4, we analyzed the advantages, disadvantages, average costs and time preparation for each of these tools. In total, we identified three neurophysiological tools (EEG, fMRI, and fNIRS) and four physiological tools (ET, GSR, ECT, fERS). Our findings suggest that neurophysiological tools are usually more expensive, time consuming and technical knowledge-based (e.g., coding) compared to physiological tools. Similarly, neurophysiological tools can only be used in lab settings, except for the wearable EEG. In contrast, physiological tools are low-cost, easy to integrate with other tools and do not require much technical-knowledge and preparation time. Furthermore, wearable physiological tools can be used outside lab settings such as supermarkets and hotels. Thus, they contribute to study consumer behavior in real-life scenarios.

To understand how these tools improve marketing research we also analyzed the cognitive processes, behavioral measurements, marketing applications and types of product for each consumer neuroscience tool (e.g., EEG, ET). Our findings show that neurophysiological tools allow the study of cognitive processes (e.g., attention, excitement) and behavioral measurement for a wide range of marketing issues. In contrast, physiological tools such as ECG, GSR, and fERS have limited applications in marketing as they only measure a few cognitive processes (arousal, attention, engagement, emotion, and valence). We found that consumer neuroscience tools are currently used to improve marketing strategies for advertising, branding, product experience, online experience, product development and pricing. In particular, we found that the most important contribution consumer neuroscience tools can offer to marketing is the study of consumer behavior in advertising. Consumer neuroscience research focusses on important aspects of advertisement strategies, such as advertisement effectiveness (pre- and post-testing) and target audience selection (e.g., young, adults, male, female). Based on our findings, a small number of studies used neuroscience tools to study product experience. It suggests that research in this specific marketing issues is still in an initial phase. However, there are new and promising applications of consumer neuroscience tools to marketing research. Our findings suggest that consumer neuroscience tools contribute to both theoretical and practical aspects of marketing research.

In recent years, we have seen an increase in the number of studies that integrate two or more consumer neuroscience tools. We believe that ready-to-use platforms might help researchers build more realistic theories and models in consumer neuroscience research. In fact, platforms can contribute to (1) reducing time and cost to set up experiments, (2) more reliable data processing, (3) setting up large scale studies, and (4) collecting simultaneous information on physiological and neurophysiological processes. In this study, we identified two ready-to-use platforms that integrate some of the consumer neuroscience tools discussed in this research, namely iMotions and GRAIL. The first platform, iMotions, has been previously used in consumer neuroscience studies to investigate willingness to pay and consumer satisfaction for different products (e.g., bags, clothes, FMCG, shoes) and services (e.g., booking platform). To the best of our knowledge, this is the first study to consider GRAIL (the second platform identified by us) for use in consumer neuroscience research.

Our findings show that both platforms can integrate six tools and measure both physiological and neurophysiological processes. In particular, iMotion can integrate wearable EEG, facial electromyography, ET, ECG, GSR, head motion. GRAIL integrates wearable EEG, facial electromyography, ET, ECG, GSR and head motion. GRAIL can also offer gait analysis. Compared to GRAIL, iMotion is relatively low cost and portable. Thus, iMotion can also be used outside lab settings. However, GRAIL incorporates synchronized virtual reality (VR) that can easily reproduce real-life situations. GRAIL's customizable VR allows for the recreation of different environment in one experiment. This platform can help the improvement of consumer experience and customer interactivity in consumer neuroscience studies.

We believe that this study provides a comprehensive overview of the consumer neuroscience tools that have been practically used by researchers. We hope that this work will help researchers and practitioners in choosing the correct tool for their experiment by providing them with necessary information to evaluate the pros and cons of available tools. We also emphasize the potential of upcoming ready-to-use platforms that can help make consumer neuroscience experiments reliable, quick, and low cost.

8. LIMITATIONS AND FUTURE WORK

This study comes with some limitations that offer opportunities for future research. Although we tried to minimize

methodological shortcomings, the present study is not completely bias-free. In this study, we consider publications in the English language only; there is a possibility that we have overlooked tools whose practical use has been explained only in non-English publications. Also, we have focussed on only a few aspects of the moral and ethical implications of the use of consumer neuroscience tools. For future work, we suggest researchers analyse the effect of consumer neuroscience research on personal privacy and ethical values and principles. We would like to invite researchers to investigate the possible contributions of neuroscience tools to others disciplines such as economics and organizational behavior.

For a successful consumer neuroscience experiment, it is also important for researchers to design the experiment well (Fink et al., 2007; Murray and Antonakis, 2019). In this review, our goal was to describe consumer neuroscience tools, hence, we do not look at the experimental design aspect of consumer neuroscience within the scope of this review. We would like to investigate the success and failure of experimental designs in consumer neuroscience research in the future.

9. SUMMARY

- Consumer neuroscience tools can be divided in three categories based on the type of measurements: (1) Self reports and behavioral, (2) Physiological and (3) Neurophysiological.
- The tools currently used in consumer neuroscience research are EEG, fMRI, fNIRS, ECG, ET, GSR, and fERS. EEG is the most commonly used tool in consumer neuroscience research.
- Physiological tools are usually cheaper and portable compared to neurophysiological ones.
- Consumer neuroscience tools have applications in several marketing domains such as advertising, branding, online experience, pricing, product development and product experience.
- Ready-to-use platforms (iMotions and GRAIL) measure behavioral, physiological, and neurophysiological responses simultaneously. GRAIL includes a personalized virtual reality setting that enhances the consumer experience and customer interactivity.

AUTHOR CONTRIBUTIONS

All authors of this article had a significant contribution in its preparation. HR's inputs were critical in research design and formulation of arguments. LA, LP, and AA were involved in reading of literature, writing, and design of figures and tables. LA specialized in neuromarketing. LP was an expert on neuroscience tools. AA specialized in technology and information systems. HR was a specialist on Marketing.

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A Minimal Setup for Spontaneous Smile Quantification Applicable for Valence Detection

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Tracking emotional responses as they unfold has been one of the hallmarks of applied neuroscience and related disciplines, but recent studies suggest that automatic tracking of facial expressions have low validation. In this study, we focused on the direct measurement of facial muscles involved in expressions such as smiling. We used single-channel surface electromyography (sEMG) to evaluate the muscular activity from the Zygomaticus Major face muscle while participants watched music videos. Participants were then tasked with rating each video with regard to their thoughts and responses to each of them, including their judgment of emotional tone ("Valence"), personal preference ("Liking") and rating of whether the video displayed strength and impression ("Dominance"). Using a minimal recording setup, we employed three ways to characterize muscular activity associated with spontaneous smiles. The total time spent smiling (ZygoNum), the average duration of smiles (ZygoLen), and instances of high valence (ZygoTrace). Our results demonstrate that Valence was the emotional dimension that was most related to the Zygomaticus activity. Here, the ZygoNum had higher discriminatory power than ZygoLen for Valence quantification. An additional investigation using fractal properties of sEMG time series confirmed previous studies of the Facial Action Coding System (FACS) documenting a smoother contraction of facial muscles for enjoyment smiles. Further analysis using ZygoTrace responses over time to the video events discerned "high valence" stimuli with a 76% accuracy. Additional validation of this approach came against previous findings on valence detection using features derived from a single channel EEG setup. We discuss these results in light of both the recent replication problems of facial expression measures, and in relation to the need for methods to reliably assess emotional responses in more challenging conditions, such as Virtual Reality, in which facial expressions are often covered by the equipment used.

Keywords: facial expressions, valence, surface electromyography, emotion detection, v-commerce metrics

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1. INTRODUCTION

Humans display emotional responses in a variety of ways, including changes in facial expressions, skin conductance, heartbeat, brain signals, body temperature, and pulse rate. These measurable body changes are the foundation of Affective Computing, a discipline that studies how to detect emotions and their effect on cognition, perception, learning, communication, and decision-making (Picard, 2003). Among the physiological variables for emotion assessment, those most commonly

applied are electroencephalography (i.e., EEG, for a review; Solnais et al., 2013), electrocardiogram (i.e., ECG), galvanic skin response (i.e., GSR, for a review; Caruelle et al., 2019) and heart rate variability (i.e., HRV). However, the most immediate and natural way humans share their emotions are through facial expressions. Seemingly simple, yet highly intricate, the dynamics of facial expressions depend upon a complex architecture of musculature surrounding the calvaria region, orbital opening, mouth, and the nose (Bentsianov and Blitzer, 2004). Among these groups of muscles, the most important one for facial expressions is in the oral area (Cohen, 2006).

Spontaneous activity of facial muscles in response to emotional stimuli is usually referred to as "facial motor resonance" to differentiate it from the movement of facial muscles in imitation of the expression of individuals with whom we are interacting (i.e., "facial mimicry") (Hess and Fischer, 2014). In addition to providing feedback on emotions we are experiencing, facial muscle moreover help to recall an emotion. For example, to evoke a positive or negative emotion subjects "re-execute" the motor pattern of the facial expression corresponding to that emotion (Baumeister et al., 2015). Indeed, contraction of facial muscles in response to emotional stimuli is linked with the activation of limbic system and amygdala (Dalgleish, 2004). Interestingly, the reverse is equally true: Hennenlotter et al. (2008) measured a reduced activation of the left amygdala and brain-stem when subjects induced with botulinum toxin attempted to imitate emotional facial expressions.

In Neuromarketing, consumer engagement can be partitioned into a triad of characteristics (behavioral, emotional, and cognitive) that can have positive or negative outcomes on market-related behaviors (Turley and Milliman, 2000; Mattila and Wirtz, 2001). The effectiveness of a marketing stimulus as an exchange of behavioral, cognitive, and emotional factors is directly related to the purchase intention. From a consumer psychology perspective, emotional aspects of decision making have been at the core of our understanding of how consumer choices are made ever since Damasio and Bechara proposed the "somatic marker hypothesis" (Bechara and Damasio, 2005). Since then, multiple studies have demonstrated the relevance of emotional responses to understanding consumer-relevant behaviors from ad memory (Missaglia et al., 2017), brand name (Ramsøy and Skov, 2014), or product preference (Groeppel-Klein, 2005), among others. However, emotions are sometimes negatively related to willingness to pay for a certain product. Incidental emotions are responses that influence the decision we take but are caused by sources outside the decision-making process (for example, an argument with one's partner or a frustrating day at work). They are carried over in the decision-making process without our awareness: for example, an incidental feeling of anger automatically triggers a motive to criticize other individuals in another context (Quigley and Tedeschi, 1996). Indeed, neuroscience studies of financial decisions showed a positive correlation between incidental emotions elicited by a sunny day and the performance of the stock market (Kamstra et al., 2003), or the negative correlation between being eliminated at the football world cup and the stock returns for a specific country (Edmans et al., 2007). To attenuate the effect of incidental emotions in marketing context there are several moderating factors that could be considered. Conversely, integral emotions are related to the decision itself. According to Rozin et al. (1986), integral emotions that are linked to a decision target are difficult to remove, discrediting or benefiting the decision. Integral emotions as part of the "decision-making" process should be related the brain activity in the ventromedial prefrontal cortex (i.e., vmPFC), an important region of the brain for integrating emotion and cognition (Naqvi et al., 2006). One of the roles of neuromarketing is to provide insights able to shape integral emotions to optimize purchasing decisions in the presence of conflicting cognitive information (Loewenstein, 1996; Loewenstein and Lerner, 2003).

Facial expressions are a way to discern the emotional states of customers offering insights into their opinions. Indeed, neuromarketing employs facial electromyography, the Facial Action Coding System (Ekman and Keltner, 1997) through a trained scorer or using a video-capture software that automatically interprets facial landmarks. Marketing research typically relies on self-reports to gather emotional information, forcing individuals to consciously convert their feelings into numerical values with the possibility of introducing "cognitive interferences" (Poels and Dewitte, 2006). Facial expressions have been successfully employed as a non-verbal medium to predict the positive emotional engagement of marketing stimuli when predicting the popularity of YouTube videos (Lewinski, 2015), and in evaluating social media marketing campaigns of two banks over time. However, some authors (Hamelin et al., 2017) used facial expression to relate emotionality of public service announcements with long-term safe driving attitude, concluding that highly emotional advertisements do not impact customer attitude over time compared to low emotional ones.

Recently, doubt has also been raised about facial expressions as a reliable measure of emotional responses. For example, there has been doubts and failed replications of the traditional theory of facial expressions by Ekman (Keltner and Cordaro, 2017), and recent reviews have suggested that facial expressions do not reliably provide sufficient clues to infer emotions from facial movements (Barrett et al., 2019). Indeed, it has been demonstrated that remote facial coding can produce high degrees of false positives and false negatives (Ramsøy, 2015). This implies that the business of using facial expressions as reliable measures of emotional experiences is rather doubtful, and that there is a need for additional research.

The combination of valid and reliable neuroscience with physiology tools to track emotional and cognitive responses can provide solutions for marketers for both off-line and on-line commerce (Ramsøy, 2019). Recently, a new trend of on-line commerce involving virtual reality platforms has emerged, named v-commerce, where web-stores displayed dynamic 3D models of their products (Zhang et al., 2004). However, the future lies in creating immersive VR shops allowing consumers to navigate and interact as in physical ones. Neuromarketing research is trying to simulate these environments to gather information on consumer behavior when immersed in virtual worlds. For example, consumer intentions were analyzed in a

virtual grocery when subjects were exposed to tri-dimensionally reconstructed fruits or vegetables (Verhulst et al., 2017). Another recent paper addressed state of the art and future challenges of this emerging sector offering a panoramic view of different immersive techniques applicable in v-commerce (Alcañiz et al., 2019). The adoption of immersive technologies is further encouraged by the rapidly decreasing prices of VR helmets, spurring the potential of v-commerce environments. In virtual settings, future investigations will decode how virtual worlds influence behavioral, emotional, and cognitive factors in their convergence to the decision-making process. Thus, there is an explicit need for solutions that allow low-intrusive, valid, and reliable measures of emotional responses in VR solutions.

1.1. Previous Literature on the Relation Between Surface Electromyography From Zygomaticus Major and Emotions

Zygomaticus Major is a muscle of the lower face that has a large cortical representation over the primary motor area (cortical homunculus) (Rinn, 1984). A study based on a large population of women (Larsen et al., 2003) reported that there are mainly two muscular groups of interest for emotion detection: muscles surrounding the eyes (mainly Orbicularis Oculi for frowning) and those of the cheek for smiling (primarily the Zygomaticus Major). The joint activation of these muscles is commonly called Duchenne smile. The authors found a linear relation between these two muscles and the pleasantness of stimul i. Moreover, for affective stimuli, it seems that surface electromyography (i.e., sEMG) changes on the Duchenne smile muscles are present even if they are not visible (Cacioppo et al., 1986; Tassinary and Cacioppo, 1992). This last observation could lead to the conclusion that sEMG is a superior methodology compared to facial expression detection by video capture. In fact, a recent review of facial configurations as universal expression of emotions (Barrett et al., 2019) suggested to re-evaluate facial expression in the daily life context where they are produced together, with how they are perceived in a "sender" and "receiver" relationship.

In the field of Neuromarketing, facial EMG was already proposed in the past as a way to understand consumers' emotional experiences (Bolls et al., 2001) in advertising research. While listening to radio commercials, if the tone of the voice was more positive a greater activation was noticed over the Zygomaticus muscle, while negative tones elicited more frowning activity. In consumer judgment and decision making, "fluency" of information perception can be associated with positive valence and has facial sEMG correlates over the region of the Zygomaticus Major as shown by Winkielman and Cacioppo (2001) with easy-to-process pictures. "Fluency" becomes important when individuals have to decide between products: products with higher fluency are usually preferred (Schwarz, 2004), and the Zygomaticus major could be an indicator of it.

1.2. Study Aim : Assessment of Zygomaticus-Based Metrics as Viable for 3D VR Shopping Scenarios

In the present study we tried to evaluate spontaneous muscular activation leading to smiles evoked by screening of musical videos. This study does not consider the social context of smiling, but solely spontaneous smiling in response to a stimulus when subjects are alone. This situation is similar to VR where subjects are isolated from the outer reality. We focused our research on the Zygomaticus major because it is a muscle easily accessible with a low level of intrusion, with a potential application in neuromarketing studies. The corrugator supercilii may provide similar insights into the affective state of a subject (Larsen et al., 2003), yet its suitability is hindered due to the frequent coupling of eye-tracking in neuromarketing studies leading to potential interference in electrode placement. Moreover, the increasing adoption of virtual commerce studies in neuromarketing and corresponding use of VR headsets which occupy the areas surrounding the brows impede the attachment of sEMG electrodes near the eyes. Likewise, the presence of VR headsets limits the usage of video-cameras to automatically detect facial expressions through software able to categorize facial features, as in on-field neuromarketing research with eye-trackers.

For these reasons, we focused on the time course of the zygomaticus major, a paired facial muscle of the cheek area that lifts the angle of the mouth upwards and laterally to allow a person to smile. Usually this area of the face is not occupied by devices used in neuromarketing studies or VR equipment, and requires only a minimal setup of two electrodes for muscular activity detection. Our aims were to provide an alternative method to video-based emotion detection and to find an interpretable connection between the activity of the zygomaticus major and emotional states applying a minimal sEMG montage.

Here, we sum up some advantages of introducing sEMG from the Zygomaticus in Neuromarketing studies for emotional state detection:

- Zygomaticus can be recorded in neuromarketing studies when the eye area is unavailable due to being covered by a VR headset or eye-tracking devices. In this case, the region of the eyes is also hidden to camera-based facial recognition techniques reducing their applicability.
- The Zygomaticus can be recorded from a single cheek with a pair of self-adhesive gelled electrodes (positioned as in **Figure 1**). This minimal setup could be justified considering that spontaneous smiles representing enjoyment are more symmetrical compared to deliberate smiles (Skinner and Mullen, 1991; Hager and Ekman, 1997). This minimal setup is suitable in case of large-scale studies.
- sEMG, like other neurophysiological techniques, suffers from artifacts, notably power line interference and movement artifacts. Signal processing can reliably isolate spurious activity. Electromagnetic noise is usually suppressed by a notch filter. During head turns, the movement of the cable connecting the electrode to the amplifier could produce a low oscillation on the sEMG signal cancelable by the

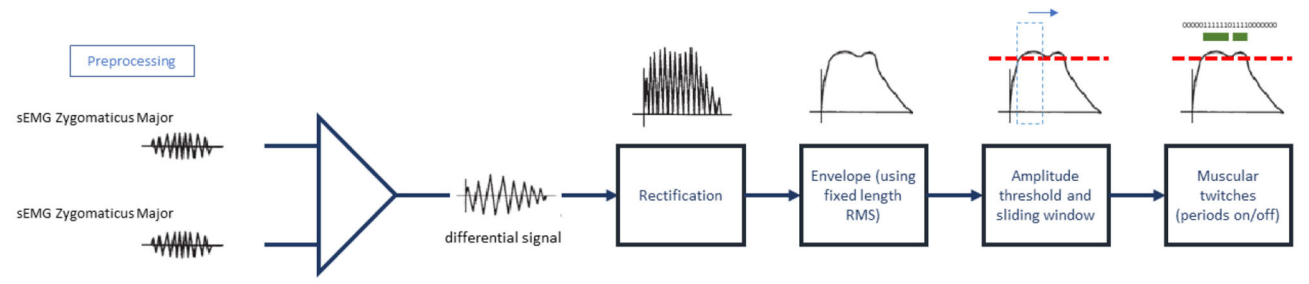


FIGURE 1 | Detection of "on" periods (muscular contractions).

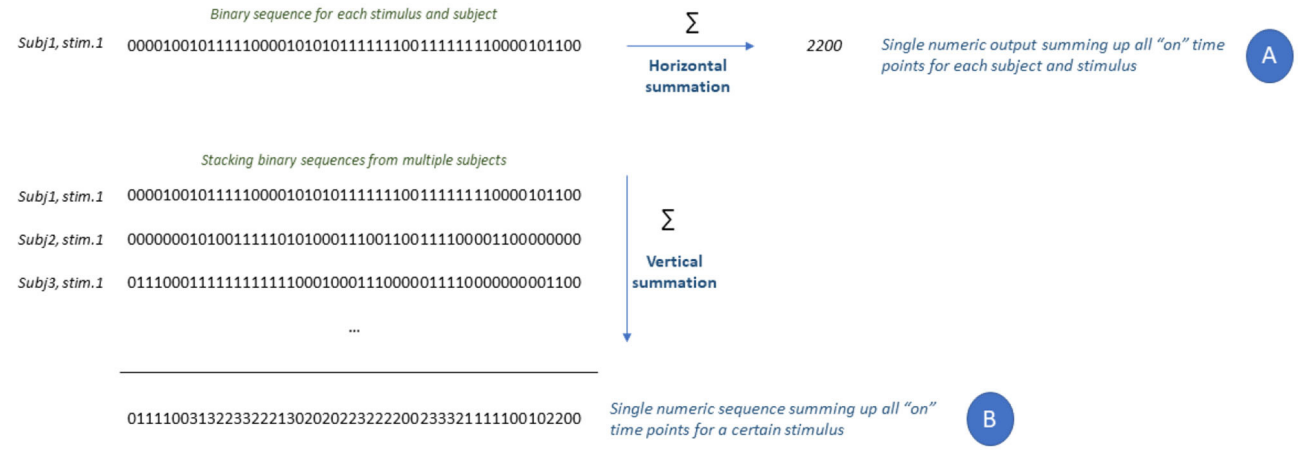


FIGURE 2 | Additive properties of the binary vector.

highpass filter. Both artifacts can be addressed by designing proper filters.

- In women, makeup usually requires stronger algorithms for automatic detection of facial expressions (Moeini et al., 2014) yet sEMG technique overcomes this and only requires the correct application of electrodes with an acceptable contact impedance.

1.3. Number of Emotional Dimensions Investigated in This Study

Each participant judged his/her emotional state in response to audio-visual stimuli through questionnaires at the end of video exposure. Participants rated each musical video in terms of arousal, valence, dominance and liking. Arousal and valence are the main dimensions of the circumplex model of affect (Posner et al., 2005): valence is the degree of pleasantness usually related to the frontal cortex, while arousal is associated with subcortical and parietal circuits. Arousal grades stimulus intensity from neutral or boredom responses to high excitement. Dominance is an addition to the classic valence and arousal dichotomy, and attempts to capture psychosomatic aspects of control. It expresses the feeling of control over a given stimulus. Valence, arousal and dominance could be linked in some way to affect, cognition, and behavior in the so-called ABC model or to the concepts of feeling, thinking, and acting (Bakker et al., 2014). Together with the three emotional dimensions, we included Liking scores ranging from 1 to 9 representing how much the participants liked the musical video-clip they watched.

1.4. Neural Basis of Emotions

Emotions are conveyed by vision, hearing and touch to the central nervous system to trigger both behaviors and feelings. Feelings of emotions are mental states that follow a behavior caused by external circumstances. Amygdalae are the center of the best know emotion that is fear (Feinstein et al., 2011) while disgust, another human protective emotion, arises from a small portion of the anterior insula (Harrison et al., 2010). Emotions enclosed in the circumplex model of affect seem involving different neral loops. Stimuli evoking arousal showed an activity over the left thalamus, globus pallidus, caudate, parahippocampal gyrus, amygdala, premotor cortex, and cerebellar vermi (Colibazzi et al., 2010), with some differences between genders (Canli et al., 2002) regarding the activation of the amygdala. Valence instead involved midbrain, ventral striatum, and caudate nucleus as portions of a "reward" loop while unpleasant experiences activated supplementary motor, anterior midcingulate, right dorsolateral

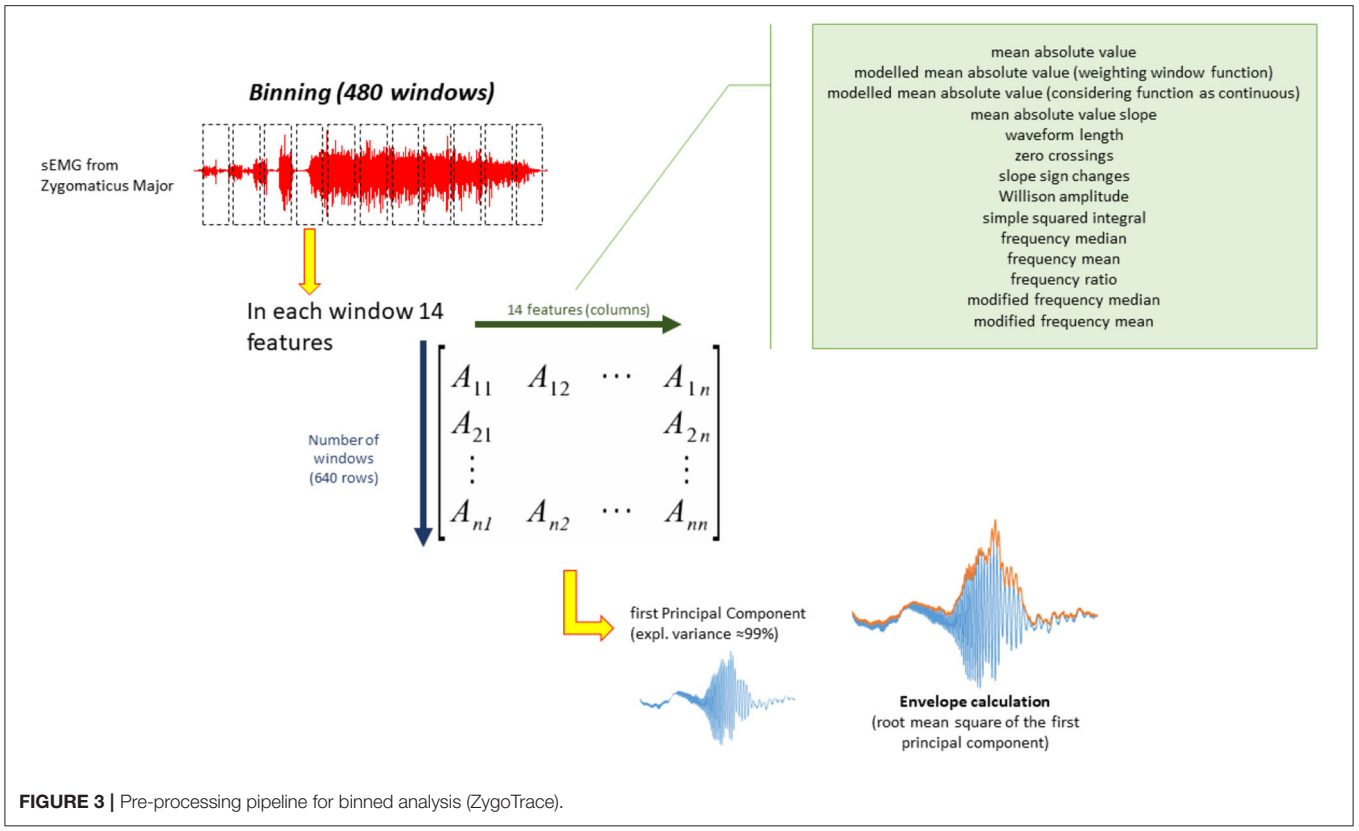


FIGURE 3 | Pre-processing pipeline for binned analysis (ZygoTrace).

prefrontal, occipitotemporal, inferior parietal, and cerebellar cortices (Colibazzi et al., 2010).

2. MATERIALS AND METHODS

The dataset used for this analysis is a public-domain benchmark collected by Koelstra et al. (2011). The dataset represents physiological recordings from 32 participants during exposure to 40 musical videos for 60 s each. The videos included different kinds of musical genres. We focused our analysis on the sEMG recordings from the zygomaticus major to highlight muscular patterns in response to the emotional content of the musical videos. Data was recorded at a sampling frequency of 512 Hz with an Actiview software (Biosemi BV, The Netherlands). Electrode placement is shown in **Supplementary Figure 1**: one electrode was placed one centimeter above the corner of the mouth and the other 1 cm from it following a straight line (blue circles).

2.1. Behavioral Data

All participants rated each video on a continuous scale from 1 to 9 in terms of valence (pleasantness or unpleasantness), arousal (boredom or excitement), dominance and liking (**Supplementary Figure 2**). Authors of the dataset invited participants involved in the study to evaluate their affective reactions on self-assessment manikins (i.e., SAM) for valence, arousal, and dominance. Dominance was intended as a measure of self-control, and participants had to estimate the degree of control musical videos could inspire, ranging from "without control" or helpless to "everything under control" or empowering. For liking scores (i.e., "how much did you like the video?"), researches included icons with thumbs up and thumbs down instead of SAM mannequins.

2.2. Pre-processing of Surface Electromyography From the Zygomaticus Major

During the preprocessing stage we initially removed power line noise with a notch filter centered on 50 Hz, and high-passed the sEMG signals at 5 Hz to remove any DC offset. Cut-off frequency of the high-pass filter was selected in accordance with the International Society for Electrophysiology and Kinesiology recommendations for surface EMG (Merletti and Di Torino, 1999). Other publications involving sEMG followed the same standards: for example, in research for muscular prosthetic control (Polygerinos et al., 1996) or in clinical settings for physiatry (Thuresson et al., 2005). After filtering, we calculated the differential mode signal converting the two sEMG traces in a single time series resulting from the difference in voltage between the two recording electrodes.

2.2.1. sEMG Signal Analysis: Muscular Contractions on Whole Window (ZygoNum)

To highlight time instants during which subjects smiled, the signals were further processed with full wave rectification and envelope calculation. Root-mean-square envelopes were

determined with 25 ms sliding window (De Luca, 1997). On the envelopes, we detected the number of times at which zygomaticus muscles turned "on" and "off" using a voltage threshold. Threshold was calculated as $\mu + J * \sigma$ where μ and σ are the mean and standard deviation of the envelope during the 3 s baseline recorded before presentation of each video (period of muscular inactivity). Parameter $J = 3$ was selected as in Di Fabio (1987). In accordance with (Hodges and Bui, 1996), we counted that window as an "on" period in each 25 ms window when the mean voltage exceeded the threshold, we counted that window as an "on" period (**Figure 1**). Muscular contractions lasting <125 ms were filtered out to remove micro-expressions. This measure is closer to the upper limit of the original definition of micro-expression given by Ekman and Friesen (1969), Ekman (2009), and Ekman (2003) that quantifies the duration of facial micro-expressions ranging from 1/25 to 1/5 of second. This inclusion limit also removes transient muscular contractions or isolated occurrences of facial tics. The outcome of this procedure is a one-dimensional vector containing a binary sequence with length equal to the original length of the sEMG signal. In the binary sequence, zeros represent time instants where the muscle is "off," while ones are instants of muscular activation ("on"). The binary vector has two additive properties: binary sequences can be summed up horizontally or vertically as shown in **Figure 2**. Horizontal summation of all binary values will result in a single score (**Figure 2** "A," called ZygoNum) that could be averaged among subjects to return a general score for a specific stimulus (in our case musical videos). The horizontal summation procedure can be considered as the amount of the time spent by Zygomaticus Major in active state and the time spent smiling by the subject. Instead, vertical summation could show the time instants where subjects smile in the same moment, identifying single events of enjoyment during video screening (**Figure 2** "B"). For a practical illustration on the usage of the vertical summation of the binary vector we prepared an example shown in **Supplementary Figure 3**. In **Supplementary Figure 3A**, we plotted the valence-arousal plane (Russell, 1980) for each musical video. The green dashed line represents the second order polynomial fit of the data. On the scatter-plot we identified two points with a similar arousal value: one corresponding to a high valence score and one corresponding to a low valence score. We decided for two videos with similar arousal level because induced mood changes fade quickly for arousal but are more consistent over time for valence (Gomez et al., 2009). For the corresponding two musical videos, the sum of the binarised vectors from all subjects was plotted as in **Supplementary Figure 3B** obtained with vertical summation. Observing **Supplementary Figure 3B**, it could be noticed that the high valence video had a time interval around 8 s where 5–8 people used to smile for some seconds. In contrast, there are no evident grouped activation in the lower Valence trace. To facilitate the interpretation and visualization of **Supplementary Figure 3B** we calculated the root-mean-squared upper and lower envelopes of the time series and shaded the area between them. The vertical summation metric will not be used in this work but could be considered for future extension of present findings. Single patterns of muscular contractions could also be analyzed following the procedure exemplified in **Figure 2** counting the duration of consecutive "on" instants. We called this measure ZygoLen (**Supplementary Figure 4**). ZygoLen was mainly added to evaluate, at single subject level, which metric (ZygoNum or ZygoLen) is more effective in detecting emotions and to check whether together they could improve the characterization of affective states (in section 4). Both ZygoNum and ZygoLen provide a single numeric value as output: this characteristic could be useful not only to quantify the sEMG activity with an index, but also because it could be used directly as input feature in combination with other biometric indicators for machine learning approaches focusing on emotion detection.

TABLE 1 | Correlation between Self-reported ratings and ZygoNum.

$N = 40$, df = 38	r	F-value (p-value)	R^2 (adjusted R^2)
Arousal	0.2661	2.9 (0.0970)	0.0708 (0.0463)
Valence	0.4848	11.7 (0.0015)	0.235 (0.215)
Dominance	0.5595	17.3 (0.0002)	0.313 (0.295)
Liking	0.3426	5.05 (0.0305)	0.117 (0.0941)

2.2.2. ZygoTrace: Binned Analysis of Zygomaticus Major

We used disjoint segmentation (Oskoei and Hu, 2008) using a sliding window of 64 time points as predefined length (equivalent to 125 ms) to identify a subset of signal segments. In each segment we calculated 14 parameters: mean absolute value of the signal, modeled mean absolute value using a weighting window function (Phinyomark et al., 2012), modeled mean absolute value considering the function as continuous (Phinyomark et al., 2012), mean absolute value slope estimating the difference between neighbor mean absolute values (Phinyomark et al., 2012), waveform length as cumulative length of the waveform over the segment (Englehart et al., 1999), zero crossings as the number of times the waveform changes sign (Phinyomark et al., 2012), slope sign changes, Willison amplitude as the number of times the first derivative exceeds a threshold (Oskoei and Hu, 2008), and squared integral as energy feature (Oskoei and Hu, 2008). In frequency domain, from power spectral density, we gathered information about the frequency median, the frequency mean, frequency ratio (Han et al., 2000), and the modified frequency median and mean (Phinyomark et al., 2012). The time course of the 14 features (640 points each feature) was collected for each subject and each video (32 subjects × 40 musical videos = 1,280 trials in total). To evaluate feature redundancy and retain only relevant information principal component analysis was performed on each trial. It appeared that the first principal component was able to explain nearly 99% of variance in the data. For this reason, the envelope of the first principal component was calculated to simplify the comparisons. Upper envelope was calculated using the root mean square and window length of 16 points. The whole process is depicted in **Figure 3**.

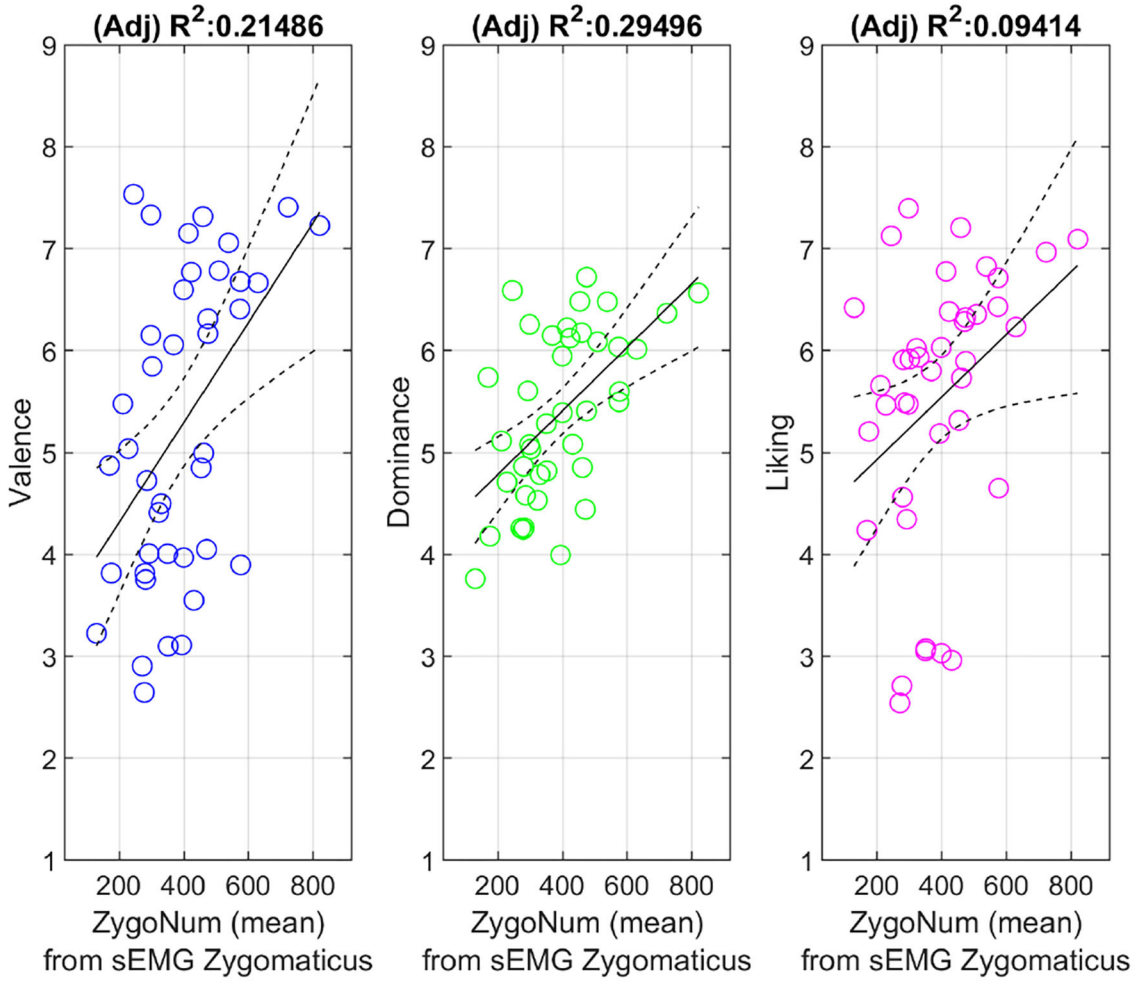


FIGURE 4 | Linear regression models between ZygoNum and Emotional scores for each video (average across subjects). Figures include least square fit and confidence limits.

3. RESULTS

The sum of all activations ("on" periods) of the Zygomaticus major (ZygoNum) were averaged over subjects and compared to the average scores of Arousal, Valence, Dominance, and Liking as shown in **Table 1**. The linear dependence is reported with the Pearson correlation coefficient r and the *p*-value testing the hypothesis that there is no relationship between self-reported ratings and number of muscular activations in the zygomaticus major. The number of time instants spent smiling appears to correlate with Valence, Dominance and Liking. Relationships between behavioral data and sEMG activations are portrayed in **Figure 4** as linear regressions. Arousal was not included in **Figure 4** because it did not reach the threshold of significance and this does not allow us to model a linear relation with the number of muscular contractions. So far, we noticed that ZygoNum has higher correlation with Valence, Dominance and to a lesser extent with Liking. Dominance usually shows lower variance in subjective scores compared to Valence probably because it is more difficult to estimate through surveys: Dominance requires the estimation of an abstract concept like the degree of empowering sensation a musical video could elicit. Valence instead is a more immediate response and its values float more consistently between participants: it could be probably easier for a subject to rate a musical video in terms of Valence using a scale ranging from unpleasant (e.g., sad, stressed) to pleasant (e.g., happy, elated) rather than in terms of Dominance, from "without control" to "under control." It could be argued that Dominance does not represent a strictly emotional feeling compared to arousal and valence (Russell et al., 1981) and probably it has a cognitive or conative nature.

3.1. ZygoTrace for Emotion Detection: Emotional Dimension Detection

In **Table 2**, trials are grouped in three levels for Arousal (i.e., A), Valence (i.e., V), Dominance (i.e., D), and Liking (i.e., L): "high" level means an affective ranking above the mean + half standard deviation (i.e., H), "low" level is an affective score below

TABLE 2 | Emotional dimensions grouped by score.

	Count	Percent
AROUSAL		
High (HA)	428	33.44
Neutral (NA)	436	34.06
Low (LA)	416	32.50
VALENCE		
High (HV)	460	35.94
Neutral (NV)	376	29.38
Low (LV)	444	34.69
DOMINANCE		
High (HD)	409	31.95
Neutral (ND)	453	35.39
Low (LD)	418	32.66
LIKING		
High (HL)	500	39.06
Neutral (NL)	394	30.78
Low (LL)	386	30.16

mean minus half standard deviation (i.e., L) and "neutral" level is between "high" and "low" levels (i.e., N). Each group has a similar number of observations to maintain an acceptable level of statistical power.Data distribution of averaged ZygoTrace metric in the three emotional levels ("H," "L," "N") is shown in **Figure 5**. Analysis of variance to test the effects of the three emotional levels (H, L, and N) on the mean values of ZygoTrace was performed for each emotional dimension (**Table 3**). The null hypothesis was tested at significance level of $\alpha = 0.05$ adding "subjects" as random factor to the main factor "emotional dimension" ($n = 1{,}280$, df $= 1{,}278$). It should be mentioned that data comes from a not normally distributed sample (verified with Jarque-Bera test). However, the sample size is large enough to ensure that the non-normality should not impact test's validity (Stevens, 2012). Valence scores were furtherly investigated in a *post-hoc* test with Bonferroni correction. It returned a significant outcome for comparisons between HV vs. NV ($p = 5.44\text{e-}7$) and HV vs. LV ($p = 2.31\text{e-}07$) while NV vs. LV was not significant. Independent two samples *t*-tests with assumption of inequality of variances were performed for all the groups on the averaged ZygoTrace signal (**Table 4**). Statistical tests report a significant link between ZygoTrace and Valence. In particular, it seems that ZygoTrace can detect "high valence" stimuli compared to the other two emotional levels.

3.2. Identified Relation Between Valence and ZygoTrace: Characterization of Their Affinity

Time course of the metric derived from sEMG with the procedure illustrated in **Figure 3**, is shown in **Supplementary Figure 5A**. We plotted the time course of the averaged response for each of the three groups. For further analysis, we kept the same categorization of emotional scores in "H," "N," and "L" as used before. In the legend of **Supplementary Figure 5A** we abbreviate Arousal with "A," Valence with "V," Dominance with "D" and Liking with "L." In **Supplementary Figure 5B**, the nonparametric representation (kernel) of the probability density function of the signals in **Supplementary Figure 5A** is shown. Observing the distribution of data point for Valence in **Figure 3** and **Supplementary Figure 5B** we can visually appreciate the different distribution of values in the three emotional levels (H, L, and N) as previously highlighted by the statistical tests. Taking advantage of statistical outcomes, we also built a model able to predict the relation between the statistical distribution of ZygoTrace and Valence scores (pleasant vs. unpleasant). Fifteen descriptive statistics were collected from each subject and trial: mean, median, mode, variance, standard deviation, maximal, minimal value, and range between them, inter-quartile range, 5 and 95% percentile, skewness, kurtosis (Stevens, 2012), Hjorth mobility, and complexity (Hjorth, 1970). Mobility parameter is the square root of the variance of the first derivative divided by the variance. Complexity is the mobility of the first derivative of the time series divided by the mobility of the time series. All these parameters were statistically tested one against the other using independent t-tests to assess the significance of each feature in separating the "H" class against the others (we grouped "L" and "N" in one class as direct consequence of significant comparisons shown in **Table 4**). Neutral and Low Valence were merged in a single class to have a binary classification representing the negative and neutral classes against the "highly pleasant" class. Absolute value two-sample *t*-test with pooled variance estimate are displayed in **Table 5** together with their rank. Kurtosis and skewness are the best statistical descriptors because they could be more helpful in categorizing ZygoTrace between "HV" and the other levels of Valence ("LV" and "NV"). Considering a cut-off value of $|t| = 1.96$ (two tailed, df $= 1{,}280$, $\alpha = 0.05$). Inter-quartile range and Mobility could be excluded from further analysis because they do not have enough discriminatory power (they are "redundant" features).

3.3. Predictive Ability of ZygoTrace to Detect "High Valence" Musical Videos Among Others

The predictive ability of ZygoTrace to detect high valence musical videos was tested using a Support vector machine classifier (i.e., SVM) setup for a two classes problem: detecting "High Valence" against "Other levels of Valence" stimuli. The predictive ability was tested on 13 features (same features as in **Table 5** except redundant ones) collected on 1280 ZygoTrace time series (32 subjects watching 40 videos). The SVM classifier had its hyperparameters optimized using a Bayesian iterative procedure. We also introduced in the model a penalization parameter to account class imbalance in form of the relative dimension of each class (**Supplementary Table 1**). The SVM model had a linear kernel function and it was tested in a 10-Fold stratified cross-validation with training size of 1,152 and test size of 128 samples (**Supplementary Table 2**).

4. DISCUSSION

Modern interpretations of facial expressions are reconsidering their connection with emotions. Facial expressions are not just a mirror of the emotional state, but part of the relation between a sender and a receiver (Russell et al., 2003). However,

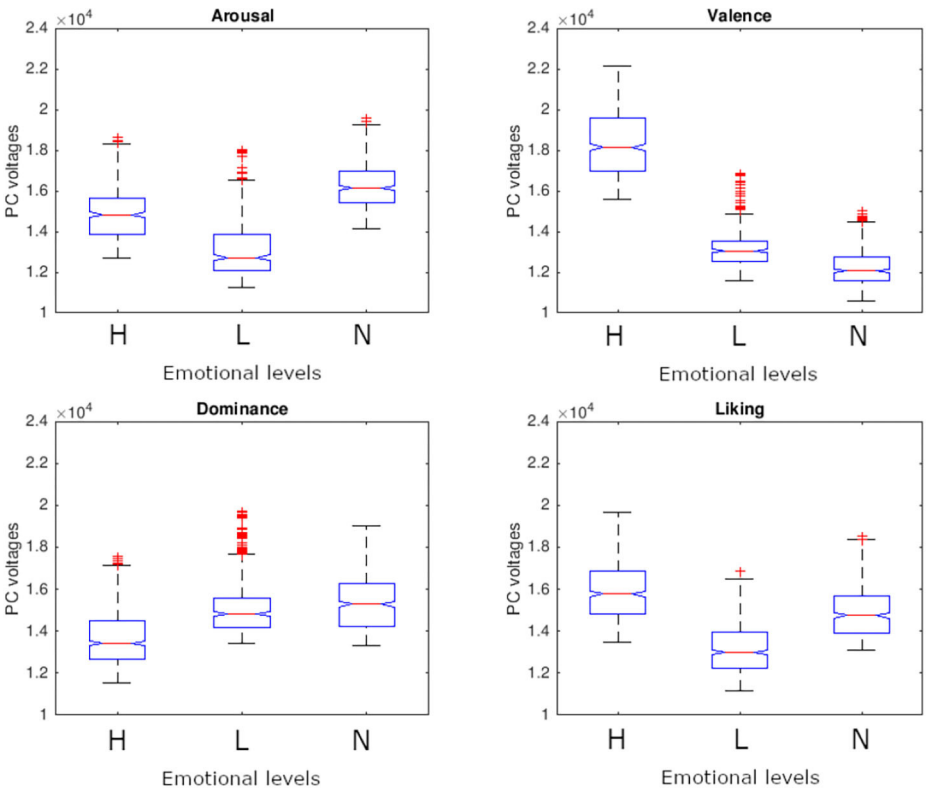


FIGURE 5 | Averaged ZygoTrace grouped by emotional dimensions.

spontaneous facial expression while watching a video streaming on a screen without a human interlocutor may provide a more genuine emotional feedback. Spontaneous facial expressions can be related to a wide range of psychological phenomena but the contraction of the zygomaticus major to raise the angle of the mouth in a smile it has been proved to be a marker of enjoyment in different populations and cultures (Ekman, 1997). Hence, we sought to test the possible relation between the muscular activity of the Zygomaticus Major and four different emotions. Emotions were self-rated using surveys while the muscular activity was recorded using a pair of surface electrodes. We proposed two different ways to interpret the sEMG data from the Zygomaticus called ZygoNum and ZygoTrace. From the binarization of sEMG signals (a sequence of 0 and 1 s) we obtained a vector representing the time instant when the muscle is active ("on" state). We introduced a single score summing up the number of "on" periods of the Zygomaticus (horizontal summation procedure) called ZygoNum. From the binary vector, we also established that it is possible to obtain a time series summing up the sequence of activations from all subjects (vertical summation, time series used only for illustrative purposes in **Figure 2** "B"). We also presented a way to extract features from the binned sEMG trace using time and frequency domain parameters. The time series obtained with binned analysis (called ZygoTrace) has characteristics that can identify "high valence" stimuli among others. This feature is important in neuromarketing as highly emotional marketing stimuli are related to stable purchasing intentions over time (Hamelin et al., 2017).

TABLE 3 | Analysis of variance on ZygoTrace over three emotional levels (H, L, N).

Emotional dimension	*F*	*p*-value
Arousal	1.85	0.1628
Valence	4.61	0.0134 [*]
Dominance	<0.0005	Inf
Liking	1.34	0.2677

**Means $p < 0.05$ for statistical significance.*

4.1. ZygoNum and FACS: Testing "Duration" and "Smoothness" of Smiles

The "Facial Action Coding System" (i.e., FACS) method does not use sEMG, but relies on a trained scorer to measure visible facial behavior or on software to automatically detect facial expressions. Previous reports (Frank et al., 1993) using the FACS found that smiles expressing joy and enjoyment show a smoother contraction of facial muscles compared to non-enjoyment smiles together with a less variable duration of the activation. Authors studied duration of smiles with or without the Duchenne marker (contraction of Orbicularis Oculi) and their findings were confirmed for Duchenne smiles only. Our aim was to test how a minimal sEMG montage can support identification of valence

TABLE 4 | *t*-test values comparing the averaged ZygoTrace for each group.

	t-value	*p*-value
AROUSAL		
H vs. L	0.89	0.3735
H vs. N	−0.71	0.4719
N vs. L	−1.73	0.0837
VALENCE		
H vs. L	2.60	0.0095 [*]
H vs. N	3.00	0.0028 [*]
N vs. L	0.84	0.3987
DOMINANCE		
H vs. L	−0.86	0.3870
H vs. N	−0.84	0.3976
N vs. L	−0.12	0.8973
LIKING		
[0.7ex] H vs. L	1.47	0.1408
H vs. N	0.54	0.5882
N vs. L	−1.02	0.3073

**Means p < 0.05 for statistical significance.*

TABLE 5 | ZygoTrace features ranking.

Descriptive statistics	*t*-value	Rank
Mean	2.88	8
Median	2.81	11
Variance	2.16	13
Maximal value	2.84	9
Minimal value	2.93	4
Range	2.75	12
Inter-quartile range	1.60	14
5% percentile	2.93	7
95% percentile	3.14	3
Skewness	4.25	1
Kurtosis	3.46	2
Mode	2.93	5
Standard deviation	2.84	10
Mobility	1.54	15
Complexity	2.93	6

in experimental stimuli and for this reason we could not detect Duchenne smiles. To display Duchenne smiles we should have included electrodes near the eyebrows with potential conflict with VR or other devices involving ocular region. Moreover, in the presence of VR devices, the FACS method to detect facial expressions does not work due to the same physical obstacles. However, we tried to test the outcomes of FACS research with our minimal setup proposing two ways to relate the duration and smoothness of the Zygomaticus with self-reported emotions.

4.1.1. Features Derived From Binarized Signals of the Zygomaticus Major to Evaluate Duration of Muscular Contractions (Single Subject Study)

We introduced a new metric that measures the length of consecutive "on" periods from the Zygomaticus (called ZygoLen). We used this index to test the effectiveness of ZygoNum in discovering emotional states and to examine if a mixed model together with ZygoNum could be more precise for emotional state detection. Moreover, we decided to pinpoint which definition of "duration" could fit better the previous findings on the Duchenne smiles. With these two metrics we can evaluate if the total duration or if the mean duration of the muscular contractions of the Zygomaticus are more effective in identifying the affective outcomes. We also calculated the linear relation at single subject level for each stimuli (1,280 total observations, 1,278 degrees of freedom), as shown in **Table 6**. The results are weak in terms of generalization because self-reported emotional scores are scattered around ordinal numbers while at averaged level we can consider them as nearly continuous. In addition, emotional responses are not pre-defined but affective reactions are under the effect of various subject-dependent variables. Considering these limitations, we can observe that duration of muscular contractions shows a "trend" with the subjective measures of Valence (for example, Pearson coefficient of correlation is 0.1137 for ZygoNum and 0.0569 for ZygoLen, **Table 6**). ZygoNum seems to show a score nearly double than ZygoLen in determining stimuli pleasantness. Regarding Liking, metrics have a closer value to each other. We also run a multinominal logistic regression study using duration features of Zygumaticus's sEMG as predictors (ZygoNum and ZygoLen). We used the total sum of muscular "on" periods (horizontal summation, ZygoNum) and their mean duration (ZygoLen) as input features to investigate their relationship with self-reported emotional dimensions (**Table 7**). To build an ordinal model we had to round self-reported scores (the responses) that were decimals to the nearest integer. In this way the model used the natural ordering of the self-reported emotional scores to describe the relationship between cumulative probabilities of the emotional categories and predictor variables. As link function we used the logit function, assuming that the effects of the predictor variables are the same for all categories on a logarithmic scale. It seems that the original notion of ZygoNum as single number resulting from the total sum (horizontal sum) of "on" time instants could be able to describe a relation with Valence and Liking. Also, in this case, the model identifies a "trend" between smiling time and pleasantness (valence) or liking: more time participants spend smiling and higher could be the Valence or Liking score they will assign for that video. We also report the *p*-values of the interaction terms for the relative probability of being scored a number between 1 to vs. 9 (9 is the highest score the participants could select in the emotional scale and it is our

TABLE 6 | Correlation coefficients at single subject level.

N = 1,280, df = 1,278	ZygoLen		ZygoNum	
	r	*p*-value	r	*p*-value
Arousal	0.0267	0.91 (0.3403)	0.0337	1.45 (0.2283)
Valence	0.0569	4.15 (0.0418)	0.1137	16.7 (4.54e-05)
Dominance	−0.0076	0.0736 (0.7863)	0.0270	0.934 (0.3340)
Liking	0.0719	6.64 (0.0101)	0.0951	11.7 (0.0007)

TABLE 7 | Significant differences ("*" when $p < 0.05$) between emotional scores and the reference category (highest value i.e. 9).

		1 vs. 9	2 vs. 9	3 vs. 9	4 vs. 9	5 vs. 9	6 vs. 9	7 vs. 9	8 vs. 9
Arousal	ZygoNum	0.1014	0.0746	0.0612	0.0614	0.9279	0.4654	0.5791	0.1385
	ZygoLen	0.4129	0.2915	0.4503	0.7735	0.4661	0.1638	0.8159	0.0941
Valence	ZygoNum	0.2453	0.127	0.0164*	0.0154*	0.0012*	0.0074*	0.0209*	0.0003*
	ZygoLen	0.4726	0.23	0.4311	0.4137	0.6374	0.1064	0.63	0.5129
Dominance	ZygoNum	0.514	0.3581	0.2176	0.0338*	0.1304	0.3985	0.9821	0.3864
	ZygoLen	0.3478	0.4918	0.4613	0.4096	0.8951	0.266	0.1971	0.0389*
Liking	ZygoNum	0.1008	0.1131	0.1218	0.0273*	0.0087*	0.4359	0.0508	0.0004*
	ZygoLen	0.973	0.7428	0.8342	0.9405	0.7049	0.0437*	0.3702	0.5098

TABLE 8 | Correlation coefficient between self-reported ratings and smoothness of the Zygomaticus major (averaged across subjects).

	r	*F*-value (*p*-value)	R^2 (adjusted R^2)
Arousal vs. FD of the Zygomaticus	−0.2124	1.79 (0.188)	0.0451 (0.02)
Valence vs. FD of the Zygomaticus	−0.3972	7.12 (0.0122)	0.158 (0.136)
Dominance vs. FD of the Zygomaticus	−0.4978	12.5 (0.00108)	0.248 (0.228)
Liking vs. FD of the Zygomaticus	−0.1763	1.22 (0.277)	0.0311 (0.00558)

"reference category"). At the end of each stimuli (each musical video), participants rated emotions the video-clip inspired them on a scale from 1 to 9 for all the three emotional dimensions (Arousal, Valence, Dominance) and Liking. In **Table 7**, we can observe that the total time spent smiling (ZygoNum) has more discriminative power in detecting emotional scores for Valence and at lesser extent for Liking. Using FACS system and Duchenne smiles Frank and Ekman found that enjoyment smiles have less variable duration of activation. We cannot prove this concept using only with the Zygomaticus Major, but we could report a trend between the total number of time instants the Zygomaticus is active (ZygoNum) and the degree of pleasantness felt after watching a musical video (Valence). With less precision, results are extendable to Liking.

4.1.2. Smoothness of Activation Patterns in the Zygomaticus Major

We tested this hypothesis measuring the degree of smoothness of the sEMG activity from the Zygomaticus through Higuchi's Fractal Dimension (i.e., FD). This non-linear method has a long history of application in neurophysiology (Kesić and Spasić, 2016) and we interpreted this fractal measure of irregularity as the degree of smoothness of the sEMG time series. We preferred this method instead of the classic calculation of the number of "onsets" and "offsets" as in Hess and Kleck (1990) because the FACS method does not assume a return to the neutral position (Frank et al., 1993). We calculate Higuchi's fractal dimension on the sEMG envelope previously obtained as in **Figure 1** (skipping the last two steps, without proceeding with the sliding window for the "on" period calculations). Each single envelope was down sampled by a factor of 16 to reduce the RAM usage and we calculated Higuchi's fractal dimension using 126 sub-series composed from the original signal. The correlation was measured between the degree of smoothness and the emotional dimension using the coefficient of correlation (**Table 8**) and fitting a linear regression method (**Figure 6**). From the data we examined it seems that a certain degree of relation exists between the smoothness of the sEMG from the Zygomaticus and the emotional dimension of each stimuli (only Valence and Dominance have a linear inverse relation with $p < 0.05$). When Valence of the musical video increases the complexity of the sEMG activity from the Zygomaticus decreases, leading to a more smoothed envelope. The models are an approximation and probably the portion of variance they explain is limited but a trend seems to emerge from this investigation: this tendency seems aligned with previous findings using the FACS method.

4.2. ZygoTrace and Previous Literature: Usage of Zygomaticus for Valence Prediction

ZygoTrace is obtained using a binned analysis: in each window we extracted 14 features in time domain and frequency domain. We processed the data to obtain a single time series using principal component analysis for dimensionality reduction and root-mean-square envelope for smoothing the redundant fluctuations of the signal. From the resulting signal we extracted 13 statistical descriptors and used them as input features of a Support Vector Machines classifier: it resulted that it is possible to detect "High Valence" stimuli with a mean accuracy of 76.63% at cross validation (**Supplementary Table 2**). We compared our method that uses a single channel sEMG (ZygoTrace) with a recent work on valence classification using a single channel EEG device (Ogino and Mitsukura, 2018). It seems that methods perform similarly, with the single channel EEG valence predictor achieving 72.40% accuracy on binary classification of valence levels (**Table 9**). Both methods use Support Vector Machines as machine learning approach. Considering the good predictive ability shown by ZygoTrace to detect Valence we could suggest for future research to include sEMG in EEG models for emotion classification, using respectively sEMG to detect Valence and choosing EEG to measure Arousal. In this way the circumplex model of affect

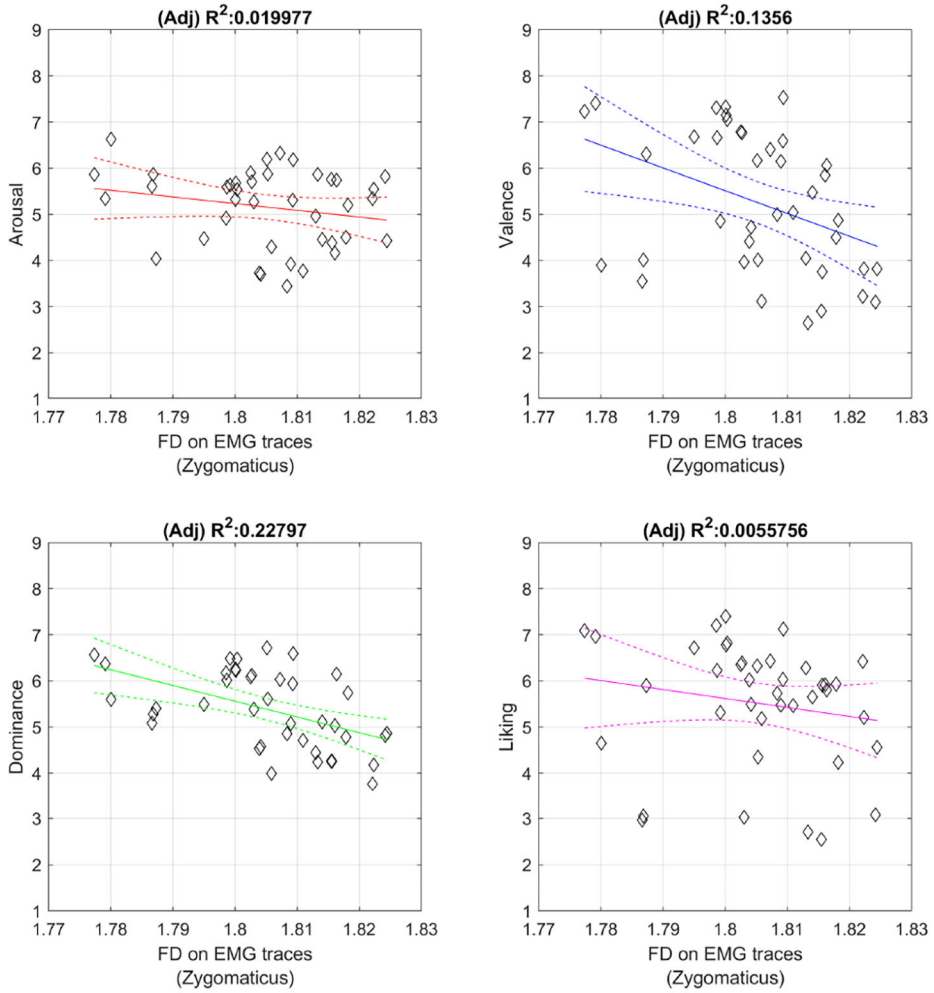


FIGURE 6 | Inverse relation between FD and Emotional dimensions. Figures include least square fit and confidence intervals.

TABLE 9 | Single channel sEMG vs. EEG for Valence detection.

Input type	Number of classes	Targeted emotion	Accuracy
1 channel sEMG (ZygoTrace)	Binary (2 classes)	Valence	76.63%
1 channel EEG (Ogino and Mitsukura, 2018)	Binary (2 classes)	Valence	72.40%

that reduces all emotions as a linear combination of valence and arousal (Colibazzi et al., 2010), could be reconstructed with machine learning models using sEMG from the Zygomaticus for Valence and EEG channels for Arousal. Alternatively, sEMG and EEG could be both used as single inputs or as fused or agglomerated input features to enhance Valence prediction. The overall findings that we report on facial EMG seem in accordance with previous literature (Cacioppo et al., 2000) where facial sEMG from Zygomaticus can detect pleasant versus unpleasant stimuli but cannot categorize different emotional states.

4.3. Role of Valence in Neuromarketing

Emotional valence as the concept ranging from attractiveness to averseness has a natural application in marketing and customer choice. In the rationalistic theory of decision making, reasoning leads to the optimal choice optimizing utility for a customer. Under this view, emotions are distortion of the rational thinking due to their irrational nature. However, emotions play an important role in decision making before and after taking a decision (Loewenstein and Lerner, 2003). The emotions felt before taking a decision build the expectations while emotions after the decision is taken have a somatic or outward expression. In our study we evaluated Valence after stimulus presentation, but Valence could have important impact before a decision is taken. For example, in Ma et al. (2010) the Authors asked to the participants of their experiment to rate a picture with negative or neutral valence before viewing beverage brand names and product names of other categories. Outcomes from evoked potentials suggested that "brand extension" (using an established brand name on new products to increase sales) would not be accepted when a

negative emotional valence was induced. Similar outcomes are reported in Bastiaansen et al. (2018) where the vision of a video-clip with positive valence showing a touristic destination before judging pictures of the same or other touristic places could have an effectiveness on tourism marketing. Regarding emotional valence, Authors of Bercik et al. (2015) detected valence from EEG signals investigating the influence of lights position and colors on non-packed food displayed in grocery shops. Authors suggest that a correct combination of light position and colors could enhance the perception of a positive valence in the displayed fruit or vegetable. Relation between valence and information fluency was already mentioned in the Introduction: information fluency is important in customer experience because it can lead to increased feeling. Cited papers of neuromarketing literature indicate that valence seems important in product evaluation, brand extension, and information fluency.

4.4. Further Notes on sEMG Application for Neuromarketing Studies

- sEMG from the Zygomaticus cannot detect spontaneous smiles covertly: EMG electrodes attached to one's face may induce a less naturalistic behavior. However, a minimal montage of only one muscular channel should minimize this problem. Moreover, we tested this technique on a dataset that evaluates spontaneous smiles of subjects alone in a room while watching musical videos. In this context there are not social biases that could rationally affect our unconscious behavior. During VR, we think that the same pattern could be found because the subject is isolated from the outside world both in terms of visual and audible stimuli.
- Zygomaticus has a large cortical representation (cortical homunculus) but it could have a dominant side (as we have for the hand) and the position of the side of the face where to place the electrode should be evaluated. It should be noted that here we are evaluating only spontaneous smiles outside the social context where facial expressions are usually more complex. It was also demonstrated that spontaneous smiles are less asymmetric (Skinner and Mullen, 1991; Hager and Ekman, 1997).

5. CONCLUSIONS

In this paper we analyzed the relation between muscular activations of the Zygomaticus major and affective responses elicited by musical video-clips. We proposed two ways to characterize the muscular activity using a minimal setup of one sEMG channel: a duration index extracted from muscular contractions representing the total time spent smiling and another method that produces a time series whose statistical features can detect "high valence" stimuli at 76% of accuracy. From analysis of muscular onsets, we found a connection between the activity of the Zygomaticus and Valence (and at lesser extent with Liking). The relation between the muscular activity of the Zygomaticus Major and the degree of pleasantness was already identified in previous literature and we confirmed previous findings using the proposed metrics. We hypothesize that these metrics could be used in future to detect the degree of pleasantness of stimuli in neuromarketing studies that cannot use computer programs to detect facial expressions. For example, in v-commerce when the area near the eyes is covered by VR headsets, video-capture methods for emotion detection cannot be applicable. For Valence detection while wearing VR headsets, researcher could consider the inclusion of a single channel EMG trace from the Zygomaticus Major.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: https://www.eecs.qmul.ac.uk/mmv/datasets/deap/readme.html.

AUTHOR CONTRIBUTIONS

MN processed the data, conceived the metrics and performed the analysis, and drafted the manuscript. TR contributed to the interpretation of the results and revised the manuscript. TR and MN contributed to the final version of the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.566354/full#supplementary-material

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SYSTEMATIC REVIEW
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Is EEG Suitable for Marketing Research? A Systematic Review

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Background: In the past decade, marketing studies have greatly benefited from the adoption of neuroscience techniques to explore conscious and unconscious drivers of consumer behavior. Electroencephalography (EEG) is one of the most frequently applied neuroscientific techniques for marketing studies, thanks to its low cost and high temporal resolution.

Objective: We present an overview of EEG applications in consumer neuroscience. The aim of this review is to facilitate future research and to highlight reliable approaches for deriving research and managerial implications.

Method: We conducted a systematic review by querying five databases for the titles of articles published up to June 2020 with the terms [EEG] AND [neuromarketing] OR [consumer neuroscience].

Results: We screened 264 abstracts and analyzed 113 articles, classified based on research topics (e.g., product characteristics, pricing, advertising attention and memorization, rational, and emotional messages) and characteristics of the experimental design (tasks, stimuli, participants, additional techniques).

Conclusions: This review highlights the main applications of EEG to consumer neuroscience research and suggests several ways EEG technique can complement traditional experimental paradigms. Further research areas, including consumer profiling and social consumer neuroscience, have not been sufficiently explored yet and would benefit from EEG techniques to address unanswered questions.

Keywords: consumer neuroscience, neuromarketing, EEG, eletroencephalography, consumer behavior, decision-making

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INTRODUCTION

In recent years, the idea of applying neuroscience techniques to marketing has given rise to a new field of research known as consumer neuroscience or neuromarketing, and to a multitude of specialized consultant companies. Their list of services includes predicting sales, discovering unconscious drivers of consumer behavior, and identifying preferences and willingness to pay. Eminent authors tried to systematize the proliferating works from this emerging field (e.g., Fortunato et al., 2014), but their first effort was entirely aimed to offer an overview of the variety of available tools and to eventually compare them, stressing limitations and plausible scenarios of application (Harris et al., 2018). Functional Magnetic Resonance Imaging

(fMRI) and Electroencephalography (EEG) are the most frequently adopted neuroscientific techniques to address marketing questions. One of the main limitations in the analysis of studies on consumer neuroscience relied on a jargon barrier. Neuroeconomics, neuromarketing and consumer neuroscience are terms often confused in the common speech, and even among scholars of adjacent fields (e.g., Hubert and Kenning, 2008). Their boundaries remain undefined, since the field is so recent. The term neuromarketing was first introduced in 2002, followed by other definitions (see Fortunato et al., 2014 for a brief description of their history and diffusion). In 2008 Hubert and Kenning proposed to refer to consumer neuroscience as an academic literature definition, while maintaining neuromarketing for industry. Ramsøy et al. (2018) tried to resolve this definition ambiguity in order to clarify the underlying conceptual framework.

The aim of this systematic review is to respond to the need of focusing exclusively on studies applying EEG. It is beyond the purpose of this review to explain the methodological features and results obtained with other techniques, e.g., fMRI [discussed extensively in Ariely and Berns (2010) and Fortunato et al. (2014)]. A decade ago, Ariely and Berns (2010) separated "hope from hype" in the use of brain imaging applied to marketing and scaled down the legitimate expectations for companies that are willing to test innovative methods. The authors mainly referred to functional Magnetic Resonance (fMRI), but similar concerns might be raised with respect to the other neuroscientific techniques as well.

The need of focusing on EEG studies in marketing comes from the increasing number of works on consumer neuroscience using EEG published over the last few years, and it is reinforced by three specific reasons related to certain intrinsic characteristics of this technique. First, EEG data are characterized by high temporal resolution (milliseconds) compared to other brain imaging techniques (e.g., seconds for fMRI) (see Michel and He, 2010). This feature is commonly used by neuroscientists to classify techniques and it is critical for marketing research, as it permits the identification, within a functional time window, of neurophysiological correlates of the exposure to stimuli, such as advertisements (e.g., music and videos). Second, standard EEG devices are non-invasive and allow participants to act normally either in the lab (watching pictures or videos on a screen) or in a store (in the case of field experiments). Finally, the cost of EEG is significantly lower if compared to other brain imaging techniques, and the equipment required to conduct studies is commonly found in neuroscience departments. For these reasons, we consider EEG to be one of the most readable and promising neuroscientific tools for consumer neuroscience studies.

The final aim of our systematic review is to address researchers and managers who wish to explore the consumer neuroscience literature and are possibly considering starting using EEG for their marketing purposes, or who are interested in extending the use of EEG to other disciplines.

We provide a conceptual framework of the contribution of neuroscience in terms of theoretical knowledge, methodological approach and technological implementation to marketing (see **Figure 1**). By assessing the mental states of the consumers, consumer neuroscience explains the cognitive, emotional, and perceptual structures underpinning human decision-making, thus conferring a higher degree of methodological rigor to the most common marketing research questions. Neuroscientific techniques offer a valuable support at every stage of the creative workflow process, from the creation of a concept, passing throughout the production of a product, its dissemination, to a service or a commercial; and yet, they are useful to verify the efficacy of an advertising campaign (Plassmann et al., 2012; Cerf and Garcia-Garcia, 2017; Opris et al., 2020). In the quest for brain-region-specific localization of mental functions, a versatile technique as EEG can become a compass for consumer thoughts. However, despite the proliferation of peer-reviewed articles in a similar variety of directions, even the most promising results suffer from limits in the interpretation and in the universal applicability of the evidence. In parallel, most neuroimaging approaches are affected by a reverse inference problem in the interpretation of the results. For a complete discussion of this aspect we direct the reader to consult papers that focus on the methodological challenges of neuroimaging (e.g., Poldrack, 2011; Hutzler, 2014).

The rest of the paper is structured as follows: a brief paragraph on EEG provides more details on the technique for those readers who are less familiar with this approach. The Method section contains a description of the search criteria (**Figure 3**), classifications (**Table 1**), and statistics regarding recent consumer neuroscience experiments (**Figures 4**, **5**). Next, the Results section offers a more detailed description of the main findings and managerial implications (**Table 3**). Finally, the Discussion section summarizes the main contributions, lists general indications about how to design an EEG experiment of consumer neuroscience, and offers our recommendations regarding future research (**Table 4**).

The Technique: Electroencephalography (EEG)

EEG is a non-invasive electrophysiological technique based on brain-generated electrical waves measured via sensors (electrodes) applied to the scalp. Electrodes can be directly applied to the scalp or a head cap can be worn instead. Electrodes are located according to the international 10–20 system (see **Figure 2**) (Sharbrough et al., 1991). The number of sensors used for exploring brain activity can vary from one single electrode to hundreds. Electrodes measure the voltage of electrical potentials and the frequency of oscillations (Hz) in the brain activity. EEG is conventionally divided into fundamental frequency bands: delta (0.5–4 Hz), theta (5–7 Hz), alpha (8–14 Hz), beta (15–30 Hz), gamma (30–50 Hz), each typical of a rather specific behavioral state (Ahlert et al., 2006; Sanei and Chambers, 2007; Banich and Compton, 2011).

From its first recordings in the 1920s on human beings by Hans Berger (Berger, 1929), EEG received great attention in neuroscience for its versatility. For decades it represented the preferred approach to brain imaging, with a wide set of applications in neurology, neurosurgery, and psychiatry. Its

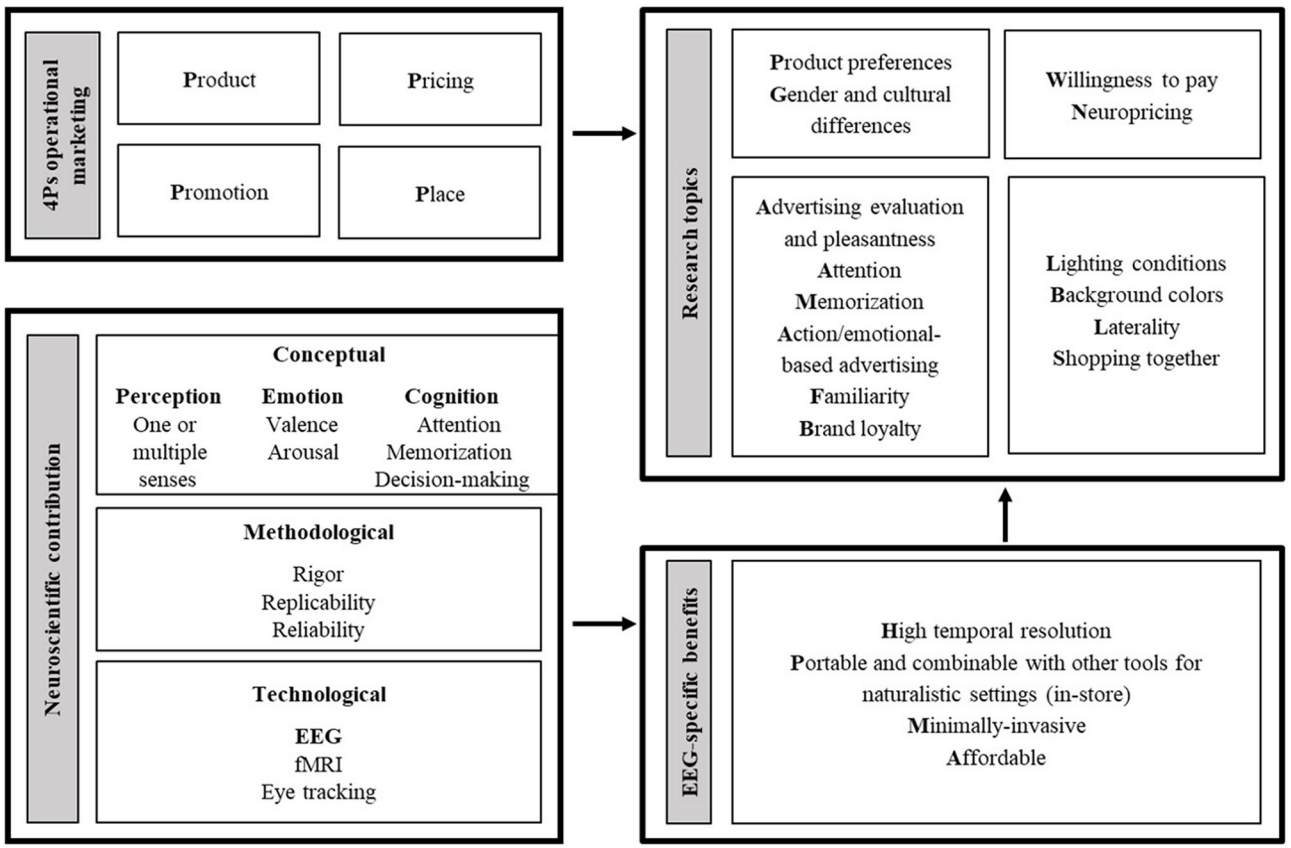


FIGURE 1 | Conceptual framework. The four Ps of operational marketing indicate a map of the research topics ranging from brand loyalty to pricing. Research in this area can be improved by the adoption of tools from neuroscience. In addition to the technological contribution (and the EEG-specific strengths highlighted in this review), marketing researchers can also benefit from the conceptual and methodological contributions offered by the neuroscience literature.

TABLE 1 | Classification: topics and research questions.

4 Ps	Research Topic	Keywords
PRODUCT	*Product* characteristics and preferences	Liking, preference prediction, consumer profiling, and success prediction
	Gender and cultural *differences*	Differences (in preference, attention, or willingness to pay) across populations
PRICE	*Pricing* and willingness to pay	Estimation of price elasticity and willingness to pay
PROMOTION	*Advertising* rating and pleasantness	Evaluation of ads, comparison between EEG and traditional rating techniques
	Advertising attention and *memorization*	Cognitive processes (attention, memorization, evaluation) related to ads
	Rational and emotional *message*	Effectiveness of different types of messages
	Brand identity	Brand strategy, brand extension, and familiarity with the target product
PLACE	Product *context*	Packaging, lighting, and interaction with other consumers
MISCELLANEOUS		Residual category

The words in italics are used in the following tables to refer to the research topics.

high temporal resolution (milliseconds) called the attention of psychologists and social science scholars, who tried to apply EEG to study human decision-making (Heekeren et al., 2008). The analysis of Evoked Related Potentials (ERPs), which are early potentials with defined latencies (from <10 ms to more than 500 ms) (see **Figure 2**), opened interesting scenarios for the understanding of consumer decision-making. For an overview on the correspondence between neural correlates and marketing research topics explored we refer the readers to Harris et al. (2018). Electroencephalography data are rather complex to interpret, particularly when compared to behavioral data, as they include spatial and temporal dimensions of low amplitude electrical signals. Internal (e.g., eye-movements) and external (e.g., environmental noises) factors can influence EEG signals, that are hence commonly cleaned from artefacts by using dedicated computer software for amplification, filtering,

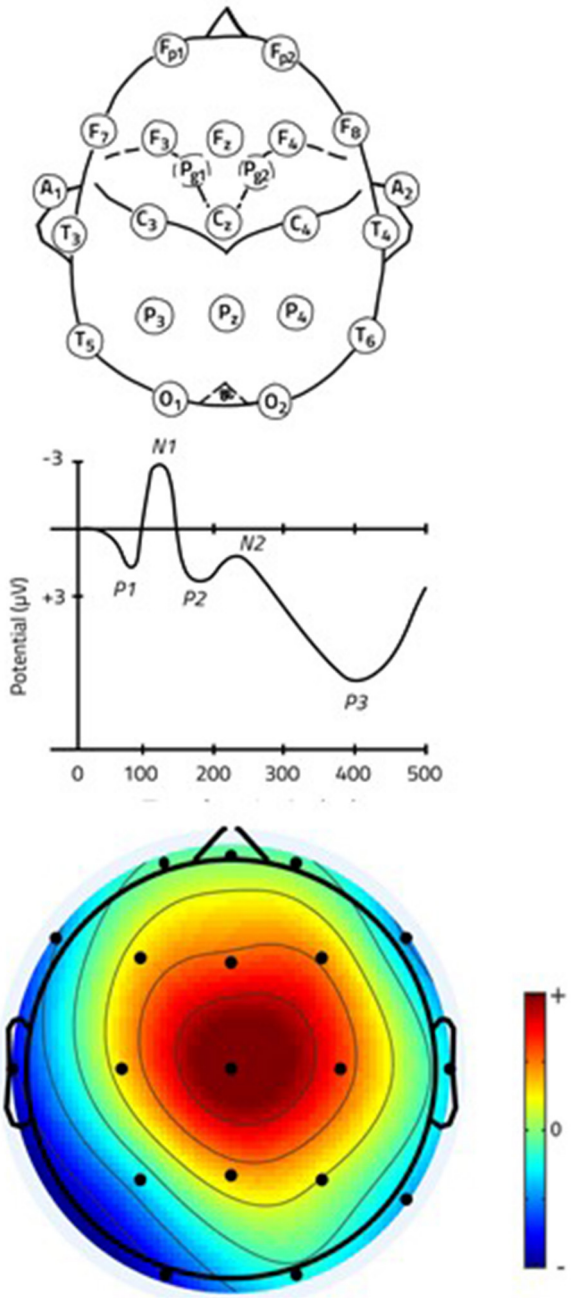


FIGURE 2 | EEG set-up, ERPs and spectral map. Top: Position of 24 electrodes according to the International 10–20 system. Front to back: Fronto-polar, Frontal, Pharyngeal, Auricular, Central, Temporal, Parietal, Occipital (Sazgar and Young, 2019); Center: Event-Related Potentials (ERPs) classified based on latency with respect to the stimulus; Bottom: Spectral map showing EEG activation at P200 latency (the color code represents the topographic distribution of the voltage values).

preprocessing of raw data, and component analysis (see e.g., Urigüen and Garcia-Zapirain (2015) for an extensive review on artifact removal and Michel and Brunet (2019) for a practical review of the analysis steps). Each signal can, and often must, be separated into multiple components. Most of the studies include a power spectrum analysis. The signal from each channel (electrode) is broken down into multiple frequency bands. Alpha, beta and theta frequency bands are usually included in the analysis, and full analysis contains gamma and delta bands as well. The intensity of the signal associated with each channel and frequency can be compared across time. Alternatively, they can be used to create indexes. Given the large variability between research groups in the implementation of the aforementioned steps applied to EEG signal analysis, recent standardization efforts led to the publication of recommendations and guidelines for EEG and ERPs data processing (e.g., see Keil et al., 2014; Babiloniet al., 2020; Pernet et al., 2020). Previous EEG studies tried to associate EEG features to behavioral patterns, or even predictions, despite the potential problem in the interpretation of the results of the reverse inference (Poldrack, 2011; Hutzler, 2014). Such indexes are, for instance, vigilance (alpha band, Hoefer et al., 2016), emotional (Pozharliev et al., 2015), approach and avoidance motivation (alpha asymmetry, Kelley et al., 2017), arousal (beta band, Gupta et al., 2016), pleasantness (alpha and beta bands, Guixeres et al., 2017), and activation (alpha and beta bands, Bertin et al., 2013). The EEG metrics applied in consumer neuroscience, their predicted values, and their limitations have been comprehensively reviewed also by Hakim and Levy (2019). Since the location of the source remains the major limitation of EEG, estimation of cortical activity and reconstruction of 3D configurations are useful for improving the spatial accuracy of the analysis and identifying specific brain areas involved in a task. Useful techniques include the LORETA method (low resolution brain electromagnetic tomography, e.g., Cook et al., 2011) and Global Field Power (GFP, e.g.,, Kong et al., 2013).

The temporal dimension is also explored in different ways. Time frequency analysis focuses on the change over time of a signal, and our list of articles includes two different techniques: Event-Related Potentials (ERPs) and Steady-State Probe Topography (SSPT). ERPs extract the variation in the signal that is recorded at the beginning of each trial, aligned with a specific event or administration of stimulus (see Camarrone and Van Hulle, 2019). The intensity of the peak within a certain time window (for example 300 ms using a P300 analysis scheme) is compared under different conditions (see Uva et al., 2015). Since ERPs have amplitudes of the order of a few microVolts, occurring on background oscillations ranging up to 200 microVolts, the analysis needs to average multiple trials from each individual (see Srinivasan, 2007). This aspect can represent a limit for the experimental design. Steady-State Probe Topography (SSPT) has a high signal-to-noise ratio and overcomes this critical aspect, so data can be analyzed based on a single trial per individual (see Rossiter et al., 2001). Final results are extracted from frequency bands, indexes, cortical activities, and signal peaks by using statistical models that analyze differences between experimental conditions. Finally, decoding analysis has taken advantage of machine-learning algorithms to forecast behavior from brain imaging data; both spectral analysis and ERPs can be used as classifiers (see Fudali-Czyż et al., 2016).

For all these reasons, choosing the proper analysis technique is a craft that still requires experience and is strongly dependent

on the type of information the experimenters want to extract from available data. Recent attempts of standardizing EEG data analysis have been made and are promising in the perspective of increasing the replicability of results (e.g., see Keil et al., 2014; Babiloniet al., 2020; Pernet et al., 2020).

METHOD

Systematic Review Protocol

We used a PICO framework to guide the literature search and determine the boundaries of the review (Schardt et al., 2007).

- Population: healthy adolescents or adult humans (potential consumers or users).
- Intervention: presentation and/or interaction with stimuli (audio, visual, audiovisual, tactile, olfactory, taste, or real product) while recording brain activity with an Electroencephalography (EEG) device.
- Comparators: Assessment: neutral task or presentation of neutral stimuli; Methodology: traditional measures (e.g., questionnaires) or combination of techniques (e.g., eye-tracking).
- Outcomes: assessment of brain activity patterns recorded using EEG related to consumer behavior.

We conducted a systematic review by consulting five datasets (Scopus, ISI Web of Science, PubMed, Emerald, and EconLit) and searching the terms and keywords EEG AND (Neuromarketing OR "Consumer neuroscience"). Based on preliminary research, the use of the term "EEG" instead of "electroencephalography" in the research leads to more numerous lists of results with few or no studies removed. We limited our research to the keywords "Neuromarketing" and "Consumer neuroscience" because it is beyond the scope of this review to include papers whose findings contributed to the development of the field without having a clear marketing focus. We screened 264 articles published between January 2000 and June 2020 and analyzed 113 of them selected based on the focus on marketing and consumer behavior research questions (see PRISMA diagram, **Figure 3**, based on Moher et al., 2009), summarizing the main results and coding the characteristics of the study (see Online **Appendix**).

The inclusion criteria led to the selection of original and peer-reviewed articles containing the description of the experimental design and the analysis of the data collected, with a marketing focus and based on collection of EEG data. The exclusion criteria ruled out studies not published in the English language, book chapters, conference proceedings, reviews, commentaries, and preliminary versions of studies by the same authors which were subsequently published as full articles. We also excluded papers that contained only a vague description of the experimental paradigm, insufficient for the replication of the study. We included 32 additional articles identified from the bibliographies of the papers consulted for this review, using the same inclusion criteria described above.

Finally, we want to clarify the reason we restricted our attention to articles published from 2000 onwards. Earlier articles (e.g., Rothschild and Hyun, 1990) are not easily comparable with current methodology because of their strong exploratory nature, the limited sample size, and the different methods used to display stimuli.

We assessed the quality of the articles selected grounded on: (a) the quality of the study design; (b) the number of citations; (c) the ranking of the journal where the paper was published. With respect to the study design, we assessed the studies using an adapted version of the "Quality Assessment Tool for Before and After Studies" (adapted from the National Health Institute NHLBI study quality assessment tools, see details in the Online **Appendix**). This method is based on the evaluation of several dimensions of the experimental study, including clarity of the research question and selection criteria, adequacy of the sample size, and completeness of the analysis. In the Online **Appendix** we reported, for each paper, the individual items and the final quality, the number of citations normalized by publication date from Google Scholar (updated in September 2020), and the ranking of the journal according to SCImago Journal Rank (SJR, September 2020).

Classification Criteria

We classified the papers based on the research topic and the characteristics of the experimental paradigm, including study design and the type of stimuli used. **Table 1** contains the classification of the articles by research topics. We started from the famous four Ps of marketing (Product, Price, Promotion, Place; McCarthy, xbib1960) and we divided each of them in sub-topics, indicating some common keywords.

In a similar manner, we considered the main characteristics of the experimental paradigm. **Table 2** contains a variety of examples with the associated references.

Tasks

The most common protocol involves displaying a list of stimuli (pictures, videos, or TV ads), but an increasing number of studies contains more sophisticated tasks, such as like/no-like ratings, evaluation with Likert scales, choices, or elicitation of the participants' willingness to pay. Measures of memorization and ease of recall are also possible by arranging multiple sessions.

Stimuli

Most of the studies adopt visual stimuli (e.g., product images, brands or logos, 42% of the reviewed articles), audiovisual (44%, e.g., TV commercials or movie trailers), or both (7%). More rarely we observe real products or other types of stimuli (7%, including tactile, olfactory, and taste stimuli).

Participants

The combination of research questions and type of stimuli often suggest what kind of population is chosen as the primary target for the study. Articles that provide detailed information about recruitment and categorization of the participants range from balanced samples (based on age, gender and/or income) to specific target groups selected based on demographic characteristics. Other studies focus on habitual consumers for

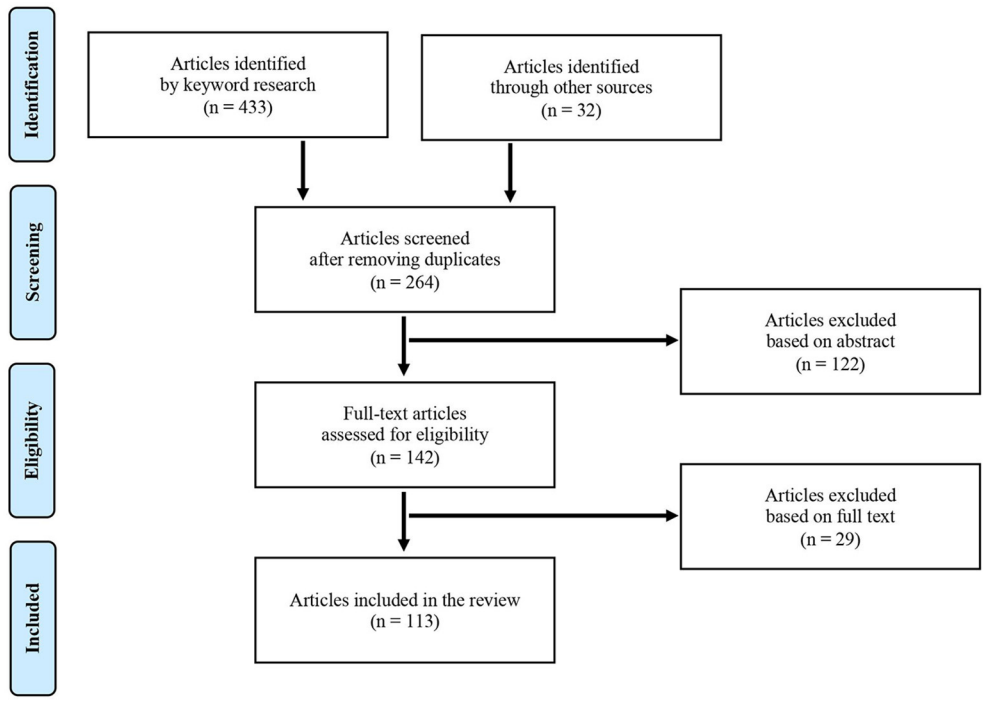


FIGURE 3 | PRISMA flow diagram. The diagram indicates the number of articles in each step of the systematic review, from the initial identification to the application of the exclusion criteria.

a specific product category or analyze the differences between habitual and novel consumers. The number of participants for a study must be chosen carefully based on initial hypotheses, number of trials, expected magnitude of the effect from the literature, and power analysis. Across the studies in this review, we observe an average pool size of 34 participants, with a long tail (up to 331 participants), and larger pools usually observed for studies published in high-rank journals (43 for the top SJR quartile, 30 for the bottom quartile).

Additional Techniques

EEG is compatible with a wide range of tools to collect non-behavioral data, and 32% of the experiments combine EEG with eye tracking or electrooculography (ET and EOG, that record eye movements), facial electromyography (EMG, for facial expressions), functional near-infrared spectroscopy (fNIRS, analysis of oxygenation level), or other physiological measures (e.g., heart rate, galvanic skin response).

Some noteworthy trends (see **Figure 4**) include the increase in the usage of multiple concurrent techniques (from 6% of the papers in 2007 to 2011 to 36% in 2015 to 2019), and the reduction in the average number of electrodes used for the collection of EEG data (from 56 in 2006 to 2010 to 33 in 2015 to 2019), in addition to the steep increase in the overall number of publications (annual averages: 3 in 2006–2010, 14 in 2015–2019).

RESULTS

The four Ps of marketing offer a way to navigate the literature, also described in **Table 1**, by classifying the articles based on their main research question. This taxonomy is used for the rest of the section to introduce and discuss the main results in the existing literature. **Figure 5** contains the distribution of articles in the review according to research topic and type of stimuli used (audio, visual, tactile, etc.). Visual and audiovisual stimuli have been widely used across topics, whereas others received less attention so far. We summarize the results in **Table 3**: for each category of stimulus, we include research and managerial implications, a reference paper, and we indicate the usual number of participants and EEG channels used.

Product

EEG techniques have been used in studies involving the evaluation of widely different products, and using one or multiple senses. The studies reviewed include wine tasting, scents smelling, textile touching, evaluation of food, clothes, and music, among the others. We consider separately the studies that explore perception and preferences over the characteristics of the products, and the studies that aim to identify the differences across market segments (e.g., divided by age, gender, or nationality).

Product Characteristics and Preferences

Marketers want to understand how the separate characteristics of a product contribute to the overall evaluation. In a study

TABLE 2 | Experimental characteristics: tasks, stimuli, participants, and additional techniques.

Experimental characteristic	Example	Description	Reference
Tasks	Observation	The participant observes the stimulus and is not required to complete any specific task	Rossiter et al., 2001
	Questionnaire	The participant evaluates the stimulus based on one or multiple dimensions (e.g., Likert scales)	Rosenlacher et al., 2018
	Choices	The participant chooses one product or bundle of product out of a choice set	Ravaja et al., 2016
	Willingness to pay	The participant observes a product (e.g., image, price, and description) and indicates if the product is cheap or expensive	Lee, 2016
Stimuli	Audiovisual	TV commercials, movie trailers, movie clips, TV series scenes	Gupta et al., 2016
	Visual	Images, description, and price of a product, brands or logos, ads pictures, app screenshots	Ramsøy et al., 2018
	Real products	Interaction with the real product (e.g., brew coffee using a coffee machine)	Sargent et al., 2020
Participants	Balanced sample	Subgroups of participants with different age, gender, and/or income	Vecchiato et al., 2014b
	Target age/gender	Target group (e.g., young females) for the product category used as stimulus in the study	Baldo et al., 2015
	Segmentation	Participants recruited in two or more groups (e.g., based on the familiarity with the product)	Royo et al., 2018
Additional techniques	Eye tracking (ET)	Eye movements are used to investigate attention and acquisition of information	García-Madariaga et al., 2019
	Electromyography (EMG)	EMG is used to collect movements for facial muscles and infer expressions and emotions	Boshoff, 2016
	Galvanic Skin Response (GSR)	GSR indicates the electrodermal activity, whose changes can be caused by emotional stress	García-Madariaga et al., 2020

involving preferences over crackers, Khushaba et al. (2013) vary shape, flavor, and topping of the stimuli and ask the participants to indicate the preferred items. By combining behavioral, EEG, and eye-tracking data, the authors analyze the spectral activity associated with preferences (delta, alpha, and beta activity in the frontal area) and use mutual information analysis to identify the most salient attributes. Hoefer et al. (2016) worked in the same direction by using different fabrics and analyzing neurophysiological reactions toward tactile stimuli. By comparing vigilance (alpha-activity), emotional valence (alpha-asymmetry) and cognitive resources (ERP) across repeated trials, they can identify and interpret the consumers' preferences over fabrics.

Gender and Cultural Differences

Market segmentation is crucial for many firms, and marketers want to understand what drives differences between demographic groups. In a study involving TV advertisements and gender differences, Uva et al. (2015) adopt the LORETA analysis to identify differences in the brain activation between males and females while they watch video segments. Brain correlates are used to predict attention (P300 signal), cognitive processing (beta and gamma waves), and brain activity in different areas are associated with likeability and attractiveness (prefrontal cortex) and with emotion (prefrontal cortex and ACC). The systematic heterogeneity in the activations suggests structural differences in the way different market segments process ads (e.g., higher frequencies' power, ERPs' components, and anterior circulate cortex activation for female participants) and are used to assess the ad's effectiveness. In a similar study focused on cultural differences, Vecchiato et al. (2014a) show the Western and Asian versions of the same TV smartphone commercial to Italian and Chinese subjects. The two groups display no significant difference in attention or memorization (defined using theta and alpha signals), but pleasantness and emotion (theta and alpha signals, heart rate) depend on the cultural differences.

Price

Neuroimaging techniques have been used to identify the adequate price for a product, especially when social or ethical aspects can be incorporated in the evaluation. In a study involving the pricing for various product categories (including apparel and fast-moving consumer goods) Ramsøy et al. (2018) find that willingness to pay correlates with prefrontal asymmetry in the gamma oscillation bands and with the trend in the beta frequency band during the first second of product viewing, a result that can be interpreted in terms of approach behavior and attentional gating. In a series of studies on corporate social responsibility and pricing, Lee (2016) displays different products accompanied by price and neutral or prosocial messages. The higher willingness to pay for the latter products can be explained by an empathic reaction to the stimulus. This result is supported

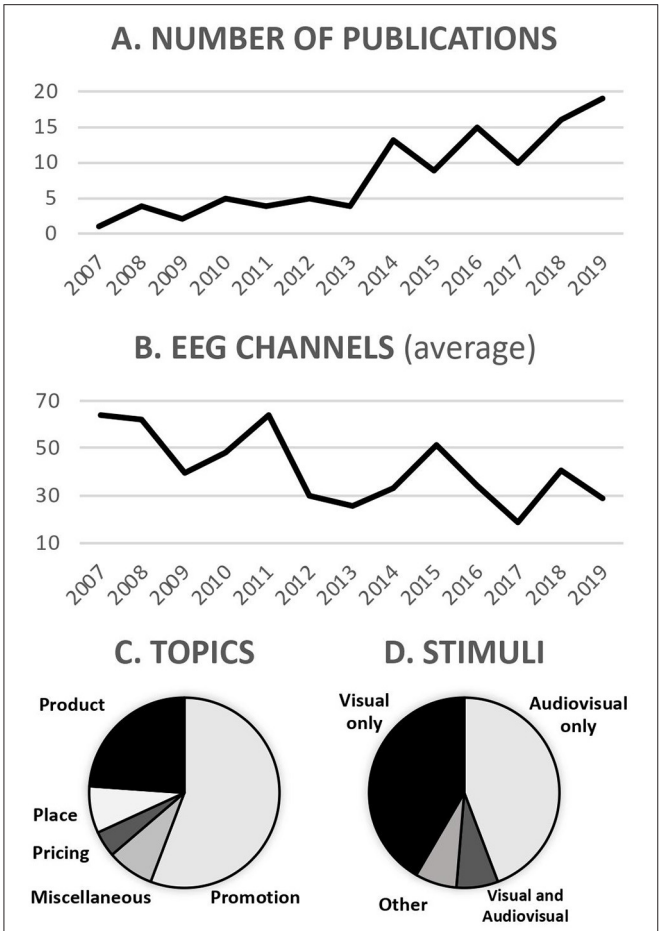


FIGURE 4 | Literature review. **(A)** Number of publications between 2007 and 2019. **(B)** Average number of EEG channels between 2007 and 2019. **(C)** Distribution of research topics. **(D)** Distribution of stimuli used. Visual indicates static visual stimuli (e.g., picture), audiovisual indicates dynamic stimuli (e.g., commercial).

Topic \ Stimuli	Audiovisual	Visual	Visual + Audiovisual	Real products	Tactil	Olfactory	Taste	Audio	Tot
Product	3	14	1	2	1	1			22
Message	13	5	4						22
Memorization	14		1						15
Brand		12	1				1		14
Advertising	10	1	1						12
Context	3	4		2					9
Differences	4	1							5
Pricing		5							5
Miscellaneous	3	5						1	9
Tot	50	47	8	4	1	1	1	1	113

FIGURE 5 | Distribution of articles based on research topic and type of stimuli used. Visual indicates static visual stimuli (e.g., picture), audiovisual indicates dynamic stimuli (e.g., commercial).

by the correlation between product type and consumer empathy (theta-band activities of the anterior cingulate cortex).

Promotion

The promotion of products and brands have been explored in many directions using visual and audiovisual stimuli in studies involving pleasantness and memorization of commercials, effectiveness of rational and emotional messages, and brand identity.

Advertising Rating and Pleasantness

After correctly designing the product and setting its price, it is crucial to promote it, for example through advertisement. One common experimental paradigm for EEG studies involves displaying a sequence of static images, several times each. In a study with frequently encountered objects, such as icons and logos, Handy et al. (2010) use ERPs to identify the emotional value. Stimuli are divided into liked and disliked ones, and the results show a significant effect of hedonic evaluation (central/parietal ERP component in the 150–200 ms post stimulus, and in the parietal/occipital ERP component in the 200–400 ms post stimulus) in a pattern that allows the classification of the pleasantness based on neurophysiological data. The paradigm can be adapted to analyze the characteristics of dynamic stimuli such as TV commercials, and use them as predictors of market-level response to advertising. Venkatraman et al. (2015) use a group of TV ads to compare the predictive power of different techniques (including EEG, eye tracking, and fMRI) and discuss how alpha activity (occipital alpha activity and frontal asymmetry) can be used to integrate the information from traditional self-reports to predict the aggregate real-world impact of the advertising campaign.

Advertising Attention and Memorization

The success of a commercial campaign depends also on whether the consumer will remember the promotional message after several days, and EEG patterns can be used as a measure of attention and predictor of memorization. In the first study on advertising memorization, Rossiter et al. (2001) investigate whether brain electrical can identify the video segments remembered 1 week later. One week after the first session (watch a documentary with short commercial interruptions) participants are shown various frames and are asked to indicate whether each frame was extracted from a commercial. Frames with the fastest and slowest SSVEP responses (steady-state visually evoked potential) are used for the memory test, and the scenes with fast SSVEP response in the left-hemisphere are more easily recognized. This paradigm has been extended to include repeated measures of the same commercial over a longer time span, with participants attending multiple sessions on five subsequent days,

followed by an interview ten days later to determine which ads were remembered. Astolfi et al. (2008) adopt a head model and identify for the remembered ads significant differences in beta and gamma bands and higher spectral power in several cortical areas.

Rational and Emotional Messages

Advertisements usually contain both rational (such as product characteristics and benefits) and emotional parts (music, evocative scenes). Finding a good balance between them is a basic objective of effective communication. In order to understand the different brain activities associated with these two categories of messages, Cook et al. (2011) consider a series of ads with a clear prevalence of rational or emotional content. LORETA analysis shows different brain activation patterns according to the type of message. Rational messages are processed by the orbitofrontal cortex (involved in the evaluation of the rewards), whereas emotional messages activate the anterior cingulate cortex (attention and emotion processing), amygdala and hippocampus (vigilance and memory). In a study on the effectiveness of rational-based and action/emotion-based public health and social cause (HSC) advertisement, Harris et al. (2019) compare brain activity and survey data. They find theta synchronization and alpha desynchronization in the frontal area during all the campaigns, but alpha desynchronization appears in the parietal area only during one ad, suggesting that it would be the most effective one to adopt for the HSC campaign.

Brand Identity

Promotion is not just advertising: companies invest resources to create and protect their own brand identity. Consumer neuroscience offers new tools to evaluate the potential of branding strategies and understand how brand familiarity generates value. For example, understand what are the mechanisms that make the consumers willing to choose the familiar brand instead of switching to a new private label. Brown et al. (2012) use a simple study with soft drinks to answer this question: even when the taste of a soft drink is identical, participants tend to prefer the known brand, reporting higher perceived pleasantness, showing low price elasticity, and displaying high amplitude value in the alpha spectrum over the frontal lobe area (associated with emotions). In a study on brand association, Camarrone and Van Hulle (2019) present a series of combinations of familiar brands and common words. The amplitude of the event-related potential components N400 indicates the incongruence between two concepts and is used to reveal associations between brands, product categories, and consumers' emotions. For example, the N400 response reveals a stronger association of the on-demand brand Netflix with relax-related words compared with TV-related ones.

Place

A small number of articles studied the presentation of the product, instead of its attributes. In order to explore the influence of light and color on consumer behavior, Horská and Berčík (2014) introduced an experimental paradigm in a naturalistic environment. Participants wearing wireless EEG devices and cameras freely navigate a food store, while the products are presented under different lighting conditions. Light characteristics, including intensity and color temperature, can affect conscious and subconscious response to the visual stimuli (beta and alpha activity) and help the creation of positive emotional responses (measured by the asymmetry in the response between brain hemisphere), but the effect of light is different across demographic segments (the emotional response is mediated by age and gender). The social interaction with other consumers is another aspect of the purchase context, and Pozharliev et al. (2015) explore it in a highly innovative study on emotional experience with luxury products. The authors inquire whether consumers have a different response to luxury products when they are shopping with other people, compared with shopping alone. Pictures of various products (chocolate, beverages, shoes, lingerie) were classified into luxury or basic brands during a pre-test and used as stimuli for an observing task under two conditions. In the "alone" condition subjects participate individually, whereas in the "together" condition they are randomly paired with another participant. Luxury products score higher on the emotional value dimension (enhancement of the LPP amplitude) compared to basic brands, and ERP amplitudes associated with attention and motivational significance (P2 and P3 components in the visual cortex) occur more often in the together condition.

DISCUSSION

After summarizing the research and managerial implications emerging from the papers reviewed (**Table 3**), we provide now some guidelines to design EEG experiments (**Figure 6**) for both research and managerial applications. After emphasizing potentials and limitations of EEG in marketing research, we highlight some open questions in the literature that would benefit from EEG studies (**Table 4**).

Exploring Non-conscious Behavior

Alongside with most neuroimaging approaches, EEG concedes the exploitation of brain processes bypassing the filter of conscious awareness. This notion becomes particularly relevant when dealing with decision-making processes in which non-conscious mechanisms are involved. As an example, using EEG and ERP, Camarrone and Van Hulle (2019) were able to reveal associations between brands, product categories, and emotions that would have otherwise gone unnoticed with conventional surveys. Further promising is the identification of EEG-derived indices as predictors of commercial success. Boksem and Smidts (2015) elegantly showed how individual self-declared willingness to pay is a poor predictor of population preference, while EEG gamma activity and medial-frontal beta power can well predict both individual preference and commercial success.

Research Implications

The advantages of using EEG for marketing research can be summarized in four main points. First, the high temporal resolution of EEG is desirable for studies that involve videos (including TV commercials) and other dynamic stimuli (3D

TABLE 3 | Research design, frameworks, and managerial implications.

Stimuli Topic	Number of papers	Average # subjects	Average # EEG channels	Reference	Research Implications	Managerial Implications
Visual	**47**	**27**	**32**	Gholami Doborjeh et al. (2018)	Multiple repetitions of visual stimuli (promotional messages, logos, price formats, etc.) represent a solid paradigm for EEG data collection. Event Related Potentials (ERP) analysis can be easily combined with pictures displayed multiple times. Additional techniques such as eye-tracking and galvanic skin conductance provide further insights and are frequently combined with EEG recording.	Static advertisements are commonly used in printed as well-online promotional messages. Similarly, the products displayed on a shelf in the supermarket are akin to the visual stimuli commonly used in experiments with EEG, often combined with behavioral measures, familiarity, and attention. Stimuli repetition paradigms can be helpful to test consumer loyalty.
Advertising	1	16	29	Guo et al. (2016)		
Brand	12	23	40	Yang (2018)		
Context	4	30	20	García-Madariaga et al. (2019)		
Differences	1	39	32	Jones et al. (2012)		
Message	5	28	25	Cuesta-cambra and Rodríguez-terceño (2017)		
Miscellaneous	5	27	32	Shen et al. (2018)		
Pricing	5	48	45	Ramsøy et al. (2018)		
Product	14	22	27	Khushaba et al. (2013)		
Audio-visual	**50**	**42**	**39**	Barnett and Cerf (2017)	Low-cost EEG equipment and support vector machine (SVM) techniques increase accuracy in terms of ranks and binary answers, reducing the sample size compared to traditional tools. Audiovisual stimuli can be used during natural memorizations tasks. EEG and additional techniques can investigate measurable physiological responses and reactions without relying on verbal reports.	EEG techniques are able to record brain activity with high temporal resolution and identify the reactions to TV commercials or other videos. Behavioral and neurophysiological measures allow to recognize the drivers of engagement and memorization, and select the parts of the commercials that are leading its success (or failure). Audiovisual stimuli are helpful for evaluating the novelty of a product/service, since they avoid the erosion of attention typical of stimuli repetition paradigms.
Advertising	10	33	39	Wei et al. (2018)		
Context	3	60	13	Rosenlacher et al. (2018)		
Differences	4	32	35	Cartocci et al. (2016)		
Memorization	14	47	53	Guixeres et al. (2017)		
Message	13	49	30	Harris et al. (2019)		
Miscellaneous	3	28	35	Boksem and Smidts (2015)		
Product	3	21	35	Dmochowski et al. (2014)		
Visual and audiovisual	**8**	**26**	**57**	Gordon et al. (2018)	EEG is a low invasive technique and can be combined with active and passive tasks from traditional marketing research, as well as novel tasks based on the replication of familiar environments and choice scenarios.	Behavioral and neurophysiological measures can be combined in the analysis of the effect on consumer behavior of price, promotions, displaying formats, and other variables of interest.
Advertising	1	30	14	Pileliene and Grigaliunaite (2017)		
Brand	1	26	32	Camarrone and Van Hulle (2019)		
Memorization	1	21	256	Daugherty et al. (2018)		
Message	4	25	36	Cartocci et al. (2017)		
Product	1	32	10	Ramsøy et al. (2019)		
Real products	**4**	**34**	**19**	Alvino et al. (2019)	EEG techniques can be used to measure the perception of products in multisensory settings and the impact of the surroundings on consumers' evaluation and choices. In this setting EEG can also be combined with additional techniques.	EEG measurements have been used to improve product display in the store. Despite the initial hope, EEG provides limited guidance in the phase of product development.
Context	**2**	**41**	**15**	Berčík et al. (2016)		
Product	**2**	**26**	**22**	Sargent et al. (2020)		
Audio miscellaneous	**1**	**26**	**32**	Lin et al. (2014)	Machine-learning methods improve the classification of emotions using EEG multimodal approach.	Voices, sounds and music play a key role in consumer engagement. Soundtracks, that are an essential part of TV and online ads, as well as jingles contribute to ads recall.
Tactile product	**1**	**24**	**64**	Hoefer et al. (2016)	Neurophysiologic measurements obtained with EEG may replace questionnaires in defining product perceived characteristics.	EEG can be implemented to test consumer pleasantness for all those products with a relevant tactile component (e.g., fabrics, mobile phones and covers, accessories, etc.).
Taste brand	**1**	**26**	**32**	Lucchiari and Pravettoni (2012)	Marketing actions such as brand manipulation can influence brain activity and change consumers' perception of a product. EEG provides objective measures of these effects.	Consumers often prefer branded products (including drugs) to the generic ones. EEG measures can be used to identify the role of a brand in developing consumption preferences and habits.

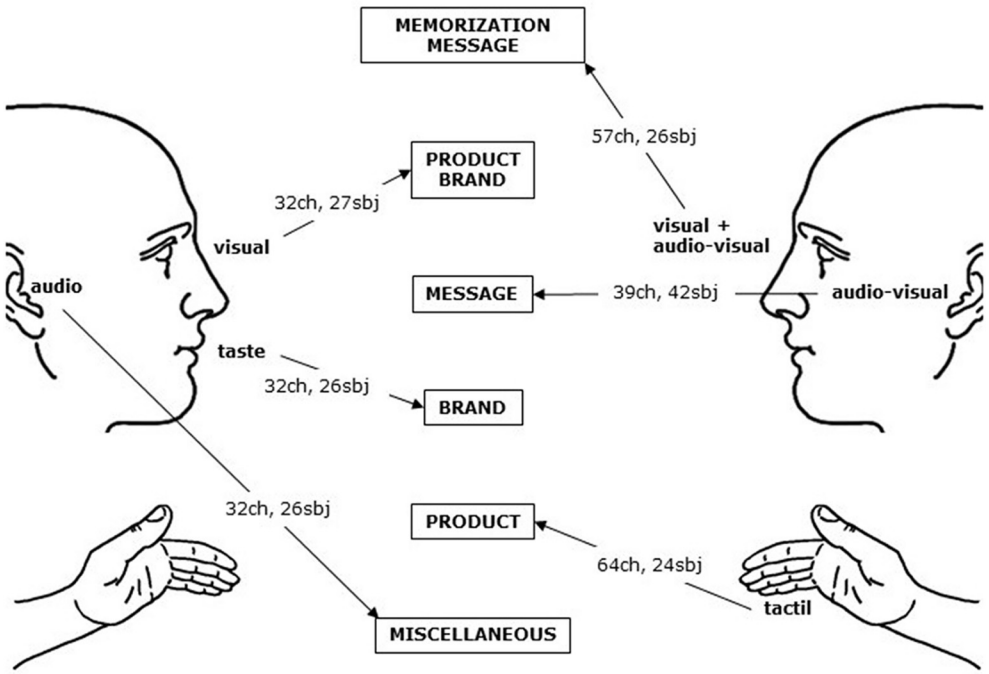


FIGURE 6 | Average number of participants and EEG channels in the reviewed studies, grouped by stimulus category, and most frequent research topics for each category. Visual indicates static visual stimuli (e.g., picture), audiovisual indicates dynamic stimuli (e.g., commercial).

shapes and mobile apps), commonly adopted in conventional and unconventional marketing. The ability to investigate events spanning time windows on the order of milliseconds makes EEG particularly suitable for the investigation of relatively rapid neural and behavioral processes (Ratcliff et al., 2009). Second, EEG is convenient for naturalistic studies, as many EEG systems are portable and can be combined with other tools such as eye-tracking and wearable monitoring devices. In addition, increasingly used techniques such as hyperscanning turn a light on the promising fields of two-person neuroscience and social consumer neuroscience (Schilbach et al., 2013; Pozharliev et al., 2017). Third, EEG is minimally invasive, making recruitment of participants easier and their compliance higher, as compared to other neuroimaging tools (e.g., fMRI or MEG). On the one hand, this facilitates the involvement of large numbers of subjects, an essential advantage in the quest of robust results. On the other hand, the low invasiveness ensures that EEG protocols are more sustainable compared to other neuroscientific approaches, and therefore more likely to be approved by ethical committees. The resulting high compliance aids longitudinal studies based on repeated observations of the same pool of subjects to identify priming, habits, and learning effects. Fourth, EEG is considerably more affordable than other functional imaging approaches, like fMRI, and is accompanied by a long experimental literature (Brown and Behrmann, 2017).

Managerial Implications

The technical and methodological advantages outlined above suggest how novel EEG results can aid managers in their strategic decisions. Companies are rarely willing to invest in a research project unless the results are expected to be clear and reliable. Neuroimaging research often does not lead to immediate indications about internal or external policy to implement (Ariely and Berns, 2010), but solid experimental designs might improve this. The difficulty in the interpretation of the results arises within the subject (as neural noise), but compared with traditional marketing tools these techniques allow to focus on general mechanisms underlying decision making, reducing other confounding factors such as market complexity (Karmarkar and Yoon, 2016). Since the very early days, the modulation of EEG power bands (the alpha one in particular) has been used as a proxy of attentional processes (Berger, 1929; Klimesch, 2012). A wide variety of well-investigated indices have since been developed and can offer an immediate application of EEG to the investigation of salient marketing stimuli. Another rather practical outcome relies on the objective comparison of the emotional charge of commercials. As in Ohme et al. (2010), EEG frontal asymmetries can be used as a diagnostic measure of emotional perception upon the exposure to different advertisements of the same product, assisting in the selection of the most appropriate stimuli. This helps marketers to go beyond verbal declarations of consumers. One more managerial implication of EEG application to marketing falls within the realm of pricing, as respondents tested using common self-reported verbal measures are more likely to give biased and socially acceptable answers (Nighswonger and Martin, 1981). Well-known research topics such as consumer profiling and price formats would benefit from the complementarity between

TABLE 4 | Research agenda.

Topics	Key insights	Open questions	Added value brought by EEG
Multisensory and immersive experiences	Promotional contents are expanding beyond traditional visual and audiovisual stimuli (TV ads, printed magazines, etc.), ranging from sophisticated home theater systems to 360 degrees "virtual reality" videos, and even including scents or tactile experiences, in order to offer the consumer multisensory and immersive experiences, which have been little studied so far.	Do immersive experiences surprise consumers because of their novelty only, or they provide a systematically more effective way to engage consumers? Can immersive experiences become a systematic way to engage consumers? Are multisensory stimuli more effective than the unisensory and traditional ones? Or do they end up overstimulating and confuse the consumers? Where is the balance?	EEG provides cardinal measures of engagement for both unisensory and multisensory stimuli. Pleasantness and surprise, among the main drivers of engagement, can be clearly individuated with EEG.
Consumer profiling	Behavioral differences in product rating and likelihood to purchase can be the result of multiple forces (willingness to pay, brand loyalty, curiosity, etc.) that are difficult to disentangle with traditional techniques.	How can we identify key differences across potential consumers? Do heterogeneous groups (based on personal data, socio-demographic and psychometric measures) display systematic differences in the way they understand, process, and react to promotional messages? Which message is more effective for different targets?	EEG data are not only complementary to questionnaires, but in an objective way they shed light on the neural processes underpinning consumers subjective answers.
Price formats	Pricing strategies include price level and format: gifts, add-ons, discounts, fixed or recurrent costs, are often used to differentiate products and encourage buyers to complete the purchase promptly.	Which price formats should be used to make a product or a service more appealing for new, recurrent, or loyal consumers? Do price formats affect the perception of price? Do they affect the process of search across alternative options? How do price formats affect the ease of comparison between similar products?	EEG provides objective measures of the effect of price on consumers, showing the neural correlates of rational and emotional reactions to price variations.
Social consumer neuroscience	Purchase decisions are rarely made in isolation. The same brain areas involved in self-referential cognition are indeed also those activated when buyers rely on other people's opinions and judgments, and interact with other customers, assistants, and experts. Mechanisms of word of mouth, trust, reputation, rating, and transmission of values play a major role in the purchase process (social facilitation). Little is known whether they are universal or domain-specific (e.g., necessities vs. luxury products).	How do recommendation modalities differ in their ability to convey information and convince consumers? Do they affect the purchase decision or (also) the future opinion about the product? Does the effectiveness of a suggestion depend on the product type, the person who gives the advice, or the consumers' current "state of mind?"	EEG can highlight the differences in brain activity during information processing according to the social communication modalities used.
Shopping in digital and physical stores	Digital and physical stores still coexist for many products, but it is unclear if there is complementarity or substitutability between them.	Do digital and physical stores cannibalize the same audience or strengthen the brand position? Should companies think of them as two different channels to reach the same buyers, or two different shopping experiences for different types of consumers? Which products should be sold (uniquely) in digital or physical stores?	EEG allows us to observe brain activity for different types of stimuli, including visual or audiovisual (digital stores), but also tactile and taste (physical stores).

Overview of five research topics that would benefit from the adoption of neuroscientific techniques.
For each topic, the table contains a statement of its relevance in the current marketing literature, a list of open questions that traditional techniques may not be able to address, and an explanation of the value added to the research by collecting EEG data.

new and old approaches. Several EEG measures including P300 ERPs and frontal asymmetries have been successfully applied in the identification of the willingness to pay in relation with consumers' expectations (Schaefer et al., 2016; Ramsøy et al., 2018). In parallel, EEG-based metrics, combined with behavioral observations, allow to recognize the drivers of engagement and memorization, familiarity, and loyalty, and therefore they can help in the selection of promising commercials. The adoption of multiple concurrent techniques, together with the knowledge accumulated through the last ten years of EEG experiments in marketing, is progressively leading to a less invasive approach. In recent years we have observed a reduction in the number of electrodes (**Figure 4B**) and an increase in the adoption of mobile devices.

How to Design an EEG Study

We provide some basic guidelines that should help those readers who are approaching this kind of study for the first time to orient themselves in experimental design. We are well aware that the complexity of designing an experiment with EEG is far from being easily subsumed into fragmented wisdom pills. However, these general indications should provide some initial resources for a non-expert reader. Starting with your research question, you should first choose the type of stimulus. **Figure 6** displays the average number of participants and EEG electrodes used in the studies included in this review, grouped by type of stimulus (see also **Figure 5** and **Table 3**). These numbers should not be interpreted as optimal for every study, and you should select the number of participants based on a power estimation analysis. In addition, reference papers reported in **Table 2** and in **Table 3** (e.g., Ramsøy et al., 2019) contain several examples of well-designed studies. The current literature provides little information about the use of multisensorial or interactive stimuli. We expect to see in the future more research activities exploring these aspects (see Areas for future research), and advise to consult methodological papers (e.g., Cline et al., 2018) to address the challenge of setting new standards. After the data collection, EEG data require a pre-processing phase, which is rather homogeneous across the studies we reviewed, as far as the adoption of analysis toolboxes (Delorme and Makeig, 2004). Finally, the choice of a suitable analysis technique almost entirely depends on the type of information the researcher aims to derive from the available data. This decision usually requires solid expertise.

Limitations

The results of the papers reviewed do not always provide conclusive evidence, or they emphasize the contingent results in a way that is difficult to generalize. Results from studies that focus on methodological aspects are often difficult to apply to practical scenarios. These issues lead us to strongly advise merging different competences in the research group that is designing the experiments and analyzing the results. Collaborative efforts can indeed balance the correct approach to consumer neuroscience, made of rigorous methodology applied to questions relevant to marketing. Companies are already able to interpret the results of conventional marketing studies and decide whether they are aligned with the expectations. Instead, brain imaging results are harder to explain and to apply to the crucial variables for companies. As a result, many firms are skeptical about consumer neuroscience research and not all promises have been fulfilled. The authors believe that it is possible to overcome skepticism by pointing out that brain imaging can go beyond the boundaries of any behavioral study and offer insights into the mechanisms of unconscious decision-making process, but certain conditions must be met in order to make it worthwhile. Designing experiments of consumer neuroscience according to protocols of common practice in scientific literature (e.g., randomized control trail, RCT), researchers and marketers who apply consumer neuroscience techniques might provide additional reasons to companies to overcome their skepticism. Indeed, the definition of precise research questions and of standardized protocols for treatments, control groups or stimuli, and for robustness checks might improve the reliability and replicability of the studies in this emerging field and make findings clearer also to non-experts.

Areas for Future Research

In this review we have highlighted the extensive use of consumer neuroscience techniques in studies with visual and audiovisual stimuli. The high time resolution of EEG markers and the adoption of objective indices for decision-making processes can be extended further, to more complex multisensory stimuli and immersive experiences, including virtual reality environments. Plausible prospects regarding future consumer neuroscience research include an increased spread of research questions toward the consumer's interaction with the environment, including physical characteristics of the store, and social interactions (experts, friends, or other consumers, e.g., Pozharliev et al., 2017). The few recent articles that explore these areas successfully combine well-designed experiments and clear managerial implications. Research on pricing should move away from a "willingness to pay" approach, that can be successfully explored with traditional techniques, and focus on market segmentations and drivers of the perceived value. This novel approach seems promising in the studies that use environmental-friendly products and communication strategies based on corporate social responsibility as stimuli and suggests that a broader scope is possible. Finally, user experience in digital and physical environments—and the difference between the two—deserves broader space for future consumer neuroscience research. The opportunity to investigate the subconscious processes underlying the purchase behavior seems a natural complement to the high amount of data about online search and purchase. For example, to the best of our knowledge, there is no study exploring the search process within and between online shopping platforms.

Neuro-psycho-physiological, biometric, psychometric, and behavioral data can be jointly used to move beyond the limits of subjective and self-declared tools, such as questionnaires. However, brain imaging techniques (and other combined tools) are not intended to replace traditional surveys. On the one hand, we underlined the advantages of exploring hybrid solutions between neuroscientific and more consolidated marketing tools. On the other hand, the current lack of conclusive findings on the most promising EEG metrics, or the rationale of their combination, for the prediction of decision-making, might be attributable to an inappropriate experimental design rather than to the limits of the technique itself. For this reason, we provided basic suggestions to design an experiment with EEG. For instance, ERPs need several repetitions of the stimulus to be registered, thus compromising the novelty of a stimulus. The use of a neutral video interspersed with a repeated stimulus (e.g., a picture) over time can prevent this undesired effect. We advise against extremely specific paradigms whose results are difficult to be generalized and exported to adjacent scenarios, as well as against too-broad research questions that do not help researchers, and even companies, in a concrete way. **Table 4** offers a list of five areas for future research, which would benefit from an interdisciplinary approach. We also give a brief explanation of how EEG would provide a valid technique to explore these

plausible perspectives. The research areas satisfy three criteria: (1) neuroscientific techniques can provide new evidence with respect to traditional ones; (2) the current literature provides little or no answers to them; and (3) they also address direct managerial implications.

CONCLUSION

This review has shown the limits of the current literature: we do not advise blind optimism, and we claim that successful research and trust from companies will depend on achieving the suggested improvements. Traditional marketing techniques capture customers' conscious actions and choices, whereas neuroimaging tries to offer objective and replicable measures of neural processes occurring during decision-making. The relatively low cost, minimally-invasiveness, and portability are the key points that make EEG a suitable tool for both lab and field experiments, providing results and recommendations that can improve marketing actions. The long path of EEG since 1929 and the extensive use of this technique in the field of neuroscience might offer a wide range of markers of attention, cognition, and emotions to be applied to naturalistic stimuli such as advertisements. We believe that a complete and rigorous consumer neuroscience project requires joint contributions from an interdisciplinary group. From a methodological point of view, we expect research projects to be designed like clinical studies: sample selection criteria, information allowing replicability, selection of additional techniques, and data acquisition, filtering, preprocessing and cleaning, need to be finely tuned to each study and well-reported in the final report. Research questions should be precisely defined and include treatment, control, and robustness checks according to the protocol of a randomized control trial (RCT), as common practice in experimental scientific literature.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

AB, SR, UF, and GT contributed to conceive and design this systematic review. SR, AB, and LT conducted the study selection, they extracted the data from the selected articles, and discussed among them in case of controversy on the classification of articles. SR ran the data analysis. AB and SR drafted the manuscript with the supervision from UF and GT. AB conceived the conceptual framework and under the supervision of UF edited the technical part of the manuscript related to EEG technique. All authors contributed to the interpretation of data and to the final version of this article, that they all hence approved to be submitted.

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SUPPLEMENTARY MATERIAL

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BRIEF RESEARCH REPORT
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The Relation Between Consumers' Frontal Alpha Asymmetry, Attitude, and Investment Decision

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The frontal alpha asymmetry (FAA) is a neurophysiological measure of motivation and preference. Despite the FAA is associated to commercial pleasantness, conflicting evidence emerged in the literature regarding its relationship with behavior. To study the association between FAA and consumers' decision, we manipulated a commercial script to elicit diverse consumers' attitudes and decisions and to evaluate whether the FAA score is associated to their final investment. A little informative script (S1) was used to polarize consumers' attitudes and investments toward unfavorable scores, while a more personalized message (S2) to elicit in customers a favorable attitude and higher investments. Twenty-one participants listened to the scripts, and their FAA, attitude, and monetary investment were measured. In S1, the FAA did not correlate with neither attitude nor the investment decision, while a robust negative correlation between these variables was found in S2. No other peripheral body and neural measures associated with attitude or final decision. Our data suggest that the FAA correlates with attitude and decision, when a commercial script is customized and provides an adequate information, likely leading the consumer to a more reasoned and planned decision-making process. When facilitating a favorable attitude toward an offer, the negative correlation of FAA and behavior may reflect the involvement of a control system, whose role is to monitor and govern possible conflicts between approach and avoidance motivations. This observation provides additional indication on the value of FAA as a marker of consumer behaviors, and how it could be affected by experimental and contextual bias.

Keywords: frontal alpha asymmetry (FAA), EEG-electroencephalogram, decision-making -investments, consumer attitude, pupil diameter, consumer choice

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INTRODUCTION

So far, research in Consumer Neuroscience developed different approaches to determine consumers' attitude toward a given commercial message—i.e., the tendency to respond to a stimulus with some degree of favorableness or unfavorableness (Ajzen, 2008)—and their final choice, through behavioral, body peripheral, or neural measures (Vecchiato et al., 2014; Cherubino et al., 2019). An index that specifically measures consumers' motivation toward the stimulus and reflects their intention and volition is the frontal alpha asymmetry (FAA—for a comprehensive review, see Hewig, 2017; Hakim and Levy, 2018). The FAA is computed as the difference between

the frontal right and left hemispheres in the alpha band spectra (Hakim and Levy, 2018). Typically, the frontal Alpha rhythm (8–12 Hz) is linked to brain functions related to information processing, attention, decision-making, and emotion regulation (Cohen et al., 2009; Klimesch, 2012; Zhang et al., 2018; Misselhorn et al., 2019); high alpha power has been related to inhibitory control, while low power to neural activation (Larson et al., 1998; Benedek et al., 2011). To date, this neural marker has been interpreted to reflect a motivational direction and preference toward the stimulus (regardless of the experienced positive or negative affective valence) that occurs just prior to the behavior outcome (Harmon-Jones et al., 2010; Hewig, 2017). As such, Vecchiato et al. (2011) measured the FAA during the presentation of different TV commercials and reported a relation between participants' ratings of the pleasantness of the video clips and the frontal asymmetry. A great left hemispheric activity in the alpha domain has been interpreted as an approach motivation, while a right may indicate an avoidance drive from the stimulus. This interpretation has been confirmed in other investigations (Coan and Allen, 2003; Hakim and Levy, 2018). However, although the evidence in favour of this classical interpretation is widely documented, alternative perspectives on the FAA are emerging in the literature. In this vein, a review by Gable et al. (2017) pointed out that, although the relationship between left frontal activity and the approach motivation results more solid, defined as the behavioral approach system (BAS), the findings in support of a relationship between a right frontal activity and the avoidance motivation are mixed, and further research are needed.

Despite the association between FAA and the pleasantness of the stimulus is widely documented, the extent to which FAA is also able to predict consumers' attitude and final decision is still a matter of debate. To this aim, Cherubino et al. (2019) underlined the importance of unveiling brain processes and behaviors that are not possible to observe with self-reported measures (e.g., questionnaires) and to boost the research for physiological markers able to predict consumers' attitude and choices. The FAA, being an index of consumers' motivation toward the stimulus (i.e., a commercial offer) could be a possible candidate. However, few studies—and with mixed observations—investigated the association between consumers' FAA and both the attitude and their final choice. Purposely, Fischer et al. (2018) highlighted how the FAA was a reliable predictor and a potential neural marker of the online information-sharing behavior that is an indirect measure of final consumer decision. Similarly, Ravaja et al. (2013) found that a high activation of the left frontal cortex (approach motivation) during the predecisional phase, predicted the decision to purchase grocery products with different prices. On the contrary, Ramsøy et al. (2018) asked potential consumers how much they would have paid for some commercial products (i.e., willingness to pay) and did not find an association between FAA and consumers' decision, thus challenging the assumption that the FAA may be related to customers' final choice. Accordingly, a well-defined correlation between FAA and both consumers' attitude and final decision is still missing, especially when considering different contextual factors, or diverse processes by which the decision is made.

In this context, to better characterize this relation, we could rely on the overt manipulation of the stimuli (i.e., commercial offers) both to elicit diverse attitudes of disfavor and favor in the customers and, consequently, to impact consumers' decision (i.e., different willingness to pay). Indeed, the modulation of a commercial through the amount of provided information and the personalization of the message may have a significant influence on consumers' attitudes and final choice (Hahn et al., 1992; Coulter et al., 2001; Goldsmith and Freiden, 2004; Xu, 2006; Ünal et al., 2011; Bostrom et al., 2013; Boerman et al., 2017; Gironda and Korgaonkar, 2018), with a possible impact also on the FAA and on the consequent relation between these variables. Specifically, when information is limited, customers hardly undertake an in-depth commercial evaluation and an accurate final decision; conversely, when the information load increases, the capacity for information processing and the consistency of decision-making increase (Hahn et al., 1992). Moreover, a more informative message may stimulate consumers toward a more positive attitude (Coulter et al., 2001; Ünal et al., 2011). Equally, after a careful evaluation of individual past behaviors, needs, and interests, the presentation of tailored commercial potentially prompts a general positive attitude on consumers' intentions and choices (Goldsmith and Freiden, 2004; Xu, 2006; Bostrom et al., 2013).

Consequently, through the manipulation of a commercial offer to induce diverse consumers' attitudes and investment decisions, the present study aimed at assessing whether the FAA score correlates to consumers' attitude and final decision. According to our experimental modulation, we developed two fictitious commercial offers. In the first frame, we presented a commercial call, limited in the amount of information and formulated in a general standard message. This type of call was expected to elicit an unfavorable and polarized attitude in participants and stimulate them to invest a small and less variable amount of money. Conversely, in a second frame, we presented a highly informative and personalized message compared with the first frame that was expected to produce a more favorable and less polarized attitude and a larger and more variable amount of money invested than the other condition. Given this experimental manipulation, we investigated the correlation between the FAA and consumers' attitudes and decisions (i.e., the percentage of investment), and also compared this neural marker with other control measures (e.g., the pupil diameter), to verify whether the FAA would specifically reflect consumers' intention and volition other than a general index of information processing and attention.

MATERIALS AND METHODS

Participants

We recruited 21 native Italian and right-handed participants (11 females; mean age ± SD: 38.4 ± 11.3 years) by means of the Edinburgh Handedness Inventory (Oldfield, 1971). Participants had normal/corrected-to-normal vision, no history of auditory or psychiatric disorders, and were selected from a pool of volunteers at the IMT School for Advanced Studies Lucca whose age range (25–60) matched the representative target population

of customers for the insurance policy used in the experiment. The study was made in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2013). Participants were provided with an exhaustive description of all the experimental procedures and were required to sign a written informed consent. The study was conducted under a protocol approved by the Area Vasta Nord Ovest Ethics Committee (protocol n. 24579/2018).

Experimental Design

The experiment was conducted during weekdays' mornings (10–12 a.m.) and afternoons (2–6 p.m.). After reading and compiling the informed consent, participants sat comfortably in a soundproofed and shielded box. The room was illuminated exclusively with artificial lights. Accordingly, the brightness of the room was maintained stable and equal for all the participants in the experiment. They were in front of a table on which there were a computer screen and audio speakers used for the projection and reproduction of experimental stimuli. The investigators controlled the experimental protocol being outside the shielded box, and they were in contact with the participants through a microphone.

Firstly, participants were asked to perform a gambling game in which 15 matrices adapted from the Raven Matrices test were shown (Raven et al., 1998). The stimuli were presented by means of the PowerPoint software controlled by the experimenters. Participants had to complete each figure choosing one from six possible missing pieces. Before the choice, participants bet a fictitious amount of money using a real-like monetary system (1,000, 5,000, 10,000, and 20,000 Italian Lire) based on how much they felt confident in providing the correct answer. If participants guessed the answer, they won the amount bet, otherwise, they won nothing. Participants' answers were manually recorded on a paper grid by the experimenter. At the end of the gambling game, participants collected a virtual amount of money given by the sum of the bets won. Eventually, participants had to use this virtual wallet to be invested in each of the commercial offers presented later.

After this phase, participants were fitted with an EEG cap (Electrical Geodesic, 64 electrodes) suitable for their head circumference and an eye-tracker device (Tobii Pro Glasses 2). Then, the experimental protocol was administered by using the E-Prime software (version 2)[1]. The EEG signal and the pupil diameter were recorded throughout the duration of the protocol. After reading the instructions, a black screen with a white fixation cross was projected for 5 s (rest phase). Then a first commercial call started. Script 1 (S1) lasted 51 s. In this frame, the consultant claimed to have selected just 50 clients in order to propose new insurance policies at advantageous conditions. A few general details were provided on the policy, namely that the modules of the policy were adaptable to specific personal needs and the offer was valid only in the current month. Participants were instructed to listen to the entire audio script while continuing to stare the fixation cross, limiting body movements to a minimum and their interaction with the voice. The same pattern was performed also for the second commercial call. Script 2 (S2) lasted 87 s. In this frame, the consultant claimed that the offer was tailored according to participants' specific needs because their personal profiles were examined. Three main pieces of information were provided to the customers: the name of the insurance policy, the presence of different modules that were adaptable according to personal needs by making some practical example (e.g., work, family, etc.), and the presence of a progressive discount related to the purchase of multiple modules.

Accordingly, the two commercial scripts differed in the specificity of the product (i.e., insurance) details and the customization of the offer, so that the commercial S2 resulted to be more detailed and personalized, according to our experimental modulation aims. The transcripts of each script in Italian and translated into English language are attached in the **Supplementary Material 1**. Each commercial offer was presented once (one trial) to participants. Both of the audio scripts were recorded *ad hoc* by one of the experimenters. We used a female voice that acted as a fictitious consultant. A male actor was not used, supported by the evidence that the voice gender does not have a significant impact on advertising effectiveness (Rodero et al., 2012). The scripts were presented in the Italian language and differed in the duration, number of information, and personalization of the message provided by the fictitious consultant about the insurance policy. The PC screen brightness was maintained at the same level across participants both in baseline and experimental conditions because we presented the same black screen with a central white fixation cross.

After the end of each audio script, participants were asked to answer four closed questions which measured participants' attitude of disfavor and favor toward the offer with two response options and how much of the virtual wallet previously collected in the gambling game they wanted to invest in the just-presented offer. Participants answered directly by voice to the investigator by means of a microphone and without any time constraints. The experimenters manually collected the answers on a paper grid. The presentation of the two scripts was counterbalanced across participants in order to avoid possible problems and confounds derived from the presentation order. The start and the end of each event of the protocol, such as the rest and the audio script listening, were recorded through a parallel port by the EEG acquisition software.

Measures

Sentiment Analysis

To check whether the traces did not use words that could evoke an *a priori* difference in participants' emotional valence that could account for both the attitude toward the stimulus and the EEG responses, we made a sentiment analysis on the English translation of each script in Python (version 3.8)[2] by means of the vederSentiment (version 3.3.2)[3] package. The vederSentiment classification score proved a large correlation with other well-established sentiment analysis indexes that include also the use

[1]E-Prime (Version 2.0) [Computer software].

[2]Python (Version 3.8) [Computer software]. (2020).

[3]VederSentiment (Version 3.3.2) [Computer software]. (2020).

of social words in their scores (i.e., the Linguistic Inquiry Word Count—Hutto and Gilbert, 2015). For each commercial offer, the algorithm divided the lexicon in sentences by means of the spaCy (version 2.3.2)[4] package. For each sentence in each commercial offer, a normalized weighted composite valence index called compound score was obtained (Hutto and Gilbert, 2015). For each commercial offer, a whole compound score was computed by averaging the scores obtained in each sentence. The compound score ranged from −1 (most extreme negative) to 1 (most extreme positive—Hutto and Gilbert, 2015). The algorithm that we produced for the sentiment analysis is attached in the **Supplementary Material 2**.

Attitude Toward the Offer

For each condition and participant, the answers collected to the questions made at the end of the commercial offer were transformed in a metric scale: (a) Do you think the offer is disadvantageous or advantageous for you? (bias toward the offer, yes = 1, no = 2); (b) Do you think that the information in the offer was inadequate (vague/excessive) or adequate? (opinion on the adequacy of information, inadequate = 1, adequate = 2); (c) Did the personalized features of the offer give you a negative or positive impression? (opinion on the personalization of the offer, negative impression = 1, positive impression = 2); (d) Do you reject or accept to schedule a meeting with the consultant? (decision on planning a meeting with the consultant, reject = 1, accept = 2). Then, for each condition and participant, we summed up these scores and computed a whole index of attitude toward the offer, ranging from 4 (highest disfavor) to 8 (highest favor). We computed a whole score instead of using each single variable for the analysis given the small sample size and because this approach limits the number of variables to be analyzed and the multiple comparison correction in the statistical tests.

Monetary Investment

For each participant and condition, the monetary investment (%) was calculated according to the percentage formula, where participants' willingness to pay was divided by the total amount of money available won in the gambling game. We computed the percentage of investment score separately for each participant and each offer, without averaging the score across subjects or conditions. With this operation, we normalized the willingness to pay and made the scores comparable across participants.

Pupil Diameter

The pupil diameter (measured in mm) of the left and right eyes was obtained with a sampling rate of 100 Hz. For each participant, condition, and eye, the signal in the data segments between −5,000 ms (the onset of the rest phase) and −200 ms before the starting of the audio script, were considered baseline, while from 0 ms (the onset of the audio script) to the end of the commercial offer as the task. Because we only recorded one trial both for the baseline and the task, for each participant, condition, and eye, both the baseline and the trial were divided into two epochs of equal length. This operation contributed to make a separate preprocessing of the signal within the initial and final period of the trial. Then, each epoch was preprocessed by means of the CHAP[5] toolbox of MATLAB (Version R2018b)[6] (Hershman et al., 2019). The CHAP software merged the pupil diameter of both eyes together and computed the z scores according to the mean and SD of each epoch. For each epoch, the data points above and below 3 SD were considered outliers and excluded from the analysis. Then, the blinks were identified and excluded by the CHAP algorithm and the pupil size of all the missing values (e.g., blinks, outliers, or other missing) was reconstructed by means of the linear interpolation. For each condition, the mean pupil diameter of each epoch (initial and final period) was computed and averaged within the baseline and the task data segments. Then, for each condition, we computed the relative change of pupil diameter by subtracting the mean pupil diameter of the task with that of the baseline (Hershman et al., 2019). Accordingly, positive and negative values corresponded to a high and low pupil diameter changes with respect to the baseline.

EEG Preprocessing

EEG recordings (500 Hz sampling frequency, NetStation[7] acquisition Software) were downsampled to 250 Hz and band-pass filtered between 1 and 40 Hz. The signal was visually inspected by an EEG expert (well trained in artifact recognition) and prominent artifacts removed by manual rejection. The noisy channels were excluded and interpolated *via* spline interpolation by visual inspection of the EEG expert. The electrode was classified as noisy if completely flat or showed a much higher magnitude than nearby electrodes (Cohen, 2014). Then, an average re-reference was applied on the retained signal (Ferree, 2006). Muscular, ocular, and electrocardiographic artifacts were removed using independent component analysis (ICA) in the EEGLAB toolbox (version 2019.1)[8] of MATLAB (Delorme and Makeig, 2004). For each participant and condition (S1 and S2), the signal was divided in small epochs of 200 ms and evoked responses were removed from each epoch. This operation increased the stationarity of the signal without any event of interest linked to each epoch (Cohen, 2014). The epochs in the data segments between −5,000 ms (the onset of the rest phase) and −200 ms before the starting of the audio script, were used as baseline for trial normalization. Then, the fast Fourier transform analysis was performed with the Brainstorm software version 3.200818[9] (Tadel et al., 2011).

EEG Asymmetry

First, for each participant, condition, and EEG epoch, we run a fast Fourier transform to obtain the power at 10 Hz, that is approximately the central frequency of the alpha spectrum domain (8–12 Hz—Klimesch, 2012). Then, for each participant, the alpha power was averaged between epochs in order to

[4]SpaCy (Version 2.3.2) [Computer software]. (2020).

[5]CHAP. (2020). *Open Source Software for Processing and Analyzing Pupillometry Data [Computer software]*. Retrieved from: https://in.bgu.ac.il/en/Labs/CNL/chap/default.aspx

[6]MATLAB (Version R2018b) [Computer software]. (2018).

[7]NetStation (Version 5) [Computer software].

[8]EEGLAB (Version 2019.1) [Computer software]. (2019).

[9]Brainstorm (Version 3.200818) [Computer software]. (2020).

TABLE 1 | The interpretation of the B_{10}, that is defined as the probability in support of the alternative hypothesis (H1, values higher than 1) with respect to null hypothesis (H0, values below 1 - Wagenmakers et al., 2017a).

Interpretation	BF_{10}
Extreme evidence for H1	>100
Very strong evidence for H1	30–100
Strong evidence for H1	10–30
Moderate evidence for H1	3–10
Anecdotal evidence for H1	1–3
Equal evidence for H1 and H0	1
Anecdotal evidence for H0	1/3–1
Moderate evidence for H0	1/10–1/3
Strong evidence for H0	1/30–1/10
Very strong evidence for H0	1/100–1/30
Extreme evidence for H0	<1/100

reduce the noise in the power spectrum and to consider only the frequency domain and not the time domain, since the two experimental conditions, S1 and S2, had different total durations. Then, for each participant, we baseline normalized the resulting power spectrum using the Decibel (dB) conversion formula (Cohen, 2014). This operation was performed in order to control and exclude possible trait differences in the EEG signals across participants and because "(…) raw power values are not normally distributed because they cannot be negative, and they are strongly positively skewed. This limits the ability to apply parametric statistical analyses (…)" (Cohen, 2014; p. 219). The left and right frontal (F3 and F4) and parietal (P3 and P4, as control) electrodes according to the 10–20 International System were used. These frontal sensors are EEG sites where the alpha asymmetry was classically reported (Allen et al., 2004). The parietal sensors in a specular position with respect to the frontal ones were considered control. In our study, we performed dB normalization instead of the classical log-transformation of EEG data performed by Allen et al. (2004). Thus, FAA and parietal (PAA) alpha asymmetries were calculated by subtracting the left from right normalized EEG activity [i.e., FAA = dB alpha (F4)—dB alpha (F3)]. Accordingly, we obtained the FAA index, where positive values reflect a higher alpha power in the right compared with the left hemisphere and consequently an approach motivation, while negative values correspond to a higher power in the left compared with the right hemisphere, thus reflecting an avoidance motivation toward the stimulus.

Data Analysis

Preliminary, within the two scripts, we verified whether the compound score of the sentiment analysis reflected a negative (score ≤ -0.05), neutral (score between -0.05 and 0.05), or positive (score ≥ 0.05) valence (Hutto and Gilbert, 2015).

Then, the Bayesian statistical analyses were performed with the JASP software (Version 0.13.0)[10]. Firstly, unlike the frequentist approach, with the Bayesian statistics, starting from the prior probabilities on the two hypotheses (H0 and H1), we obtain the magnitude of the evidence in support of both H1 and H0 (Wagenmakers et al., 2017b). This allows us to estimate how confident we are in supporting, for instance, H0 (e.g., evidence in favor of a noncorrelation between the pupil diameter and the percentage of investment in S2) despite our small sample size. In fact, the Bayes Factor (BF_{10}) that is the probability in support of H1 (values higher than 1) with respect to H0 (values below 1), could be interpreted as anecdotal, moderate, strong, very strong, and extreme, as evidenced in **Table 1** (Wagenmakers et al., 2017a). In case the BF_{10} falls within the anecdotal evidence, we cannot fairly support our hypothesis (H1 or H0). Contrariwise, if the BF_{10} falls from the moderate to the extreme magnitude, we get progressively strong evidence in support of the hypothesis (H0 or H1). Secondly, the Bayesian statistic outperforms the frequentist approach in a small sample size scenario because offers the possibility to choose *a priori* how confident we are to find the evidence in support of H1 (Mcneish, 2016; Wagenmakers et al., 2017b; Zondervan-Zwijnenburg et al., 2017). The value of the prior could be set based on the current scientific knowledge about the topic of investigation (informative priors), or, if an extensive background lacks—such as the case of the relation between FAA and the willingness to pay—the use of a default uninformative prior is recommended. In the latter case, it is still possible to check the robustness of the evidence setting progressively wide and ultrawide prior values (robustness analysis), that is enhancing the expected probability of finding evidence in support of H1 with a high effect size (Van De Schoot et al., 2017; Zondervan-Zwijnenburg et al., 2017). Accordingly, the BF_{10} is considered fairly robust if the magnitude of the evidence is stable for most of the default, wide, and ultrawide prior values. Thus, the evidence taken from the results is the mostly supported one (e.g., if the evidence is anecdotal for the default but moderate for the wide and the ultrawide priors, the evidence in support of the hypothesis is considered mostly moderate).

As preliminary analysis, two one-tailed Bayesian paired-samples *T* tests were performed to control if the attitude score and percentage of investment, respectively, were higher in S2 than S1. Other three Bayesian paired samples *T* test were carried out to compare the score of the FAA, PAA, and pupil diameter between S1 and S2. As a further control, within each condition, we performed two Bayesian one-sample *T* test against zero to find possible unbalances in the FAA and PAA scores. Then, within each condition, we performed a Bayesian Kendall's Tau-b correlation to compare the attitude score and the percentage of investment with each other and with the FAA, the PAA, and the pupil diameter.

Each Bayesian *T* tests was redone three times setting a default (0.707), wide (1), and ultrawide (1.41) Cauchy prior, respectively (Wagenmakers et al., 2017a). Similarly, each Bayesian Kendall's Tau-B correlation was performed three times setting a default (1), wide (1.5), and ultrawide (2) stretched Beta prior (Wagenmakers et al., 2017a). The multiple comparison correction of the BF_{10} is recommended for pairwise comparisons when uninformative priors are used (De Jong, 2019; Han, 2019). Thus, we applied the

[10]JASP (Version 0.13.0) [Computer software]. (2020).

TABLE 2 | The sentiment analysis' compound score and the mean (±SD) of the percentage of investment, the attitude toward the offer, the EEG power asymmetry scores (computed in dB), and the pupil diameter in the little informative and standard script (S1) and in the highly informative and personalized script (S2).

Variables	S1	S2
Sentiment analysis' compound score	0.09	0.25
Investment (%)	14.762 (17.346)	32.143 (31.81)
Attitude toward the offer	5.095 (1.221)	6.095 (1.375)
EEG asymmetry F4-F3	−0.768 (1.366)	−0.095 (1.740)
EEG asymmetry P4-P3	0.650 (1.749)	0.173 (2.433)
Pupil diameter	0.283 (0.333)	0.391 (0.299)

For the EEG asymmetry, we considered the right and left frontal (F4-F3) and parietal (P4-P3) electrodes.

false discovery rate Benjamini-Hochberg (FDR B-H) procedure to the Bayesian correlation test because for each condition and analysis, we performed seven pairwise comparisons. According to the Vovk-Sellke formula[11], the BF_{10} of 2.46 (H1) and 0.406 (H0), that corresponded to a p value of 0.05 was used as threshold to consider a result as a false positive (Sellke et al., 2001; De Jong, 2019). Moreover, a false discovery rate of 0.25 was chosen to find the FDR B-H critical value. For each correlation analysis and separately for H1 and H0 significant results, firstly, the results were sorted in a descending (H1) or ascending (H0) order and then ranked according to their BF_{10}. Then, according to the FDR B-H formula, we divided the rank of each false-positive result by the total number of tests (7) and multiplied the outcome by the false discovery rate (0.25). The resulting p value was then transformed in BF using again the Vovk-Sellke formula (Sellke et al., 2001; De Jong, 2019). This value represented the critical BF within which correctly accepting the hypotheses (H1 and H0). If the BF_{10} was below (H1) or above (H0), its critical value, we considered the result as a false positive. The FDR B-H correction was applied with the same procedure also when we redone the analysis with wide and ultrawide priors.

RESULTS

The descriptive of the variables involved in the analysis are presented in **Table 2**, while further details on the robustness analysis, as well as the prior and posterior distributions, are attached in the **Supplementary Material 3**.

Sentiment Analysis

The sentiment analysis revealed that both the commercial offers used a type of language which has a positive sentiment classification (compound score >0.05). The Script 1 assumed a compound score of 0.09, while the Script 2 of 0.25. Thus, we could exclude that the words presented in the two scripts had a connotation that could have evoked an *a priori* difference in participants' emotional valence.

[11]To compute the BF from the p value the formula is: $BF = 1/(-e\ p \ln(p))$.

Bayesian Paired Samples *T*-Test

Two separate Bayesian paired samples T-test were performed to examine whether the attitude toward the offer score and the percentage of investment, respectively, where higher in S2 compared with S1. We found a moderate evidence in support of this hypothesis for both the attitude toward the offer (**Figure 1A**, $BF_{-0} = 6$) and the percentage of investment (**Figure 1B**; $BF_{-0} = 8.8$). The Bayes factor appears to be stable in both the analyses, ranging from $BF_{-0} = 5.109$ (wide) and $BF_{-0} = 4.1$ (ultrawide) for the attitude toward the offer, and from $BF_{-0} = 7.7$ (wide) and $BF_{-0} = 6.2$ (ultrawide) for the percentage of investment.

Moreover, we conducted other three separate Bayesian paired samples T-test (two-tailed) to compare pupil diameter, FAA, and PAA scores between conditions (S1 and S2). We found anecdotal evidence ($BF_{10} = 0.5$) in support of an equal FAA between S1 and S2. The BF_{10} was mostly anecdotal, because it was stable also for a wide prior ($BF_{10} = 0.4$) but moderate only for an ultrawide prior ($BF_{10} = 0.3$). Contrariwise, the evidence in support of an equality of the PAA scores between S1 and S2 is moderate ($BF_{10} = 0.3$). The BF_{10} remained stable also for wide ($BF_{10} = 0.2$) and ultrawide priors ($BF_{10} = 0.2$). For the pupil diameter, we found a $BF_{10} = 0.5$ that indicated an anecdotal evidence in support of H0, that is an equality between the pupil diameter scores between S1 and S2. The BF_{10} was mostly anecdotal and remained stable setting a wide prior ($BF_{10} = 0.4$) and became moderate only for an ultrawide prior ($BF_{10} = 0.3$).

Bayesian One-Sample *T*-Test

As further control analyses, two separate Bayesian one-sample T-tests were performed within each condition (S1 and S2) to check whether the FAA and the PAA scores were unbalanced with respect to zero (**Figure 2**).

In S1, a moderate evidence in support of a polarization of the FAA toward negative (avoidance) scores ($B_{-0} = 6.1$) was found (one-tailed). The BF was robust also for wide ($B_{-0} = 5.2$) and ultrawide ($B_{-0} = 4.2$) priors. Another Bayesian one-sample T-test (two-tailed) was performed in S1 to compare the PAA score against zero. The analysis retuned a $BF_{10} = 0.8$ in favor of H0. Across wide and ultrawide priors, the BF_{10} appears to be stable, ranging, respectively, from $BF_{10} = 0.6$ to $BF_{10} = 0.5$. Thus, we obtained an anecdotal support in favor of an equality between the PAA score and zero in S1.

In S2, we found moderate evidence in support of an equality of the FAA against zero ($BF_{10} = 0.2$) that indicated a moderate evidence in support of H0 (two-tailed). This evidence is robust, because the BF_{10} across priors ranged from 0.2 (wide) to 0.1 (ultrawide). Similarly, we obtained a moderate evidence in support of an equality of the PAA score against zero with a $B_{10} = 0.2$ (two-tailed). The BF_{10} in support of H0 was stable, because it was moderate also for wide ($BF_{10} = 0.2$) and ultrawide ($BF_{10} = 0.1$) priors.

Bayesian Kendall's Tau-B Correlation

Two separate nonparametric Bayesian Kendall's Tau-B correlation were performed within each condition (S1 and S2) to compare the attitude toward the offer and the percentage

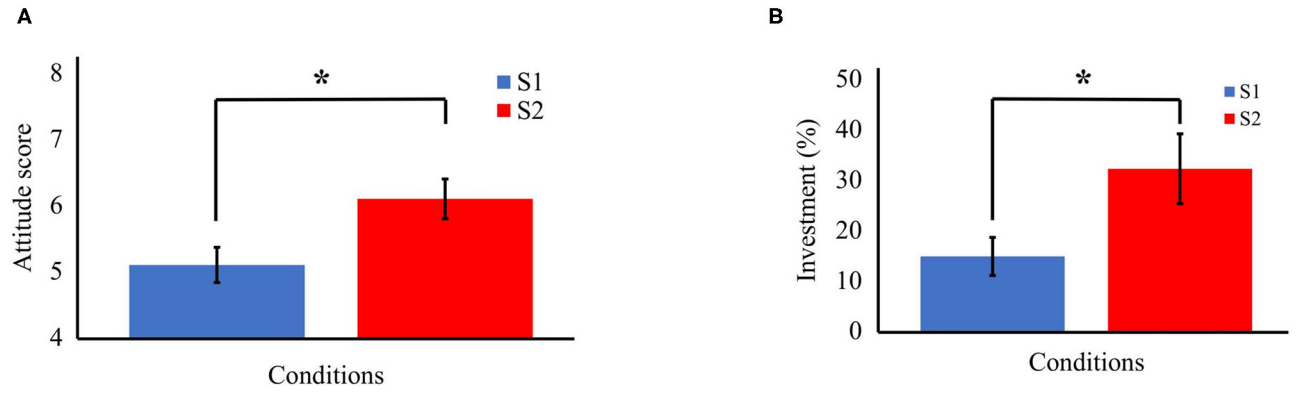


FIGURE 1 | The significant results in support of H1 in the Bayesian paired-samples *T* test. **(A)** The attitude toward the offer score (vertical axis) in the two conditions (horizontal axis). In the highly informative and personalized script (S2), participants assumed a more-favorable and less-polarized attitude compared with the poorly informative and standard script (S1). The colored bars represent the mean in the two conditions, and the black lines the standard error with respect to the mean (*BF_{10} = 6). **(B)** The percentage of participants' investment (vertical axis) in the two conditions (horizontal axis). In the highly informative and personalized script (S2), participants invested a higher and more variable amount of money compared with the poorly informative and standard script (S1). The colored bars represent the mean in the two conditions, and the black lines the standard error with respect to the mean (*BF_{10} = 8. 8). *Moderate evidence in support of H1.

of investment between each other and with the FAA, the PAA, and the pupil diameter, respectively. The moderate, strong, very strong, and extreme BF reported were all accepted because they fall within the FDR B-H critical value.

In S1, we found an extreme evidence (BF_{10} = 102.3) in support of a positive correlation between the attitude toward the offer and the percentage of investment (**Figure 3A**—r_t = 0.559) that remains stable for wide (BF_{10} = 103) and became very strong for ultrawide (BF_{10} = 97.6) priors. Thus, the greater was the attitude of favor, the higher was the percentage of investment. When the attitude score was compared with the FAA score, we found an anecdotal evidence (BF_{10} = 2.8) in sustaining a positive correlation (**Figure 3B**—r_t = 0.347) that remains stable setting wide (BF_{10} = 2.4) and ultrawide (BF_{10} = 2.1) priors. Conversely, we found moderate evidence (BF_{10} = 0.3) in support of a noncorrelation between the attitude score and the PAA score (r_t = 0.006), confirmed also setting wide (BF_{10} = 0.2) and ultrawide (BF_{10} = 0.2) priors. Moreover, we found an equal evidence (BF_{10} = 1) in favor of a correlation and a noncorrelation between the attitude score and the pupil diameter (r_t = −0.259) that was mostly anecdotal in favor of a noncorrelation for wide (BF_{10} = 0.8) and ultrawide priors (BF_{10} = 0.7). When the percentage of investment was compared with the FAA score, we found an anecdotal evidence (BF_{10} = 0.7) in favor of a noncorrelation (**Figure 3C**—r_t = 0.219) that remained stable with wide (BF_{10} = 0.6) and ultrawide (BF_{10} = 0.5) priors. Moreover, we found an anecdotal evidence (BF_{10} = 0.4) in favor of a noncorrelation (r_t = 0.120) between the percentage of investment and the PAA, that was, however, mostly moderate because when setting wide (BF_{10} = 0.3) and ultrawide (BF_{10} = 0.2) priors became moderate. Similarly, we found an anecdotal evidence (BF_{10} = 0.3) in favor of a noncorrelation (r_t = −0.100) between the percentage of investment and the pupil diameter, that, however, became moderate setting both wide (BF_{10} = 0.3) and ultrawide priors (BF_{10} = 0.2).

In S2, we found a strong evidence (BF_{10} = 13.7) in support of a positive correlation (r_t = 0.453) between the attitude score and the percentage of investment (**Figure 3D**) that remained stable also for wide (BF_{10} = 12.5) and ultrawide (BF_{10} = 11.3) priors. Thus, the greater was the attitude of favor, the higher was the percentage of investment. When the attitude score was compared with the FAA score, we found a moderate evidence (BF_{10} = 6.2) in favor of a negative correlation (**Figure 3E**—r_t = −0.404) that remained stable also for wide (BF_{10} = 5.5) and ultrawide (BF_{10} = 4.9) priors. Thus, the greater was the favorable attitude, the higher was the avoidance motivation. Moreover, we found a moderate evidence (BF_{10} = 0.3) in support of a noncorrelation (r_t = −0.076) between the attitude score and the PAA, that remained stable also setting wide (BF_{10} = 0.2) and ultrawide priors (BF_{10} = 0.2). Similarly, we found a moderate evidence (BF_{10} = 0.3) in support of a noncorrelation (r_t = −0.044) between the attitude score and the pupil diameter, which remains stable also for wide (BF_{10} = 0.3) and ultrawide (BF_{10} = 0.2) priors. When the percentage of investment was correlated with the FAA score, we found a strong evidence (BF_{10} = 15.3) in favor of a negative correlation (**Figure 3F**—r_t = −0.460) that remains stable also for wide (BF_{10} = 14.2) and ultrawide (BF_{10} = 12.8) priors. Thus, the higher was the investment, the smaller was the FAA. Contrariwise, we found a moderate evidence (BF_{10} = 0.3) in support of a noncorrelation (r_t = 0.015) between the percentage of investment score and the PAA that remains stable also setting wide (BF_{10} = 0.2) and ultrawide priors (BF_{10} = 0.2). Similarly, we found a moderate evidence (BF_{10} = 0.3) to sustain a noncorrelation (r_t = 0.054) between the percentage of investment score and the pupil diameter that remained stable also for wide (BF_{10} = 0.2) and ultrawide (BF_{10} = 0.2) priors.

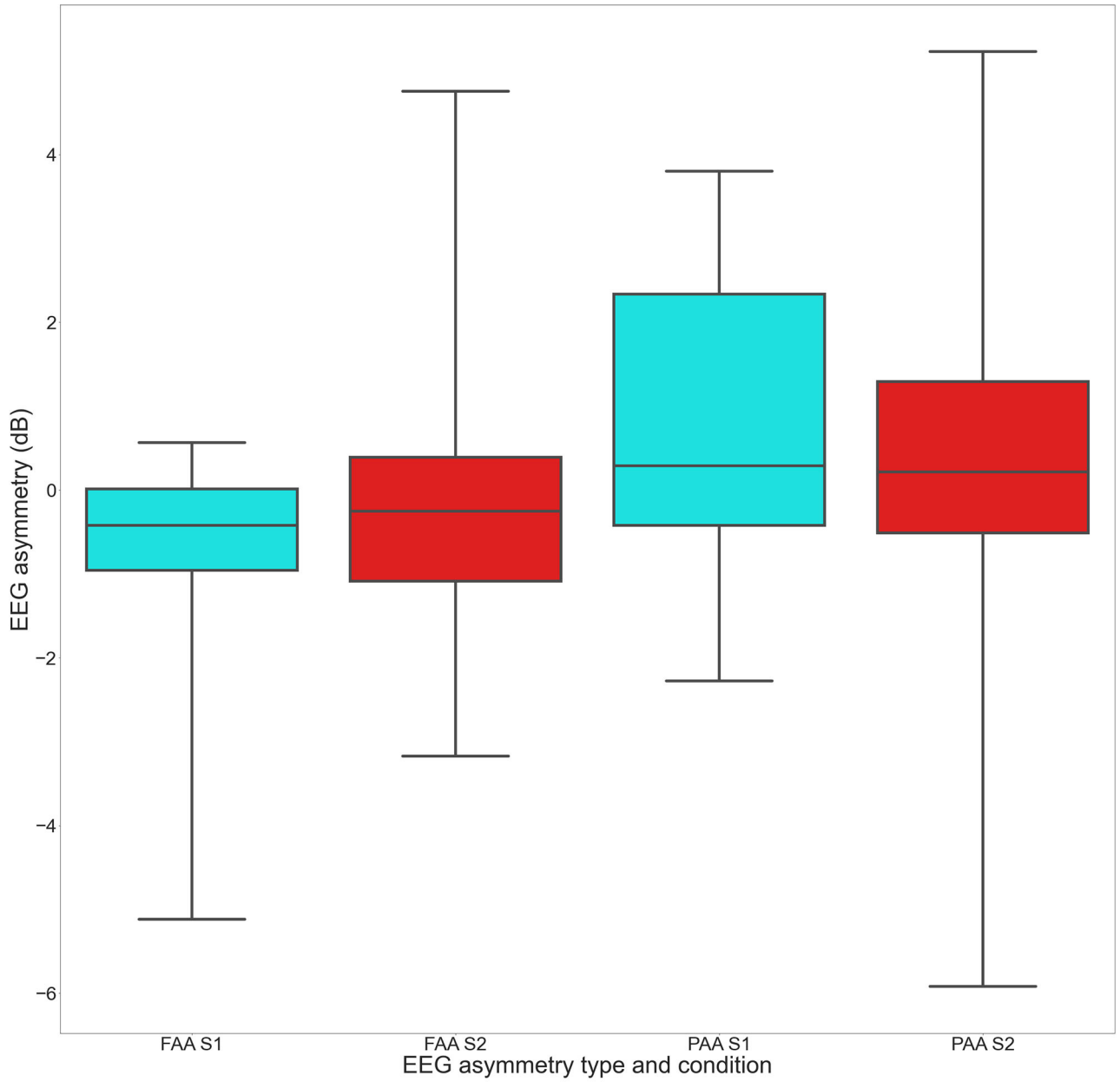


FIGURE 2 | The EEG asymmetry score boxplots of the FAA and PAA in the two conditions (horizontal axis). The colored boxes represent the 25th to 75th percentiles of the scores, the line inside the box shows the median, and the whiskers represent the minimum and maximum scores. In S1 (cyan boxes), the FAA was polarized toward negative (avoidance) scores ($B_{-0} = 6.$), while in S2 (red boxes), we found moderate evidence in support of an equality of the FAA against zero ($BF_{10} = 0.2$). Similarly, in S2, we obtained a moderate evidence in support of an equality of the PAA score with respect to zero ($B_{10} = 0.2$).

DISCUSSION

The main aim of this study was to evaluate whether the FAA score was correlated to customers' attitude and to their investment decision. With this aim, we manipulated a commercial offer in order to elicit diverse customers' attitudes and investment choices. Our results highlighted that the FAA, but not other peripheral body or neural control measures, has a robust association with participants' attitude and final decision, selectively when a highly informative and tailored commercial offer is presented. Consequently, this observation suggests that the reliability of the FAA as a marker of consumers' choices may be differentially affected by the specificity of different contextual factors, or diverse processes by which the decision is made, and could not be considered a general marker of individual decisions.

According to our experimental modulation, we verified that a poorly informative and "standard" commercial message elicited

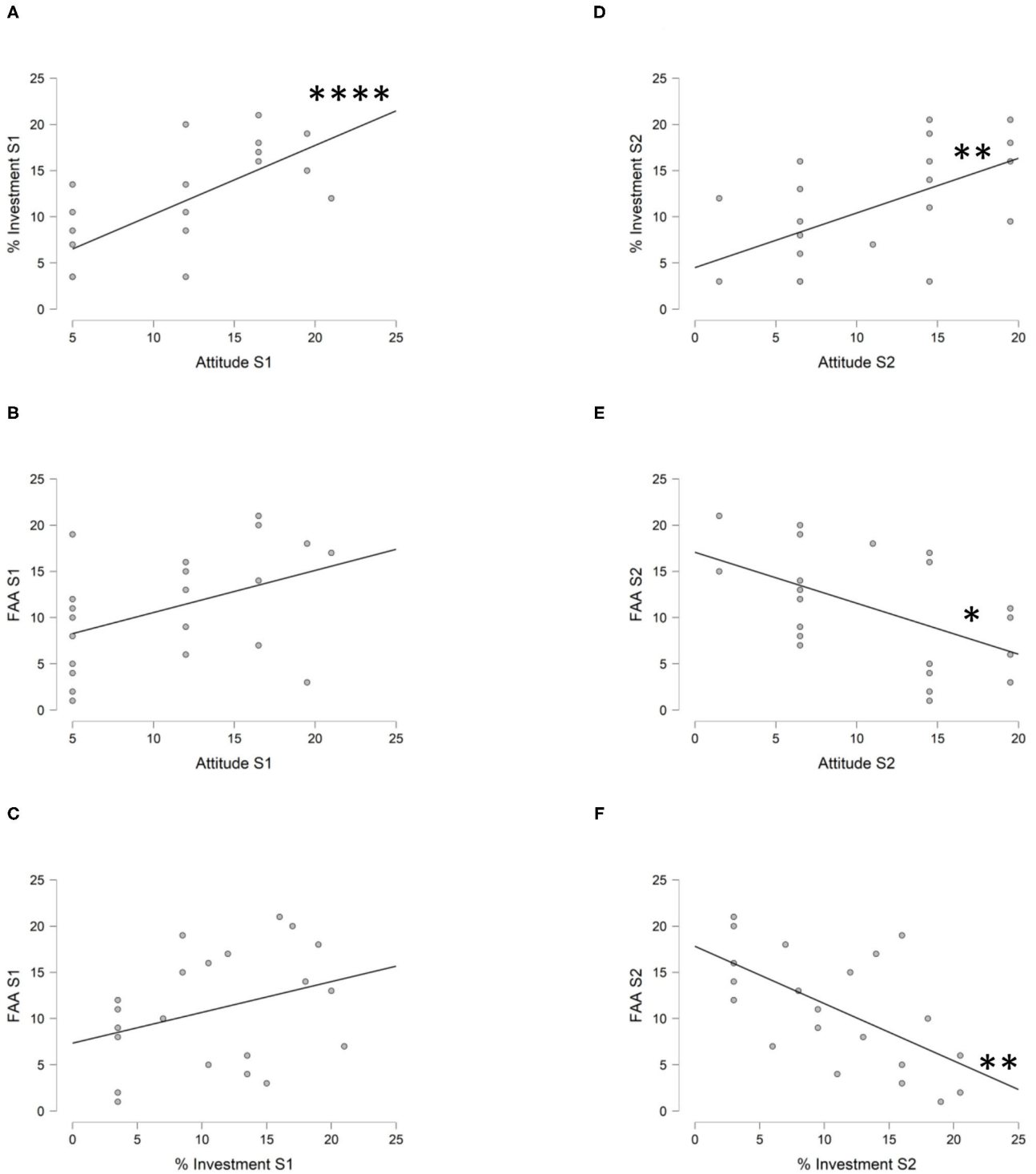


FIGURE 3 | The Bayesian Kendall's Tau-B Correlation between attitude, investment and FAA within S1 and S2. **(A)** The scatter plot between the ranks of the attitude score (horizontal axis) and the percentage of investment (vertical axis) in the poorly informative and standard script (S1). In this condition, we found extreme evidence ($BF_{10} = 102.3$) that the more favorable is the attitude, the high is the percentage of investment, as well as the more unfavorable is the attitude, the low is the percentage of investment (****$r_t = 0.559$). **(B)** The scatter plot between the ranks of the attitude score (horizontal axis) and the FAA (vertical axis) in the poorly informative and standard script (S1) where we found anecdotal evidence ($BF_{10} = 2.8$) to sustain a positive correlation ($r_t = 0.347$). **(C)** The scatter plot between the ranks of the percentage of investment (horizontal axis) and the FAA (vertical axis) in the poorly informative and standard script (S1) where we found anecdotal evidence

(Continued)

FIGURE 3 | (BF_{10} =0.7) in favor of a noncorrelation ($r_t = 0.219$). **(D)** The scatter plot between the ranks of the attitude score (horizontal axis) and the percentage of investment (vertical axis) in the highly informative and tailored script (S2). In this condition, we found a strong evidence ($BF_{10} = 13.7$) that the more favorable is the attitude, the high is the percentage of investment, as well as the more unfavorable is the attitude, the low is the percentage of investment (**$r_t = 0.453$). **(E)** The scatter plot between the ranks of the attitude score (horizontal axis) and the FAA (vertical axis) in the highly informative and tailored script (S2). In this condition, we found that the more favorable is the attitude, the more is participants' avoidance motivation toward the offer, as well as the more unfavorable is the attitude, the more is participants' approach motivation toward the offer (*$r_t = -0.404$; $BF_{10} = 6.2$). **(F)** The scatter plot between the ranks of the percentage of investment (horizontal axis) and the FAA (vertical axis) in the highly informative and tailored script (S2). In this condition, we found strong evidence ($BF_{10} = 15.3$) that the high is the investment, the more is participants' avoidance motivation toward the offer, as well as the low is the investment, the more is participants' approach motivation toward the offer (**$r_t = -0.460$). *Moderate evidence in support of H1; **strong evidence in support of H1; ****extreme evidence in support of H1.

an unfavorable and less variable attitude as well as a limited and less variable percentage of investment in consumers compared with S2. Contrariwise, a highly informative and tailored message produced a more favorable and variable attitude and a larger and more interindividually variable percentage of investment compared with S1. This observation confirmed the success of our experimental manipulation. In fact, the mean and standard deviation of both the attitude and the percentage of investment were lower in S1 as compared with S2.

In S1, we found an extreme evidence of a positive correlation between the attitude score and the percentage of investment, likely due to the (negative) polarization that the scores assumed in this condition. In S1, the FAA is unbalanced toward negative (avoidance) scores (greater activity of the right frontal hemisphere compared with zero) and no significant correlation between the FAA and consumers' attitude or final investment scores was found. Conversely, in S2, we found a negative correlation between the attitude, the investment, and the FAA. This confirms that the FAA can be related to both consumers' attitude and final decision when a highly informative and tailored commercial offer is presented. This result is strengthened by the evidence that, unlike the FAA, the control variables (i.e., the PAA and the pupil diameter) did not correlate neither with the attitude nor with the percentage of investment. Therefore, the specific reliability of FAA as an indicator of consumers' decision appears to be influenced by the specificity of different contextual factors or diverse processes by which the decision is made.

From one side, we hypothesize our overt manipulation of the commercial offers could have biased individual mindsets so to influence both their attitude and final decision (Korteling et al., 2018). Especially for the poorly informative and "standard" commercial message (S1 condition), strong evidence demonstrates that a consumer commonly gives a little value to any advertisement, especially when the offer is uninformative and not personalized (Coulter et al., 2001; Goldsmith and Freiden, 2004; Xu, 2006; Ünal et al., 2011). In line with previous observations, our attitude score, that measured participants' perception of the offer, including their bias of perceived advantage versus disadvantage of the offer, was found lower in S1 compared with S2. Accordingly, we could hypothesize that in S1, participants may have interpreted the offer as unfair, thus polarizing both attitude and investment toward a low and little variable score, while in S2 the more informative and personalized offer may have invited consumers to use a less biased mindset, rather adopting rational stage of the decision-making process (Korteling et al., 2018).

Moreover, we found that a lower FFA corresponded to a favorable attitude toward the offer or a high investment, and, analogously, an unfavorable attitude and a low investment were related to a higher FFA. These observations may appear as counterintuitive as compared with the classical interpretation of approach and avoidance motivation of the FAA (Coan and Allen, 2003; Harmon-Jones et al., 2010; Ramsøy et al., 2018). Actually, alternative interpretation arises from studies that highlighted an association between the activity of the frontal right hemisphere and a regulatory system, namely the revised Behavioral Inhibition System (r-BIS; Gable et al., 2017), in both healthy subjects and brain-injured or psychiatric patients. This r-BIS would be responsible to supervise, govern, and regulate motivation and analyze the possible risks that arise when a decision has to be made. Thus, the r-BIS is a superordinate inhibitory control system that would intervene in case of conflicting motivation between approach and avoidance and "[…] *is thought to govern cognitive constructs of executive control and inhibitory function. This may result in suppression of a behavioral response or overriding motivational impulses* […]" and "[…] *is thought to alleviate tension between approach and avoidance systems by enhancing aversion of one behavior or the other*" (Gable et al., 2017, p. 3). A reduced recruitment of the r-BIS, corresponding to a low activation of the right frontal hemisphere and a consequently greater left activation, would be related to a more impulsive behavior, while an increased involvement of the r-BIS—associated with an increased activity of the right frontal cortex and a consequent less left hemispheric activation—would be associated with an active top-down control. In this view, we can consider that the results of the correlation that emerged between FAA and both attitude and investment choice reflected the activity of the r-BIS. Indeed, our experimental design in S2 could have forced participants to make a conflicting choice between an approach (i.e., positive attitude toward the offer) and avoidance (i.e., careful evaluation of individual past behaviors and needs) motivation and the r-BIS could have been used to regulate this conflicting decision. Furthermore, in line with our previous interpretation, the relationship with the attitude and investment would emerge only in S2, a condition in which the number of information and the personalization of the message invited consumers to assume a more rational mindset to get a reasoned decision. Specifically, in S2, a more positive attitude and a greater investment would correspond to a greater involvement of the r-BIS. We could therefore imagine that during the S2 condition, the r-BIS may have been involved in inhibiting the avoidance with respect to the approach motivation that may

have supported consumers' more favorable attitude and higher investment compared with a lower response of the r-BIS. Thus, it is reasonable to speculate that in a situation in which participants decide to invest a large amount of money, there would be more need to inhibit the little value that consumers would commonly ascribe to advertisements (Coulter et al., 2001; Goldsmith and Freiden, 2004; Xu, 2006; Ünal et al., 2011) which may be reflected in a greater activation of the r-BIS.

To summarize, although it is not possible to sharply separate consumers' rational and intuitive mindsets, because both of them are involved and interact within the same decision-making process (Calabretta et al., 2016; Amidu et al., 2019), as well as we did not directly assess this aspect, the hypothesis that the FAA correlates with both attitude and decision, when consumers assume a more rational mindset to get a rational decision, could account for the results of both the S1 and S2 conditions. Three aspects support this hypothesis. Primarily, we evidenced how our attitude score, that measured participants' bias of perceived advantage and disadvantage of the offer, was found higher in S2 than in S1. Secondly, the direction of the correlation between the FAA and both attitude and investment, which emerged in S2, could reflect the activity of the r-BIS, a top-down control and monitoring system of the motivation of approach and avoidance located in the right frontal hemisphere (Gable et al., 2017). Thirdly, Hewig (2017), referring to the "Rubicon Model of Action Phases" framework (Heckhausen and Gollwitzer, 1987), argued that the FAA may reflect the volitional and intentional phase that occurs just prior to the action, as an intermediate step of a reasoned and planned decision-making process. Similarly, the consistency and the rationality of the decision-making process improve when we are exposed to highly informative messages (Hahn et al., 1992; Korteling et al., 2018). Accordingly, it might be possible that a link between the FAA and the final decision may not emerge when the characteristics of the message lead consumers to use a less rational, but more spontaneous, decisional process, as may have happened in S1. Although partly accounting for the conflicting evidence present in literature on the relation between FAA and consumers' decision—neither Ramsøy et al. (2018), nor Ravaja et al. (2013) manipulated consumers' attitude and final investment—this suggestion must be confirmed by further experiments, but could represent a starting point for future studies on this topic.

The present study has limitations that future investigations should consider and improve. Firstly, we did not have preferences and investment decision scores of the commercial offers in a larger and independent sample of customers for a large-scale generalization of the link between the FAA and their decision (Hakim and Levy, 2018). However, in our study, we used a representative sample of the population of possible insurance policy customers. For these reasons, although further efforts will be required in future studies to increase the experimental sample, we are confident that our results can be generalized at the population level. Secondly, although the sample size is consistent with other similar EEG studies in marketing research (e.g., Vecchiato et al., 2010; Daugherty et al., 2016; Gordon et al., 2018; Ramsøy et al., 2018), the participant number could be increased, in order to carry out parametric statistical tests, such as linear regression, which could determine whether the FAA score predicts consumers' attitude and decision. However, to overcome the small sample limitation, we used Bayesian statistic that outperforms the frequentist approach in a small-sample-size scenario (Mcneish, 2016; Wagenmakers et al., 2017b; Zondervan-Zwijnenburg et al., 2017) and allows future researchers to use our results to set more informative priors compared with our case when investigating this topic. Thirdly, we did not integrate the EEG and the eye tracker with other psychophysiological measures and techniques. The specific objective of the present study was to investigate the relation between the FAA with consumers' attitude and decision. For this reason, we used only the specific measures required for our goal. However, future research based on our results may broaden the range of measures and objectives also by using different body peripheral and neural parameters, in order to investigate other possible psychophysiological measures related to consumers' decisions (Cartocci et al., 2017; Hakim and Levy, 2018; Ocklenburg et al., 2018). Fourth, although we have preliminarily checked our scripts for their positive, negative, or neutral valence, future research could make a further step by controlling more specific categories of words that could influence a priori participants' attitudes and therefore their brain activity (O'Donnell et al., 2015). Fifth, although we only used the frequency domain in the EEG analysis, we designed two commercial script (S1 and S2) with different lengths, and we cannot account the extent of how this might have affected the results. Finally, it would be interesting to test an additional experimental condition that polarized consumers' attitudes and investments toward high and favorable scores, to understand whether, even in this case, the relation between FAA, attitude, and decision is similar to our S1 results. Beside these explanations, some methodological procedures that we peculiarly adopted with respect to other research could also account for our evidence. Firstly, we increased the external validity of the experimental design by presenting a gambling game that motivated and let participants gain the virtual real-like wallet that was then used for the investment. Secondly, we baseline-normalized the EEG signal acquired during the presentation of the commercial scripts by using the Decibel conversion formula. As a matter of fact, some studies highlighted that possible interindividual trait predispositions of FAA, measured during a baseline EEG registration, may shape the variability of the FAA collected during an experimental task (i.e., Uusberg et al., 2014).

In conclusion, in our research, we underlined how the FAA has a robust association with consumers' attitude and final decision, though this relation emerges specifically when the commercial script provides an adequate number of information and is customized, likely leading the consumer to a more reasoned and planned decision-making process. This correlation is specific of the FAA because both peripheral body and neural control measures (such as the PAA and the pupil diameter) were not associated with both attitude and final investment. Moreover, we also underlined how in a tailored and more informative commercial script the FAA may reflect the involvement of the r-BIS. This control system could intervene to monitor and

govern possible conflicts between an approach and avoidance motivation. This evidence provide further indications on the possible association between the FAA and both attitude and final decision, although further researches are needed. Finding and validating psychophysiological measures, such as the FAA, might have a fundamental impact on Consumer Neuroscience, but the reliability and modifiability of this index has still to be validated across different (experimental) conditions. With the advent of low-cost EEG headsets, this index could even be easily used in ecological settings, both in applied research and in business consultancy, and could be useful evidence-based measure beside self-reports of customers' attitude and choices.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Area Vasta Nord Ovest Ethics Committee (protocol n. 24579/2018). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

FDG, MO, AM, NL, and ER contributed to the design and the conception of the research. FDG and MO contributed to the implementation and the analysis of the results. FDG contributed to writing the manuscript. MO, AM, NL, and ER contributed to the manuscript revision. SD'A, as member of Intesa Sanpaolo Innovation Center S.p.A., has contributed to research funding. MO, AM, SD'A, NL, and ER read and approved the submitted version of the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2020.577978/full#supplementary-material

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Do You See What I See? Effectiveness of 360-Degree vs. 2D Video Ads Using a Neuroscience Approach

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This study compares cognitive and emotional responses to 360-degree vs. static (2D) videos in terms of visual attention, brand recognition, engagement of the prefrontal cortex, and emotions. Hypotheses are proposed based on the interactivity literature, cognitive overload, advertising response model and motivation, opportunity, and ability theoretical frameworks, and tested using neurophysiological tools: electroencephalography, eye-tracking, electrodermal activity, and facial coding. The results revealed that gaze view depends on ad content, visual attention paid being lower in 360-degree FMCG ads than in 2D ads. Brand logo recognition is lower in 360-degree ads than in 2D video ads. Overall, 360-degree ads for durable products increase positive emotions, which carries the risk of non-exposure to some of the ad content. In testing four ads for durable goods and fast-moving consumer goods (FMCG) this research explains the mechanism through which 360-degree video ads outperform standard versions.

Keywords: 360-degree advertisement, effectiveness, electroencephalography, eye tracking, facial-coding, electrodermal activity, consumer neuroscience

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INTRODUCTION

Online video ad spend is growing exponentially (Zenith, 2019) and the watching time of online platforms such as YouTube is increasing (Google, 2019). Among the viewing technologies employed, 360-degree videos are widely used by realtors/real estate agents, tourism suppliers, and manufacturers across multiple product categories. Indeed, large companies such as Disney, McDonalds, Coca-Cola, BMW, and Audi have conducted 360-degree video-based campaigns. The use of 360-degree videos is one of the newest trends in online marketing (Gudacker, 2016; Castellanos et al., 2018; Feng et al., 2019). Due to their interactive nature, rich imagery, and spatial sound design, 360-degree videos have been termed "the ultimate empathy machine" (Feng et al., 2019).

A 360-degree video is a monoscopic video viewed as one image directed to both eyes. It provides free and omnidirectional viewpoints from all the angles of a 360-degree radius under the control of the viewer. The use of 360-degree ads has highlighted two complementary features of research interest. First, the change from static to an interactive view provides a new customer experience. Due to its interactivity, the 360-degree video seems to provide a stronger connection than does traditional video with the human mind and increases users' immersive settings (Sundar et al., 2014).

Second, when users control the angle of view they may feel a sense of active viewing, which demands higher cognitive effort. Moreover, the higher cognitive load associated with 360-degree videos might result in different levels of brand memory and persuasion in comparison with 2D videos. Although 360-degree videos give viewers a higher degree of immersion than do 2D formats, and a significant level of control, that shapes their viewing experiences, the viewers may become confused and not enjoy the experience as they try to figure out the "correct" viewing path (Feng, 2018). Therefore, the efficacy of 360-degree video ads should be examined (Feng, 2018). Surprisingly, despite the growth in the use of 360-degree videos, and their distinctive features, there has been little academic research into their effectiveness in advertising; and the scarce research that has been undertaken has used self-reported measures of consumers' responses (Feng et al., 2019; Oh et al., 2020).

The features of 360-degree videos can drive new research that might capture the dynamic view and emotional responses they evoke by using continuous implicit measures. The literature shows that unconscious responses and emotions, measured through implicit metrics, influence decision-making (Eijlers et al., 2019). Unlike explicit responses, which are associated with conscious thoughts and emotions that can be assessed through self-report measures, implicit responses are associated with subconscious, automatic, and moment-to-moment reactions that lie outside the individual's awareness. Implicit responses are highly influential in decision-making processes (Khushaba et al., 2013). As Li (2019) pointed out, a high proportion of consumer responses are unconscious and intuitive. Thus, there is a need to assess the emotional and unconscious responses to advertising (for details, see Pozharliev et al., 2017). Furthermore, neuroscientific-based methods measure response changes in subjects on a continuous basis and are not, thus, affected by *post-hoc* reflection (McDuff, 2017). Eye-tracking (ET) has been extensively used as a tool for measuring visual attention in advertising (for a review, see Pieters and Wedel, 2004). The nature of 360-degree videos, which provide different viewing angles, makes gaze behavior (e.g., eye movements and fixations) an appropriate metric for measuring the visual attention paid to ad content (Jacob and Karn, 2003). Greater fixation time is associated with more detailed processing, and a lower number of fixations with poorer processing (Zhang and Yuan, 2018). Frontal asymmetry (FAA) is one of the most popular electroencephalography (EEG) metrics used to measure consumer choice (Telpaz et al., 2015). Based on the alpha band, right or left asymmetry is related to approach/withdrawal behaviors (Davidson, 1993, 2004). In this paper we refer to approach-related tendencies (or left-hemispheric dominance) as "positive emotional reactions," and withdrawal-related tendencies (or right-hemisphere dominance) as "negative emotional reactions" (for a technical review, see Harmon-Jones et al., 2010; Fischer et al., 2018). Electrodermal activity (EDA) measures the electrical conductance of the skin based on its moisture (i.e., sweat) levels. An increase in conductance shows physiological activation (for a review, see Caruelle et al., 2019). Facial coding (FC) measures emotions through observing human facial muscle movements (McDuff, 2017). FC uses an objective-coding scheme, the Facial Action Coding System (FACS) (Ekman and Friesen, 1978), which describes facial muscle movements and the emotions related to the movements. Despite the advantages of neuroscientific measures, they have been very little used in advertising research (Chang, 2017). 360-degree video ads can help advertisers create emotional connections with their customers, and elicit neurophysiological responses that can be used to measure their effects.

No previous consumer neuroscience studies have compared 360° and 2D ads. Therefore, this study compares cognitive and emotional responses to 360-degree and static videos watched on PC screens; the neurophysiological metrics are based on electroencephalography eye-tracking, facial-coding and electrodermal activity. This study differs from others reported in the previous literature in: (i) the type of responses measured, that is, unconscious measures; (ii) the scope of the analysis is a continuous measure of the unconscious responses evoked by, and attention paid to, specific elements of ads.

Based on the interactivity and cognitive overload literature, and on the motivation, opportunity, and ability theoretical frameworks, and the advertising response model (ARM), we compare the effects of existing dyads of 360-degree and standard video ads on consumers' emotions and cognition. The research goal is 2-fold. First, to measure the effectiveness of 360-degree video ads vs. standard format video ads based on visual attention paid to specific elements of the ads, such as the embedded brand logo, and the emotional connectivity developed between the consumer and the brand. Second, to analyze whether interactivity and users' control result in higher levels of engagement in the viewer's prefrontal cortex.

Through this research we provide a theoretically grounded explanation for the persuasive power of 360-degree ads. The study contributes significantly to the knowledge of how consumers process interactive advertising. First, we explain the information processing of online video ads by assessing the influence of interactivity on the visual attention paid by the viewer to the ad, and on central (brand logo recognition) and peripheral information processing (emotions and asymmetry). Second, using unconscious measures, the present study is the first to explain the mechanism through which 360-degree video ads outperform standard versions.

CONCEPTUAL FRAMEWORK

Interactivity in 360-Degree Video Ads

With its ability to give the user the control to manipulate his/her point of view, a 360-degree video provides two-way communication between the viewer and the message/interface and touches on a core concept in communication technology, that is, interactivity (Macias, 2003; Sundar et al., 2014; Feng, 2018). The ability to interactively change one's viewpoint resembles real-world navigation, which enhances the customer experience and increases emotional responses.

In a 360-degree format, in contrast to the traditional video format where the point of view is determined by the creative director, and viewers are passive, viewers have a free and

omnidirectional viewpoint which they can move arbitrarily through all the angles of a 360-degree radius. Thus, consumers have the freedom to explore ad content based on their interests, and are not restricted by the creator's or the director's choices, to "navigate" in real time through the video scenes (Wijnants et al., 2015), and to decide "where and what" to look at (Hsiao and Grauman, 2017). That is, consumers are able to control, customize, and change their viewing experience and information flow. Active control, as a dimension of interactivity, has been described as a voluntary, instrumental action that directly influences the controller's experience (Liu and Shrum, 2002). Previous evidence suggests that, overall, viewers prefer dynamic videos (e.g., 360-degree) over 2D, static view videos (Broeck et al., 2017; Feng et al., 2019).

Interactivity in this context may result in users paying different levels of attention and varied amounts of cognitive workload (Feng, 2018). Consumer interaction with online ads can be categorized into a hierarchy of stages: pre-attention, attention, and behavioral decision (Chatterjee, 2001). A successful ad must initially grab the consumer's attention and then elicit emotions and induce recall. The multiple views provided by 360-degree videos make it necessary to address their effectiveness on a continuous basis to capture these dynamics.

Visual Attention and Persuasion in Advertising

Attention has been recognized as the primary factor in advertising effectiveness since the appearance of the earliest models, such as AIDA (Edward, 1925). Without attention, advertising cannot persuade the consumer (Edward, 1925; Cao, 1999). The advertising response model (ARM) provides a framework for evaluating advertising performance; it integrates several measures and explains that winning the customer's attention is the most important feature in advertising (Wells and Loudder, 1997). Two alternative persuasion routes are described in the ARM, the central and the peripheral. During central processing the focus is on the product/brand, whereas during peripheral processing the creative executional aspects of the advertising are dominant. Both central and peripheral processing lead to ad liking and, ultimately, to purchase intention. Both routes were adopted also in the earlier formulated elaboration likelihood model (ELM) (Petty et al., 1983). Both processing routes are influenced by involvement levels. Under high involvement, recipients process information via the central route using a high level of brand-related message elaboration. Peripheral processing occurs under low-involvement conditions, and subjects typically rely on available peripheral cues, such as music, the source, or the spokesperson.

The advertising literature suggests that the motivation, opportunity, and ability (MOA) to process information are key factors in advertising content processing (MacInnis and Jaworski, 1989). *Motivation* relates to areas of the consumer's interest that condition his/her *opportunity* to view some parts of the ad, and *ability* relates to the users' competence in navigating in 360-degree videos. Therefore, the MOA approach provides a good explanation for the differential responses to 360-degree and standard videos. The attention capture and transfer model by elements of advertisements (Pieters and Wedel, 2004) describes a top-down (person and process) and bottom-up (stimulus) mechanism of the visual attention paid to brands, pictorial content, and text in print advertisements. Extending this model to 360-degree videos it can be argued that bottom-up factors (e.g., the angle of view of the ads) determine the level of attention paid. Furthermore, the top-down factors, which are driven by the viewer's motivation and interest, are in line with the motivation and ability variables of the MOA model, and also determine attention.

Central Processing Route of Advertising

The advertised brand is widely recognized as one of the relevant cues in any ad (Geuens and De Pelsmacker, 2017; Belch and Belch, 2018). Attention and memory are the processes through which viewers become aware of, encode, store, and retrieve information. Thus, brand awareness plays a key role in advertising effectiveness. Brand awareness has been described as the recognition, or memory, of a brand (Huang and Sarigöllü, 2012). In 360-degree videos an interesting research question is whether the consumer's interactivity with video ads impacts on his/her processing of brand logos embedded in online video ads. As previously mentioned, in traditional ads the advertiser drives, and schedules, attention flow. However, in 360-degree ads the viewer selects the focal points and might avoid, even unintentionally, some parts of the ad, such as the brand name or logo. Accordingly, and irrespective of the consumer's interest in the ad, his/her exposure to the brand might be influenced by the reduced attention (s)he might pay to the brand. Following the MOA approach, certainly, if consumers are motivated by the brand as a key communication element, their attention will be high in either format (e.g., traditional and 360-degree). However, an interactive format may lead to less attention being paid to the brand logo because the angle of view adopted by consumers might reduce their opportunity to be exposed to some specific cues, such as the brand.

Peripheral Processing Route of Advertising

In 360-degree ads consumers view some elements based on their personal choice. This active way of watching ads has been associated with the "functional view" of interactivity, as opposed to the "contingency view" as suggested by Sundar et al. (2003). Functional interactivity leads to higher peripheral processing (Sundar and Kim, 2005). On the basis of distinctiveness theory (Rosenkrans, 2009), it can be argued that motion supports salience because human beings prefer moving objects (Sundar and Kalyanaraman, 2004). Furthermore, in web ads, the dynamism conveyed by changes in ad content (e.g., animated ads) is more appealing than the static content in traditional ads (Sundar and Kim, 2005). Extending previous research to 360-degrees ads, the ad elements that viewers look at under their own control elicit positive attitudes. The limited capacity model (Lang, 2000) proposes that consumers encode, store, and memorize only a few information cues. This view suggests that the salience of information is determined by the consumer's goals or by the novelty and unexpectedness of the stimuli (Lang,

2000). The ARM suggests that the attitude formation process is shaped by the novelty of the interaction, which is dominant in peripheral processing.

Contradictory Emotions and Processing Over Time

The advertising effectiveness literature discusses the positive influence of emotional responses on post–exposure attitude and recall (Holbrook and Batra, 1987; Morris et al., 2002). From the cognition perspective, emotions are mental states of readiness that arise from cognitive appraisals elicited by consumption; and they are accompanied by physiological processes (e.g., facial features) (Bagozzi et al., 1999, p. 184). The basic emotion approach (Plutchik, 1982; Li et al., 2015) proposes there are eight basic emotions innate to all humans (i.e., fear, anger, joy, sadness, disgust, surprise, trust, and expectancy) and many secondary emotions derived from these primary emotions.

When consumers are exposed to continuous stimuli (e.g., online video ads), their information processing might evolve over time from cognitive to emotional reactions, and from positive to negative encodings. Furthermore, Feng (2018) found that 360-degree videos evoked positive or negative emotions based on ease of navigation. In neuroscience studies these effects have been associated with the term "frontal brain asymmetry." To explain frontal brain asymmetries in valence emotional processing, Davidson's model (1979) proposed that emotion-related lateralization is observed because emotions contain approach and/or withdrawal components. Therefore, emotion will be associated with right or left asymmetry to the extent to which it is accompanied by approach or withdrawal behavior (Davidson, 1993, 2004). In the present study we refer to approach-related tendencies (or left-hemispheric dominance) as "positive emotional reactions," and withdrawal-related tendencies (or right-hemisphere dominance) as "negative emotional reactions" (for a review, see: Fox, 1991; Davidson, 1993; Davidson and Rickman, 1999). Frontal brain asymmetry has been applied in consumer choice (Ravaja et al., 2013; Telpaz et al., 2015) and advertising studies (Ohme et al., 2009, 2010; Daugherty et al., 2016; Guixeres et al., 2017). In interactive environments, to measure moment-to-moment emotions the optimum approach is to undertake brain wave analyses (e.g., EEG) in parallel with eye-movement observations. This form of integration can enrich the understanding of what emotional reactions consumers experience when they view an advertisement (Ohme et al., 2011; Guo et al., 2018).

HYPOTHESES DEVELOPMENT

Grounded in the ARM model, this study posits that 360-degrees video ads have superior advertising effectiveness in terms of affective responses to the ad (engagement with the ad and intensity and arousal of the emotions evoked by the ad), and that 2D ads are more effective in terms of the cognitive processing of the brand logo. In this section, we discuss the expected relationships among the model variables and propose a set of hypotheses. **Figure 1** shows the conceptual framework scheme and the neurophysiological tools used to measure the unconscious responses of consumers to online video ads with high/low interactivity.

Interactive Advertising and Visual Attention

During 360-degree interactive ads the consumer has to focus his/her attention more and make higher cognitive processing effort than with traditional ads (Jung et al., 2014), which increases the use of his/her cognitive resources (Ariely, 2000; Tremayne and Dunwoody, 2001; Hupfer and Grey, 2005; Feng, 2018). Lang (2000) argued that people have limited information processing capacity. When an individual is faced with an overwhelming amount of information, (s)he needs to use a large amount of cognitive resource to process it. During these processes, if the individual's allocated cognitive resources fall short of the required level, cognitive overload can occur (Feng, 2018). In this regard, Hernández-Méndez and Muñoz-Leiva (2015) used eye-tracking to demonstrate that tourists' visual attention differed based on the degree of interactivity of online advertising. They found that, as animated banners require higher cognitive resources than static banners, less visual attention is paid to animated than to static banners (consumers fixate first on static banners, then on animated banners). Using FMRI, Oren et al. (2016) showed that performing a secondary task while viewing a video impaired viewers' memories of those videos. In the context of this study, given that the consumer decides the angle at which (s)he views the 360-degree ad, his/her visual attention may vary. Therefore, it is expected that higher interactive content will lead to higher cognitive processing levels. As curiosity stimulates interactivity, it leads to lower attention being paid to each piece of information. Interactivity is driven by the computer's mouse and, therefore, it requires more brain activity, which creates a negative impact on other physiological activities, such as viewing. Thus, the dynamic nature of 360-degrees ads means that fixation time, and the number of fixations, on specific parts of an ad will be lower in 360-degrees ads than in 2D-ads. Thus, we posit that the greater is the consumer's interactivity with video ads (360-degree vs. 2D), the lower will be the visual attention (s)he pays to the ad content.

H1. The visual attention paid to 360-degree video ad content is lower than the visual attention paid to 2D video ad content.

Effects of Interactivity on Cognitive Processing: Brand Recognition

It is still unclear how 360-degree videos affect the processing of the different pieces of information embedded within ads. Of particular interest is the brand logo. Several explanations have been proposed in other contexts. First, previous research has demonstrated that television viewers have poorer recall of ad content in high-involvement program contexts, compared with low-involvement contexts (Coulter and Sewall, 1995; Coulter, 1998; Coulter and Punj, 1999). Pieters and Wedel (2004) found that the content of animated online ads is remembered less than the content of static online ads. Second, although a highly interactive ad helps immerse consumers in the brand story, this may cause cognitive overload (Feng, 2018). Pleyers and Vermeulen (2019), using eye-tracking, showed that the attention viewers pay to an ad, and ad effectiveness, can be impaired by

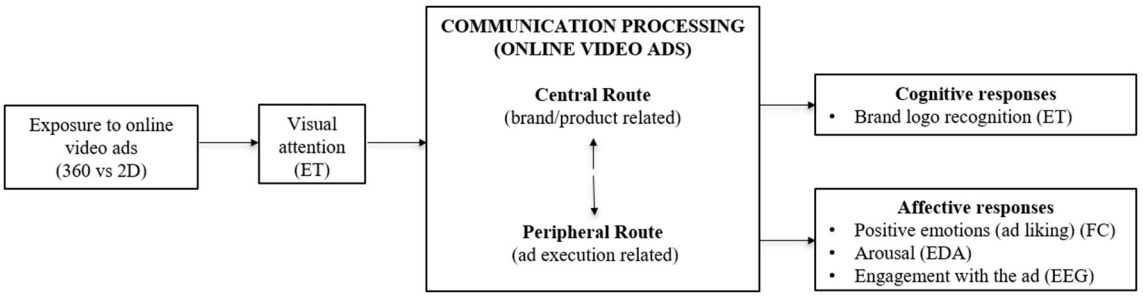


FIGURE 1 | Conceptual framework scheme and neurophysiological measurements. ET, Eye-tracking; EEG, electroencephalography; EDA, Electrodermal activity; FC, Facial coding.

interactivity and the control offered by interactive online media. Compared with the traditional television medium, memory for the ad is significantly reduced when it is shown with surrounding stimuli in interactive online media. These explanations fit well with the MOA and the ELM, as follows. The opportunity to watch a specific piece of information, such as the brand logo, is conditioned by navigation behavior, that is, the viewer can choose to look at it, or not. In 360-degrees video ads the least novel piece of information is the brand itself. Therefore, it is expected that consumers will look at it less or, at least, for a shorter period. Also, the brand is part of the central processing domain. As previously discussed, the novelty or unexpectedness of a stimulus relates to peripheral processing. Based on the above discussion, we argue that the greater is the consumer's interactivity with a video ad (360-degree vs. 2D), the less (s)he will look at the brand logo. Therefore,

H2. The visual attention paid to brand logos embedded in 360-degree video ads is lower than the visual attention paid to brand logos embedded in 2D video ads.

Effects of Interactivity on Affective Processing: Engagement With the Ad

The digital communications' literature has shown that engagement with the media context increases advertising effectiveness (Calder et al., 2009). As Van Doorn et al. (2010) suggested, customer engagement behavior evolves over time; this perspective can be applied to 360-degree video ads because their content varies over time, albeit a short period of time. Therefore, a moment-to-moment measurement of the user's response (i.e., emotions) should be undertaken. The previous customer engagement literature is still inconclusive, depending on the conceptual framework used. In this study we adopt frontal alpha asymmetry (FAA), captured by the alpha wave of the EEG, that reflects engagement in paying attention to, or avoiding, an external stimulus (Clark et al., 2018; Ramsøy et al., 2018). Greater activation in the left or right brain hemispheres has been shown to indicate an approach toward the stimulus, and activation on the right shows avoidance (Harmon-Jones et al., 2010). At a cognitive level, the brain response literature (Berka et al., 2007) and advertising research (Ohme et al., 2010; Ravaja et al., 2013; Venkatraman et al., 2015) have proposed that frontal asymmetry is an indicator of user preference and engagement with advertisement content (Çakar and Gez, 2017). Thus, higher lateralization in the left part of the brain is an antecedent of positive connection with an ad (Ohme et al., 2011). Emotional connectedness is a process guided by dialogue, authentic connection, and relevance to the customer. Ohme et al. (2010) and Vecchiato et al. (2011) found that left hemisphere dominance was related to the pleasantness of TV commercial advertisements. Smith and Gevins (2004), using EEG, demonstrated that faster paced TV ads with frequent scene changes engaged viewers because they needed to continually redirect their gaze. In 360-degree video ads viewers can enjoy an engaging experience by deciding from moment-to-moment the angle from which to view the video scenes, and by arbitrarily moving their viewpoints to each one of the angles of a 360-degree radius. Customer participation, customization, and emotional connectedness are intrinsic to the 360-degree format, and have been identified as important drivers of customer engagement (Kumar and Pansari, 2016; Bleier et al., 2018). Thus, it is proposed that the more the consumer interacts with the video ad (360-degree vs. 2D), the greater will be his/her prefrontal cortex engagement with the ad.

H3: 360-degree video ads elicit higher frontal asymmetry than 2D video ads.

Effects of Interactivity on Affective Processing: Emotions Evoked by the Ad

Emotions play an essential role in consumer behavior and, thus, understanding them is crucial for marketers (Laros and Steenkamp, 2005). Viewers usually experience a mixture of emotions (Hemenover and Schimmack, 2007). The literature argues that emotions are characterized by high excitement (Berger, 2011), such as joy and frustration (Gross and Levenson, 1995). Conversely, sadness or liking activate low excitation.

Previous studies have shown that viewer-ad interactivity evokes positive emotions in the viewers. For example, Horning (2017) examined the impact of second screen interactions on viewers' perceived enjoyment of news content. Oh et al. (2020) demonstrated that 360-degree videos had a greater indirect effect on the positive emotions evoked by video content, through enhanced perceived interactivity, than did 2D videos. Recent automatic facial expression detection-based studies measuring emotions evoked by ads have demonstrated that interactive

advertising elicits positive emotions (e.g., Teixeira et al., 2012; Lewinski et al., 2014; Castellanos et al., 2018; Lacroix et al., 2020). Castellanos et al. (2018) used facial coding to compare the percentage of time viewers expressed joy when viewing interactive video ads and 2D video ads. Lacroix et al. (2020) used face reader facial expression recognition software to evidence that advertising perceived as highly experiential (highly interactive) produces more positive emotions (happiness) than advertising perceived as less experiential. Lewinski et al. (2014) used face reader to demonstrate that amusing video ads elicit greater happiness than non-amusing video ads. Teixeira et al. (2012) used facial coding to demonstrate that emotions such as joy and surprise can be leveraged to engage consumers watching Internet video ads. The higher interactivity and richer content of 360-degree video ads, indeed, may provide more amusement to consumers than 2D video ads, and therefore elicit positive emotions.

We expect that 360-degree videos will elicit positive emotions. The interactivity between a viewer and stimuli captivates the viewer and engenders positive moods through visual and auditory stimulation (Batat and Wohlfeil, 2009). Thus, it is proposed that the greater is consumers' interactivity with video ads (360-degree vs. 2D), the greater will be the intensity of their positive emotions.

H4. The positive emotions elicited by 360-degree video ads are more intense than the emotions elicited by 2D video ads.

A higher level of excitement leads to more effective message processing (Belanche et al., 2017). Previous research has suggested that interactivity affects involvement (Petty et al., 1983) and arousal (Fortin and Dholakia, 2005), which, in turn, elicit higher levels of attention and interest (Kensinger and Corkin, 2003). Bettiga et al. (2017) demonstrated, using EDA, that the higher is the consumer's interactivity with the product, the greater will be the influence of unconscious arousal on his/her attitude. Barreda-Ángeles et al. (2020) used EDA to evidence an increase in arousal associated with the immersive mode of viewing non-fictional videos. If we extend this reasoning to the context of this study, it is expected than the higher is consumers' interactivity with 360-degree video ads, the higher will be the arousal evoked by these ads, than that evoked by 2D video ads. Therefore, we propose the following hypothesis:

H5. The arousal evoked by 360-degree video ads is greater than the arousal evoked by 2D ads.

MATERIALS AND METHODS

Sample

The study was conducted in the neuromarketing laboratory of a large European university. The sample consisted of 100 participants (47 females and 53 males, 19–67 years old, M = 43.09, SD = 6.49) recruited in the city where the laboratory is located. The participants were recruited by a professional market research company. The initial sample was reduced to 91 due to corruption in some of the acquired signals, that is, disconnection of a sensor during the test (3 subjects) and signals affected by artifacts (6 participants). The participants all had normal, or corrected-to–normal, vision and hearing. They were compensated for their participation with a gift card of 20. The study was approved by the ethical committee of the institutional review board of the university. Written informed consent was obtained from all subjects, in accordance with the Declaration of Helsinki.

Experimental Design and Stimuli

A 2 factor (ad video format display: 360-degree vs. traditional ad) X 2 (product type: FMCG vs. durable product) between-subjects experimental design was implemented. Car and beverage brand ads were chosen because of their popularity and because one is a durable product and one a FMCG. The criteria for selecting the ads were: (i) to find two official advertisements for each brand in the two different formats (360-degree and 2D) (**Table 1**); (ii) two products within the same category were needed to control for brand influence and different market share levels, and to address brand familiarity.

Based on these criteria the following four brands were chosen: BMW, Honda, Nescafe, and Lipton. BMW has 6 times the sales of Honda in the market under study (Statista, 2019). Nescafé is the leading instant coffee brand in Spain (5.9 million drinkers); Nestea is the leading iced tea brand in Spain (6.4 million drinkers), much more popular than Lipton iced tea (1.6 million drinkers) (Statista, 2019). Furthermore, per capita consumption of coffee is 3.8 times that of tea in the market under study (Ministerio de Agricultura, Pesca y Alimentación, 2019).

After the participants were welcomed into the laboratory, they were asked to complete an informed consent form and the study was explained. The EEG/EDA device was placed on the subjects while they listened to the explanation about the visual stimuli they were about to be shown. The ET and FC devices were embedded in the desk monitor. A specific baseline for EEG was used, which included a three-choice psychomotor vigilance task (3CVT), an eye-open task (EO), and an eye-closed task (EC), each of which were 3 min long. Next, the participants' brain and eye movements were calibrated. ET was calibrated through 9 points that appeared on the monitor. When the calibration was excellent, or good, the participants were randomly assigned (to avoid bias in the data gathering) to one of the four scenarios depicted in **Figure 2**. Depending on the scenario to which they were assigned, the participants viewed four video ads in the sequence shown in **Figure 2**. For example, participants in the first group were exposed to the ads as follows: (i) 360-degree video ad for Nescafé; (ii) 2D video for Lipton; (iii) 360-degree video ad for Honda; and (iv) a 2D video for BMW. The resolution of the ads was 1920 × 1080 pixels in both formats. The 360-degree format was viewed using Kolor 3.2. software that allows the users to interact with the videos; the quality is similar to YouTube videos.

After watching the videos the participants completed a short survey about their likeability for the ads (one item, five-point scale -"none" to "a lot"-), and their willingness to buy the product if money was available (1 item, 5 point scale –"definitively not" to "definitively yes"). **Table 2** shows the behavioral measures of purchase intention and ad liking. The two ads most liked by the viewers were the 2D version of the Nescafe video ad and the 360-degree version of the Lipton video

TABLE 1 | Ad description.

	2D	360-degree
Nescafe	https://youtu.be/VOOvpXFOPpY	https://www.youtube.com/watch?v=beo_Ln00RGc
Lipton	https://www.youtube.com/watch?v=7Myri_gIqT4andt=2s	https://www.youtube.com/watch?v=S_hpD7teoowandt=11s
Honda	https://vimeo.com/158687455	https://youtu.be/p3JKK32xkaU
BMW	https://www.youtube.com/watch?v=AfmMAVWK4Sw	https://www.youtube.com/watch?v=EEmuY2bC3SE

TABLE 2 | Behavioral measures.

Brand	Variable	2D ads		360-degree ads		*p*-value
		mean	S.D.	mean	S.D.	
BMW	Purchase intention	2.96	0.87	2.94	0.94	0.929
	Ad liking	3.71	1.07	3.52	1.16	0.400
Honda	Purchase intention	2.50	0.85	2.25	0.86	0.147
	Ad liking	3.13	0.87	3.19	1.09	0.733
Nescafe	Purchase intention	3.08	0.84	3.08	0.85	0.969
	Ad liking	4.02	0.87	3.56	0.72	0.661
Lipton	Purchase intention	3.00	0.77	2.88	0.79	0.423
	Ad liking	3.65	0.99	4.10	1.09	0.599

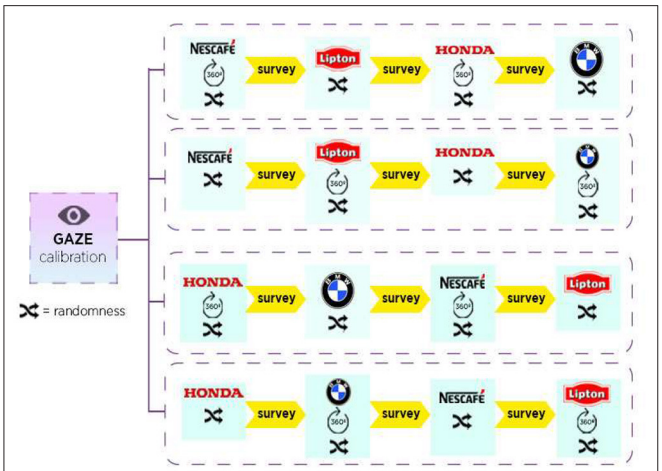


FIGURE 2 | Stimuli and experimental design.

ad; no significant differences were found across the brands in each format.

Measurement of the Neurophysiological Responses

Visual Attention: Eye-Tracking

Visual attention was analyzed using the Tobii Pro TX300 eye-tracking device. This records at 300 Hz and has a built-in 23-inch monitor. Following the recording of the gaze behavior, a speed-based fixation detection algorithm, with a threshold of 30 degrees/second, was used to identify the number of fixations and the average fixation time for each stimulus. To measure brand exposure, every second that the brand logo was shown in the advertisement was monitored through a dynamic AOI (area of interest) (Guixeres et al., 2017). We analyzed the percentage of visitors who fixated at least once on the AOI, the number of fixations, and the time spent viewing the brand-related AOI. The signals were synchronized with the stimuli through the iMotions Attention Tool (https://imotions.com/guides/).

Consumer Engagement With the Ad: Frontal Asymmetry

To compute the FAA an EEG spectral analysis was performed in each epoch using Welch's method, with 50% overlapping. In particular, we calculated the spectral power of the alpha band (8–12 Hz), and frontal asymmetry was calculated using the following formula:

$$\left[Frontal\ asymetry = \log\left(F3_{alpha}\right) - \log(F4_{alpha})\right]$$

Electrical brain activity was recorded using the B-Alert X10 device (Advanced Brain Monitoring, Inc., USA). This records in nine channels, located in the frontal (Fz, F3, and F4), central (Cz, C3, and C4), and parietal—occipital areas (POz, P3, and P4), using the international location system 10-20. The recording was made at 256 Hz. First, data from each electrode were analyzed to identify corrupted channels using the fourth standardized moment (kurtosis). If a channel presented more than 10% of flat signal the electrode was classified as corrupted. The EEG baseline was removed and a bass pass filter between 0.5 and 40 Hz was applied. The signal was segmented into epochs of one second, and an intra-channel kurtosis level of each epoch was used to reject the epochs with high noise levels. To detect artifacts caused by eye movements, blinking, and muscular activation, independent component analysis (ICA) (Gao et al., 2010) was

applied; a trained expert manually analyzed all the components, rejecting those caused by artifacts.

Emotions: Electrodermal Activity and Facial Coding

The consumers' emotions were measured using EDA and FC. The EDA signal was measured using the Shimmer 3 device. The signal was pre-processed in two phases. First, the signal was down sampled to 10 Hz (Lang, 2000). Second, in the re-sampled signal, the artifacts were visually diagnosed and corrected using Ledalab (v.3.4.8,www.ledalab.de) via Matlab (v.2016a; www.mathworks.com). The EDA was measured in micro-Siemens, the number of peaks and their amplitudes being identified during each stimulus. These measures are correlated with an increase in the subject's arousal caused by external stimuli (Bach et al., 2010).

The FC was assessed with a Logitech QuickCam Pro 900 webcam (1,600 × 1,200, 30 fps) using the Emotient FACET library (Stöckli et al., 2018). This is based on the Facial Action Coding System, and it recognizes the probability from 0 to 1 that a subject is experiencing a specific emotion. It offers a set of seven basic emotions (joy, anger, surprise, fear, contempt, disgust, sadness). For each stimulus, we calculated the percentage of time that a subject was experiencing a specific emotion, using a threshold of 0.75.

Data Analysis

The Gaussianity of the data was checked using the Kolmogorov-Smirnov test ($p > 0.05$, with null hypothesis of having a Gaussian sample). To explore the differences between the subjects' responses, in both the 2D and 360-degree formats, we carried out an unrelated two-tailed *t*-test. The data analysis was performed using Matlab 2018b. To simultaneously compare the four ads a Bonferroni correction was applied, decreasing the threshold to consider a test significant to $p < 0.0125$.

RESULTS

H1 predicts that the visual attention paid to a 360-degree video ad is lower than the visual attention paid to a 2D video. As **Figure 3** shows, the number of fixations was higher in FMCG 2D ads than in FMCG 360-degrees ads. Furthermore, the average fixation time was greater in three out of the four ads. Overall, the participants paid more attention (longer fixation time) to the 2D video ads, except for BMW, than to the 360-degree ads. Therefore, H1 is supported for FMCG, but not for durables. It seems that the 360-degree format elicits a more dispersed view pattern that ultimately leads to a smaller number of fixations (except for durables with a high degree of narrative structure) and less average fixation time.

The higher number of fixations for the durable products can be attributed to the greater attention needed to choose a durable, based on their multiple product attributes, the narrative structure of the ad, and the complexity of the task to be performed in the car ad. The FMCG ads analyzed had a low, or moderate, level of narrative structure (Feng et al., 2019), with no clear plot connections between the scenes. Lipton's "Magnificent Matcha Tea" transports the viewer to a world of flavor represented by a series of exotic scenes (e.g., a woman stands in front of cherry blossoms outside a temple, a woman practices yoga beside the sea, a woman holds a cup of tea she intends to drink), and the Nescafé ad presents multiple scenes simultaneously featuring people from different countries at their breakfast tables drinking cups of coffee, while the song "Don't Worry" by Madcon plays in the background. In contrast, in the BMW ad the viewers are immersed in a simulated ride where they have to keep sight of a fashion model (Gigi Howard) driving a car in a race with other BMW cars (high narrative structure and goal-directed task). A close look at the BMW ad shows that it demands a task be undertaken; "Can you keep your eyes on Gigi?" If the consumer wishes to perform the task it would not be logical for him/her to change the angle of view because some pieces of the ad content would be lost and, consequently, it would be harder to "keep your eyes on Gigi." Therefore, in the 2D format it is expected that participants will make fewer fixations. These fixations would be focused only on Gigi's position, not the rest of the ad. Conversely, in the 360-degree video, the participants might be motivated to look at other parts of the ad. The interactive viewing experience and the control needed to manipulate the point of view requires higher visual attention to be paid to specific parts of the BMW ad in the 360-degree version, than is required in the 2D version, to perform the task.

H2 addresses brand recognition through their logos. **Figure 4** shows the eye-tracking results for the brand logo area of interest in both the 2D and 360-degree video ads. Results are shown for the three metrics used: percentage of visitors, number of fixations, and time spent viewing the brand. The 2D stimuli attracted a higher percentage of visitors ($p = 0.000$), a higher number of fixations ($p = 0.000$), and more time spent ($p = 0.013$) viewing the brand, confirming H2. As expected, the visual attention paid to the brand logo is lower in the 360-degree video ads, because exposure to this specific element is influenced by the navigation paths adopted by the consumers. This finding is consistent with the MOA model and, more specifically, with the motivation and opportunity to process some parts of the ad. Furthermore, the areas viewed by the participants can be explained by the attention capture and transfer model (Pieters and Wedel, 2004), that is, they are based on a combination of personal factors and stimuli.

FAA was measured using EEG. The results of the brain responses comparing the 2D and 360-degree stimuli were analyzed using the mean and standard deviations of the asymmetry. The higher the FAA index, the higher is the approach behavior, with low values indicating withdrawal behavior. This metric has been related to the level of the engagement of the prefrontal cortex caused by content viewed (Ramsøy et al., 2018). Again, the consumers' unconscious responses produced an interesting result (see **Table 3**). The high interactivity of the 360-degree ads had a more positive impact on the engagement of the prefrontal cortex for high-involvement products (durables), than for low-involvement products (FMCG). However, the durables showed no significant differences in frontal asymmetry (H3 not supported). One possible explanation of the higher engagement of the prefrontal cortex in the participants who viewed the 2D version of the Nescafe ad, compared to those

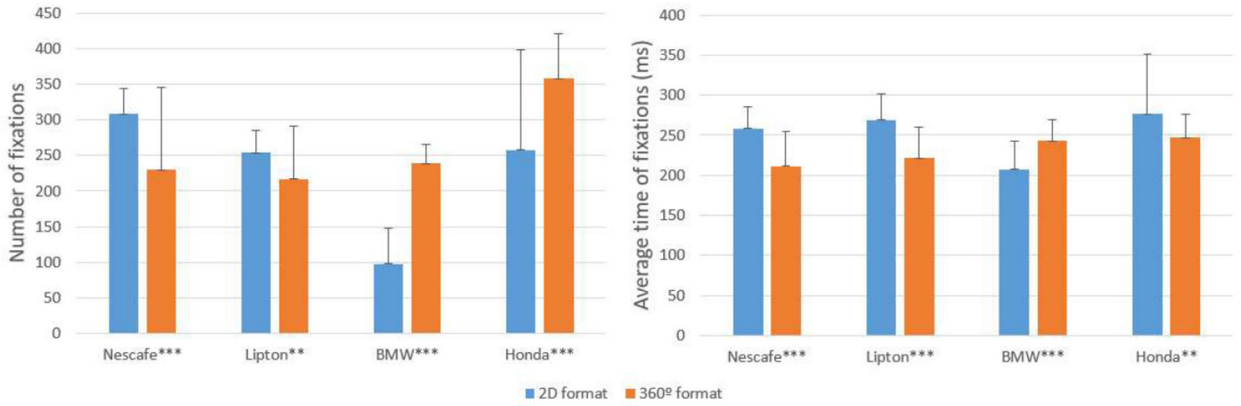


FIGURE 3 | Visual attention paid to the ads. Values with significant differences: $^{**}p < 0.0125$; $^{***}p < 0.001$. Bars represent the means, vertical lines represent the standard deviation of the means.

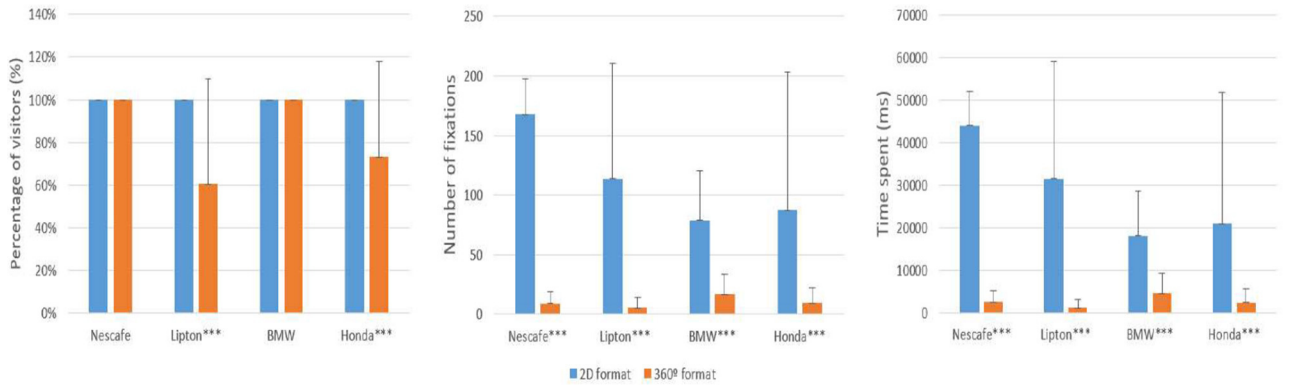


FIGURE 4 | Visual attention paid to the brand logo. Values with significant differences: $^{***}p < 0.001$. Bars represent the means, vertical lines represent the standard deviation of the means.

who viewed the 360-degree version, may be that the viewers of the 360-degree version suffered from cognitive overload. The ad simultaneously presents multiple scenes, featuring people from different countries at their breakfast tables, that don't follow any causal order. The multiple self-directed navigation possibilities offered to viewers by the 360-degree version may make it even more difficult to understand the chronology and causality of the narrative structure of the ad, leading to cognitive overload.

H4 relates to the positive emotions elicited by the 360-degree and 2D ads; the FC results (depicted at **Table 4**) demonstrated that the 360-degree format provoked significantly high levels of joy and surprise, but only for the durable products. In the 360-degree ads the viewer is transported to vicariously share the story character's positive feelings and thoughts through an identification process which generates positive affect. The differences observed between the durables and the FMCGs can be attributed to the higher cognition needed for durables and to the focus of the ads. In the car ads the product (the car), is central, whereas the FMCG ads are based on fantasy.

TABLE 3 | Frontal asymmetry.

Stimulus	Mean of frontal asymmetry		
	2D format	360-degree format	*p*-value
Nescafe	0.0259 (0.097)	−0.0302 (0.108)	0.0105**
Lipton	−0.00155 (0.102)	−0.0188 (0.113)	0.454
BMW	−0.0255 (0.122)	0.00854 (0.077)	0.121
Honda	−0.0347 (0.101)	0.0124 (0.084)	0.0206

Values with significant differences: $^{**}p < 0.0125$. Frontal asymmetry is measured as the logarithm of alpha Power Spectral Density (μV2/Hz). Standard deviations are presented in parenthesis.

Unsurprisingly, it seems that ad content type may elicit different emotions. Moreover, and based on the differences between integral and incidental emotions proposed by Achar et al. (2016), the FMCG ads, which focus on fantasy, may be evoking incidental emotions, while the durable product ads, where the product is

TABLE 4 | Positive emotions.

Emotions	Stimuli	Mean of the percentage of time experiencing the emotion		
		2D format	360-degree format	*p*-value
Joy	Nescafe	38.35% (37.01%)	39.61% (33.86%)	0.870
	Lipton	20.64% (22.00%)	28.96% (29.53%)	0.146
	BMW	16.96% (19.92%)	44.57% (38.35%)	<0.001***
	Honda	21.78% (28.29%)	43.37% (34.60%)	<0.001***
Surprise	Nescafe	19.60% (21.63%)	15.51% (16.07%)	0.341
	Lipton	20.75% (23.47%)	21.71% (24.57%)	0.851
	BMW	12.38% (15.72%)	26.54% (23.72%)	<0.001***
	Honda	21.10% (21.13%)	33.99% (28.35%)	0.030

*Values with significant differences: ***$p < 0.001$. Standard deviations are presented in parenthesis.*

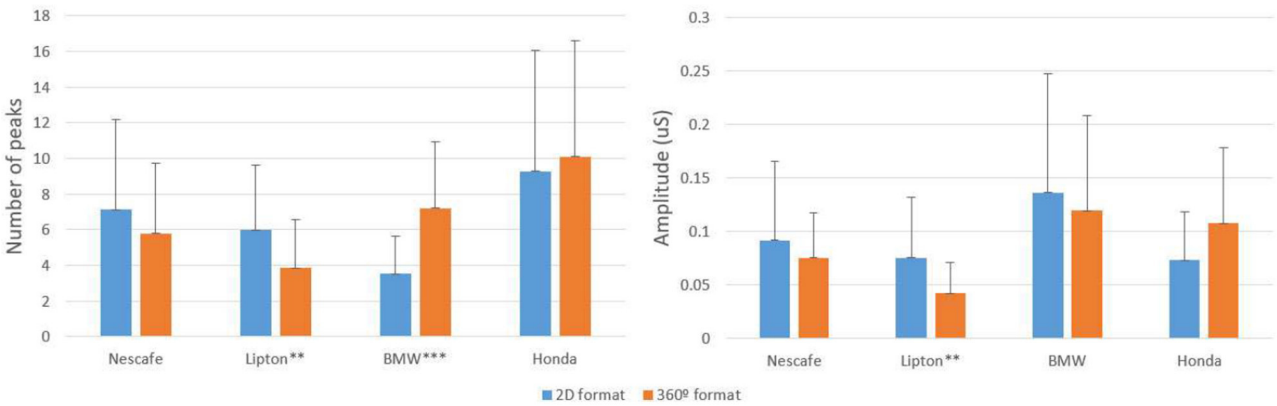


FIGURE 5 | Number of peaks and amplitude of arousal. Values with significant differences: **$p < 0.0125$; ***$p < 0.001$. Bars represent the means, vertical lines represent the standard deviation of the means.

the focus, may be eliciting integral emotions. Therefore, H4 is partially confirmed.

H5 predicted that 360-degree ads would elicit higher arousal; the EDA results comparing the 2D and 360-degree stimuli were analyzed using the mean and standard deviations of the number of peaks and their amplitude (**Figure 5**). Significant differences were found in the number of peaks, as follows. A greater number of arousal peaks were found in the FMCG ads with 2D formats than in the 360-degree versions, with the Lipton ad showing significant differences in the amplitude of its peaks. In the durable ads, on the other hand, more peaks were observed in the 360-degree ads. Therefore, H5 is supported for durables.

DISCUSSION, CONCLUSIONS, AND IMPLICATIONS

The main goal of this study is to compare the effectiveness of traditional and 360-degree video ad formats through consumers' unconscious and continuous (e.g., moment-to-moment) responses to advertisements, obtained from EEG, ET, FC, and EDA.

The results showed significant differences in the visual attention paid, measured through ET, in the 360-degree vs. 2D ads. Indeed, the number of fixations and the time spent metrics were lower in the 360-degree videos than in the traditional, 2D videos. Therefore, 360-degree videos motivate viewers to watch specific parts of a video less than do 2D ads. This finding is consistent with the nature of 2D format ads. The 360-degree format allows viewers to look from multiple angles and, therefore, fixation can be dispersed, and the time spent on each stimulus will be lower. As previously stated, this conclusion is consistent with the MOA model and the top-down and bottom-up paths suggested by Pieters and Wedel (2004). Thus, motivation and top-down and bottom-up (i.e., stimuli) factors drive visual attention.

Although it is well-recognized that audiences actively participate in the online video advertising process by going beyond the messages presented in the videos themselves, and draw conclusions about brands, this inference process has received little attention in studies into interactive video ads. The application of the ARM model to online video ads provides insights that help to explain how online video advertising is actually processed, and to identify the strengths and weaknesses

of 360-degree videos in comparison to standard versions. Brand recognition, measured through brand logo exposure and fixation time, was higher in the 2D ads. In other words, the gaze view directed toward the brand logo was higher in the 2D format than in the 360-degree format. Lower visual attention values are related to the viewer's freedom to explore content based on his/her interests (Su and Grauman, 2017). This finding is of importance for the design of brand communications as it is consistent with the MOA model. As in the 360-degree format the consumers' gaze cannot be directed, consumers will pay attention to stimuli based on their motivations. Therefore, exposure to the brand logo cannot be guaranteed as it is conditioned by consumers' opportunity to view the logo, and by their ability to handle the mouse to access different angles of view. In this vein, the present study advances our understanding of interactive advertising by examining cognitive overload from the perspectives of Lang's (2000) LC4MP and the interactivity literature. The results of this study challenge the proposal made in previous research that there is a positive relationship between degree of interactivity and ad persuasion effectiveness. Another interesting finding is that frontal asymmetry is higher in the 2D online FMCG video ads (Nescafe and Lipton) than in the 360-degree ads. Therefore, engagement with the ad depends on a combination of the interactivity of the ad and the cognitive overload caused by the ad.

This research assesses the influence of ad interactivity on emotions through facial recognition and EDA; 360-degree videos evoked more positive emotions, such as joy and surprise, than did traditional ads. As previously discussed, it is expected that greater interactivity will lead to more positive emotions (Rossiter and Bellman, 2005; Bellman et al., 2017). Our results also showed that the participants experienced joy and surprise for longer with the 360-degree ads. Moreover, the required active task in the 360-degree ad might have elicited higher viewer-brand interaction for the BMW ad which, in turn, might have evoked more positive emotions. In 360-degree ads viewers have to interact with the brands through the mouse; this evokes higher joy and surprise. We found that arousal, measured through number of peaks and EDA amplitude, was higher for FMCG 2D ads than for 360-degree ads. This unexpected result might have arisen because other variables, such as involvement with the ad or with the brand, are exerting a mediator effect. Also, in the 2D videos the creative director and producer decide the view sequence. If viewers change their point of view of the content, as they can in 360-degree videos, they can lose the thread of the story, which might cause lower levels of arousal. This result is quite close to the findings of Fortin and Dholakia (2005), who found no direct relationship between interactivity and arousal in a website setting. However, they found an indirect relationship mediated by involvement.

As regards the managerial implications, it is recommended that practitioners use 360-degree technologies to enhance positive emotions and customer engagement. However, the specific attention paid to the brand logo may vary depending on the viewing angle adopted by the users. The 360-degree video ads conveyed positive emotional responses, but these must be analyzed carefully throughout the entire ad. Thus, the 360-degree format is recommended under certain conditions. First, level of brand awareness must be high. This would mitigate the effect of the viewers not looking at particular stimuli, such as the brand logo, name, and other brand-related elements that may not be recognized by the consumer. Second, the length and content of the videos must be controlled to produce a balanced combination of joy and surprise. As 360-degree videos provide more emotional and immersive experiences for customers, they are powerful tools through which to create emotional connectedness. Third, advertisers of FMCG goods might use 2D online ads, which can cause higher prefrontal cortex engagement than 360-degree versions. 360-degree commercials need to be more detailed than 2D ads. Instead of looking at a scene from one angle, as in the 2D format, producers must take into account other angles, which will entail more sophisticated and expensive production. Four, advertisers need to make the effort to pre-test how ads are viewed, and from what angles. The challenge is to get the consumers to stick with the 360-degree video and keep them engaged.

From an academic viewpoint, this study makes the following contributions. First, it has been demonstrated that interactivity in video ads boosts positive emotions and enhances engagement. These two variables are commonly described as mediated objectives in advertising campaigns (Pavlou and Stewart, 2000). A strong relationship between interactivity, emotions, and prefrontal cortex engagement has been demonstrated in other digital formats, such as social media and websites. As Pavlou and Stewart (2000) noted, interactive advertising opens up new avenues for communication, but requires new measures of consumer responses (information search, visual attention, and ad information processing). Second, unconscious and continuous metrics based on neurophysiological tools are excellent means of accurately measuring advertising effects in interactive ads. Measures cannot be only explicit, they must also dynamically capture unconscious attention paid, and view angles. To the best of the authors' knowledge, the present study is first to assess 360-degree video ads using neurophysiological tools. Third, 360-degree ads represent customized visual communication driven by user participation. That is, they allow the viewers to take an active role that challenges the traditional assumptions about senders and receivers of advertising messages. This new view is in line with customer participation approaches.

Despite the benefits they provide in measuring continuous stimuli types, such as online videos, the physiological methods used in this study have some limitations and challenges. The study results have some limitations that can be sorted into two groups, the stimuli and the participants. First, our results derive from only four ads, and thus conclusions cannot be generalized to other types of ad, that is, with different creative content. Although the study controlled for brand influences and market share levels within the same category, we did not control the categories. The authors sought to analyze both well-known brands, such as Nescafe and BMW, and others with lower brand awareness in the market under study (Lipton and Honda). However, previous consumer experience with the brand might also bias the results of the study. Furthermore, participant-related factors, such as involvement with the brand, and with the ad, might also have exerted some influence. Another limitation is that we did not

directly compare the preferences of the participants for the study stimuli. In future studies we will use a preference-based filter to better control this aspect.

Future research might expand in the following directions. First, the influence of content and executional factors, such as music and motion, might be considered. These executional factors might impact on emotions and cognitive workload. Second, the device used might have an impact. In this sense it would be interesting to analyze 360-degree videos viewed on mobile phones or on social media, and include cross-platform synergies, as suggested by Lim et al. (2015). Future research might also explore other 360-degree formats, such as 3D, and immersive settings based on augmented and virtual reality (Alcañiz et al., 2019; Wedel et al., 2020). This study measures engagement of the prefrontal cortex using frontal asymmetry; future studies might complement our findings by employing other measures of engagement. This work uses neuroscientific metrics (eye-tracking, FC, EDA, and EEG) to measure consumers' responses to advertising; to increase the robustness of the results obtained they might be compared to results of self-reported measures of the variables analyzed.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Local ethics committee of the Polytechnic University of Valencia. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

JA-A has developed the intellectual concept and experimentation part of the paper. MA has done part of the writing and planning of the experiment. JM-M together with JG have helped to collect and analyze the data. CR has helped the writing of the article and contribution in the experimental test. EB together with JA-A has helped to conceptualize the tasks and methodology of the experiment. All authors contributed to the article and approved the submitted version.

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Neural Correlates of Garment Fit and Purchase Intention in the Consumer Decision-Making Process and the Influence of Product Presentation

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In today's competitive e-commerce markets, it is crucial to promote product satisfaction and to quickly identify purchase intention in decision-making consumers. The present investigation examined the relationship between perceived garment fit and purchase intention, together with how product presentation methods (mannequin versus self-model) contribute to decision-making processes of clothing. Thirty-nine female volunteers were scanned using fMRI while performing an online shopping task. In Part 1, univariate analysis was conducted between garment fit and product presentation factors to assess their effects on purchase deliberation. In Part 2, univariate, multivariate pattern, and psychophysiological interaction analyses were carried out to examine the predictive ability of fit evaluation and product presentation on purchase intention. First, garment fit × product presentation interaction effects on purchase deliberation were observed in the frontopolar cortex, superior frontal gyrus, anterior cingulate cortex, and posterior cingulate cortex. Part 2 demonstrated neural signals of the dorsomedial prefrontal cortex, premotor cortex, supplementary motor area, superior parietal lobule, supramarginal gyrus, superior temporal sulcus, fusiform gyrus, and insula to distinguish subsequent purchase intentions. Overall, the findings denote directed exploration, visual and action processing as key neural processes in decision-making that uniquely reflect garment fit and product presentation type during purchase deliberation. Additionally, with respect to the effects of purchase intention on product evaluation, the evidence conveys that mental interactions with products and social cognition are fundamental processes that capture subsequent purchase intention at the product evaluation stage.

Keywords: e-commerce, fit satisfaction, purchase intention, consumer decision, product presentation

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INTRODUCTION

Consumers go through complex internal processes before making purchase decisions. As consumers are the backbone of all businesses, understanding the buying behavior is critical. Consumer purchase intention informs businesses about customers and purchase intention is one of the strongest indicators of future purchase decisions (Brown, 2003). Marketplace globalization and a shift toward e-commerce have contributed to highly competitive consumer environments

(Wind and Mahajan, 2002). With the phenomenal growth of e-commerce in retail, it has become even more critical to discern consumer's inclination to purchase early in the decision process. Evident in studies that model early purchase intention prediction in e-commerce settings, the way one interacts with websites and products is meaningfully different before making a purchase decision (Mokryn et al., 2019; Esmeli et al., 2020; Kim et al., 2020).

With the application of neuroscience to the understanding of consumer psychology (Smidts et al., 2014), extensive research has identified how various factors influence the consumer behavior and elucidating their neural basis has opened doors to many possibilities. For example, Knutson et al. (2007) presented evidence of the involvement of the nucleus accumbens, mesial prefrontal cortex, and insula in predicting decision outcomes prior to making the decision. More specifically, this instrumental study had subjects engage in a shopping task, where they viewed the product ("preference period") and the price ("price period"), and then chose to buy or not. The comparison of time courses of several brain regions indicated that the nucleus accumbens and mesial prefrontal cortex were activated during the preference period and price period, respectively, when subjects chose to buy, whereas insula activity was increased at the price period when they chose not to buy. Another study reported a role of the superior frontal gyrus (SFG) and occipital gyrus in decoding product choices (Van der Laan et al., 2012). These reports provided undoubtedly compelling evidence that consumers' purchase intentions can be predicted prior to the decision stage. Yet, our knowledge on these regarding purchasing clothing in an e-commerce setting is still insufficient.

When it comes to the fashion industry, there are numerous factors that influence the overall fit satisfaction of apparels, such as color, fabric texture, comfort, body type, function, personality, garment fit, and how products are presented to customers (Radeloff, 1991; Chattaraman and Rudd, 2006; Pisut and Connell, 2007; Tiggemann and Lacey, 2009; Kim and Damhorst, 2010). In general, the overall fit satisfaction of clothing is evaluated through both visual and tactile information, and thus physical evaluation is important in the decision to purchase clothes (Ashdown and DeLong, 1995; Le Pechoux and Ghosh, 2002). Despite the growth of digital sales within the fashion industry, the risk of dissatisfaction with a choice without physical evaluation remains one of the downsides of e-commerce shopping. Subsequently, the importance of visual information over tactile ones has emphasized in an e-commerce setting. In particular, the perception of physical or esthetic fit of the garment is among the most critical attributes that shape purchasing behavior and attitudes in clothing (Alexander et al., 2005; Hwang et al., 2016). Another important factor is product presentation. Images of products on models and mannequins attract more attention from consumers than zoomed images of items and enhance purchase intention (Boardman and McCormick, 2019). Providing consumers with dynamic imagery, such as virtual try-on, have been shown to reduce the gap between online and offline shopping experience and mitigates the perceived risk (Kim and Forsythe, 2008). Even though these two factors, garment fit and product presentation, are important for purchase deliberation in e-commerce shopping, the brain mechanism of the process remains unexplained.

Several probable brain regions can be proposed for the neural basis of factors influencing consumer behaviors toward fashion products. For example, different methods of product presentation have not only indicated greater engagements of neural regions related to visual processing, mental imagery, and reward processing, but also have shown the effectiveness in altering purchasing behavior (Jai et al., 2014). Reward-related regions including the ventral striatum and ventromedial prefrontal cortex (vmPFC) may be important because they are involved in one's desires for stimuli (Pool et al., 2016). Since sensory experiences are essential in consumer behavior (Krishna, 2012), the superior parietal lobule (SPL), supramarginal gyrus (SMG), and inferior frontal gyrus (IFG) can be recruited. The SPL is regarded as a key contributor in mental imagery (Gourtzelidis et al., 2005) and sensory aspects of decision-making (Zhou and Freedman, 2019). There is evidence that a robust intention-to-purchase is induced through mental imagery by the SPL (Liu et al., 2018). The SMG has abundant mirror neurons (Chong et al., 2008) that integrates reward and other factors for action-reward associations (Vickery and Jiang, 2009). The IFG has also been implicated in the mental imagery network and mirror neuron system (Rizzolatti and Craighero, 2004). These mirror neuron-rich areas, often implicated in mental imagery, may possibly predict the presence of purchase intention during product evaluation. Purchasing processes for apparel also involve both personal and social components (Tiggemann and Lacey, 2009; Shin and Damhorst, 2018). Since consumers formulate fit satisfaction from both their own and others' perspectives, the engagement of self-referential processing by the dorsomedial prefrontal cortex (dmPFC) (D'Argembeau et al., 2007) and mentalization by the temporoparietal junction (TPJ) (Saxe and Kanwisher, 2003) and superior temporal sulcus (STS) (Deen et al., 2015) may be essential in the consumer decision-making process of fashion products.

Despite the intricate workings of the factors that influence the consumer process for fashion products, neural underpinnings of these factors have not yet been elucidated. This study aimed to understand the neural basis underlying garment fit, purchase intention, as well as mannequin and self-model product presentation methods through two parts. Part 1 investigated the neural effects of garment fit and presentation type on purchase deliberation. Here, we hypothesized that the items with garment fit presented on self-models would particularly engage the reward network including the ventral striatum and vmPFC during deliberation of purchase decision. Part 2 sought to identify brain regions that predict purchase intention under the hypothesis that the way decision makers interact with products during fit evaluation would uniquely capture the subjective intention-to-purchase and product presentation types, and this way would be reflected in neural areas associated with mental imagery, such as the SPL, SMG, and IFG, and social cognition, such as the dmPFC, TPJ, and STS.

MATERIALS AND METHODS

Participants

A total of 39 healthy female participants between the ages of 20 and 29 years were recruited via online advertisement (age, 23.5 ± 2.1 years; education, 16.3 ± 1.9 years). Exclusion criteria included left-handedness, pregnancy, and neurological or psychiatric diseases. All participants were provided informed written consent prior to partaking in the study, and the study was approved by the Institutional Review Board of Yonsei University Severance Hospital and carried out in accordance with the Declaration of Helsinki.

Experimental Procedure

During the fMRI scanning session, participants engaged in an apparel-purchasing task. Task stimuli were prepared before the scanning session. A set of 42 articles of top-only clothing was selected from various online shopping websites. To maximize generalizability, selected items consisted of short-sleeved shirts, long-sleeved shirts, and sweaters. Using Adobe Photoshop (Creative Suite 6, Adobe, United States), all products were traced for manipulation and all brand labels (or any indication of such) were erased to eliminate the brand effects. Then, the manipulation-ready products were transposed onto a generic mannequin and a female model. The images of both the mannequin and female model were framed to show the bodies from the top of the head to above the knees and from shoulder to shoulder. Participants completed an online survey to approximate an appropriate market price for each item of clothing a few days prior to the fMRI scan and provided a picture of their own face. Self-model images of each participant were produced by superimposing participants' faces onto the female model's body to make each shopper feel like she was wearing the clothes (**Figure 1A**).

The task sequence included two runs and 42 trials in each run of approximately 7 min 52 s. In the first run, 42 different articles of clothing were used in the form of 21 self-model and 21 mannequin images, with one per trial. The same 42 clothes were used interchangeably between self-model and mannequin images in the second run. Each trial consisted of two phases of 3 s, representing fit evaluation and purchase deliberation, to emulate the consumer decision-making process. In the fit evaluation phase, one of the prepared superimposed images of either the mannequin or the participant herself wearing an apparel was presented. At the bottom of the image appeared the question, "Will the clothes fit you well?" Together with this, a four-ticked Likert scale appeared with scores of 0: "not at all," 1: "somewhat," 2: "moderately," 3: "very much." Participants were instructed to indicate the level of garment fit by pressing a button, and the response was referred to as the fitness score. In the purchase deliberation phase, the identical image from the fit evaluation phase was displayed with the price along with the question, "How much do you want to buy?" Also displayed was the identical Likert scale. Participants' responses were referred to as the intention-to-purchase score. In order to limit the influence of price information as the standards for the price of apparels vary from person to person, the prices were adjusted and presented in reference to the individual's pre-reported price point. On average, the prices the participants saw were approximately discounted by 12%, where the highest markdown was by 50% and the highest markup was by 130% of the pre-reported price points. To encourage serious participation in the task, participants were informed that they could purchase one product of high intention-to-purchase at the end of the scanning session. The intervals were jittered with an average of 2.5 s (range: 1–4.5 s) between the phases and 3 s (range: 2–6 s) between the trials. The schedule of events and jitters were obtained using Optseq2.[1]

Imaging Data Acquisition and Preprocessing

All functional scanning was performed on 3.0 Tesla MRI scanner (Ingena 3.0T CX, Philips Healthcare, Best, Netherlands) with a 32-channel head coil. For each participant, echo-planar imaging scans were acquired with the following parameters: repetition time = 2,000 ms, echo time = 30 ms, flip angle = 90°, number of acquisitions = 235, number of slices = 31, slice thickness = 3 mm with 1 mm interstitial gap, and matrix size = 80 × 80. A high-resolution T1-weighted structural scan was also obtained from each participant using a 3D gradient echo (matrix size = 256 × 256, number of slices = 180, and slice thickness = 1 mm) after the functional scan.

All images were preprocessed using Statistic Parametric Mapping 12 (SPM 12[2]). To allow for the stabilization of magnetization, the first five scans were discarded. The remaining images were corrected for slice-timing, realigned to correct for head-motion, and co-registered on the individual T1-weighted image. Then, the T1-image was spatially normalized to the MNI template and the resulting transformation matrices were applied to the co-registered functional images. The normalized images were smoothed with a Gaussian kernel of 6-mm full-width at half-maximum (FWHM).

Behavioral Data Analysis

Part 1: Effects of Fit Satisfaction

To assess the effects of garment fit and product presentation on purchase intention in the purchase deliberation phase, differences in the intention-to-purchase scores and reaction times (RTs) among the categories were examined using repeated-measures ANOVA. To determine garment fit, the participants' responses during the fit evaluation phase were separated according to each participant's fitness rating obtained during in-scan behavior; a score of 0 was deemed as having no garment fit (fit-absent) and scores of 1, 2, and 3 were deemed as having at least some garment fit (fit-present). The trials during the purchase deliberation phase were then labeled depending on the product presentation conditions (self-model and mannequin), thereby creating four categories (garment fit × product presentation). *Post hoc* analysis of any significant main effects or interaction effects was then performed using paired *t*-tests.

[1] https://surfer.nmr.mgh.harvard.edu/optseq/

[2] https://www.fil.ion.ucl.ac.uk/spm/

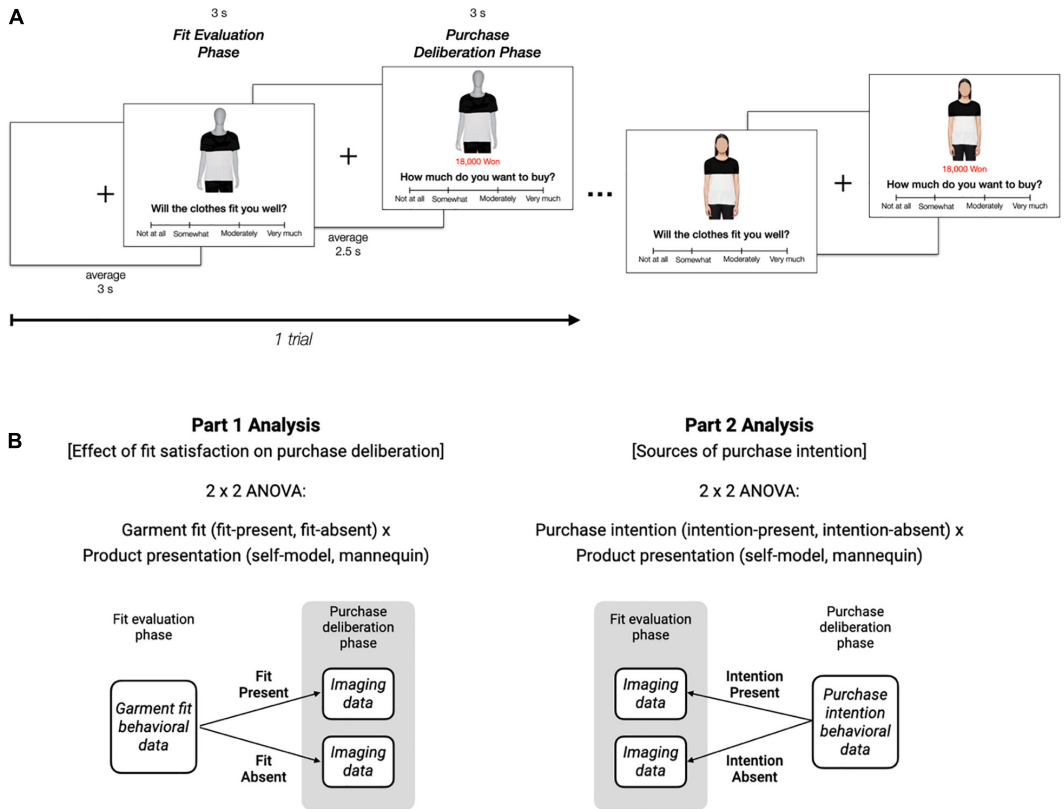


FIGURE 1 | Experimental and analysis design. **(A)** Each participant was presented with an apparel either on a mannequin or on a model with the participant's face superimposed (self-model). First, participants were instructed to disclose their garment fit rating (fit evaluation phase). Next, they were asked to indicate how much they would like to purchase the clothing (purchase deliberation phase). **(B)** In Part 1, trials were separated based on participant's behavioral responses of garment fit-present and fit-absent, and then neuroimaging data of the subsequent purchase deliberation phase were analyzed. In Part 2, trials were separated based on participant's behavioral responses of purchase intention-present and purchase intention-absent, and then neuroimaging data of the previous fit evaluation phase were analyzed.

Part 2: Sources of Purchase Intention

To assess the predictive ability of garment fit and product presentation on the subsequent purchase intention, differences in the fitness scores and RTs among the categories were assessed using repeated-measures ANOVA.

To determine purchase intention, participants' responses during the purchase deliberation phase were categorized into intention-absent and intention-present for an intention-to-purchase score of 0 corresponding to having no intention to buy and scores of 1, 2, and 3 corresponding to having some purchase intention, respectively. The trials during the fit evaluation phase were then labeled depending on the product presentation conditions (self-model and mannequin), thereby creating four categories (purchase intention × product presentation). *Post hoc* analysis was carried using paired *t*-test. All analysis of behavior data was computed using SPSS 25.0 (SPSS Inc., Chicago, IL, United States).

Mass Univariate Imaging Analysis

Once preprocessed, imaging data was analyzed using a general linear model (GLM) at a single-subject level. The preprocessed images were separated into eight categories; the images obtained during the purchase deliberation phase were divided according to garment fit (fit-present and fit-absent) and product presentation (self-model and mannequin), and those obtained during the fit evaluation phase were divided according to purchase intention (intention-present and intention-absent) and product presentation (self-model and mannequin). Then, the BOLD signals for each category were modeled at the onset of each stimulus for the duration of RT ("variable epoch") to factor out the effects of RTs (Grinband et al., 2008), and the signals were convolved with the Hemodynamic Response Function. Additional six rigid head motion parameters acquired during preprocessing were included as regressors of no interest, and high-pass filter was applied at 128 Hz to reduce low-frequency drift and physiological noise. Fixation was not modeled. To investigate the effects of garment fit and product presentation on purchase deliberation (Part 1) and find the neural sources predicting purchase intention (Part 2), the contrast images of garment fit × product presentation at the purchase deliberation phase and those of purchase intention × product presentation at the fit evaluation phase were entered into the flexible factorial model at the group level analysis (**Figure 1B**). Statistical

inferences were set at a threshold of $P_{UNC} < 0.001$. The multiple comparison problem was addressed using family-wise error correction at $P_{FWE} < 0.05$ at the cluster level.

Multivariate Pattern Analysis

For Part 2, as a complementary analysis to the mass univariate analysis, we performed multivariate pattern analysis (MVPA) for whole brain searchlight to demonstrate the brain correlates that are predictive of purchase intentions from the fit evaluation phase. The decoding toolbox optimized for SPM was used to decode brain regions showing unique neural patterns reflecting subsequent intention-to-purchase. As recommended by Hebart et al. (2015), non-normalized and non-smoothed preprocessed data were used. Similar to the setup used in "Mass univariate imaging analysis," the GLM was estimated for the purchase deliberation phase of each trial according to garment fit and product presentation, and the fit evaluation phase of each trial according to purchase intention behavior and product presentation as a separate and single regressor, creating a maximum of 84 separate beta images per run for every participant. The regressors were modeled at the onset of each stimulus with RT as duration, and the six rigid head motions were included as regressors of no interest.

The regressors of the fit evaluation phase were labeled by the intention-to-purchase category, and data were split into half by the first and second run. Next, we took a cross-validated pattern correlation approach (Haxby et al., 2001). A spherical searchlight with a radius of 10 mm was defined for every voxel in a brain mask. In each voxel, the mean signal was subtracted across all categories. The neural activity of voxels within each searchlight was averaged across trials and categories. To identify the spatial pattern unique to each category, we compared the correlations between the response pattern to one category in the first data set and the pattern of the same category in the second data set, namely within category correlation. Then, we compared the correlations between the two categories, known as between-category correlation. Results of analysis were reported in terms of the area under the receiver operating characteristics curve, a graphical plot that represents graded decision values and better addresses any possible classification bias. The chance level was set at 50%.

The resulting map of the decoded brain was normalized and smoothed with a Gaussian kernel of 6-mm FWHM. Then, the map was entered into one-tailed one-sample *t*-tests to examine the unique neural patterns predictive of subject's subsequent intention-to-purchase. As MVPA has been known to increase sensitivity of cognitive states (Norman et al., 2006), a stricter threshold was set at uncorrected $P < 0.0001$ voxel-wise and $P_{FWE} < 0.05$ cluster-wise correction.

Psychophysiological Interaction Analysis

Computation of the functional coupling between one of the chosen seeds and the entire brain in response to a task (Friston et al., 1997) was conducted using the CONN toolbox optimized for SPM12 (Whitfield-Gabrieli and Nieto-Castanon, 2012). The setup of the model was as described above in the mass univariate GLM. Any hypothesized region (SPL, SMG, IFG, dmPFC, TPJ, and STS) observed in our mass univariate analysis of purchase intention was defined as seed ROIs. Each spherical ROI mask with 5 mm radius around the peak coordinate was created. The interaction regressor between time series of each seed region (physiological term) and the task conditions (psychological term) was modeled for the difference between intention-present and intention-absent categories during the fit evaluation phase. The interaction regressor produced the connectivity modulation for each category across every voxel. Individual seed-to-voxel connectivity maps were entered into paired *t*-tests to assess between-category effects. The statistical threshold was set as described in the mass univariate analysis.

RESULTS

Effects of Fit Satisfaction

Behavioral Results

The summary of behavioral data is presented in **Table 1**. In the fit evaluation phase, an average of 35 versus 65% of the trials were identified as fit-absent and fit-present, respectively. Repeated-measures ANOVA of the intention-to-purchase scores revealed a main effect of garment fit ($F_{1,38} = 334.87$, $P < 0.001$), but no main effect of product presentation or interaction effect of garment fit × product presentation. *Post hoc* analysis showed that the intention-to-purchase scores for fit-present items were significantly higher than the scores for fit-absent products ($t_{38} = 18.37$, $P < 0.001$). Analysis of RTs showed main effects of garment fit ($F_{1,38} = 102.96$, $P < 0.001$) and product presentation ($F_{1,38} = 8.14$, $P = 0.007$), but no interaction effect. *Post hoc* analyses indicated that RTs were significantly longer for fit-present than for fit-absent clothing ($t_{38} = 10.43$, $P < 0.001$) and showed shorter RTs toward self-models than toward mannequins ($t_{38} = -4.94$, $P < 0.001$).

Results From the Mass Univariate Analysis

Table 2 presents the significant brain regions showing significant main effects of garment fit and product presentation and interaction effect between the two factors at the purchase deliberation phase. The main effect of garment fit was observed in the bilateral supplementary motor area (SMA), left SPL, and left SMG (**Figure 2A-1**). All of these regions activated more for fit-present than fit-absent conditions. The main effect of product presentation was seen in various cortical and subcortical regions (**Figure 2A-2**). *Post hoc* tests demonstrated that the bilateral dmPFC, right dorsolateral prefrontal cortex (dlPFC), right inferior temporal gyrus, bilateral midcingulate cortex, left hippocampus, and bilateral caudate showed greater activity for self-models than for mannequins, whereas the right SMG, bilateral precuneus, left STS, and bilateral fusiform gyrus exhibited greater activity for mannequins than for self-models.

The interaction effect of garment fit × product presentation was evident in the right frontopolar cortex (FPC), right SFG, bilateral anterior cingulate cortex (ACC), and bilateral posterior cingulate cortex (PCC). Results from *post hoc* analysis are presented in **Figure 3**. In the right FPC (**Figure 3A**), its activity was significant higher for fit-present/self-models than for fit-absent/self-models ($t_{38} = 2.07$, $P = 0.046$), lower for fit-present/mannequins than for fit-absent/mannequins

TABLE 1 | Summary statistics (mean ± SD) of behavioral data.

Part 1	**Self**		**Mannequin**	
	Fit-present	**Fit-absent**	**Fit-present**	**Fit-absent**
Data obtained at purchase deliberation phase				
Intention-to-purchase score	1.39 ± 0.46	0.10 ± 0.14	1.32 ± 0.37	0.10 ± 0.16
Intention-to-purchase RT (ms)	1322.41 ± 236.14	977.56 ± 223.13	1375.96 ± 224.87	1016.24 ± 238.78
Part 2	**Self**		**Mannequin**	
	Intention-present	**Intention-absent**	**Intention-present**	**Intention-absent**
Data obtained at fit evaluation phase				
Fitness score	1.64 ± 0.36	0.34 ± 0.23	1.77 ± 0.37	0.54 ± 0.42
Fitness RT (ms)	1622.98 ± 240.94	1426.22 ± 257.74	1598.16 ± 261.43	1428.69 ± 256.22

RT, reaction time.

TABLE 2 | Significant brain regions in the mass univariate analysis showing the effects of garment fit and product presentation type during the purchase deliberation phase.

Region	**HEM**	**Cluster size**	***F***	**MNI coordinates**			***Post hoc***
				x	***y***	***z***	
Main effect of garment fit							
SMA	B	118	15.10	4	16	46	Present > absent
SPL	L	93	20.83	−12	−70	46	Present > absent
Supramarginal gyrus	L	323	23.57	−44	−42	40	Present > absent
Main effect of product presentation							
dmPFC	B	101	25.30	2	58	22	Self > mannequin
dlPFC	R	230	20.10	44	32	8	Self > mannequin
Inferior temporal gyrus	R	168	29.92	52	−62	−8	Self > mannequin
MCC	B	123	19.93	0	−6	34	Self > mannequin
Hippocampus	L	220	26.96	−30	−14	−10	Self > mannequin
Caudate	L	465	58.17	−10	8	2	Self > mannequin
	R	306	19.67	10	8	6	Self > mannequin
Supramarginal gyrus	R	196	23.11	46	−30	18	Mannequin > self
Precuneus	B	410	27.35	6	−54	48	Mannequin > self
	R	119	12.40	16	−54	16	Mannequin > self
STS	L	480	37.95	−46	−28	10	Mannequin > self
Fusiform gyrus	L	255	25.11	−26	−48	−14	Mannequin > self
	R	396	27.41	34	−46	−10	Mannequin > self
Interaction effect of garment fit × *product presentation*							
Frontopolar cortex	R	212	30.31	26	50	16	**Figure 3A**
SFG	R	108	20.50	24	12	52	**Figure 3B**
ACC	B	1,389	58.34	−4	32	14	**Figure 3C**
PCC	B	94	16.29	−2	−38	42	**Figure 3D**

HEM, hemisphere; MNI, Montreal Neurological Institute; B, bilateral; L, left; R, right; SMA, supplementary motor area; SPL, superior parietal lobule; dmPFC, dorsomedial prefrontal cortex; dlPFC, dorsolateral prefrontal cortex; MCC, middle cingulate cortex; STS, superior temporal sulcus; SFG, superior frontal gyrus; ACC, anterior cingulate cortex; PCC, posterior cingulate cortex.

(t_{38} = −3.24, P = 0.003), and lower for fit-absent/self-models than for fit-absent/mannequins (t_{38} = −4.49, P < 0.001). In the right SFG (**Figure 3B**), fit-present items prompted significantly higher activation for self-models than for mannequins (t_{38} = 2.33, P = 0.025), whereas fit-absent items generated significantly lower activity for self-models than for mannequins (t_{38} = −3.24, P = 0.002). There was no significant difference in activation between fit-present and fit-absent within products displayed on mannequins (t_{38} = −1.05, P = 0.302), but the SFG activation was greater for fit-present than fit-absent items within self-models (t_{38} = 3.72, P = 0.001). In the bilateral ACC (**Figure 3C**), the activation was greater for fit-present/self-models than for fit-present/mannequins (t_{38} = 4.26, P < 0.001), whereas its activity was lower for fit-absent/self-models than fit-absent/mannequins

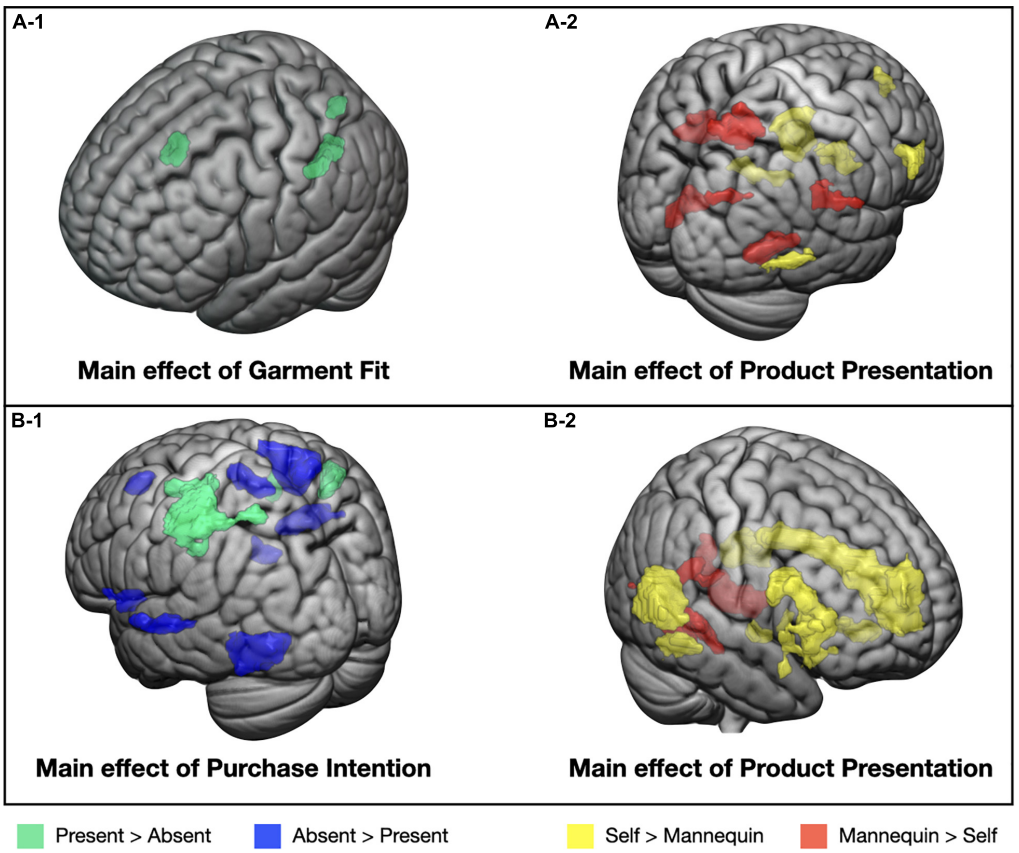


FIGURE 2 | An illustration of significant main effects from the univariate analysis. Significant neural clusters were illustrated for the main effects of garment fit **(A-1)** and product presentation **(A-2)** in Part 1 and for the main effects of purchase intention **(B-1)** and product presentation **(B-2)** in Part 2.

($t_{38} = -5.16$, $P < 0.001$). Fit-present items induced significantly lower activity than fit-absent items ($t_{38} = -4.26$, $P < 0.001$) within mannequins, but no significant difference was observed between fit-present and fit-absent items within self-models ($t_{38} = 1.57$, $P = 0.125$). In the bilateral PCC (**Figure 3D**), the activity was significantly higher for fit-present/self-models than for fit-present/mannequins ($t_{38} = 1.07$, $P = 0.045$), whereas it was significantly lower for fit-absent/self-models than for fit-absent/mannequins ($t_{38} = -2.86$, $P = 0.007$). Within mannequins, the activity of fit-present condition was lower than that of fit-absent condition ($t_{38} = -4.82$, $P < 0.001$), but no difference was observed between fit-present than fit-absent products within self-models ($t_{38} = -0.08$, $P = 0.934$).

Sources of Purchase Intention

Behavioral Results

The summary of behavioral data is also shown in **Table 1**. In the purchase deliberation phase, an average of 48 versus 52% of the trials were identified as intention-absent and intention-present, respectively. Analysis of the fitness scores based on the presence of intention-to-purchase and product presentation revealed significant main effects of purchase intention ($F_{1,38} = 491.84$, $P < 0.001$) and product presentation ($F_{1,38} = 10.58$, $P = 0.002$), and a moderately significant interaction effect between the two factors ($F_{1,38} = 3.03$, $P = 0.09$). The fitness scores were significantly higher for garments that participants later identified as having intention-to-purchase than those without intention-to-purchase ($t_{38} = 23.81$, $P < 0.001$) and toward clothing displayed on a mannequin than on the participants themselves ($t_{38} = 3.25$, $P = 0.002$). Specifically, the fitness scores were higher for garments displayed on mannequins that were later identified as intending to purchase than for garments displayed on mannequins that participants did not intend to purchase ($t_{38} = 20.12$, $P < 0.001$). Also, the fitness scores were higher for intention-present clothing displayed on mannequins in comparison to intention-present clothing displayed on self-models ($t_{38} = 2.29$, $P = 0.027$). In contrast, the scores were higher for intention-present garments displayed on self-models than for intention-absent garments displayed on self-models ($t_{38} = 21.47$, $P < 0.001$). Regarding intention-absent products, the scores were higher when items were presented on mannequins than on self-models ($t_{38} = 3.74$, $P = 0.001$). The RTs showed a main effect of purchase intention ($F_{1,38} = 50.63$, $P < 0.001$), but displayed no main effect of product presentation and interaction effect. *Post hoc* analysis indicated that the RTs for intention-present apparels were significantly longer than for intention-absent clothing ($t_{38} = 7.00$, $P < 0.001$).

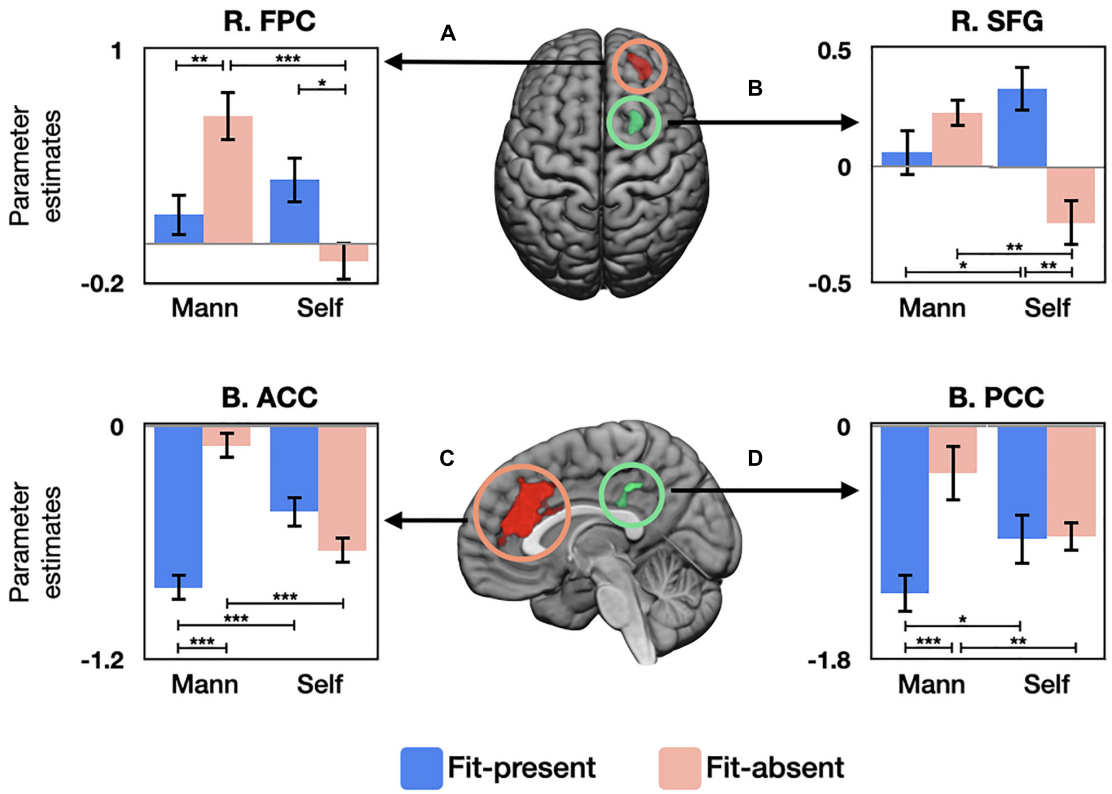


FIGURE 3 | Graphs of parameter estimates of neural regions. Panels **(A–D)** showing interaction effects between garment fit and product presentation type during purchase deliberation. Mann, mannequin; R., right; L., left; B., bilateral; FPC, frontopolar cortex; SFG, superior frontal gyrus; ACC, anterior cingulate cortex; PCC, posterior cingulate cortex. $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

Results From the Mass Univariate Analysis

Table 3 presents brain regions showing significant main effects of purchase intention and product presentation and interaction effect between the two factors during the fit evaluation phase. The main effect of purchase intention was observed in various cortical regions (**Figure 2B-1**). *Post hoc* analyses showed that the right premotor cortex, left SPL, and right SMG were more activated for intention-present than for intention-absent clothing, whereas the bilateral dmPFC, right SMA, right SPL, left STS, left fusiform gyrus, left anterior insula, right posterior insula, and right dorsal striatum were more activated for intention-absent products than for intention-present products. Several clusters also showed the main effect of product presentation (**Figure 2B-2**). Specifically, the bilateral dmPFC/rostral ACC, right posterior orbitofrontal cortex (pOFC), bilateral TPJ, right fusiform gyrus, bilateral anterior insula, right nucleus accumbens, and midbrain showed greater activation toward products displayed on self-models than on mannequins, whereas the bilateral fusiform gyrus activated more for products displayed on mannequins than on self-models. No brain region showed the significant interaction effect.

Results From the Multivariate Pattern Analysis

Table 4 lists neural regions where patterns of activity correctly identified the presence of purchase intention above the chance level of 50% during participants' fit evaluation. In the order of highest to lowest classification accuracy, identified regions were the bilateral SPL, right fusiform gyrus, right SMG, left middle temporal gyrus, right thalamus, right middle temporal gyrus, right pOFC, left dmPFC, right STS, left superior temporal gyrus, and right premotor cortex. Furthermore, as exploratory MVPA was performed to confirm the mass univariate results showing activational differences between the subsequent presence and absence of purchase intention, **Figure 4** overlays the common regions from mass univariate and multivariate pattern analyses. Common regions include the SMA, SPL, and SMG in the right hemisphere, as well as the SPL and STS in the left hemisphere.

Results From the PPI Analysis

Figure 5 presents the results from the psychophysiological interaction (PPI) analysis. Among the clusters showing the main effect of purchase intention in the mass univariate analysis, the bilateral dmPFC, bilateral SPL, right SMG, and left STS were regarded as the hypothesized regions for this analysis. Thus, these regions were selected as the seed ROIs. Significant functional connections in the contrast of intention-present > intention-absent were found in the right fusiform gyrus and left cerebellum with the right SMG. Significant functional connections in the contrast of intention-present < intention-absent were found in the left SPL with the bilateral dmPFC. No other functional connections were significant with the SPL or STS.

TABLE 3 | Significant brain regions in the mass univariate analysis showing the prediction ability of the imaging data during the fit evaluation phase for purchase intention and product presentation type.

Region	HEM	Cluster size	*F*	MNI coordinates			*Post hoc*
				x	*y*	*z*	
Main effect of purchase intention							
Premotor cortex	R	117	30.00	50	4	28	Present > absent
SPL	L	1,382	34.53	−32	−24	58	Present > absent
Supramarginal gyrus	R	373	28.96	46	−40	48	Present > absent
dmPFC	B	141	31.90	−6	48	32	Absent > present
SMA	R	274	39.54	8	−26	50	Absent > present
SPL	R	1,529	18.69	24	−46	64	Absent > present
STS	L	270	21.23	−56	−6	−6	Absent > present
Fusiform gyrus	L	905	26.81	−28	−58	−14	Absent > present
Anterior insula	L	178	26.77	−36	20	−10	Absent > present
Posterior insula	R	386	37.58	46	−22	20	Absent > present
Dorsal striatum	R	136	28.06	32	−10	−2	Absent > present
Main effect of product presentation							
dmPFC/rACC	B	2,408	42.22	4	56	20	Self > mannequin
pOFC	R	205	31.41	26	20	−18	Self > mannequin
Temporoparietal junction	L	512	36.13	−54	−66	6	Self > mannequin
	R	825	60.84	52	−58	6	Self > mannequin
Fusiform gyrus	R	184	79.14	44	−46	−20	Self > mannequin
Anterior insula	L	213	32.53	−28	16	−18	Self > mannequin
	R	1,047	35.49	36	26	0	Self > mannequin
Nucleus accumbens	R	165	24.57	4	6	−8	Self > mannequin
Midbrain		122	18.50	−6	−18	−14	Self > mannequin
Fusiform gyrus	L	582	44.29	−28	−56	−14	Mannequin > self
	R	764	36.48	34	−44	−10	Mannequin > self
Interaction effect of purchase intention × product presentation							
None							

HEM, hemisphere; MNI, Montreal Neurological Institute; B, bilateral; L, left; R, right; SPL, superior parietal lobule; dmPFC, dorsomedial prefrontal cortex; SMA, supplementary motor area; STS, superior temporal sulcus; rACC, rostral anterior cingulate cortex; pOFC, posterior orbitofrontal cortex.

TABLE 4 | Multivariate pattern analysis results of purchase intention during the fit evaluation phase in the order of highest to lowest classification accuracy.

Region	HEM	Cluster size	*T*	MNI coordinates			Classification accuracy %
				x	y	z	
Purchase intention (present versus absent)							
SPL	R	3,219	17.37	42	−24	54	83.1
	L	3,973	9.41	−38	−24	54	80.3
Fusiform gyrus	R	185	5.87	24	−54	−22	70.0
Supramarginal gyrus	R	325	6.11	52	−22	24	68.8
Middle temporal gyrus	L	130	6.12	−52	−34	−2	67.9
Thalamus	R	245	6.52	18	−10	−2	67.3
Middle temporal gyrus	R	29	4.79	58	−34	−6	65.4
pOFC	R	31	4.49	34	36	−4	64.4
dmPFC	L	102	4.48	−14	48	42	62.2
STS	R	36	4.47	66	−22	−12	61.5
Superior temporal gyrus	L	43	4.84	−56	14	−6	58.5
Premotor cortex	R	160	6.35	66	8	28	53.1

Results are reported at voxel-level $P_{UNC} < 0.0001$ and cluster-level $P_{FWE} < 0.05$. HEM, hemisphere; MNI, Montreal Neurological Institute; R, right; L, left; B, bilateral; SPL, superior parietal lobule; pOFC, posterior orbitofrontal cortex; dmPFC, dorsomedial prefrontal cortex; STS, superior temporal sulcus.

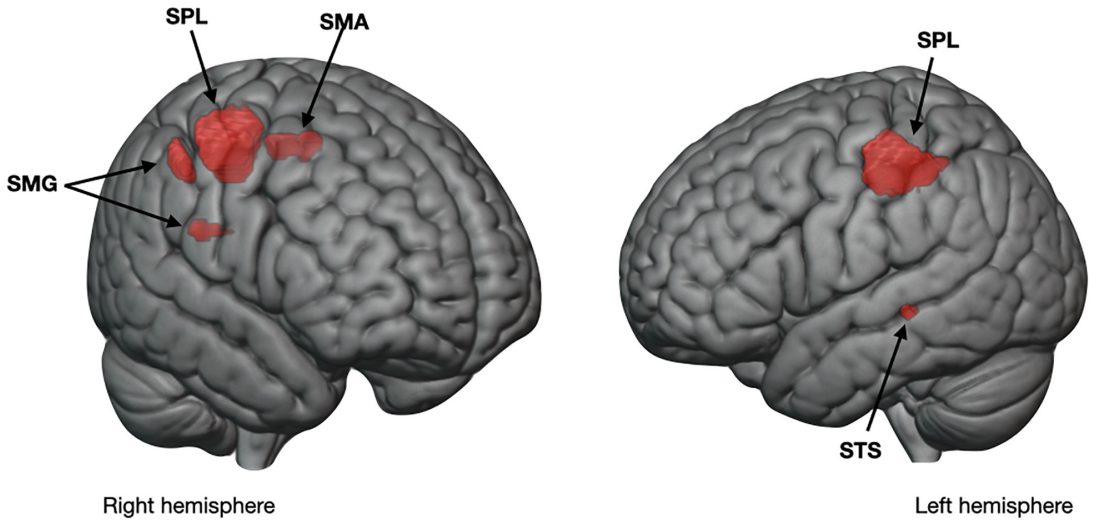


FIGURE 4 | Overlapping neural areas of purchase intention. An overlay of significant clusters obtained from mass univariate analysis showing a main effect of purchase intention and from multivariate pattern analysis demonstrating classification accuracy above the chance level (50%). SPL, superior parietal lobule; SMA, supplementary motor area; SMG, supramarginal gyrus; STS, superior temporal sulcus.

DISCUSSION

The present study aimed to elucidate the neural effects of garment fit and purchase intention on the decision-making process, together with how product presentation influences the relationship. Specifically, we studied how garment fit and product presentation are demonstrated while considering buying a product, then examined the neural signals of fit evaluation period reflecting subsequent purchase intention. Prediction of subsequent purchase intention was further complemented by exploratory MVPA and PPI analyses.

Effects of Fit Satisfaction

As expected, the intention-to-purchase scores were higher for apparel with garment fit than fit-absent products, but there was no difference in the scores between the presentation types. Participants took longer to disclose purchase intention for fit-present items and toward mannequins than their respective counterparts, suggesting a sense of hesitation when making decisions for items with garment fit, which is an inherent problem of e-commerce shopping. Yet, self-models possibly offer a way to mitigate the perceived risk.

In the garment fit effect, the SMA, SPL, and SMG activated more for fit-present than fit-absent products during purchase deliberation. The SMA is considered to contribute to motor-related activities, cognitive control, sensorimotor representation, and complex motor planning, as well as action, time, and spatial sequence processing (Cona and Semenza, 2017). The SPL has been implicated in sensory aspects of decision-making (Zhou and Freedman, 2019), mental imagery, and mental rotation (Vingerhoets et al., 2002), especially in terms of body part imagery (Overney et al., 2005). In addition, with dense population of mirror neurons, the SMG is thought to integrate information for action-reward associations. These garment fit-related activations may indicate more involvement of mental imagery and perception coupling or reflection when making purchase decisions for clothing with fit satisfaction.

The product presentation effect during purchase deliberation seems to emphasize the involvement of a number of regions related to self-projection. Among the regions where activity increased more in self-models than in mannequins, the dmPFC is a key player for self-referential processing and mentalization (D'Argembeau et al., 2007), while the dlPFC contributes to self-initiated elaborative encoding process (Hawco et al., 2013). It has been reported that the inferior temporal gyrus, hippocampus, and caudate are also involved in self-projection (Kurczek et al., 2015; Herold et al., 2016; Vatansever et al., 2018). On the other hand, mannequins recruited self-related imagery more than self-models through activated structures like the SMG and precuneus (Cona and Semenza, 2017; Grol et al., 2017). Interestingly, the fusiform gyrus and STS, which are activated when viewing a face directly (Pageler et al., 2003), showed increased activity in mannequins than in self-models, which may be a compensatory action for the formation of stronger self-related imagery in mannequins.

In the current study, the interaction effect is of greater interest in light of our hypothesis regarding the brain regions involved in the processing of the items with garment fit presented on self-models. Several regions exhibited interaction effects between garment fit and product presentation. The FPC is a key structure for higher order cognitive functions, including strategy (Domenech and Koechlin, 2015), tracking options (Boorman et al., 2009), and exploration in the explore-exploit dilemma—specifically, directed exploration in uncertain environments (Daw et al., 2006). *Post hoc* tests showed higher activity for fit-present/self-models than fit-absent/self-models and for fit-absent/mannequins than fit-present/mannequins and fit-absent/self-models. These findings may implicate greater

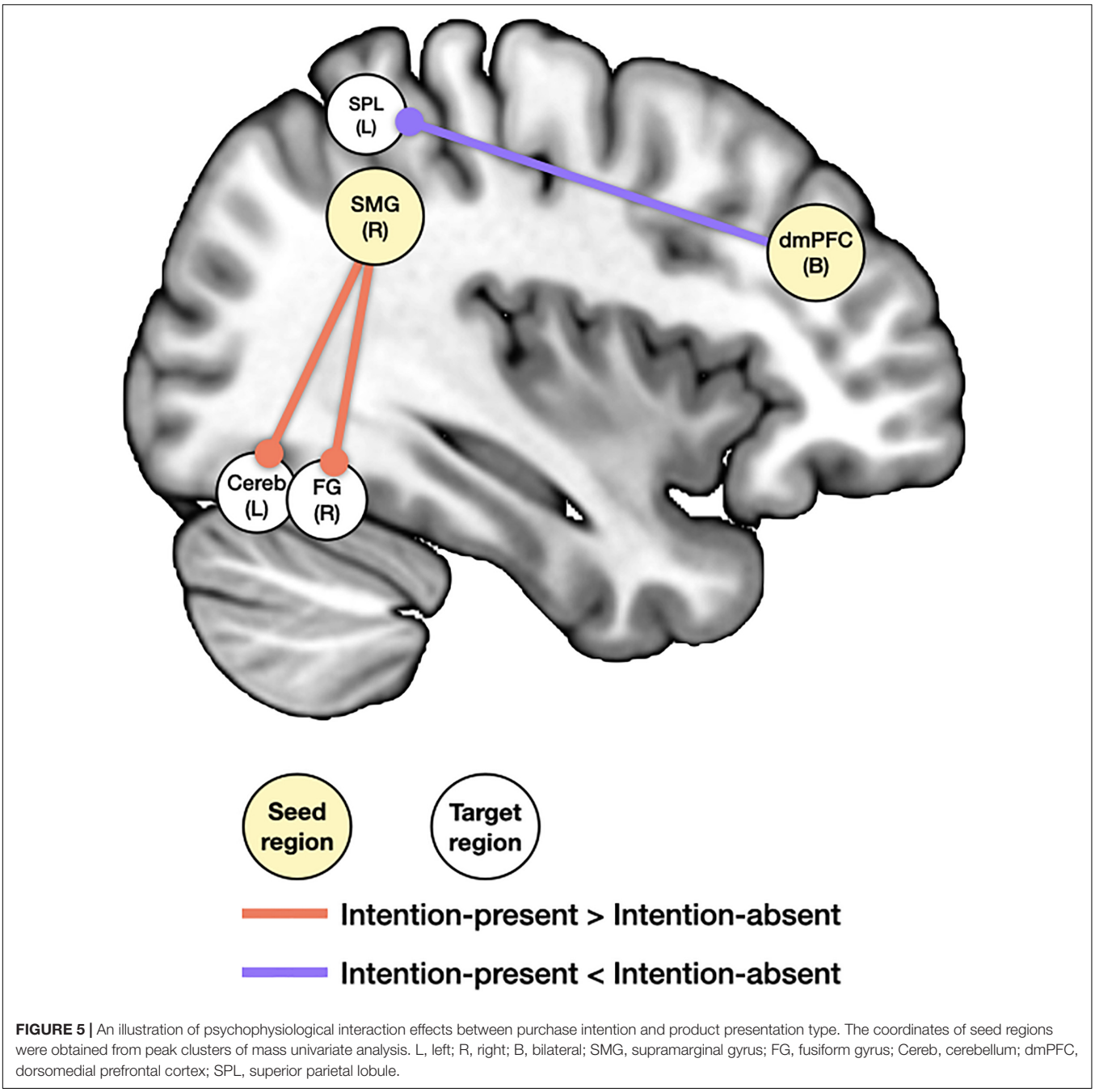


FIGURE 5 | An illustration of psychophysiological interaction effects between purchase intention and product presentation type. The coordinates of seed regions were obtained from peak clusters of mass univariate analysis. L, left; R, right; B, bilateral; SMG, supramarginal gyrus; FG, fusiform gyrus; Cereb, cerebellum; dmPFC, dorsomedial prefrontal cortex; SPL, superior parietal lobule.

engagement of exploratory decision strategy and efforts to gain more information for fit-present/self-models and fit-absent/mannequins merchandise. Interestingly, the particular affinity toward self-models when fit-present and toward mannequins when fit-absent was also observed in the ACC activity, where it responded higher for fit-present/self-models than fit-present/mannequins and for fit-absent/mannequins than fit-absent/self-models and fit-present/mannequins. The rostral ACC is implicated in the computation of positive expected errors, and the dorsal ACC is involved in communicating conflict and error terms of choices (Marsh et al., 2007). As uncertainty is an inherent problem with online shopping, the evidence seems to highlight conflict when making purchasing decision for fit-present products shown on self-models and for fit-absent products displayed on mannequins. Taken together, in the context of purchasing products, participants might have engaged in a directed exploration strategy and information seeking efforts, perhaps due to a heightened sense of ambiguity regarding a given product—especially for fit-absent products on mannequins.

Our data emphasizes the fit-present/self-models and fit-absent/mannequins, where fit-present/self-models items prompted greater neural activity than fit-absent/self-models

and fit-present/mannequins, and the region activity was greater toward fit-absent/mannequins than toward fit-absent/self-models. Literature regards the SFG in higher cognitive functions, and more specifically, the right SFG has been implicated in impulse and inhibitory control (Hu et al., 2016). Accordingly, such results could indicate greater demand for the cognitive control mechanism by the conditions of fit-present/self-models and fit-absent/mannequins, in particular. The greater PCC activity toward fit-present products on self-models than on mannequins could be suggesting that products with fit satisfaction displayed on the subject promotes further information processing, such as greater salience detection and greater engagements of scene and action processing (Leech and Sharp, 2014). Altogether, the findings highlight the cognitive demands and information processing of stimulus during purchase deliberation, and illustrate the influence of garment fit and product presentations on the consumer process.

Despite these meaningful results, the reward-related regions we initially expected through the hypothesis did not show activational sensitivity when deliberating purchase decisions. In particular, we expected that the interaction effect would be exhibited in the vmPFC that has been associated with high choice certainty and reward outcome (Knutson et al., 2003; Bhanji et al., 2010). However, the present task seemed to have prompted participants to make decisions with high sense of ambiguity about the product. Overall, the lack of reward-related recruitment indicates that deliberating short-lived purchase decisions based on garment fit and presentation style presented on the monitor may engage cognitive and imagery processing rather than reward processing.

Sources of Purchase Intention

Not surprisingly, the fitness scores were higher toward intention-present products and mannequins than their respective counterparts. Such results were contrary to the results in Part 1. This perhaps reflects a common tendency, where the initial impression of an item seems more appealing when it is presented on mannequins, but in reality, the actual perception of clothing fit is subpar to the expectation.

In the univariate results, diffused neural regions responded differently depending on the decision maker's intention-to-purchase, though no interaction was observed with product presentation; and most of these regions were resonated in MVPA as well. Most notably, the current investigation underlines the SPL function in relation to consumers' purchase intention. The SPL is involved in mental imagery and mental rotation for body parts (Vingerhoets et al., 2002; Overney et al., 2005). The premotor cortex can also play a role in action preparation and decision commitment rather than simple motor performance (Thura and Cisek, 2014). Reflected in the longer RTs for clothing with purchase intention, the enhanced left SPL and premotor cortex for intention-present than for intention-absent conditions recommends that participants indulged a more thorough assessment of intention-present garments. Unlike the left SPL activity, the right SPL gravitated toward intention-absent garments. The lateralization of the SPL has been discussed in several studies. For example, the right is implicated in the monitoring of externally generated movements and visuospatial processing, whereas the left is suggested in the internal representation of self-generated motions and body schema (Ogawa and Inui, 2007; Sack, 2009). Together, evaluating products with subsequent purchase intention utilized more of internal processes, whereas intention-absent merchandise involved more of external processes.

The SMG is another critical structure that showed preferences toward intention-present products. The SMG contributes to decision-making under uncertainty (Vickery and Jiang, 2009) and emotion processing of fearful stimuli (Sarkheil et al., 2013), and is related to enactment effects through abundant mirror neurons (Russ et al., 2003; Chong et al., 2008). The SMG activity toward intention-present alludes that participants were envisioning themselves trying on apparel with a sense of ambiguity.

In addition to the right SPL, regions showing preferences for intention-absent clothing included the dmPFC, STS, anterior and posterior insula, and dorsal striatum. Past literature has consistently delineated the dmPFC and STS as the mentalization network, which is engaged when one makes an inference about others' mental states, especially when other agents are similar to oneself (Frith and Frith, 2006). Similarity aids in the understanding of other's mental states and promotes a sense of certainty (Faraji-Rad et al., 2015). Mentalization can be inferred from the dmPFC and STS activity during the evaluation of products without purchase intention. Intention-absent products encouraged participants to imagine how items would be perceived by others to achieve reassurance, denoting possible engagements of mentalization at the evaluation stage. Meanwhile, within the context of decision-making paradigm, the anterior and posterior insula have been associated with negative emotional states, aversive somatosensory integration, and risk assessment and potential loss (Paulus and Stein, 2006; Preuschoff et al., 2008; Canessa et al., 2013). This finding is in accordance with a previous intriguing study that had shown the involvement of the insula in social risk perception, which guides consumers when making purchase decisions (Yokoyama et al., 2014). Moreover, as the dorsal striatum is known to play a significant role in evaluating information of outcomes and action selection (Balleine et al., 2007; Haber, 2016), the coactivation of these structures perhaps suggests an intricate seesaw of processes that assess risk and potential loss to facilitate better action to be chosen.

Exploratory PPI analysis also underlines the involvement of mental imagery and cognitive control. Increased couplings of the SMG with the fusiform gyrus and cerebellum for intention-present than intention-absent presumably support our assertions that mental imageries of given visual input would be distinctly different when evaluating products that are later identified as having intention-to-purchase. On the other hand, as the dmPFC receives input from the sensory and parietal region to make appropriate actions (Eickhoff et al., 2016), the strengthened dmPFC-SPL for intention-absent products bolsters our above findings that illustrate an engagement of mentalization when evaluating products without intention to purchase.

Meanwhile, the product presentation effect during fit evaluation also seems to involve brain regions related to self-projection as it did during purchase deliberation. In all regions, activity increased more in self-models than in mannequins. In particular, dmPFC and TPJ responses to self-models are in line with the literature as they are prominent players for mentalization and social cognition (Saxe and Kanwisher, 2003; D'Argembeau et al., 2007). It is interesting to note that dopamine reward circuit regions such as the pOFC, nucleus accumbens, and midbrain (Ikemoto, 2007; Sescousse et al., 2010) gravitate toward self-models than mannequins, suggesting the hedonic effect of displaying items on the participants themselves.

Comprehensive Consideration

The results of Parts 1 and 2 offer insights into the effects of garment fit, purchase intention, and product presentation on the consumer decision-making process. Part 1 showed the importance of directed exploration and visual processing that capture the interaction effects between garment fit and product presentation at choice. The garment fit effect suggested mental imagery as critical part of garment fit during purchase deliberation. Part 2 also indicated an extensive engagement of areas known for mental imagery, high population of mirror neurons, and mentalization network. Activations in regions like the SMG and SPL suggest that mental interaction with products is a critical component for both fit satisfaction and purchase intention throughout the decision process. The combinations of univariate, multivariate and exploratory PPI analyses emphasize that items without purchase intention involved participants to take into account for the perspectives of others. With respect to product presentation, both parts especially emphasized the effects of the self-model presentation. Part 1 underlined the self-projection processing evoked by self-models during purchase deliberation, whereas Part 2 accentuated the mentalization and reward processing elicited by self-models during fit evaluation. The overall findings also convey that the product presentation factor bears greater weight on the presence of garment fit but not on the presence of purchase intention. Together with the nonsignificant influence of product presentation on the prediction of subsequent purchase intention and our behavioral data from Part 1, perhaps communicates that the way products are displayed do not play a substantial role in the final decision.

Our study presented neural substrates involved in the intricate workings among factors like garment fit, product presentation methods, and purchase intention through two parts. The neural regions identified in the two parts were to reflect the categorical factors between garment fit (absence/presence) and product presentation, and between purchase intention (absence/presence) and product presentation. Furthermore, because behavioral responses were obtained on a four-point Likert scale, it would be interesting to investigate the linear modulatory effect of behavioral data using parametric modulation in future studies.

Conducting studies only in female participants and only in young adults may limit the generalizability of our interpretations, and participants' general patterns of shopping behavior and favored styles of clothing were not accounted for. Although the price is a vital factor in shopping, this study did not allow direct examination of price effects; instead, only presented price information to control for its effects. Going forward, study designs should embrace price points to investigate how perceptions of price interact with consumer processes and product presentation types. In addition, to control for the price effect, it would have been more appropriate to include the difference between expected versus presented prices as a nuisance regressor rather than simply adjusting the prices based on each reference price. Although participants with clearly disproportionate behavioral responses between intention-to-purchase conditions were excluded, the analysis included some imbalance. Consequently, the classification accuracies of the brain regions containing intention-predictive information may have been biased by this imbalance. In similar light, the imbalance of data between fit-absent and fit-present was greater in Part 1 (effect of fit satisfaction). As such, the interpretation of the results should be read with caution.

CONCLUSION

The present investigation surveyed the neural substrates of decision-making processes in online shopping for apparels. The findings of the study further the current understanding of the relationship between garment fit and purchase intention, and provide a comprehensive overview of neural correlates that characterize respective components. First, we established neural evidence for the notion that fit of clothing and modes of display have an impact on purchase decisions, suggesting that webstores should offer virtual displays of products to mitigate uncertainty and promote optimal decision strategies chosen during deliberation of purchase decision. Then the investigation discovered the neural basis of purchase intention. Reflected in the parietal lobules, prefrontal cortex, and sensorimotor-related regions, imaging data accentuated the employment of mental imageries. Collectively, the evidence featured directed exploration, visual and action processing as key factors that capture the essence of garment fit and product display during purchase deliberation, and mental interaction with products as a critical factor of fit satisfaction and purchase intention throughout the consumer process. Furthermore, the findings marked mental imagery and social cognition as predictive factors of purchase intention during fit evaluation.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board of Yonsei University Severance Hospital. The patients/participants provided their

written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

HK and J-JK conceived and designed the experiments. HK and JK performed the experiments. HK analyzed the data and drafted the manuscript. J-JK revised the manuscript. JK edited the manuscript. All authors contributed to the article and approved the submitted version.

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Category Congruence of Display-Only Products Influences Attention and Purchase Decisions

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In e-commerce settings, shoppers can navigate to product-specific pages on which they are asked to make yes-or-no decisions about buying a particular item. Beyond that target, there are often other products displayed on the page, such as those suggested by the retailers' recommendation systems, that can influence consumers' buying behavior. We propose that display items that come from the same category as the target product (matched) may enhance target purchase by increasing the attractiveness of the presented opportunity. Contrasting this, mismatched display items may reduce purchase by raising awareness of opportunity costs. Eye-tracking was used to explore this framework by examining how different types of displays influenced visual attention. Although target purchase rates were higher for products with matched vs. mismatched displays, there was no difference in fixation time for the target images. However, participants attended to mismatched display items for more time than they did for matched ones consistent with the hypothesized processes. In addition, increases in display attractiveness increased target purchase, but only for matched items, in line with supporting the target category. Given the importance of relative attention and information in determining the impact of display items, we replicated the overall purchase effect across varying amounts of available display information in a second behavioral study. This demonstration of robustness supports the translational relevance of these findings for application in industry.

Keywords: retail, e-commerce, attention, decision making, choice-behavior, consumer neuroscience, eyetracking, neuromarketing

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INTRODUCTION

The rise of e-commerce has expanded the scope of retail design and the range of consumer choice settings. As one example, a carefully planned brick and mortar grocery store layout or planogram creates specific product adjacencies that shoppers can become accustomed to, like knowing the eggs are "always" near the milk. However, the flexible nature of digital item displays online allows for rapid updating of the choice context across multiple stages of a shopper's decision, with the possibility of viewing a particular product in settings that differ across pages designed for search, interest, selection, and purchase (see also Häubl and Trifts, 2000; Senecal et al., 2005).

Along similar lines, digital retail has created distinct and/or novel purchase decision steps and pathways. Generally speaking, models of the consumer decision-making process, or "decision funnels," begin with generalized awareness of a product, perhaps as a member of a larger set of options (e.g., Gourville and Norton, 2014). They proceed to narrow, with some form of engagement or information-seeking about more constrained consideration sets, to evaluation of specific options leading to a purchase decision or decisions. When shopping online, consumers in the information seeking and evaluation stages can arrive at product pages that are designed around a single option. In this setting, consumers can evaluate the product, and are prompted to move forward in deciding whether or not to select it for purchase via buttons for "add to cart" or "buy now."

Though the purpose of individual item pages is to offer more information about a specific product, it is common to have other information, including other products, visible on the screen. In many such settings the firm's recommendation system might display a set of similar products within the same general category. Alternately, the retailer may cross-promote products from different categories that they (or their algorithms) believe will also appeal to the shopper. These display sets are not central to the consumer's choice of whether (or not) they want to purchase the target, which is the primary purpose of the page. They are often intended to increase overall basket size by complementing or supplementing that decision, and can even appear "subsequent" to purchase or add-to-cart buttons, lower down on the page. However, they alter the choice context, and thus have the potential to influence the choice itself (e.g., Bettman et al., 1998).

Prior research using neuroscientific methods suggests that non-choice items do elicit decision-related evaluations, including representation of their value in areas such as ventral striatum and mPFC (e.g., Lebreton et al., 2009; Tusche et al., 2010; Levy et al., 2011; Smith et al., 2014). In addition, it has been shown that a network of areas including pregenual ACC and ventral striatum automatically encodes the average value of a set of items if they are viewed together, regardless of whether a person is just browsing or making an active choice (Shenhav and Karmarkar, 2019). These findings suggest that display items' values are likely to be represented in corticostriatal reward-related circuitry even when a consumer is focused on the target. Given this evidence, it seems likely that shoppers attend to display items when present, however briefly, and that these products could be integrated into the decision process.

Behavioral studies involving attractive but unavailable "phantom" items, as well as product stockouts, have shown how non-choice items can influence decisions in various ways (e.g., Pratkanis and Farquhar, 1992; Farquhar and Pratkanis, 1993; Fitzsimons, 2000; Scarpi and Pizzi, 2013; Trueblood and Pettibone, 2017). The nature of these effects can depend on whether consumers learn that the option is unavailable before or after making their choice (Pratkanis and Farquhar, 1992; Scarpi and Pizzi, 2013). Fundamentally though, these non-choice items are offered to the consumer as meaningful elements in an active choice set and indeed are able to create the same kinds of biases that would be expected if they were still valid options under consideration (e.g., Doyle et al., 1999).

The display items presented on a target product's e-commerce page are not necessarily unavailable, but they are "non-choice" because they are peripheral to the focal yes-or-no target purchase decision. Previous work has shown that they exert an influence that is dependent on their *similarity* to the target products (Karmarkar, 2017; Friedman et al., 2018). Karmarkar (2017) showed that purchase intent for a target item is increased when display and target items come from the same product category, and decreased when display and target items' categories are mismatched. This effect is consistent with findings that high value phantom products enhance interest in the most similar options that are still available (e.g., Pettibone and Wedell, 2000). Notably, though, the relative value of the display items as compared to the target does not influence purchase (Karmarkar, 2017; Friedman et al., 2018). This lies in contradiction of many choice framing or decoy effects that arise from comparisons of value among options in a choice set (e.g., Huber et al., 1982; Simonson, 1989; see also Louie et al., 2013; Webb et al., 2021).

Overall, then, it does not appear that consumers are processing display items as active or valid choice options. Instead we propose that display items create choice frames or contexts that influence the attractiveness of the purchase decision rather than impacting the perceived value of the target. This distinction can be considered as analogous to the distinction between transaction and acquisition utility (e.g., Thaler, 1985). While the definition of transaction utility is based on price perceptions, we propose a similar type of context-dependent "category-based" transaction value mechanism created by congruency between the item and the display.

In particular, our framework suggests two contributing mechanisms. First, display-only items that match the target product category may serve to enhance purchase intent by raising the attractiveness or appeal of an in-category purchase. This predicts that increased attractiveness of the display items in the matched condition could increase purchase likelihood, which we test in different ways across Study 1 and 2. Second, prior work demonstrating that consumers often neglect opportunity costs when making yes or no choices (e.g., Northcraft and Neale, 1986; Jones et al., 1998; Frederick et al., 2009; Spiller, 2011; Greenberg and Spiller, 2016). In particular, such studies showed that reframing a choice from *buy/don't buy* to *buy this product/keep the money for other products* reduces purchase intent by reminding people of other opportunities for those funds (e.g., Frederick et al., 2009). Mismatched display-only items offer a conceptual parallel to that manipulation by raising the salience of other item categories within the current decision context and engaging shoppers' attention and processing related to those categories. While matched displays may frame a choice as "Given this category, do you want to buy this item," mismatched displays may reframe it as "Given that you could spend money on any of these categories, do you want to buy this particular item?"

The proposed mechanisms offer complementary hypotheses related to information processing when considering a target product in the presence of other display-only items. First, given that increased attention is correlated with increased purchase

intent (e.g., Krajbich et al., 2010; Krajbich et al., 2012), it may be that shoppers pay more attention to the target item in the matched condition than in the mismatched condition. Similar logic then suggests that shoppers may pay more attention to the display items in the mismatched condition than the matched condition. Specifically, if the mismatched display items are raising awareness of the value of other categories, they would be predicted to capture additional attention.

In Study 1, we use an eye-tracking experiment to examine these hypotheses directly using purchase decisions about a target product made in the presence of other product images. This design features a highly simplified version of the detailed information that consumers might face on a firm's site. To help address this, in Study 2, we replicate the display-set effects in contexts that feature more information–price and product labels for the display items as well as the target items–speaking to the relevance of these findings for practical applications. Collectively this work offers an enhanced understanding of how non-choice product information, such as that generated by e-commerce recommendation systems, can influence interest and/or evaluation stages of the decision process in ways that impact subsequent purchase.

STUDY 1

Methods

The design of this study was approved by the Harvard Business School's Internal Review Board. Sixty-six individuals under the age of 40 participated in the eye-tracking experiment. Fixation detection rate was measured as the Tobii Pro Studio "weighted gaze samples" statistic calculated by dividing the number of eyetracking samples that were correctly identified by the total number of samples. Eight of the participants had a fixation detection rate that fell below 50%, and were excluded from analysis, leaving a sample of 58 (M_{Age} = 24.43, F = 25). The study was conducted as an independent experiment in a single 30–45 min session that did not include other studies or surveys beyond those reported. All participants were informed that the study involved eye-tracking in the recruitment process, gave consent prior to engaging in study activities and were given additional opportunities to ask questions and/or withdraw consent after the complete task instructions were explained.

Participants viewed the tasks on a computer screen, using a keyboard to move through the instructions and a mouse to indicate their choices and ratings. Stimuli presentation and data collection were conducted using the Tobii Studio software (v3.4.3) and a Tobii X2-60 eye-tracker (1920 × 1080 recording resolution, 60 Hz sampling rate, 4° accuracy). After individual calibration of the eye-tracker, it was explained that participants would be asked to decide whether they wanted to purchase several different target products, but that additional products or images would be displayed on the screen. Targets were familiar consumer products selected based on an age demographic of 18–40 years old, drawn from a range of categories such as office supplies, gifts, apparel, and personal electronics. Participants were further informed that they would not be able to choose or receive any of the display-only images that they might see during the experiment.

On each of the 36 decision trials, a fixation cross was presented at the center of the top third of the screen for 1 s. The screen automatically advanced to show the main stimulus, in which the target product was presented in the center of the screen together with text indicating its name and its price (**Figure 1**). The target was flanked by two display-only images falling into one of three conditions: landscapes, category-matched products, and category-mismatched products (**Figure 1**). Landscape images were selected to avoid the presence of distinct landmarks or strong individually differentiating features. Each "product page" (stimulus presentation) was shown for 5 s. After this, the screen automatically advanced and participants used a computer mouse selected their willingness to buy the target from the following set of choices [Strong No, No, Weak No, Weak Yes, Yes, and Strong Yes] (as in Karmarkar, 2017). The rating period was self-paced; after participants selected their response they clicked on a "Finished" button to submit the answer, and the next trial automatically began.

An extended description of the stimuli and trial information can be found in the **Supplementary Methods**. Briefly, 36 products that were widely available for retail purchase and generally desirable for the 18–40 year old demographic were chosen as target items. Purchase trials across the landscape, matched and mismatched conditions were intermixed across conditions, although all participants saw the target items presented in the same order. Stimulus presentation across conditions was counterbalanced among participants, such that for each target item, approximately one third of the participants viewed it with matched display products, approximately one third viewed it with mismatched display products, and the rest viewed it with landscape images. This design was intended to prevent condition-specific effects from depending on (or correlating with) the nature or attributes of any particular target item or its category.

Visual areas of interests (AOIs) used for measuring the duration of fixation times were centered on product image (target, left display image, and right display image) as well as on the target product label text and target price text (see **Figure 1** for illustration). The focal item presentation was standardized across all trials and categories with the item in a black outlined box at the center of the screen, with a rectangular AOI extending 50 px beyond this object (AOI: 171754 px). The landscape non-choice AOIs were all identically sized (103041 px), and represent the largest AOIs other than the target. This offers a conservative control for the other matched and mismatched conditions since the large landscape AOIs had the highest probability of capturing fixations. While display items varied in size, across all stimuli AOIs were non-overlapping and defined with a 50 pixel border beyond the underlying image/text boundaries. Fixations were classified with an I-VT filter (Tobii Pro Studio). Given varying rates of fixation detection across participants, fixation duration analyses reflect trials in which shoppers allocated a non-zero amount of attention to the AOIs studied.

Participants were endowed with $15 at the start of the experiment independently of the main study compensation, and

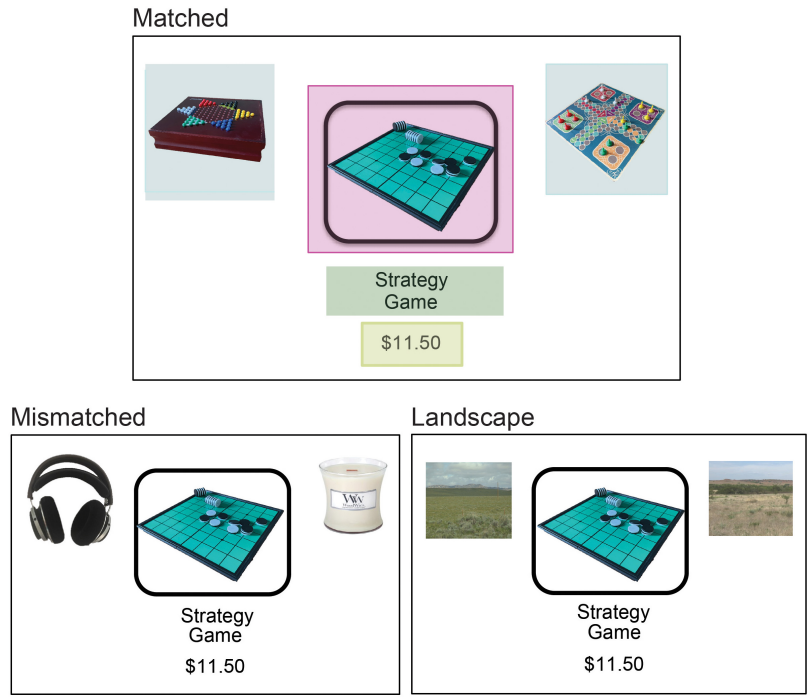


FIGURE 1 | Study 1 sample presentation stimuli. Shaded areas in the Matched condition illustrate the nature of AOI placement for the target image, display images, target label, and target price. Images are for illustration purposes only. See experimental materials for exact stimuli.

their choices were incentive compatible. Participants learned that one of their decisions would be selected at random to count "for real" at the end of the study. If the participant had selected any of the three *no* answers, they retained the full endowment. If they had selected any of the three *yes* answers, they paid the listed item price from their endowment, retained any residual funds, and received the chosen product in the mail.

After the eye-tracking portion of the experiment, participants engaged in a behavioral rating survey (Qualtrics XM) for each of 108 products (36 targets, 24 matched display products, 24 mismatched display products, and 24 unseen display products). Landscape images were not included in the ratings. For each item, participants used a computer mouse to indicate whether they remembered viewing the item during the primary task on a four point scale labeled [Definitely No, Maybe No, Maybe Yes, and Definitely Yes] and then rating their liking for the item on a seven point scale ranging from Do Not Like to Like Very Much. Three participants did not have enough time during the experimental session to complete these ratings, resulting in a sample size of $n = 55$ for analyses related to liking and recall.

Statistical analyses (behavior, eye-tracking, and their combined relationships) were conducted by importing the aggregated data into Stata/SE software. Study materials and a link to the OSF repository of the individual eyetracking raw data files can be found here: https://researchbox.org/304.

Results

While the six-point decision response scale was initially used to keep methods consistent with prior demonstrations of this effect (e.g., Karmarkar, 2017), for the purposes of incentive compatibility, purchase responses across the scale were collapsed into *yes* and *no*. This approach was also considered more representative of the yes/no choice that was explained to participants and that would be normally made on a retailer's site. As a result, purchase data is modeled as a binary choice in the following analyses.

While a range of factors can influence purchasing decisions, there is reasonable agreement that such choices are likely to reflect individual preferences for the good, balanced with sensitivity to its price (see also Prelec and Loewenstein, 1998; Knutson et al., 2007; Karmarkar et al., 2015). Thus as a control for the overall quality of the decision process captured by this experiment, the binary purchase decision was modeled with a mixed-effect logistic regression on target liking and target price (Model Wald $X^2 = 300.89$, $p < 0.001$). To represent the potential variance in individual purchasing likelihood, susceptibility to the effects, and the within-subjects design, the model included subject random effects ($n = 55$ groups, three participants did not complete the liking ratings). As might be expected, there was a significant positive coefficient on liking ($b = 1.43$, SE = 0.08, $p < 0.01$) and a negative overall effect of price ($b = -0.12$, SE = 0.03, $p < 0.001$). This analysis suggests that the choice process evoked by this task is consistent with meaningful considerations of costs and benefits as they might occur in real world purchasing. However, it is important to acknowledge that liking ratings were taken at the end of the study, and it is thus possible that they could have been influenced by the purchase decisions made during the task (e.g., Botti and Iyengar, 2004).

We then tested the impact of display on choice behavior across the three display conditions (landscape, matched and mismatched). This was done with a mixed-effects logistic regression with dummy variables for the matched and mismatched conditions (yielding the landscape condition as the reference), and subject random effects. As shown in **Table 1**, this analysis revealed a significant effect of the matched display (b = 0.313, SE = 0.140, p = 0.026), and no significant effects of the mismatched display (b = 0.02, SE = 0.143, p = 0.886; as compared to the landscape condition.) *Post hoc* comparisons of coefficients further demonstrated that purchase likelihood was higher in the matched condition compared to the mismatched one (p = 0.0365). Complementing this analysis, **Figure 2A** illustrates the average number of purchases, or "yes" responses that participants made during the twelve incentive compatible decisions in each condition. The increased purchase rate in the matched vs. mismatched condition is consistent with prior demonstrations of display-set effects (e.g., Karmarkar, 2017; Friedman et al., 2018).

A broader model of the impact of condition on purchase captured additional factors that might influence choice during the stimulus evaluation period. Specifically, it included target item price and variables for attention as measured by the total duration of fixation time (in ms) spent in the AOI centered on the image of the target product or the two display images (Note this influences the number of observations retained in the model, as fixations may not have been detected in all trials for all participants). As seen in **Table 1**, there was again a significant effect of the matched but not mismatched displays, accompanied by negative effects of price. In addition, consistent with the assumptions made in our framework, attention to the target item had a significant positive relationship with purchase likelihood, while attention to the display images had a significant negative relationship with target purchase.

Reflecting our specific hypotheses, we predict that attention to the target might be increased in the matched vs. mismatched conditions, reflecting the relationship between attention and purchase likelihood (e.g., Krajbich et al., 2010; Krajbich et al., 2012). Mixed effects regression on the fixation duration for the target revealed a significant negative effect for both the matched (b = −0.240, SE = 0.031, p < 0.001) and mismatched (b = −0.266, SE = 0.031, p < 0.001) displays (**Table 2**). Thus participants spent relatively less time attending to the target items when they were part of a multi-product display compared

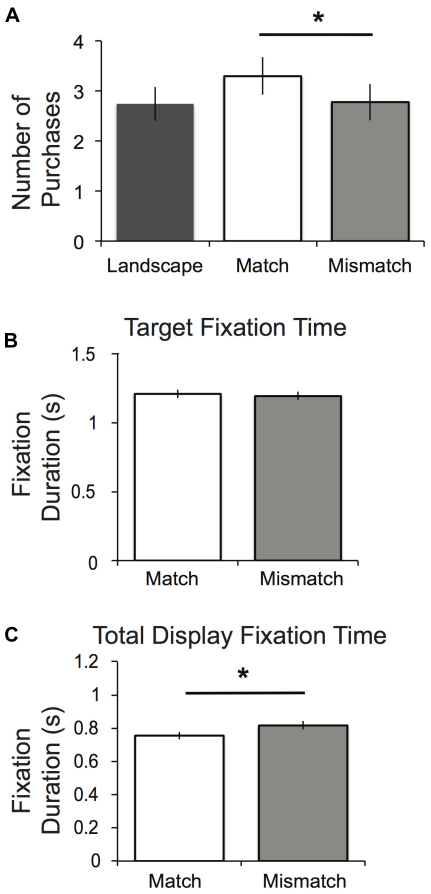


FIGURE 2 | Study 1 results. **(A)** Number of purchases (incentive compatible "yes" decisions) made in each experimental condition. **(B)** Average of the total fixation time spent on the target image per trial in the matched (M = 1.21, SE = 0.0301) and mismatched (M = 1.19, SE = 0.0312) conditions. **(C)** Average of the total fixation time spent on the display images per trial in the matched (M = 0.755, SE = 0.0222) and mismatched (M = 0.816, SE = 0.0246) conditions. Error bars reflect standard error. *p < 0.05.

TABLE 1 | Mixed effects logistic regressions examining factors related to target purchase.

	Purchase	Purchase
Match	0.313* (0.140)	0.555** (0.179)
Mismatch	0.0206 (0.144)	0.281 (0.185)
Price		−0.0865** (0.0305)
Target Fixation Duration		0.389** (0.132)
Display Fixation Duration		−0.448** (0.169)
Model Wald X^2	6.35*	33.42***
# obs	2088	1574
# groups	58	58

All models conducted with subject random effects.
Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 2 | Mixed effects regressions of total fixation times detected in target or display item AOIs.

	Target Fixation	Display Items Fixation
Matched	−0.240*** (0.031)	0.278*** (0.0290)
Mismatched	−0.266*** (0.031)	0.340*** (0.0293)
Model Wald X^2	87.67***	147.39***
#obs	2006	1606
#groups	58	58

All models conducted with subject random effects.
Standard errors in parentheses.
***$p < 0.001$.

to when they were presented with landscape images. However, our *post hoc* comparison of coefficients found no significant difference between the times for the matched and mismatched conditions, suggesting that the category of the display products did not influence the amount of attention paid to the focal item ($p = 0.406$, mean fixation duration times shown in **Figure 2B**)[1].

A complementary hypothesis suggests that individuals attend more to the display items in the mismatched condition, suggesting an increased attention to outside options and opportunity costs, compared to the matched one. As shown in **Table 2** (right column), mixed effects regressions showed that total fixation time (summed across the AOIs for the left and right display images) was increased for both the matched ($b = 0.278$, SE = 0.29, $p < 0.001$) and mismatched ($b = 0.33$, SE = 0.029, $p < 0.001$) products compared to the landscape images. In addition, a test for equality of coefficients revealed a significant difference for the mismatched display items such that they were attended to for longer ($p < 0.023$; mean fixation duration times shown in **Figure 2C**).

A few patterns emerge from this data. First, attention meaningfully differs between the landscape and the two product display conditions. Thus the presence of recognizable products appears to engage processes that go beyond those evoked by the mere presence of visual information unrelated to the target. Second, attention to the target item remains similar across matched and mismatched product displays, but the mismatched display items themselves capture more attention than the matched ones. This is consistent with our hypothesis that the mismatched display items decrease purchase of the target by highlighting the values and consideration of outside options and/or categories.

In addition to the absence of differences in fixation time on the target image, there was no significant effect of display condition on target recall or on target liking ratings. Specifically, regressing target liking on the condition dummy variables (with subject random effects) demonstrated no significant coefficient for the matched ($b = 0.0744$, SE = 0.098, $p = 0.45$) or mismatched ($b = 0.012$, SE = 0.098, $p = 0.902$) displays (with landscape again serving as the reference). Regressing target recall on condition (with subject random effects) also showed no significant effect for either matched or mismatched displays (match: $b = 0.0227$, SE = 0.0223, $p = 0.307$; mismatch: $b = 0.018$, SE = 0.0223, $p = 0.414$).

This suggests that the matched display items might exert an influence on the decision process overall rather than the target value in particular. Our framework proposes that matched display items are acting as supporting evidence for purchase within the target category, despite being unavailable themselves. If this were the case, more preferred display items would be expected to be more effective at increasing purchase likelihood for the target (see also Karmarkar, 2017), though the prediction for the mismatched condition is less clear.

[1]Regression analyses conducted on fixation times spent on the target label AOI and target price AOI similarly failed to find differences between the two display-item conditions.

We conducted a mixed effects logistic regression with subject random effects on the influence of display-item liking and condition (match vs. mismatch only) on the yes/no purchase decisions. Display-item liking was coded as the averaged liking ratings for the two display items presented in the trial. The model found a significant interaction between display-item-liking and condition ($b = 0.49$, SD = 0.100, $p < 0.001$). There was no main effect of display-item-liking ($b = 0.017$, SD = 0.071, $p = 0.808$), and a negative effect of the matched (vs. mismatched) condition ($b = -1.78$, SD = 0.44, $p < 0.001$). To interpret the interaction, we examined the impact of liking for the display items on purchase for the 12 trials in the mismatched and 12 trials in the matched conditions in separate models (**Table 3**). In the matched case, a mixed effects logistic regression showed that average display-item liking had a significant positive effect on purchase in line with our predictions ($p < 0.001$; number of observations reflects that one participant had one missing liking rating). However, the effects of display-item liking were not significant when modeled for the mismatched condition ($p = 0.626$). Again, this analysis is accompanied by the caveat that display liking ratings were conducted after the main choice task. Thus they may have been influenced by the display conditions and/or purchase decisions themselves.

Collectively our results suggest that these purchase decisions rely on perceptions of the full set of visible items rather than the information specific to the target item. For example, target liking, target fixation, and target recall were similar across matched and mismatched conditions despite differences in purchase rates. Instead, the purchase-relevant differences that did arise were primarily related to the display items and their relationship to the target. This offers an interesting clarification on the role of the display, suggesting that its impact is on the decision process rather than focused on the decision target. This is further reinforced by the differences between the landscape trials and the trials where the "non-choice" images were of recognizable products.

While the sparse design of Study 1 allows for more precise inferences about attention, it does reflect an information asymmetry between the target and display options. Thus marketers may ask whether display-set effects are still expressed when the display items also bear descriptive labels and prices, or whether an increased availability (and thus increased salience) of display-item information might moderate the results. In

TABLE 3 | Mixed effects logistic regressions of purchase on liking ratings for the display items in the matched or mismatched trials.

	Matched Only Trials	**Mismatched Only Trials**
	Purchase	Purchase
Display Liking	0.581*** (0.081)	−0.0382 (0.078)
Model Wald X^2	51.69***	0.24
#obs	659	660
#groups	55	55

All models conducted with subject random effects.
Standard errors in parentheses.
$^{***}p < 0.001$.

addition, while Study 1 shows that that liking for the individual display products is correlated with purchase of the target, our framework also proposes that this increased liking increases the overall attractiveness of the "offer," reflecting the complete set of items. Thus in Study 2, we test the robustness of the purchase effects across varying amounts of available information for the non-target products, and also examine the relationship between purchase likelihood and the value of the overall set.

STUDY 2

Methods

The research protocol was approved by the University of California, San Diego, Internal Review Board. Four hundred and fourteen individuals completed this study online for monetary compensation via the Amazon Mechanical Turk platform (M_{Age} = 37, F = 204). The reported sample reflects the exclusion of 69 participants who failed to correctly answer two comprehension questions (All participants received compensation, regardless of their performance). First, on the instruction screen, participants were asked to type in the words "I understand" to indicate their comprehension of the task instructions. Second, at the end of the survey participants were asked "Out of all of the items you saw in the survey, which one do you think you would be the most likely to buy if you were in a store?" Participants who left the question blank, or entered in inappropriate text (e.g., "GOOD" or "nice survey") were qualified as exclusions.

All participants assented to participate following reading an information sheet, and then filled in a "captcha" image recognition puzzle (not used for exclusion). Participants were randomly assigned to one of six experimental conditions based on a 2 × 3 between-subject design that varied the categories of the display options (Matched vs. Mismatched) and the individual item information (Control, Label Only, and Label + Price). The stimuli in the control condition used the same presentation design as the matched and mismatched conditions in Study 1, in which a descriptive text label and price was only available for the target item. In the label condition, a descriptive text label was presented together with all three products, and no price information was listed. Finally, in the label + price condition, a descriptive text label and price was presented for all three of the visible products. All participants were asked to imagine that they were shopping for themselves online, and that they would see a display from an online store. They further learned they would be indicating whether they would buy the item specified in the center of the screen. Participants viewed the stimuli for 4 s, and then indicated their purchase intent on a six-point scale from Strong No to Strong Yes. Participants made decisions for three different items (three trials)–an art print, a game, and bath towels. These decisions were hypothetical, such that participants did not receive any of the items they viewed. Following the decision task, participants also rated the attractiveness of the display of items overall (comprised of target and display items) on a seven-point scale from Not at all Attractive to Very Attractive.

Results

Although this experiment measured purchase intent in a hypothetical situation, for consistency with Study 1 and improved external validity, purchase intent ratings were translated into a binary purchase decision. Thus the no answers (Strong No, No and Weak No; 1–3 on the scale) were coded as 0, and the yes answers (Weak Yes, Yes, and Strong Yes) were coded as 1. This purchase decision was modeled with a mixed effects logistic regression with dummy variables for the matched condition, label condition, and label + price condition as well as subject random effects (estimated using Stata/SE software). This demonstrated a significant effect of the matched condition (b = 0.386, SE = 0.120, $p < 0.001$). However, there was no significant effect of the different information presentations as indicated by the label term (b = −0.007, SE = 0.147, p = 0.961) or the label + price term (b = 0.101, SE = 0.146, p = 0.488; test for equality of label and label + price, p = 0.457). These effects are reflected in **Figure 3**, which shows the average number of products purchase in each condition. Given that these decisions were not incentivized, participants may not have been as focused on the choice as a yes/no decision. However, the same pattern of findings arises when the data was analyzed by examining the full response scale instead of a binary purchase representation[2]. Thus the display-set effect was robust to varying the amount of available information about the display items, such as their labels and prices.

We examined the effects of the various conditions on the perceived overall attractiveness of the offer using an ANOVA with repeated-measures representing the three within-subject offers (art, game and towels; estimated using SPSS software). There was a main effect of display-only item category on the perceived attractiveness of the overall offer, such that matched sets were perceived as more attractive (M = 4.38, SE = 0.078) compared to mismatched sets (M = 3.913, SE = 0.078; $F(1,406)$ = 17.63,

[2]Using SPSS software, an ANOVA with repeated-measures across the three product decisions using the full response scale revealed a significant main effect of display item category such that purchase intent was significantly higher for matched displays (M = 3.3, SE = 0.065) compared to mismatched displays (M = 2.88, SE = 0.064; $F(1,408)$ = 21.104, $p < 0.001$). There was no significant effect of information condition ($F(2,408)$ = 0.048, p = 0.953), nor was there a significant interaction effect ($F(2,408)$ = 0.231, p = 0.794).

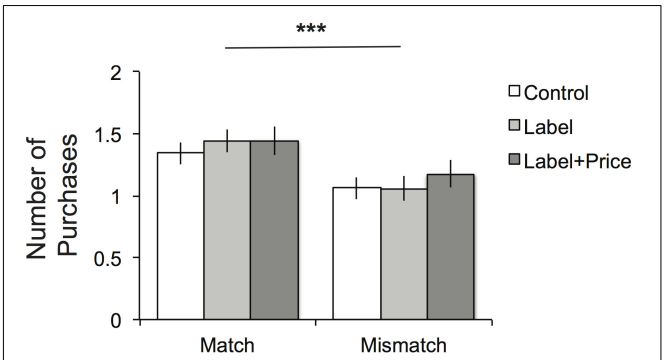


FIGURE 3 | Study 2 results. Number of purchases ("yes") decisions made in each of the six between-subject experimental conditions. ***$p < 0.001$.

$p < 0.001$)[3]. There was no significant main effect of the three information conditions ($F(2,406) = 0.647$, $p = 0.524$) nor was there a significant interaction between category and information ($F(2,406) = 1.27$, $p = 0.282$). These results suggest the display-set effect was not impacted by including the display items' labels and prices. In addition, the between-subjects nature of this study means that participants were rating offers that featured the same exact target products, which might have been expected to dominate the value of the offers since they were the only items under consideration in the purchase decision. However, an important limitation is that it is possible that the display items in the mismatched condition were perceived to be less valuable than the display items shown in the matched condition. In addition, these ratings were taken after the purchase choice, and thus might reflect the decision itself. Conservatively then, this data may be best described as consistent with the proposal that matched display-only items increase the attractiveness of the decision opportunity as a whole.

DISCUSSION

When shopping online, it is common to see information about other options displayed on product pages otherwise dedicated to facilitating the purchase of a specific target item. These display items are often generated by recommendation systems with the intent of spurring additional or subsequent buying considerations. Here, however, we replicate findings that display items can interact with and influence purchase likelihood of the target depending on whether they are matched or mismatched to the target's category (Karmarkar, 2017; Friedman et al., 2018). We used eye-tracking to enhance our understanding of this effect by exploring how attention, as measured by fixation duration, might vary across those conditions. We provide novel evidence that neither attention to (nor valuation of) the target changes depending on the nature of the display, despite differences in purchase rates. However, there are significant differences related to the display items, consistent with a framework in which display items act in multiple ways to change the perceptions of the overall decision rather than only perceptions of the target.

We hypothesized that mismatched display items might raise awareness of opportunity costs and/or engage competing consideration of other categories (e.g., Jones et al., 1998; Frederick et al., 2009; Spiller, 2011). In line with this, (conditional on shoppers allocating a non-zero amount of attention to the display-only items) Study 1 demonstrated that they spend more time looking at the display items when the target and the display come from different (mismatched) categories than when they come from the same (matched) category. This is consistent with recent results connecting increased opportunity cost salience with decreases in purchase of a target item (Smith et al., 2019). This suggests the inclusion of otherwise neglected product categories effectively change the scope of the question being asked, broadening the focus beyond a single product category, and potentially introducing other types of attribute evaluations and associations. Notably, the increase in fixation times on mismatched items might also be more broadly described as an increased saliency compared to the matched items ones. Matched items may be more fluent or easily processed under the same conceptual schema as the target. Thus the salience of mismatched items might relate to additional engagement related to retrieval of non-target category information, estimates of value and different attributes and purchase criteria.

For matched categories, we proposed that the display items could act as reinforcing or positive evidence, increasing the category's attractiveness and thus increasing the attractiveness of the decision as a whole. A similar prediction is made by the set-fit effect (e.g., Evers et al., 2014) in which sets that appear to "fit together" by an organizational principal are perceived to be more attractive than mismatched collections. Supporting this, Study 1 found that increases in the perceived value of the display items increase purchase likelihood for matched (but not mismatched) displays, and Study 2 showed that the overall offering (target + display) is rated as more attractive when the display items match the target category.

The design of the eye-tracking stimuli in Study 1 examined shopper attention in a simplified setting. Though our analyses focused on product images, only the target product was also accompanied by a descriptive text label and price information. It is likely that this additional information, particularly price, would be available for display items as well in commercial settings. This would suggest more competition for consumers' attention, and raises the possibility that attention would vary in ways other than the ones tested, leading to different purchasing outcomes. To address these concerns, in Study 2 we demonstrated that the display-set effect replicates in settings involving identical available information across target and display items (e.g., text-label only, and text-label with price). Though introducing price information can bias preferences (e.g., Lee et al., 2015) our results suggest that doing so does not disrupt the display-set effect. This offers additional translational value of these findings for practical application.

One limitation to these results is that non-target items are presented as display-only, meaning that participants have no way to access or choose them. This is intended to reflect the nature of an online product-specific page, by focusing the participants' decision-making ability on the target item. It also allows us to study the display set phenomenon in ways that are distinct from phantoms or stockouts, which are presented as attractive valid choice options that are then revealed to be unavailable (e.g., Pratkanis and Farquhar, 1992; Farquhar and Pratkanis, 1993; Fitzsimons, 2000). However, it is more rigid than a normal e-commerce experience. While it's often true that shoppers are farther along the decision funnel by the time they arrive at a specific product page, they do retain the ability to switch over to display items' pages, or navigate there subsequently to select multiple products for purchase. This raises an opportunity for future research about how the magnitude of display effects may depend on the relative switching costs, budget limitations, or inertia in forgoing the current offer to explore different opportunities.

[3]Two participants did not complete the display attractiveness ratings.

Additional considerations arise from the detection of fixations and the spatial organization of the stimuli on the screen in these experiments, as illustrated in **Figure 1**. This design was chosen to highlight the target product in the center, to "embed" the target in the context of the display items, and also to allow for clear identification of attention (fixation) on the display vs. target images. However, an absence of observed fixations in an AOI could reflect an absence of attention, or could arise from the variance in fixation detection across participants and across trials (or as cross classification as a saccade). Thus our analyses and ensuing results are conditional on detection of at least one fixation in the relevant AOIs. In addition, there is an interesting question of whether eye movements between the target and display information (saccades) could be used to investigate differences in the qualitative type of process or comparisons made during matched and mismatched trials. The current design may interfere with interpretation of such analyses because shifts in gaze between display items involve longer distances and can be interrupted by the target. Thus from a conceptual standpoint, varying the positions of the display and target images, would be a useful addition to future studies.

This research centers on the impact of display congruency in ways that align with a frequently encountered piece of the e-commerce decision-making process: when shoppers have landed on a particular product page. As outlined in prior work, we can consider online shopping behavior leading up to this situation as either experiential or goal-directed (e.g., Hoffman and Novak, 1996; Novak et al., 2003). Our setting makes no assumptions about the consumers' wants or needs prior to presenting the item, and is agnostic as to whether the product page was found by accident, direct or outside link. As such, our findings reflect more of an experiential or browsing process as defined by Novak et al. (2003). Thus they offer a useful complement to findings from research investigating the congruency of options in which shopping decisions are being made with a specific goal in mind (e.g., Reinholtz et al., 2015; Friedman et al., 2018). For example, Friedman et al. (2018) show that the presence of alternatives decreases purchase rates of a target item overall, but similar ones decrease purchase less than dissimilar ones. The authors lay out a goal theoretic model in which adding similar alternatives largely preserve the focal goal, but dissimilar ones diminish it by raising competing non-focal goals. In our studies, participants are not guided by an *a priori* goal, rather the likelihood of purchase is driven by endogenous preferences for the individual items and likely influenced by preference construction elicited by the immediate context (e.g., Bettman et al., 1998). Thus while the *relative* pattern of lower purchase rates arising from incongruent display items is conserved, the display-set effects suggest that matched products actually enhance purchase rates for experiential consumers.

Finally, this work offers a potentially useful parallel between a common incentive compatible study methodology and the consumer decision process online. Like many consumer neuroscience experiments, Study 1 involves a series of purchase decisions, with one choice being selected at random to "count for real" at the end. A practical purpose of this is to ensure that a single endowment can provide sufficient funds for participants to make multiple choices without raising budget constraints. However, this process can also reflect the idea of having participants select which options they "would" purchase by adding them to a shopping cart throughout the study, with checkout at the end, which does resemble the progression of e-commerce experiences. While academic studies can sometimes face challenges with external validity, this experiment structure highlights distinct opportunities for customer behavior research related to how display information impacts digital baskets that persist over site visits, wish lists, and other forms of purchase intentions that may be unique to the online experience (see also Senecal et al., 2005; Kukar-Kinney and Close, 2010; Popovich and Hamilton, 2020).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://researchbox.org/304, https://osf.io/mbkf9/?view_only=a00accf08563441ca313cc1bfb73f2e3.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Committee on the Use of Human Subjects (Harvard University Area Institutional Review Board) Human Research Protection Programs (UCSD Institutional Review Board). Handwritten signatures for informed consent for participation were not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

UK formulated the research question, designed the studies, and wrote the manuscript. All authors were involved in elements of study implementation, data collection, and data analysis, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2021.610060/full#supplementary-material

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Optimizing Fixation Filters for Eye-Tracking on Small Screens

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The study of consumer responses to advertising has recently expanded to include the use of eye-tracking to track the gaze of consumers. The calibration and validation of eye-gaze have typically been measured on large screens in static, controlled settings. However, little is known about how precise gaze localizations and eye fixations are on smaller screens, such as smartphones, and in moving feed-based conditions, such as those found on social media websites. We tested the precision of eye-tracking fixation detection algorithms relative to raw gaze mapping in natural scrolling conditions. Our results demonstrate that default fixation detection algorithms normally employed by hardware providers exhibit suboptimal performance on mobile phones. In this paper, we provide a detailed account of how different parameters in eye-tracking software can affect the validity and reliability of critical metrics, such as Percent Seen and Total Fixation Duration. We provide recommendations for producing improved eye-tracking metrics for content on small screens, such as smartphones, and vertically moving environments, such as a social media feed. The adjustments to the fixation detection algorithm we propose improves the accuracy of Percent Seen by 19% compared to a leading eye-tracking provider's default fixation filter settings. The methodological approach provided in this paper could additionally serve as a framework for assessing the validity of applied neuroscience methods and metrics beyond mobile eye-tracking.

Keywords: mobile eye-tracking, smartphone, mobile environment, social media marketing, validity, reliability, fixation algorithms

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INTRODUCTION

With the advent of smartphones around the turn of this decade, the use of mobile phones has now expanded well beyond regular phone calls. Smartphones are today becoming devices that are used ubiquitously around the globe (Wike and Oates, 2014), and are used not only for social interaction but for additional behaviors, such as the consumption of information and entertainment and the ordering of goods and services. As a result, there is increased interest in understanding the use of smartphones as part of the customer journey. Here, the combination of small screens packed with information at a close focal distance, coupled with vertical movement during scrolling behaviors, poses a particular challenge to those who want to use methods such as eye-tracking glasses with off-the-shelf fixation detection software in assessing different aspects of customer attention.

As interest and usage of eye-tracking methods have increased, so has the discussion of how to define and operationalize fixations, particularly how to define and measure fixations so that meaningful visual processing is captured under a specific environment. Indeed, much work has been performed related to the validity and reliability of stationary eye-tracking measures (Blignaut, 2009; Nyström et al., 2013), and it has become clear that there is no universal definition for a fixation, which varies operationally in different settings. For example, comparing the results of ten eye-movement event-detection algorithms with the ratings of two human experts, Andersson et al. (2017) showed that the resulting event durations varied substantially depending on what algorithm was used. The authors also found that while the existing approaches work well for static stimuli, the detection of fixations and saccades for dynamic stimuli is barely better than chance (Andersson et al., 2017). Additionally, Tobii, a leading eye-tracking vendor, explicitly states that the fixation filter settings have a substantial impact on the results of eye-tracking research (Olsen, 2012). With more recent advances that allow eye-tracking in mobile environments, this discussion about the validity and reliability of eye-tracking measures has received renewed interest, and along with it, a desire to establish an operationalized definition of a fixation in vertically moving mobile feeds.

One widely used application for eye-tracking research is understanding how consumers interact with information in digital platforms. Eye-tracking allows for the quantification of attention paid to crucial advertising elements, such as a brand logo. Brand attention is a critical part of advertising effectiveness. An ad that produces good attention and enjoyment of the creative, may still fail to generate brand attention and associate with the brand (Pieters et al., 2002). Therefore, the quantification of visual attention to branded elements is an important and sought-after measurement and is a suitable test case to study whether an eye-tracking solution has the necessary sensitivity and specificity to measure brand attention (Plassmann et al., 2012).

Mobile eye-tracking glasses allow the study of visual attention with minimum intrusiveness and are popularly used for consumer research. In the literature, this method has been used for studying the visual parameters during reading from different digital devices, including smartphones (Miranda et al., 2018). However, regardless of the manufacturer's recommendations, to our knowledge, there are no examples of studies where the settings of fixation detection algorithms have been adjusted to the specific viewing conditions of stimuli presentation on a smartphone. We believe this leaves room for inaccurate research results for eye-tracking studies conducted on smartphone screens with vertically moving content. In this paper, we employ brand elements in advertising presented in mobile phone screens to investigate and suggest settings for smartphone-specific fixation detection algorithms and offer a framework for selecting the parameters for other use-cases.

This paper will first present the theoretical, practical, and empirical background for the selection of eye-tracking fixation detection algorithm settings, including presenting the need for mobile-specific recommendations for fixation filters and the parameters that are under consideration. As a case for this treatment, we will focus on the most abundantly used and dominant vendor, Tobii[1], and their Pro Glasses 2 solution, alongside the challenges faced in measuring fixations on smartphones. After this, we will discuss a study designed to observe natural eye movements in mobile feed environments and compare performance of various filter options against human classification, as well as considering the validity and reliability of eye-tracking metrics. Here, we will use a model where we focus on advertising content presented on mobile phone screens. This is, to the best of our knowledge, the first study to report the results of a comprehensive and dedicated study on eye-tracking fixation detection algorithms for consumer behavior relevant behaviors on mobile phones. This work was supported by Facebook Inc and by the European Commission project RHUMBO – H2020-MSCAITN-2018-813234 TR.

BACKGROUND

Operational Definition of a Fixation

Visual attention is inferred from patterns of eye movements, where visual information is acquired during brief periods when the eye remains relatively stable, which are called fixations. Eye-tracking systems record raw eye movement samples with specific gaze coordinates and timestamps at a specific frequency, and these raw gaze samples are usually filtered according to spatial and temporal parameters in order to calculate fixations. Filtering involves applying an event detection algorithm that eliminates the oculomotor events that do not meet the preset criteria from the fixation dataset (Holmqvist et al., 2011), but what constitutes a fixation can vary significantly depending on the characteristics of eye-tracking hardware and software parameters. The lack of consensus related to defining a fixation is further emphasized in a study by Hooge et al. (2017), which demonstrated that even though human classification of fixations is a common method for validating event detection algorithms, human coders apply different thresholds and selection rules, thereby arriving at different results. In the context of this paper, we use the term 'fixation' to signify a cluster of gaze samples during which the acquisition of visual information is likely to take place, and we suggest an improved approach for quantifying eye movement data for visual attention research on smartphones.

Strengths of Measuring Fixations Instead of Relying on Raw Gaze Samples and Dwells

Mobile eye-tracking has been employed in various studies in dynamic real-life environments. In most of the cases, researchers analyze the recordings frame by frame and code the gaze behavior based on raw data samples. This means that instead of detecting and extracting fixations, the analysis of visual attention is based on dwells, i.e., gaze samples residing in the same area of interest (AOI). The problem with using raw gaze samples is that, in addition to eye movements that reflect the intake and processing of visual information, raw samples also include noise, such as saccades, drifts, tremors, and flicks. This implies that using raw

[1]https://www.tobii.com/

gaze samples is likely to lead to an overestimation of visual attention allocated to the AOIs. On the one hand, when the same data is analyzed based on dwell durations rather than the sum of fixation durations, the values are approximately 20% higher (Holmqvist et al., 2011). As this increase in total viewing time applies to all AOIs, the conclusions based on the two different approaches may be fairly similar. However, in studies with high visual clutter (as is the case for digital media related stimuli), one of the metrics commonly used is the ratio or proportion of participants who gazed or fixated on an AOI (Percent Seen). When interpreting all raw gaze samples as indicators of an AOI having been seen, the inclusion of noise will distort the data and will likely lead to erroneous results. Because of this, it is most appropriate to apply a minimum threshold when calculating total viewing time in order to remove noise from the data.

Datasets of raw samples usually contain a substantial amount of 'stand-alone' gaze points that are located in the proximity of or between two target locations. As these gaze points have the duration too short to be reflective of information processing, they are usually considered noise and removed from the dataset. Studies employing mobile eye-tracking methodology in dynamic environments have used the cutoff point for dwells ranging from 100 ms (Gidlöf et al., 2017) to 120 ms (Visschers et al., 2010; Clement et al., 2013; Gidlöf et al., 2013), which aligns with the observation that human fixations generally last between 150 and 600 ms (Duchowski, 2007). However, it has also been shown that during reading tasks the fixation durations can be as short as 50–75 ms, and in visual search tasks, the range of fixation duration is greater, with the average fixation duration similar to reading tasks (Rayner, 2009). Since natural interactions with a digital media platform can be thought of as a free-viewing task that includes a combination of both reading and visual search (that is, of engaging information), the cutoff point for dwells should be set accordingly.

The Need for Mobile-Specific Eye-Tracking Fixation Filters

One substantial challenge in applying the existing fixation detection algorithms to smartphone eye-tracking studies is that the conditions in which the default parameters for the fixation detection algorithm are developed can be markedly different from the study setup where the stimuli appear on a smartphone screen.

What is commonly overlooked about the Tobii I-VT Fixation Filter is that its default parameters were developed based on a stationary setup where participants were seated at a 65 cm distance from the screen that ranged from 43 to 61 cm in size (i.e., the resolution of 1280 × 1024 to 1920 × 1200 pixels) (Olsen, 2012). In contrast, the distance for viewing a smartphone is generally half of the viewing distance to a monitor. As an example of its application, in a study by Öquist and Lundin (2007), the distance from the smartphone was kept constant at 33 cm and smartphone screens are in the proximity of 13 cm, in contrast to the 65 cm distance and 43–61 cm screen size that the Tobii parameters were developed under. Furthermore, it is explicitly stated in Tobii's white paper that the aim of their Fixation Filter development was to identify a set of default values that are suitable for the stationary eye trackers, which excludes head-mounted eye-tracking glasses, yet the fixation detection algorithm is widely used for studies utilizing Tobii Pro Glasses 2, nonetheless.

As an example of the challenges of using the Tobii I-VT Fixation Filter, the Tobii Studio User's Manual v3.4.5 states:

"The I-VT fixation filter will fail to correctly classify eye tracking data recorded with Tobii Glasses even though the I-VT fixation filter may be enabled by default during analysis of snapshots. Tobii Glasses users should manually switch from I-VT fixation filter to Raw data filter. For information concerning limitations of the Raw data filter applied on Tobii Glasses recordings, please refer to the Tobii Glasses User manual."

Despite this, many researchers continue to use Tobii Pro Glasses 2 hardware with the Tobii I-VT Fixation Filter, such as a study investigating visual parameters during reading from paper and various digital devices – smartphone, tablet, and computer screen (Miranda et al., 2018).

Lack of Evidence for Mobile Filter Development and Usage

As previously mentioned, in a study by Miranda et al. (2018), mobile eye-tracking glasses were used to investigate visual parameters during reading from different modalities. Applying the default, I-VT Fixation Filter with the velocity threshold parameter of 30°/s, the authors suggested that similar criteria have been used also with other systems (e.g., Macedo et al., 2011). Mobile eye-tracking methodology has also been employed in various studies in dynamic real-life environments that rely on fixation data and only mention the software used (e.g., Tobii Studio), but do not discuss the parameters based on which the fixations were detected (Tonkin et al., 2011; Snyder et al., 2015). Also, the manual work of "experienced human coders" has been used for generating fixation data (Otterbring et al., 2016). There are also studies where no fixation detection algorithm is applied and the analysis of visual attention is based on dwells, i.e., gaze samples residing in the same AOI (Visschers et al., 2010; Clement et al., 2013; Gidlöf et al., 2013, 2017). A more ambiguous approach in the analysis of visual attention can be considered the "number of observations," defined as "viewing an AOI until switching away" (Wästlund et al., 2015). Thus, it can be stated that there are no standardized or preferred approaches when it comes to the analysis of mobile eye-tracking data, and to the authors' knowledge, there have not been any attempts of optimizing the parameters of the fixation detection algorithms to the viewing conditions or stimuli.

Challenges Posed by Eye-Tracking on Mobile Phone Screens

Size and Distance of Display Impacts Saccade Length and Velocity

The stimulus presentation method on a smartphone and, more specifically, the size of the display is likely to have an impact on saccade length and velocities of the eye movements. Namely, larger stimulus areas induce longer-distance saccades,

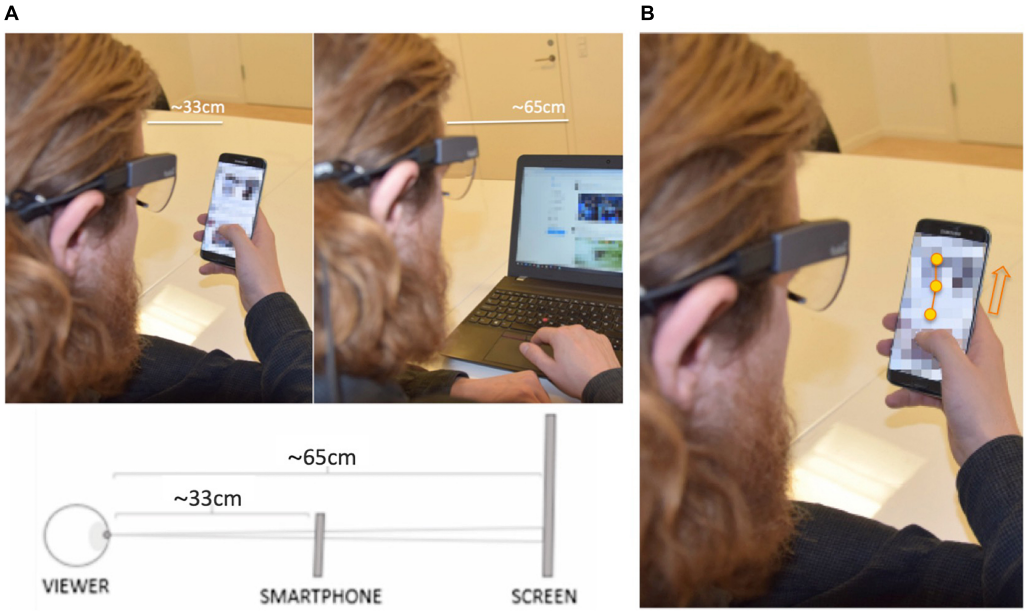


FIGURE 1 | (A) Mock image of stimulus presentation on a smartphone screen versus a computer screen (obtained and published with consent). The default settings for the Tobii I-VT algorithm are based on a stationary setup with the viewing distance of approximately 65 cm. When looking at a smartphone screen the stimulus area is smaller and located at a closer distance, resulting in reduced saccade lengths and velocity of the eye movements. **(B)** Mock image of smooth pursuit while gazing at a dynamic stimulus (obtained and published with consent). The respondent is scrolling the screen while the gaze is fixated on a moving stimulus object, resulting in smooth pursuit. The eye-tracking system recognizes the movement of the eye and depending on the parameters of the fixation detection algorithm, may classify the gaze samples as saccades, excluding them from the fixation dataset.

which have been shown to generate higher velocities than shorter-distance saccades (Collewijn et al., 1988). **Figure 1A** visualizes the two viewing conditions with the stimuli presented on a smartphone screen versus a computer screen. A small stimulus display located at a close distance to the viewer induces shorter saccades with lower velocities, as well as more eye convergence, indicating that the Velocity-Threshold Identification (I-VT) fixation classification parameters need to be adjusted to the study setup.

If the velocity parameter value of the I-VT fixation detection algorithm is set too high, short saccades will be missed and fixations that should be separated are merged together. However, a velocity threshold set too low can lead to the fixations being split into a number of short fixations due to noise or short data losses (Olsen, 2012). This becomes especially important within a smartphone experience, where the smooth pursuit of vertically scrolling content could be mistaken for saccades and discarded if suboptimal settings are used.

Smooth Pursuit of Small, Moving Areas of Interest

One of the major problems associated with detecting fixations in mobile environments is that gaze data is recorded relative to the eye tracker coordinate system (i.e., head-mounted eye-tracking glasses), not that of the stimulus. This means that when the respondent's eyes remain fixated on the stimulus while the respondent's head or the stimulus is moving, the eyes are moving relative to the eye-tracker, resulting in vestibulo-ocular reflex or smooth pursuit. If the movement of the eyes exceeds the velocity threshold of Tobii's I-VT Fixation Filter, these gaze samples are typically classified as saccades or unknown eye movements and excluded from the fixation data (Tobii Technology, 2019). **Figure 1B** explains the occurrence of a smooth pursuit while the respondent is scrolling the screen of a smartphone.

Incorrect Fixation Detection Can Create Gaze Mapping Issues

In relation to eye-tracking research that involves viewing mobile devices, there are stationary solutions where the restrictive setup allows for automated mapping of gaze locations. As an example, Öquist and Lundin (2007) used a setup with chinrest and goggles, and a smartphone that was kept at a fixed position. A downside for the setup where the participants' head is held in a fixed position is that it substantially reduces ecological validity. Researchers who prioritize investigating natural viewing behavior with minimum intrusiveness are likely to prefer head-mounted eye-tracking sensors, which inevitably require an additional phase of data pre-processing, namely, mapping the gaze positions from a video recording to reference images. This work is typically done by human coders, and considering that a device with the sampling frequency of 50 Hz records a new gaze sample at every 20 ms, the number of man-hours required to pre-process the data for even a small study, quickly becomes overwhelming and expensive. This issue has also been reported in the literature – Pfeiffer et al. (2014) utilized 30 Hz eye-tracking glasses and reported that the manual coding of the eye movements of 20 respondents in four decision situations required about 80 h. The

manual coding for the dataset presented in this paper alone required 321 labor hours, or roughly 2 h per respondent to code all raw data samples from 152 individuals. This illustrates an obstacle for running studies with larger samples, which, in turn, can have a negative impact on the reproducibility of the findings. Until there are solutions for automated annotations, one way to reduce that manual workload is by using a fixation detection algorithm, which significantly reduces the amount of data prior to remapping the eye movements and is one of the motivations for this study.

Existing, Widely Adopted Mobile Eye-Tracking Fixation Detection Algorithms and Approaches

Because Tobii Pro Lab Filters are the most widely used fixation detection algorithms in the body of research we examined and discussed above, this article will begin by focusing on the settings that can be manipulated in those filters and the function of each, in order for the findings presented in this paper to have the most relevance for industry applications. Depending on the sampling rate of the eye tracker, raw eye movement samples with specific gaze coordinates and timestamps are recorded at a specific frequency (for Tobii Pro Glasses 2, the sampling rate is 50 Hz). Tobii Pro Lab uses a fixation detection algorithm called the Velocity-Threshold Identification (I-VT) Fixation Filter (e.g., Salvucci and Goldberg, 2000; Komogortsev et al., 2010). The function calculates the angular velocity for each data point and depending on the threshold value classifies data points as being part of a fixation or a saccade (Olsen, 2012).

Tobii Pro Lab has three preset data processing functions that can be applied to the eye movement data, as presented in **Table 1**.

After having applied the data processing functions to the eye movement data, gaze samples or fixations are overlaid on a video recording. In order to aggregate gaze data and calculate eye-tracking metrics, the gaze samples or fixations need to be remapped from scene recordings to a reference image (Tobii Technology, 2019), which, as mentioned earlier, can take a substantial amount of time to map.

Tobii Pro Glasses 2 and the Fixation Detection Algorithm

The Tobii Pro Glasses 2 rely on an absolute measurement of pupils and use corneal reflection and the dark area of the pupil to detect the position of the eyes. The compensation for parallax is automatic and the method is based on binocular eye-tracking technique with 50 or 100 Hz frequency (Tobii, 2015).

Tobii Pro Lab software allows the use of preset settings for fixation detection algorithms, but also to create new fixation filters (Tobii Technology, 2019). In total there are seven different parameters that can be adjusted, including Gap fill in, Eye-selection, Noise reduction, Window length, Velocity threshold, Merging adjacent fixations, and Discarding short fixations.

Study Overview

In this study we compared the output gaze metrics produced with a commonly used fixation detection algorithm against the output of a manual mapping of raw gaze on AOIs. A difference between these two techniques is the order of mapping raw gaze data on to AOIs. The Tobii I-VT Fixation Filter calculates fixations prior to mapping gaze to AOIs, meaning any gaze data that is not counted as a fixation does not get mapped on to an AOI. Depending on the settings, this can lead to the possibility of miscounted fixations when the eye is following a moving target. Additionally, fixations on two nearby AOIs may be averaged together, making it possible for the coordinates of a fixation to be uncounted in gaze metrics if the fixation coordinates fall outside of the AOI boundaries. In contrast, the ground truth in this study relies on manual gaze mapping from raw eye gaze data, which maps all raw gaze data coordinates to AOIs prior to filtering for fixations or calculating gaze metrics at the AOI-level for moving targets. This enables researchers to capture more accurate metrics at the AOI-level — such as the percentage of people who saw the AOI (Percent Seen) or how long each person spent looking at the AOI (Total Fixation Duration)— when the eye is following a moving target. As noted in section "Operational definition of a fixation," human classification of fixations is a common method for validating event detection algorithms (Hooge et al., 2017), therefore, human classification is what we have employed for validation in this study.

In this paper, we utilized a common scenario where eyes follow moving targets, a vertically scrolling mobile phone feed, and compare outputs of the Tobii I-VT Fixation Filter to the outputs of manual mapping of raw gaze data on AOIs with a fixation defined as >60 ms consecutive gaze points within an AOI, based on the appropriate fixation length of reading and visual search described above in section "Strengths of measuring fixations instead of relying on raw gaze samples and dwells."

TABLE 1 | The three preset data processing functions of Tobii Pro Lab. Source: adapted from Tobii Technology (2019).

Preset function	Raw Gaze Filter	Fixation Filter	Attention Filter
Description:	Extracts raw gaze samples with three pre-processing functions	Applies I-VT fixation classifier algorithm with the velocity threshold of 30°/s	Applies I-VT fixation classifier algorithm with the velocity threshold of 100°/s
Data composition:	Data includes all gaze samples (including all noise)	Excludes smooth pursuit and vestibulo-ocular reflex (VOR)	Includes smooth pursuit, VOR and 10–15% of saccades
Attention allocated to the stimulus:	Overestimated	Slightly underestimated	Slightly overestimated
Best suited for:	Studies focusing on mechanisms of vision and dwells	Controlled studies with only fixations and saccades	Mobile environments with movement

The purpose of utilizing existing widely available hardware and software, as well as the application to mobile feed environments, was to ensure that the results were readily applicable to industry use-cases. In order to observe velocities and patterns of natural eye movements that occur when people view a vertically scrolling mobile feed, and for the results of the study to be applicable to future research on advertisements in a mobile social media feed, we conducted this study in a self-paced, natural environment with insertion of 10 controlled test stimuli into the feed. While this paper focuses on capturing natural behaviors in feed environments, future research is recommended to explore the spatial accuracy of eye-tracking measurement on highly controlled target stimuli on mobile phones.

Prior to the present study, we conducted studies to explore a broader space of filter settings options, and thereby to narrow down the filter settings for the present study (see Supplementary Materials). The goal of this study was to compare 56 possible fixation filter settings to determine which settings most closely align with human classification of fixations and gaze metrics in a social feed with vertical motion. The output is intended to inform settings for future research that examines eye-tracking on advertisements in a mobile social feed environment.

MATERIALS AND METHODS

This study was performed in accordance with the Declaration of Helsinki. Neurons Inc. follows the rules and laws of the Danish Data Protection Agency[2]. Neurons' data protection policy also follows the European Union law of the General Data Protection Regulation[3], as well as the ethical regulations imposed by the Neuromarketing Science and Business Association, Article 6[4]. Each person's biometric data, survey responses, and other types of data were anonymized and only contained the log number as the unique identifier. No personally relevant data can be extracted from the log number.

Tobii Pro Glasses 2 50 Hz were used for binocular data collection and Tobii Pro Controller (v.1.7.6) software was used for recording the data. Participants were exposed to 10 controlled static ads in their own Facebook feed environment. The ads were inserted using Neurons Inc's ad-insertion solution to provide a true to nature experience for the participants. All participants were exposed to all ads in a fully randomized order, with four organic posts in-between each ad. Stimuli were presented on Samsung Galaxy S7 Edge smartphones with 13 cm screens. The study took place in New York City in a quiet room with consistent overhead LED and incandescent lighting conditions of approximately 300 lux, with each participant monitored 1:1 in an individual room.

The study was conducted with 172 respondents with normal or corrected-to-normal vision and no history of neurological or psychiatric disease. Participants were permitted to wear contact lenses during the session, but glasses-wearers were excluded from the recruitment sample. Participants recruitment criteria included an even split of males and females, a mix of ethnicities, above the age of 18. The participants were individually seated at a table and held the smartphone in their hands throughout the session. Only one participant was in the room during a session. The eye-tracker was individually calibrated by participants focusing their gaze on the center of a target calibration card. The accuracy of the recording was then tested via live view function, where participants were instructed to look at static target objects displayed on the smartphone screen, which was visually validated by moderator.

After ensuring accurate calibration, the study session was started. The participants were instructed to maintain an optimal viewing posture and refrain from moving the phone during the viewing tasks. The optimal viewing posture was measured to 30–35 cm from the glasses to the phone. People held the phones themselves to provide a normal reading/browsing experience, while going through the social feed. The experimenter monitored the participant's viewing posture for the correct distance from glasses to phone and would instruct the participant to return to the desired distance as needed. All instructions related to the viewing tasks were presented in text form on a laptop screen. After the viewing tasks were completed, the accuracy of the gaze recording was again tested based on static target objects. The participants were then thanked for their time and could leave the testing area.

The study consisted of a natural browsing session in each participant's own social media feed. Participants were instructed to log in to their social media account and browse through their feed as they normally do. Ten individual static ads were inserted into each person's feed using an in-house ad insertion software running on Android 8.0.0 version. Prior internal pilot research showed that ten advertisements was the maximum number of ads that could be presented within the study time window while maintaining attention from participants. Ten ads were chosen to provide a larger sample and variance in the type of ads ensuring ecological validity for future application of the filters. A visual representation of this task can be seen in **Figure 2**. The duration of the sessions varied due to the natural exposure setting. A total of 10 advertising stimuli were presented in the feed with four organic posts in between each ad, with the order of ad presentation balanced across groups. Duration of ad exposures varied due to the natural exposure setting.

Mobile Fixation Filter Development

Defining a Fixation

The purpose of this study is to investigate the impact of different parameters of the above fixation detection algorithms on eye-tracking metrics of natural viewing behavior. Establishing an optimal fixation definition for a research study requires several considerations, such as an investigation into various aspects of natural viewing behaviors in a specific setting. It was previously established that for a study that involves interacting with digital media, the cutoff point for minimum dwell length should be set in accordance with the characteristics of the viewing behavior. Based on the argumentation that during reading and visual search

[2]https://www.datatilsynet.dk/generelt-om-databeskyttelse/lovgivning/

[3]https://ec.europa.eu/info/law/law-topic/data-protection_en

[4]https://www.nmsba.com/buying-neuromarketing/code-of-ethics

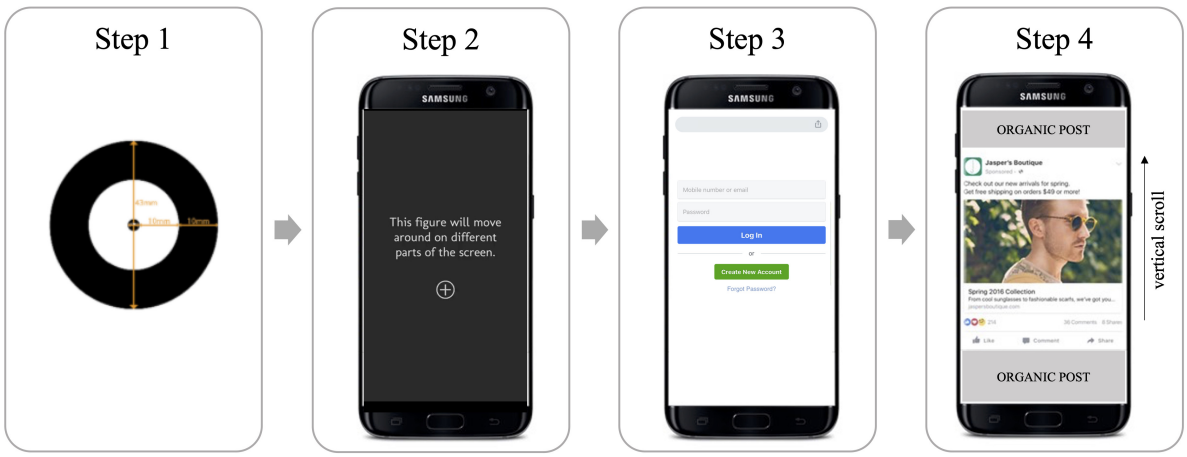


FIGURE 2 | An illustration of the participant study flow. **Step 1**: The participant goes through an eye-tracking calibration scenario. **Step 2**: The eye-tracking calibration is validated with a 5-point validation scenario presented on a smartphone screen. **Step 3**: The participant logs in to their social media account and opens the main feed. **Step 4**: The participant browses their feed in a self-paced session, where the ads have been inserted every 5th post.

tasks the fixations can be markedly shorter than fixations during scene perception, that is, as short as 50–75 ms (Rayner, 2009), we consider the cutoff point 60 ms as the optimal setting for minimum dwell length. As we are focusing on a device that has a sampling frequency of 50 Hz, this corresponds to three consecutive gaze samples in an AOI.

Considering the problems with the standard preset filters, there are strong arguments in favor of using dwells with the cutoff point of 60 ms as a more objective and accurate approach for measuring eye movements. This, however, preserves the problem of extensive resources that are needed for remapping raw gaze samples. As previously mentioned, the number of man-hours can be reduced significantly if the raw gaze samples are filtered with a fixation detection algorithm prior to remapping the eye movement data from video streams to reference images.

Selecting the Fixation Filter Parameters to Be Modified

Based on an investigation of relevant literature, together with qualitative observations of how the changes in different parameters affect the data output, it was decided to focus on and modify three parameters: Velocity threshold, Merging adjacent fixations, and Discarding short fixations. The following paragraphs explain the argumentation behind these choices.

Velocity Threshold

Velocity threshold is the parameter value based on which each data point is classified as being a part of a fixation or a saccade, whereas a fixation comprises an unbroken chain of raw data samples that have the angular velocity below the velocity threshold (Tobii Technology, 2019). It is known that larger stimulus areas induce longer saccades, which have shown to generate higher velocities than short saccades (Collewijn et al., 1988). This implies that when viewing a smartphone screen, the saccades have lower angular velocity, and the threshold for velocity needs to be set lower, to achieve more sensitive measures of eye movements and more granularity in the data. A velocity threshold set too high is likely to miss short saccades, and shorter fixations that should be considered as separate are merged into long inaccurate fixations. Combined with the qualitative insights of how changing the velocity threshold affects data output, we decided to test all thresholds between 5 and 15°/sec, and also include the thresholds 20, 25, and 30°/s for estimating the effect of increasing the velocity threshold on the validity of the data. Angular velocity values above 30°/s were not chosen as the original Tobii Fixation Filter is based on 30°/s and it has been shown in earlier research that this setting was too inclusive for larger AOIs and too exclusive for smaller AOIs.

Merging Adjacent Fixations

The function of merging adjacent fixations is aimed to correct for errors caused by noise and disturbances where a single fixation is split into multiple short fixations located close together (Tobii Technology, 2019). When enabled, this setting by default merges the fixations together if they are maximum 0.5 degrees apart and occur in a maximum 75 ms time frame. When stimuli are presented on a smartphone screen, small AOIs can be located in close proximity. In such cases the function of merging adjacent fixations may lead to reduced accuracy. Furthermore, not merging adjacent fixations will lead to a data output that is closer to raw gaze points, and thereby also closer to actual eye movements. For this reason, we decided to test the algorithms with the function of merging adjacent fixations both enabled and disabled.

Discarding Short Fixations

The function of disregarding short fixations is aimed to remove incorrectly classified fixations that are too short for actual information acquisition and processing (Tobii Technology, 2019). When enabled, this setting, by default, removes all fixations that have a duration below 60 ms. However, natural viewing of digital media stimuli on a smartphone screen often

involves scrolling, which in turn leads to smooth pursuit. This means that the participant is keeping the eyes fixated on an AOI while the stimulus is moving, but because of the movement of the eyes, fixation detection algorithms may disregard a substantial proportion of these gaze points, as illustrated in **Figure 1B**. To avoid this loss of data, it may be useful to keep the short fixations in the dataset. Disabling this setting adds more granularity to the data and will make the data output better reflective of the actual eye movements. For this reason, we decided to test the algorithms with the function of discarding short fixations both enabled and disabled.

The decision to focus only on the three above-mentioned parameters is that we considered these functions to have the most significant impact on the validity of the fixation data output, as compared to our target measure of dwells of 60 ms – which we refer to as Raw60 in this paper. All other parameters were kept at their default value, and their potential impact is out of the scope of this study. We acknowledge that adjustments to other parameters are also likely to affect the data output, but as we discuss next, we did not see the utility in testing their impact.

Parameters That Were Kept Constant

Tobii has developed three different pre-processing approaches, where two of them apply the I-VT fixation classifier algorithm to detect fixations. (*Additional details about the Tobii preset data processing functions are included in Supplementary Material*). The first option, Raw Gaze Filter, allows extracting raw gaze samples rather than fixations, but nevertheless, it applies three pre-processing functions to the data: gap fill-in or interpolation, eye selection, and noise reduction based on moving median approach. The same three functions are also applied to the two preset data processing functions that apply the I-VT fixation classifier, Fixation Filter, and Attention Filter. Considering that these three pre-processing functions are by default applied even to raw gaze data, it was decided to keep these parameters unchanged.

Another parameter that was decided to keep unchanged is the window length of the I-VT fixation classifier. By default, it is set to 20 ms, which corresponds to the sampling frequency of the eye-tracker used. Thus, it is not possible to set this value any lower, and considering that, given the stimulus presentation method and characteristics of the stimuli, the objective is to determine the settings that capture the eye movements with more sensitivity and higher granularity, we do not see the value in increasing the window length and thereby make the measures more robust.

Data Analysis

After collecting all the data, the marking process was executed by a team of human coders from Neurons Inc using the Tobii Pro Lab Software (V 1.79.10518), where each raw gaze point was mapped between the glasses coordinates and the reference frame image in the field of view, otherwise called the Scene Camera. We refer to this process as Gaze Mapping.

To specify the important parts of the recording we defined and logged stimuli events in each of the recordings. A stimulus event was logged as "on screen" from when 50% of the stimulus (Feed post) entered the screen until 50% of it left the screen (see **Figure 3A**).

Tobii Pro Glasses 2 produces eye gaze data mapped to a coordinate system relative to the wearable eye tracker and the recorded video, not to static objects of interest in the environment around the participant wearing the eye tracker. The collected eye-tracking data needs to be mapped on to objects of interest and into a new coordinate system with its origin fixed in the environment around the participant (Tobii Technology, 2019). Using the manual mapping function of the Tobii Pro Lab, our coders mapped the exact location of each gaze point on the static snapshot of the stimulus.

The *branding* AOI was drawn around the profile picture and profile name area on each of the 10 stimuli (**Figure 3B**). Gaze Mapping was done on raw gaze data and the fixation data output was exported based on 56 different combinations of algorithm settings.

Due to the importance of precision in the study, we excluded 16 participants having less than three (out of five) hits on the calibration verification task. The final sample thus included 156 participants (age range: 19–72, mean age: 36.9, Std Dev:12.54, 75 females).

Selecting Metrics of Interest

This analysis focuses on the three main eye-tracking metrics Total Fixation Duration (TFD) which is defined as the accumulated duration of fixations on an AOI, Time to First Fixation (TTFF) or the time it takes before an AOI is seen from the moment that 50% of the feed post enters the screen (Beginning of the event), and the percentage of participants that have at least 1 fixation (= "seen") on a stimulus or an AOI (Percent Seen).

Tobii Pro Lab software allows users to use preset settings for fixation detection algorithms, but also to create new ones (Tobii Technology, 2019). In all cases, the data extracted based on different algorithm settings is compared to manually mapped gaze data output, which we refer to as Raw60. To make the Raw60 metrics, the raw data has been preprocessed so that the gaze has to remain on an area of interest (AOI) for a minimum of 60 ms (3 gaze points) in order for it to be classified as "fixation" on that AOI.

Based on these parameters, the total number of setting combinations was $14 \times 2 \times 2 = 56$, based on the functions of 14 different velocity thresholds, merging/not merging adjacent fixations, discarding/not discarding short fixations.

Measuring the Error of Different Metrics Under 56 Proposed Test Filters

Because our goal was to select an improved fixation detection algorithm for vertically moving content presented on a smartphone screen, it was important to consider the impact our 56 proposed fixation detection algorithms (Test filters) had on the error of our metrics of interest. We first summarized the metrics of interest in relation to each of the stimuli and all AOI. The data covered all the three metrics of interest [Total Fixation Duration (TFD), Time to First Fixation (TTFF)] and viewer ratio (Percent Seen) and allowed to compute the differences between

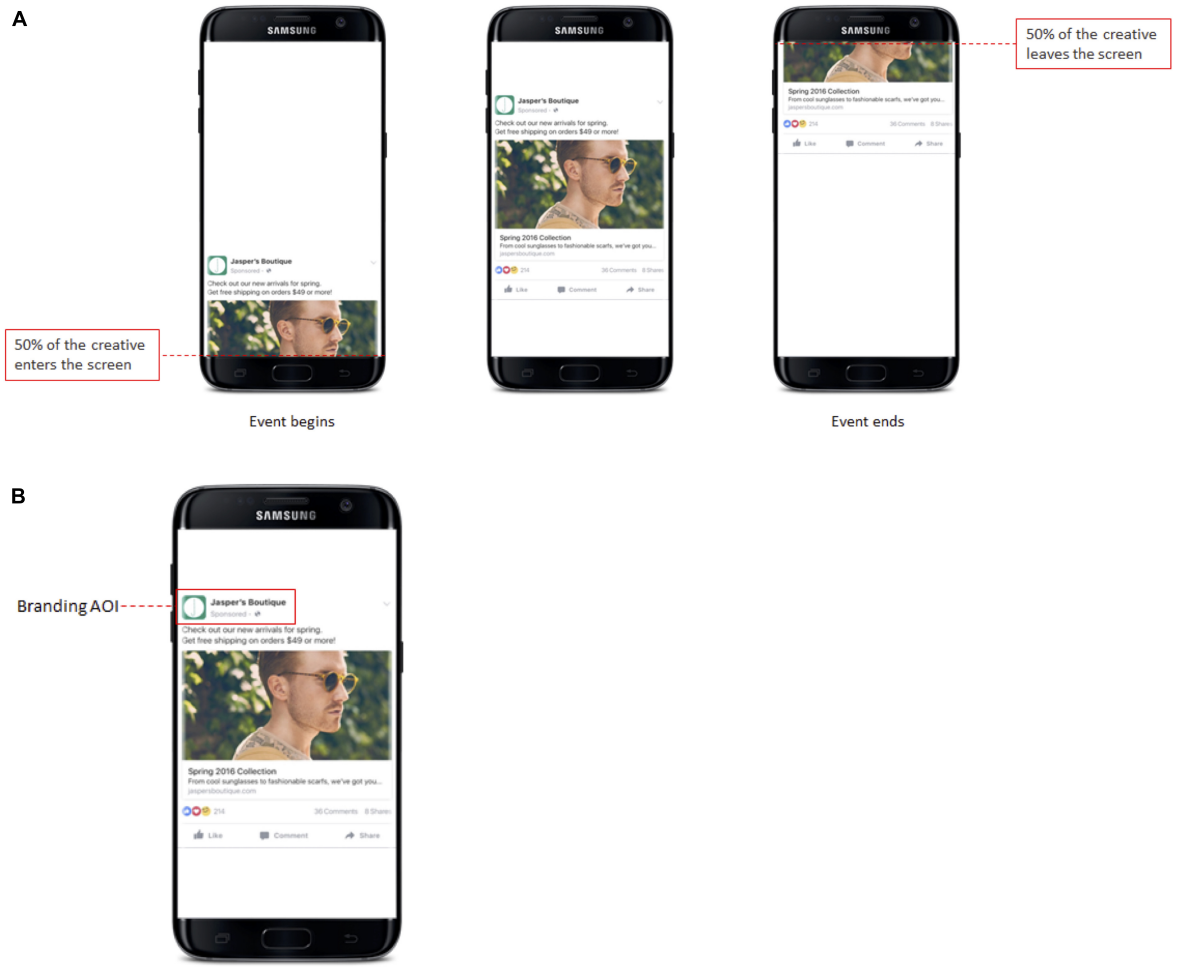


FIGURE 3 | (A) A visualization of annotating the onset and endpoint of a stimulus as an example of placing the beginning and end of events. **(B)** An example of Branding AOI.

the outputs of each of the 56 Test filters and the benchmark of Raw60 (i.e., dwells with the cutoff point of 60 ms).

Using Raw60 as the benchmark, we distinguished between overestimation and underestimation of the TFD. Overestimation of TFD (false positives) occurs when the fixation detection algorithm merges together a number of gaze points that landed outside the area of interest with gaze points inside the area of interest, bringing the TFD higher than possible. This represents an indicator of insensitivity and inaccuracy of the algorithm and sought to be kept as low as possible. The underestimation (false negatives), in contrast, reflects a situation where the TFD based on Raw60 is lower for the Test filter, showing a "loss" in data. The underestimation is seen as less impactful, when considering that Raw60 is likely to include a small share of gaze points that represent saccades or other types of noise. The improved settings of the fixation detection algorithm are expected to result in overestimation close to zero, with underestimation as low as possible.

For the metric TTFF, our objective was to minimize the difference between the TTFF (Raw60 ms) and the TTFF(Test filter). The error magnitude was computed as the absolute difference between the two variables. For the ratio of viewers who have seen an AOI (Percent Seen), on the participant level the data obtains a binary value depending on whether there are eye movements recorded on the AOI ("1") or not ("0"). It is desirable that the fixation filter with the optimized settings leads to the Percent Seen values that correspond as closely to the Percent Seen based on Raw60 as possible, and accordingly, the errors were defined as mismatches between the Seen(Raw60) and Seen(Test filter). The description of all error components is shown in **Table 2**.

Understanding the Error on a Branding Area of Interest

As the next step, we computed the mean values of the error components on the Stimulus and AOI level by averaging the data across all participants. To assess how the algorithm parameters influenced the error components for the AOI 'Branding,' we ran a linear least squares regression based on REML with the error component as the dependent variable and Discarding/Merging,

Velocity threshold, the interaction between the two as model predictors. **Figure 4** presents how the different parameters of the Test filters influenced each of the error components.

Determining the Precision of Each Test Filter

To assess the degree to which the output of different Test filters correlated with the output of the benchmark Raw60 output, we ran a linear regression between the mean values of each of the metrics (TFD; TTFF and Percent Seen) on the Stimulus and AOI level (i.e., averaged across all participants). Focusing on the AOI 'Branding', we used the coefficient of determination (R^2) as the indicator of how well each of the Test filters performs, as compared to the benchmark output. The results are presented in **Figure 5**.

Reliability of the Metrics

In addition to validity, we assessed the effect of the fixation detection algorithm settings on the reliability of the data (i.e., the consistency of the fixations across participants exposed to the same stimuli). Inter-subject reliability is relevant, as we know that stimuli should drive eye-tracking response, and inconsistency between participants can thus be a sign of measurement error or noise. To measure the inter-subject reliability of each stimulus, participant data was randomly split into two halves (78 participants in each half). For each half, we calculated the eye-tracking metric, and subsequently the Spearman correlation across ads for Branding AOI, using Spearman's Rank Correlation (Spearman *R*). This was run as a bootstrapping procedure with 1000 repetitions, each time taking a new random split from the total pool of participant data. Across all iterations and for each of the metrics, we calculated the mean Spearman R score for each of the Test filters (**Figure 6**).

RESULTS

Descriptive Statistics

Ten advertising stimuli were inserted in participants' own social media feeds. Participants were exposed to 8 of the 10 ads on average (mean: 8.25, Std Dev: 2.5, min:2, median: 10, max: 10). Duration of ad exposures varied due to the natural exposure setting, with an average of 2–3 s of view time per ad (mean: 2.67 s, Std Dev: 2.52 s). The total browsing time for the session varied due to the natural exposure, with an average session time of approximately 5 min (mean: 327.10 s, Std Dev: 115.86 s).

TABLE 2 | Parameters for assessing the differences in the outputs of the benchmark (Raw60) and the adjusted fixation detection algorithms (Test filters).

Error component	Description
Overestimation of Total Fixation Duration (TFD)	The value by which the TFD(Test filter) exceeds the TFD(Raw60)
Underestimation of Total Fixation Duration (TFD)	The value by which the TFD(Raw60) exceeds the TFD(Test filter)
Error in Time to First Fixation (TTFF Error)	The absolute value of the difference between the TTFF(Raw60) and TTFF(Test filter)
Error in the ratio of participants viewing the Area of Interest (Percent Seen Error)	Mismatch between the Seen(Raw60) and Seen(Test filter)

The Impact of the Fixation Detection Algorithm Parameters on the Error Components of Different Metrics

As visible in **Figure 4**, there was a significant positive relationship between the velocity threshold and the overestimation of TFD, and a significant negative relationship between the velocity threshold and the underestimation of TFD. This means that as the velocity threshold is increased, the test filter picks up more gaze points, but there is also a higher risk of obtaining inflated values of TFD. Thus, when optimizing the parameters for small AOIs such as the branding element of a sponsored content, there appears to be a tradeoff between the sensitivity of the algorithm (as indicated by the overestimation of TFD) and the underestimation of the total viewing time.

The Test filters with the function of 'discarding short fixations' disabled (marked with green and yellow lines in **Figure 4**) lead to decreased underestimation of TFD and lower error values for TTFF and Percent Seen. The differences are most drastic for the error in TTFF and Percent Seen.

While the impact of the algorithm parameters on error components allows assessing the directionality and magnitude of the effects, the choice of the optimized parameters often involves a tradeoff, and should, therefore, reflect the objective of the study and the characteristics of the stimuli. To directly assess how well each of the Test filters performed relative to the benchmark Raw60, we ran correlations on the outputs of different metrics, as described in the following section.

Correlations Between the Output of the Test Filters and the Benchmark to Determine Filter Accuracy

The top graph in **Figure 5** presents the correlation of determination or R^2 values for different Test filters and the benchmark Raw60 for the metric TFD. Overall, the coefficient of determination values is the highest for the setting of NoMerge_NoDiscard with velocity threshold 6°/s (R^2 = 0.975) and thresholds 7 and 10°/s (R^2 = 0.972). Across all combinations of settings of merging adjacent fixations and discarding short fixations, it is evident that there was a decline in R^2 values as the threshold was increased above 10°/s.

A one-way ANOVA comparing the R^2 values across all thresholds revealed a significant difference between the four different types of settings of merging adjacent fixations and discarding short fixations, $F(3,164) = 11.682$, $p < 0.0001$. **Table 3** presents the mean TFD values and confidence intervals for different settings, as well as pairwise comparisons with significant differences.

A one-way ANOVA comparing the R^2 values across all thresholds revealed a significant difference between the four different types of settings of merging adjacent fixations and discarding short fixations, $F(3,164) = 11.715$, $p < 0.0001$. **Table 3** presents the mean TTFF values and confidence intervals

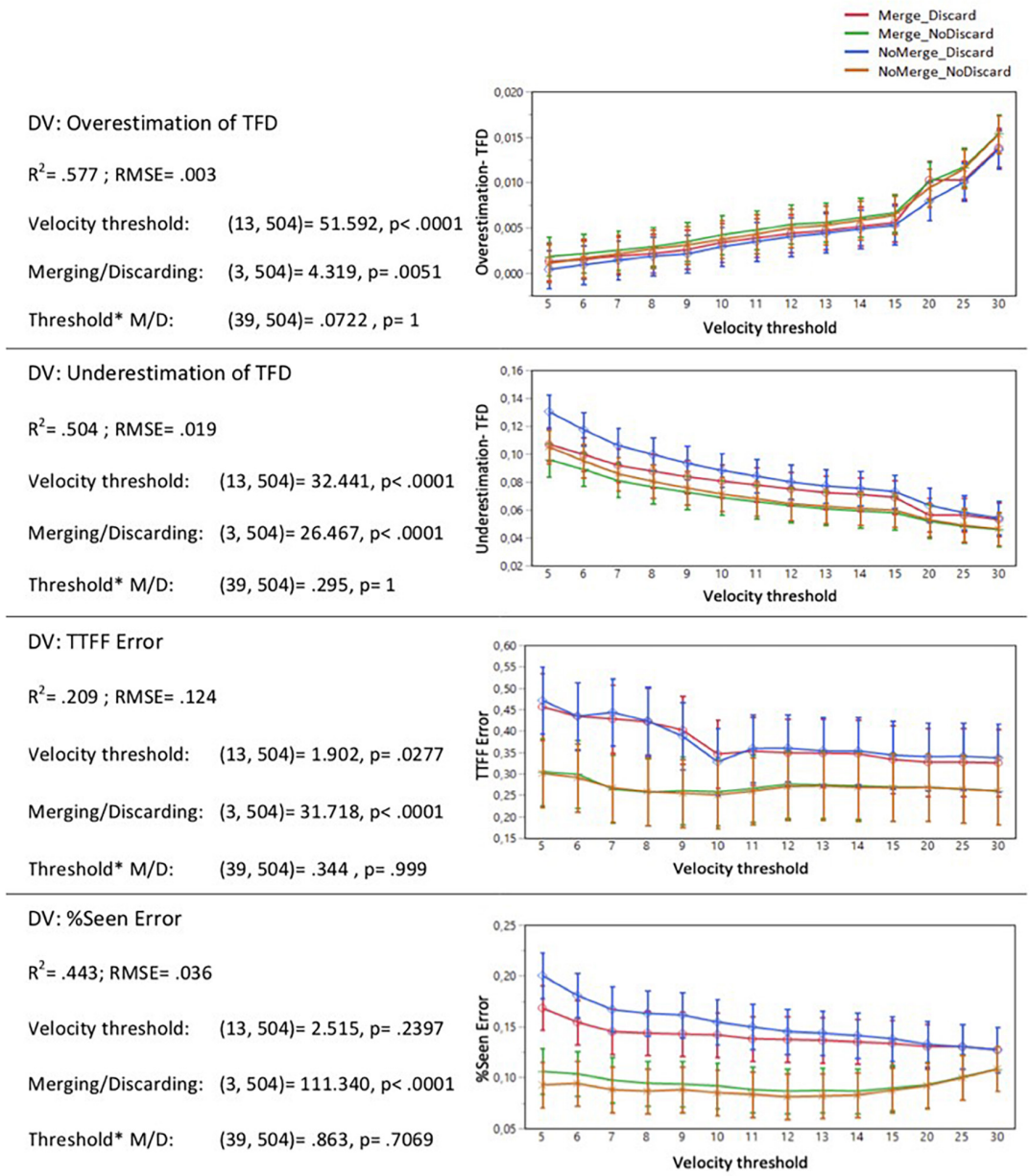


FIGURE 4 | Error components of different eye-tracking metrics as a function of different fixation detection algorithm parameters for AOI "Branding".

for different settings, as well as pairwise comparisons with significant differences.

Finally, the bottom graph in **Figure 5** visualizes the correlation of determination values for the ratio of participants who viewed the AOI – Percent Seen. Overall, R^2 values were the highest for the setting of NoMerge_NoDiscard with velocity threshold 5°/s (R^2 = 0.929), threshold 6°/s (R^2 = 0.921), and the setting Merge_NoDiscard threshold 6°/s (R^2 = 0.911). Across all combinations of settings of merging adjacent fixations and discarding short fixations, R^2 values tended to be higher for velocity thresholds up to 10°/s, as compared to thresholds 11°/s and above.

A one-way ANOVA comparing the R^2 values across all thresholds revealed a significant difference between the four different types of settings of merging adjacent fixations and discarding short fixations, $F(3,164) = 8.833$, $P < 0.0001$. **Table 3** presents the mean Percent Seen values and confidence intervals for different settings, as well as pairwise comparisons with significant differences.

Comparing the data output to the scene recordings, it was found that velocity thresholds in the proximity of 10°/s provided the closest reflection of the actual eye movements. It was found that while 5°/s threshold sliced fixation data to overly small clusters of gaze points, the threshold of 15°/s merged gaze

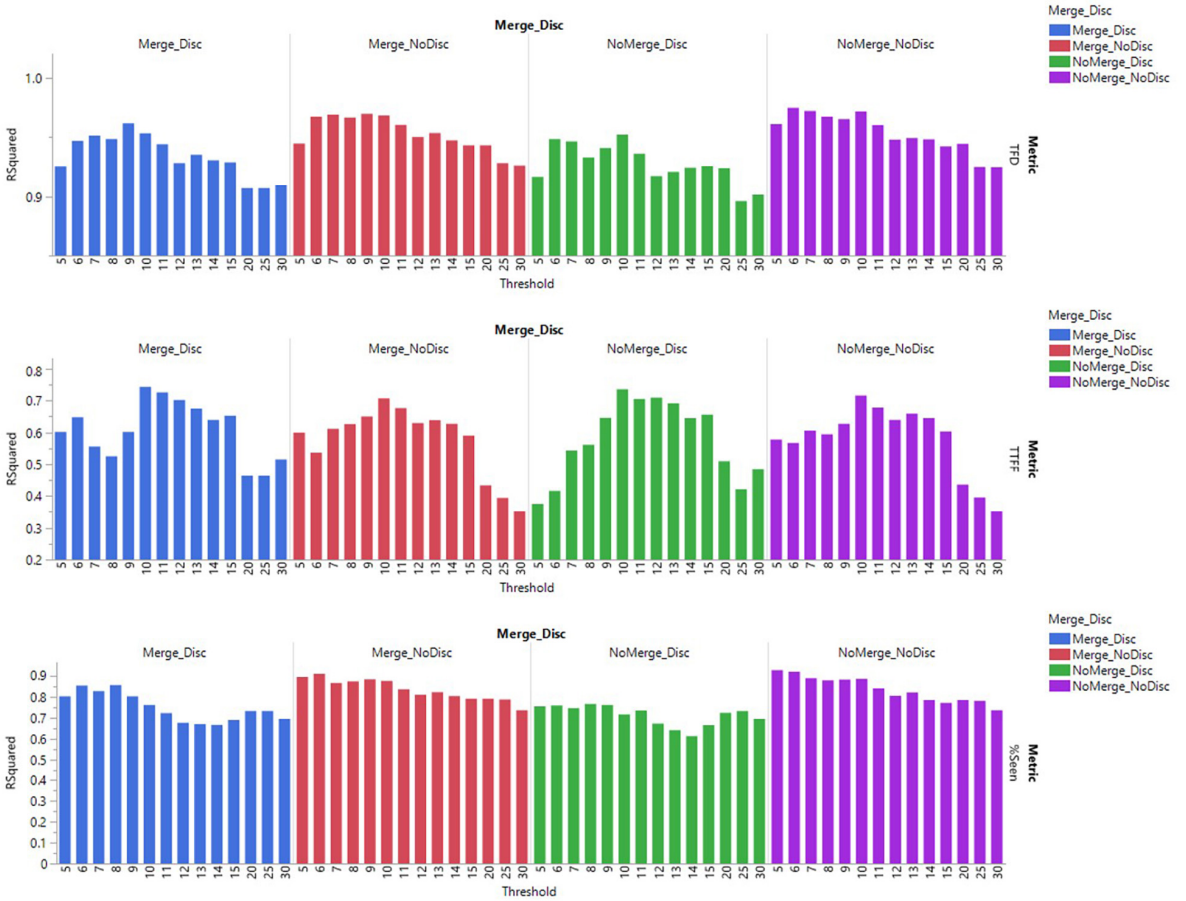


FIGURE 5 | Coefficient of determination for each of the Test filters and the benchmark of Raw60.

movements over several AOIs into long ambiguous fixations. Accordingly, these two values were decided to be taken as the two border conditions, implying that all discrete velocity values ranging from 5 to 15°/s would be tested as algorithm parameters.

Figure 7 visualizes the fixation data output when the velocity threshold was set to 30°/s (purple), 15°/s (green), 10°/s (blue), and 5°/s (yellow). Each horizontal bar signifies a chain of gaze points that are classified as a fixation.

Reliability of the Metrics

Figure 6 presents the correlation of determination or R^2 values for different Test filters and the benchmark Raw60 for the metric TFD. Overall, the coefficient of determination values was the highest for the setting of NoMerge_NoDiscard with velocity threshold 6°/s (R^2 = 0.975) and thresholds 7 and 10°/s (R^2 = 0.972). Across all combinations of settings of merging adjacent fixations and discarding short fixations, it is evident that there was a decline in R^2 values as the threshold was increased above 10°/s.

Figure 6 presents the mean scores of Spearman R across 1000 iterations of randomly split-half samples for different Test filters. For TFD metric, the Spearman R score was highest for the setting NoMerge_NoDiscard and thresholds 12 and 14°/s and also Merge_NoDiscard with thresholds 9, 12 and 14°/s (Spearman R = 0.45).

A one-way ANOVA comparing the Spearman R values across all thresholds, revealed a significant difference between the four different types of settings of merging adjacent fixations and discarding short fixations, $F(3,56)$ = 6.184, p = 0.0011. **Table 4** presents the mean values and confidence intervals for different settings, as well as pairwise comparisons with significant differences.

DISCUSSION

Study Aim

The goal of this study was to understand the performance of existing, commonly used fixation filters for applications of measuring eye gaze on vertically scrolling smartphone screens, and to identify combinations of parameters that most closely align with human classified fixations, called Raw60 above. In addition to developing filters that are valid and reliable for smartphone applications, this study offers a framework that can

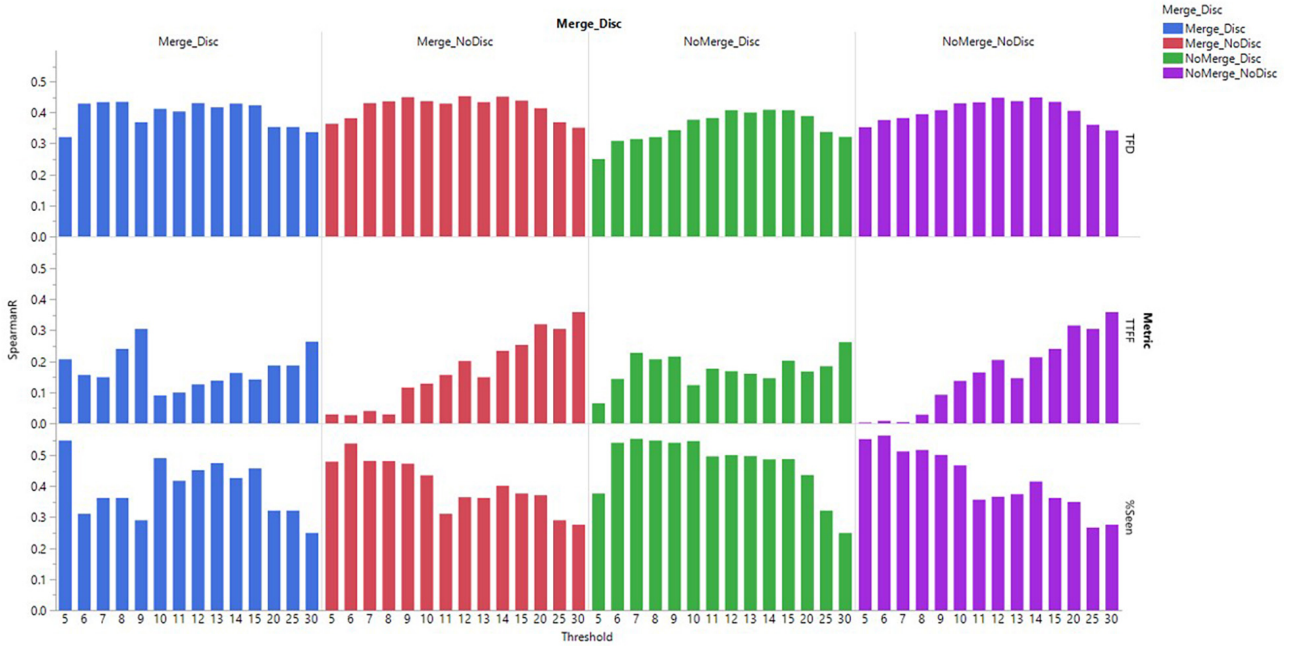


FIGURE 6 | The mean Spearman R scores across 1000 iterations of randomly split-half samples for different Test filters.

TABLE 3 | R^2 of TFD, TTFF, and Percent Seen – Mean values and standard errors of settings of merging adjacent fixations and discarding short fixations, and significantly different pairwise comparisons based on Tukey–Kramer HSD test.

Metric	Setting	Mean	Standard error mean		Mean	Standard error mean	HSD threshold	*p*-value
TFD	Merge_NoDisc	0.973	0.017	NoMerge_Disc	0.951	0.023	0.0103	**<0.0001**
	NoMerge_NoDisc	0.973	0.017	NoMerge_Disc	0.951	0.023	0.0103	**<0.0001**
	Merge_NoDisc	0.973	0.017	Merge_Disc	0.960	0.003	0.0017	**0.0174**
	NoMerge_NoDisc	0.973	0.017	Merge_Disc	0.960	0.003	0.0017	**0.0174**
TTFF	NoMerge_NoDisc	0.771	0.024	NoMerge_Disc	0.596	0.030	0.0852	**<0.0001**
	Merge_NoDisc	0.770	0.024	NoMerge_Disc	0.596	0.030	0.0844	**<0.0001**
	NoMerge_NoDisc	0.771	0.024	Merge_Disc	0.681	0.019	0.0003	**0.0490**
	Merge_NoDisc	0.770	0.024	Merge_Disc	0.681	0.019	–0.0005	0.0519
Percent seen	Merge_NoDisc	0.797	0.018	NoMerge_Disc	0.657	0.028	0.0103	**0.0003**
	NoMerge_NoDisc	0.795	0.020	NoMerge_Disc	0.657	0.028	0.0103	**0.0004**
	Merge_NoDisc	0.797	0.018	Merge_Disc	0.696	0.028	0.0017	**0.0162**
	NoMerge_NoDisc	0.795	0.020	Merge_Disc	0.695	0.028	0.0017	**0.0184**

be leveraged for future filter development as can be applied to many use-cases.

The focus of this study has been on measuring branding elements of advertising presented in vertically moving feed environments. These elements are not only necessary for establishing awareness of a brand, but also increasing brand salience, and are frequently desired to be understood by advertisers who undertake eye-tracking research for quantifying brand attention.

Main Findings

Since there is no standard approach for detecting meaningful eye movements, and as it has been shown that event-detection algorithms perform poor for dynamic stimuli (Andersson et al., 2017), a number of studies using mobile eye-tracking glasses have used dwells with a specific cutoff point to analyze eye movements. Using dwells with the cutoff point of 60 ms as the benchmark, our objective was to determine the fixation detection algorithm parameters that would lead to the data output equivalent or as similar as possible to the benchmark in a setting where small areas of interest are presented on the screen of a smartphone. We modified three parameters of the Tobii I-VT fixation filter (velocity threshold, merging adjacent fixations, discarding short fixations) and investigated how different combinations of parameter settings measure against the data output based on Raw60.

To understand how different fixation detection algorithm parameters affected the data output, and more specifically, the

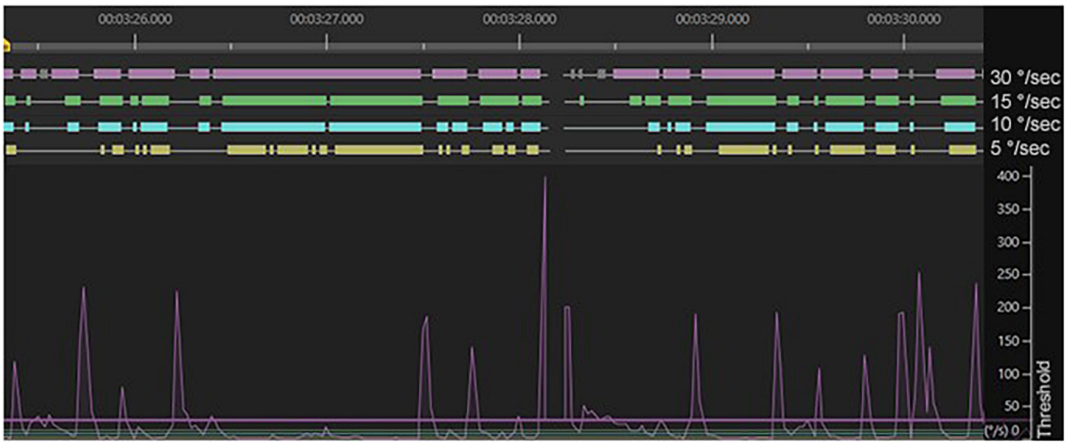


FIGURE 7 | Fixation data output as the velocity threshold is modified. The angular velocities of the eye movements (vertical axis) are captured over several seconds of natural viewing behavior (horizontal axis) and the horizontal bars above the graphs signify the chains of gaze points that are classified as fixations.

TABLE 4 | Spearman R of TFD – mean values and confidence intervals of settings of merging adjacent fixations and discarding short fixations, and significantly different pairwise comparisons based on Tukey HSD test.

Setting	Mean	Lower 95% CI	Upper 95% CI	Setting	Mean	Lower 95% CI	Upper 95% CI	p-value
Merge_NoDisc	*0.418*	*0.396*	*0.439*	*NoMerge_Disc*	*0.356*	*0.334*	*0.377*	*0.0009*
NoMerge_NoDisc	*0.404*	*0.383*	*0.426*	*NoMerge_Disc*	*0.356*	*0.334*	*0.377*	*0.0119*
Merge_Disc	*0.397*	*0.375*	*0.418*	*NoMerge_Disc*	*0.356*	*0.334*	*0.377*	*0.0446*

differences between the data output based on the benchmark of Raw60 and different Test filters, we first looked at the error components of different eye-tracking metrics by running several linear regressions with algorithm parameters as model predictors and the error component as the response variable. The data revealed that for the TFD metric, increases in velocity threshold led to an increase in overestimation of viewing time. For the error component of underestimation of the viewing time, the relationship between the two variables was the opposite. This implies that there is a tradeoff – if a lower velocity threshold is chosen, the algorithm is more sensitive and thereby less likely to overestimate the viewing time, but, concurrently, picks up fewer gaze points and is more likely to underestimate the viewing time. The data also revealed that test filters with the function of discarding short fixations disabled lead to decreased underestimation of the viewing time but performed worse for the overestimation error component. The choice of the optimized settings, therefore, depends on whether it is more important to prioritize minimizing the error in overestimation or underestimation of the viewing time given the study objective and the characteristics of the stimuli.

The error components in TTFF and the ratio of viewers (Percent Seen) were mainly driven by the combination of parameters of merging adjacent fixations and discarding short fixations. For both metrics, the errors are minimized when short fixations are not discarded. The explanation for this finding may be related to the smooth pursuit. When viewers scroll the smartphone screen and attend a dynamic stimulus, their eyes move along with the information presented on the screen. As the event detection algorithm discards the gaze samples with the angular velocity above the threshold value, it is likely that a substantial proportion of short fixations have a duration below 60 ms. Discarding these short fixations, therefore, makes the fixation detection algorithm much more restrictive and conservative, as visualized in **Figure 8**. As the data reveals, for the metrics TTFF and Percent Seen, keeping the short fixations in the fixation dataset leads to an output that is more similar to the benchmark used in this study, i.e., dwells with the cutoff point of 60 ms.

These results suggest that the algorithm parameters affect the magnitude and directionality of different error components, and that there is a tradeoff between the overestimation and the underestimation of total viewing time. Therefore, the decision related to the improved settings of the fixation detection algorithm must be driven by the study objective and the characteristics of the stimuli. In a setup based on natural viewing behavior of dynamic stimuli on a smartphone screen and focusing on a small AOI such as the branding element, these findings suggest that improved settings are the velocity threshold in the proximity of 10°/s and the function of discarding short fixations disabled. These adjustments to the fixation detection algorithm improve the accuracy of Percent Seen by 19% compared to the output of the Tobii I-VT Fixation Filter, when using the benchmark of Raw60 described above. With this in mind, however, a more practical insight into how well the different Test filters perform can be obtained by investigating the correlations between the output of different Test filters and the benchmark results.

We also find that deciding upon the improved parameter settings depends on which metrics need to be prioritized. For

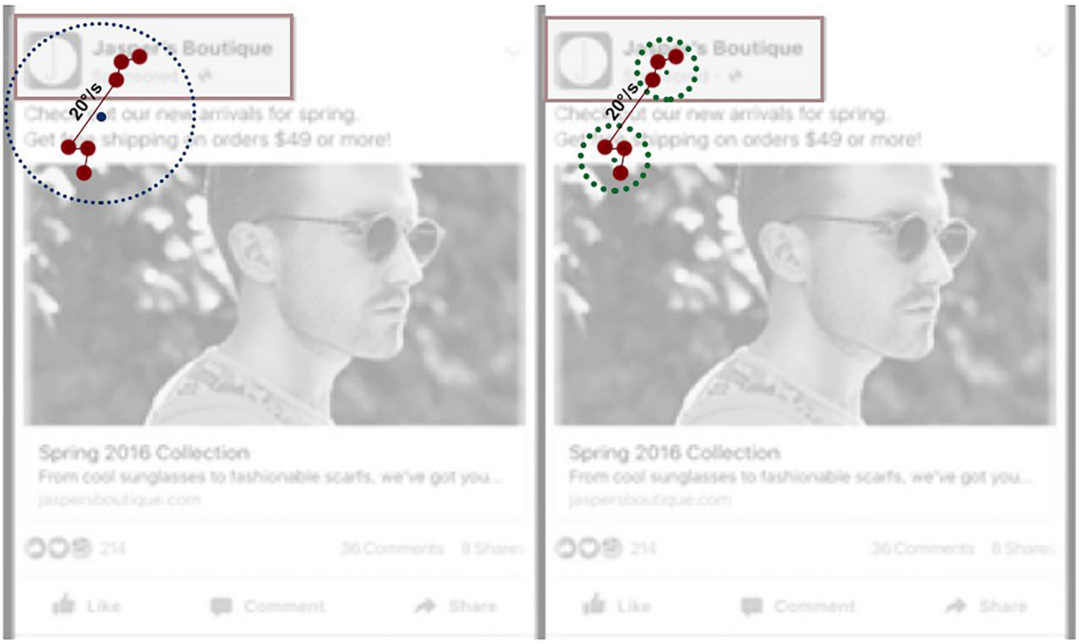


FIGURE 8 | An illustration of the impact of the velocity threshold parameter on the detection and location of fixations on a mock advertisement. On the left side, gaze samples, marked with red dots, are combined into a fixation based on the default threshold value of 30°/s, and the fixation is located outside the AOI Branding. On the right side, the velocity threshold is lowered to <20°/s, resulting in two short fixations with more accurate mean location coordinates.

all metrics, it is clear that combinations where the discarding short fixations is disabled perform significantly better than the combinations with the function enabled. The function of merging adjacent fixations has a minor impact on the accuracy of the data output. Disabling the function leads to a slightly more accurate TTFF measures, and enabling it has a slight benefit when focusing on the ratio of viewers, i.e., Percent Seen. When the study objective is related to Percent Seen, velocity thresholds of 5 and 6°/s perform the best, whereas when prioritizing the TTFF metric, thresholds 10 and 11°/s lead to the most accurate results. For TFD, threshold 6°/s yields the results that are most similar to the benchmark of Raw60, but the data output remains fairly accurate also when the velocity threshold is increased up to 10°/s.

While the coefficient of determination values can be considered as indicators of validity of the output of different Test filters, we also found it necessary to assess their reliability. To achieve this, we ran bootstrapped split-half correlations using Spearman correlation values. As Spearman $R \geq 0.4$ is generally considered acceptable (Fayers and Machin, 2013), we only considered the Test filters with Spearman R equal to or above 0.4 as sufficiently reliable.

In relation to the metrics TFD and Percent Seen, the algorithm parameter settings that displayed the best performance in terms of reliability overlapped to a considerable degree with the findings from the correlation analysis. Considering the reliability of Spearman $R \geq 0.4$ as the criterion for reliability and combining the results of the correlation and reliability analyses, it could be concluded that for the metric TFD, the algorithm settings with the velocity threshold of 10°/s and the function of discarding short fixations disabled yielded the best results. Also, for the Percent Seen metric, the setting of NoDiscard was preferable, but it is feasible to lower the velocity threshold to 5 or 6°/s. For the metric TTFF the reliability was higher for higher velocity thresholds, but it did not meet the reliability criterion of Spearman $R \geq 0.4$ for any of the Test filters.

Considering the small size of the AOI and the finding that higher velocity thresholds lead to overly conservative data output and decreased viewer ratio values, it can be inferred that in the case of TTFF reliability, higher thresholds lead to fewer data points and thereby higher reliability values. However, the finding that the TTFF reliability failed to meet the criterion of Spearman $R \geq 0.4$ regardless of the parameter settings indicates that the metric of TTFF cannot be considered a reliable metric when studying visual attention in the present conditions. For that reason, rather than focusing on TTFF as a millisecond value, it may be worthwhile to focus on the sequential order of fixating on AOIs, i.e., on scan paths instead.

Having demonstrated how different parameter settings of fixation detection algorithms influence different error components, their validity (in the form of coefficient of determination when benchmarked against dwells of 60 ms) and reliability (in the form of Spearman R based on bootstrapped split half tests), we recognize that the choice of the optimized settings of the fixation detection depends greatly on the study objectives and the characteristics of the stimuli. It is recommended by Tobii that the users modify and optimize the settings of the fixation detection algorithm. Here, we provide a framework for how the selection of the improved parameters can be done. As evident from different analyses, the differences in results when comparing the Tobii default Fixation Filter with the Test filters

TABLE 5 | Comparison of the results of eye-tracking metrics of the benchmark (Raw60), Tobii Fixation Filter (Default) and three Test filters with velocity thresholds 5, 10, and 15°/s (Test filters 1, 2, and 3, respectively).

	Raw60	Default Merge Discard 30°/s	Difference (Raw60 -Default)	Test filter1 NoMerge NoDiscard 5°/sec	Difference (Raw60 – Testfilter1)	Test filter2 NoMerge NoDiscard 10°/s	Difference (Raw60 – Testfilter2)	Test filter2 NoMerge NoDiscard 15(/sec	Difference (Raw60 – Testfilter3)
TFD	0.227	0.188	–0.039 (–17%)	0.123	–0.104 (–46%)	0.16	–0.067 (–30%)	0.174	-0.053 (-23%)
TTFF	0.565	0.904	0.339 (60%)	0.874	0.309 (55%)	0.811	0.246 (44%)	0.831	0.266 (47%)
Percent Seen	0.495	0.371	–0.124 (–25%)	0.429	–0.066 (–13%)	0.437	–0.058 (–12%)	0.441	–0.054 (–11%)

TABLE 6 | The definition and calculation of the metrics of interest.

Metric	Definition	Calculated as
Total Fixation Duration (TFD)	The accumulated duration of fixations on a stimulus or an AOI	The sum of the durations of all fixations located on an object or an AOI
Time to First Fixation (TTFF)	The time it takes before a stimulus or AOI is seen	The time that it takes measured from the moment that 50% of the feed post enters the screen until the first fixation lands on that AOI
Percent Seen	The percentage of participants that have at least 1 fixation (= "seen") on a stimulus or an Area of Interest (AOI)	On a participant level for each AOI, a binary score (SEEN) is assigned (1 or 0, indicating "seen" and "not seen" respectively). This is then aggregated as the percentage of participants that had a minimum of a single fixation on the AOI. This is done by compiling all subjects and taking the percentage of participants who had at least one fixation. For example, if 10 participants were exposed to an AOI and 8 participants saw it for at least one fixation, then %seen would equal 80%, regardless of how long participants viewed the ad for.

with modified settings are quite substantial. This is exemplified in **Table 5**. We see from **Table 5** that compared to the benchmark Raw60, the default Tobii I-VT Fixation Filter underestimates the viewer ratio (Percent Seen) value by 25%, implying that it fails to capture a quarter of the study participants who viewed the AOI. When using Test filters 2 or 3, the difference in Percent Seen is decreased to 12 and 11%, respectively. From **Figure 4** it was clear that threshold values above 10°/s lead to overestimation of the accumulated viewing time. This is likely the reason why the default Tobii I-VT Fixation filter, while missing out on the data of 25% of the viewers, still yields a TFD value that differs from the benchmark Raw60 only by 17%, as compared to the 30 or 23% difference of Test filters 2 and 3, respectively. The TTFF is 60% longer compared to the Raw60 when using the Tobii I-VT Fixation Filter. The difference becomes smaller by using the Test filters 2 or 3 yet is still 44% difference in the best case. Details of these calculations can be found in **Table 6**.

LIMITATIONS

This paper is limited to covering a specific AOI size on a mobile phone screen in a natural browsing behavior. While we focused solely on an AOI encompassing the branding area of a mobile feed environment due to the importance of branding in advertising, the findings may not apply to other AOI sizes or other stimulus presentation devices of different sizes and viewing distances. Here, further research must be conducted to answer questions about optimized filters for additional circumstances. Additionally, because we utilized a natural browsing condition in order to observe natural velocities and patterns of eye movements in a vertically scrolling feed environment, conclusions cannot be drawn about the spatial accuracy of eye-tracking on mobile

phone screens, since we can only be aware of the observed gaze location rather than the intended gaze location. A follow-up study should be conducted with controlled spatial targets to understand the reliability and validity of spatial accuracy measurements for eye-tracking on smartphone devices, utilizing ROC.

Our work focuses on both the validity and reliability of a given measure, although not a comprehensive test that focuses on the desired sample size for each score. Future studies should conduct test–retest and split-half analyses on these and similar data to assess both the general reliability of the selected fixation filter settings, as well as to determine how sample size affects the reliability for small, medium, and large AOIs.

This paper focuses on results using Tobii Pro Glasses 2 50 Hz hardware and Tobii Pro Lab software, and the findings may not apply to other types of eye-tracking hardware and software. Tobii recently released a newer version of eye-tracking glasses hardware, called Tobii Pro Glasses 3, however due to similar hardware specifications and software, we do not expect this hardware difference will have a meaningful impact on the findings presented herein.

Finally, one pertinent limitation of this study is that it does not compare the fixation filter performances to a gold standard measure of gaze movements and fixations. In fact, the study can be seen as a challenge of the long-held industry standard, especially for particular use cases such as eye-tracking on small screens. While this study and its results do not define optimal fixation filters with finality, they imply that further work can be done to improve the accuracy and reliability of eye-tracking measures under different conditions. Here, additional research is needed, and this paper provides one viable path to pursue such research.

CONCLUSION

As technology changes and advances, humans shift their behavior to interface with new devices as their primary mode of consumption. With this change in the consumption landscape, researchers often continue to utilize previously used data collection and analysis techniques. While fixations can be a helpful tool in analyzing visual attention in visually cluttered environments, such as advertisements in a social media feeds, the lack of mobile-specific fixations filters renders existing, widely utilized fixation filters ineffective in evaluating advertisements in a vertically scrolling social media feed presented on a smartphone. For improved evaluation of gaze metrics on Branding AOIs for advertisements placed in mobile social media feeds, researchers using Tobii Pro Glasses 2 with Tobii Pro Lab software should use a velocity threshold of 10°/s and disable the function of discarding short fixations, which improves the accuracy of Percent Seen by 19%. Future research should be conducted to validate the spatial accuracy of fixation filters for vertically scrolling content on smartphones. We hope that readers take away from this paper not only an increased knowledge in filter settings for eye-tracking research on smartphones, but also a framework for testing reliability, and we hope further frameworks will be developed and applied for validation testing of datasets in related fields.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article may be made available, pending legal review at the affiliated institutions. Requests to access the datasets should be directed to JT, juliatrabulsi@fb.com.

ETHICS STATEMENT

The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

JT and MS conceived and designed the original research. MS was responsible for data collection. SS, KN, and TR completed the data processing and analysis. All authors contributed to writing and editing the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2021.578439/full#supplementary-material

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Choice Hygiene for "Consumer Neuroscientists"? Ethical Considerations and Proposals for Future Endeavours

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Is the use of psychological and neuroscientific methods for neuromarketing research always aligned with the principles of ethical research practice? Some neuromarketing endeavours have passed from informing consumers about available options, to helping to market as many products to consumers as possible. Needs are being engineered, using knowledge about the human brain to increase consumption further, regardless of individual, societal and environmental needs and capacities. In principle, the ground ethical principle of any scientist is to *further* individual, societal and environmental health and well-being with their work. If their findings can be used for the opposite, this must be part of the scientist's considerations before engaging in such research and to make sure that the risks for misuse are minimised. Against this backdrop, we provide a series of real-life examples and a non-exhaustive literature review, to discuss in what way some practices in the neuromarketing domain may violate the Helsinki Declaration of Experimentation with Human Subjects. This declaration was set out to regulate biomedical research, but has since its inception been applied internationally also to behavioural and social research. We illustrate, point by point, how these ground ethical principles should be applied also to the neuromarketing domain. Indisputably, the growth in consumption is required due to current prevalent economical models. Thus, in the final part of the paper, we discuss how alternative models may be promotable to a larger public, aided by more ethical marketing endeavours, based on neuroscientific discoveries about the human brain. We propose this as a philosophical question, a point of discussion for the future, to make neuromarketing as a discipline, fit for the future, respecting the ethical implications of this research.

Keywords: ethics, consumer neuroscience, neuromarketing, aesthetic emotions, addiction, obesity, moral dilemma, moral judgement

INTRODUCTION

"You can probably make them do anything for you: Sell people things they don't need; make women who don't know you fall in love with you."

– Vance Packard, *The Hidden Persuaders* (1957)

Consumer neuroscience is a young discipline. Concepts and methods from cognitive neuroscience are applied to research questions in the field of marketing. The aim is to develop a better understanding of consumer preferences and consumer behaviour. This endeavour has obvious potential benefits for individuals, businesses, society, and the environment. However, this marriage of science and the marketing industry is not (yet) a success story at all, due to the ethical implications of such research (Fisher et al., 2010; Stanton et al., 2017; Cherubino et al., 2019).

Our paper is specifically concerned with examples of misuse of methods and unethical research in the domain of consumer neuroscience. We are academics from other domains of research than neuromarketing. Therefore, our view should be understood as an outsider's view on a domain of research that is still in the process of becoming, and where ethical concerns are still pending resolution which should be a concern for any researcher, outsider or not.

For the scope of this article, we will define neuromarketers as (neuro)scientists working in marketing departments in industry, or (neuro)scientists collaborating with industry partners on (neuro-) marketing questions from within a university (i.e., individuals with university education in psychology and/or cognitive neuroscience, working with businesses on marketing endeavours). Neuroscientists researching consumer choices without directly working with industry might also find our perspective useful. This article may also provide insights for classical marketers that seek to enhance their company's marketing strategies with neuromarketing techniques, producers of ads, artists working in the marketing business, stakeholders in politics and policy-makers, and finally, for individuals/consumers of the societies of the future who seek information about the neurocognitive processes at play in our brains when we're targetted by marketing strategies.

Within any academic and management field there is the possibility of unethical behaviour and conflicts of interest. The issues we flag in this article do not apply solely to the field of neuromarketing. Commendable initiatives like the International Neuroethics Society are concerned with such issues specifically within the realm of neuroscience. For the realm of neuromarketing, the Neuromarketing Science and Business Association (NMSBA) has provided a Code of Ethics, that members can sign up to voluntarily. These provide a useful starting point.

As in any field of research with human subjects, the neuromarketer has the responsibility to choose an ethical and sustainable research behaviour while still pursuing the strategic demands of stakeholders. If, on the contrary, no ethical code of conduct is observed, this is particularly problematic, as researchers are often based at universities, using publicly funded research facilities for their work with clients from the industry. In the words of Stanton et al. (2017):

> "*Commercial Alert, a consumer advocacy group, sent a letter to the president of Emory University in 2003 alleging that neuromarketing is a significant risk to consumers and that Emory University should immediately halt all study of neuromarketing (Grey et al., 2003). In the letter, signed by academics and leaders of non-profit consumer advocacy groups, the authors state, Emory's quest for a "buy button" in the human skull is an egregious violation of the very reason that a university exists. It also likely violates the principles of the Belmont Report, which sets out guidelines for research on human subjects in the United States. They go on to note, the real risk of neuromarketing research is to the people—including children—who are the real targets of this research. Already, marketing is deeply implicated in a host of pathologies. The nation is in the midst of an epidemic of marketing-related diseases.*"

Commercial Alert is an anti-advertising group that campaigns against many forms of marketing, not just against using neuroscientific methods in marketing endeavours. When Commercial Alert criticised neuromarketing at the beginning of the '00, calls from promoters of neuromarketing were fast to dismiss potential dangers of neuromarketing to the individual. For example, Dr. Steven Quartz (a neuroscientist at the California Institute of Technology in Pasadena, California) was quoted for having said that such comments represented "gross misunderstandings and distortions of both the power of brain imaging technology and its use in marketing" (Blakeslee, 2004). Science has moved fast since then. While examples of misuse of neuroscientific methods for marketing purposes continue to be revealed, of course, it should be said that much of this research is conducted with adequate use of neuroscientific methods that help companies understand their consumers better.

US Department of Health and Human Services (1979) (mentioned in the quote from Stanton et al., 2017), along with several other codes of ethical research conduct (for an overview, e.g., Iphofen, 2009), all set out key ethical principles for any research endeavour involving human subjects. We will revise some of these proposed ethical principles in what follows in relation to neuromarketing.

For example, the Helsinki Declaration of Experimentation with Human Subjects (World Medical Association, 1964) sets out the ethical principles that regulate medical research. These principles are based in the The Universal Declaration of Human Rights (1948). Many international universities and research institutions that work in experimental psychology, cognitive neuroscience and data science (i.e., institutions where neuromarketers may work or may collaborate with) also adhere to these same principles. The European Commission (EURAXESS) (2000) holds that:

> "*Research participants' rights are anchored in fundamental human rights and the fundamental ethical principles that govern all scientific research. [. . .] Additional central policies and widely accepted declarations that codify principles of research ethics and ethical treatment of research participants include the Nuremberg Code, the Helsinki Declaration, and the Belmont Report. Although these codes originate in the biomedical field, they encompass the*

central principles that apply to all human research." (European Commission, 2018; pp. 4–5).

In what follows, by means of a non-exhaustive review of available literature in the field, together with real life examples, we illustrate how principles set out in these codes may be relevant in the context of neuromarketing. Neuromarketers must make a personal choice and bear their share of responsibility in what products they chose to help to promote, and how they do it. There is accumulating evidence that some advertising efforts, assisted by neuromarketing research, can have detrimental effects on the health of individuals, societies and the environment, potentially making more regulatory efforts necessary in the future.

Before we proceed review the ethical principles, some definitions of the object of study and a brief historical overview are in order.

Marketing and Neuromarketing: Definitions and History

Marketing is the activity that seeks to shape and increase the sales of a product. In so doing, it seeks to create value for costumers and to capture value for the firm (Kotler and Keller, 2015). In marketing practice, there are four downstream tactics of marketing, or sub-domains of activities. Businesses develop marketing strategies for each of these four domains to ensure to market the right product to the right person, at the right price, in the right place, and at the right time (Cim, 2005). Detailed definitions from the perspective of the marketing discipline (both from the perspective of the academic study of marketing and of that of the marketplace practice of marketing) lie outside the scope of this paper. For such definitions, we recommend the work by Dolan (2019) and by Kotler and Keller (2015). We here provide short outsider insights before coming to the core of our objective with this paper, the ethical implications of some neuromarketing research.

Empirical research into people's purchasing behaviour gained momentum in the beginning of the 20th century with Edward Bernays and Ernest Dichter (Bernays, 1928/1955/2004; Dichter, 1960/2012/2017; Papakonstantinou, 2019). Ever since, the aim of marketing research has been to shape sales through all four aforementioned domains. Today, neuromarketing methods are employed to target exactly the same four domains of sales-shaping (Dooley, 2011). See **Table 1** for these four domains.

Neuromarketing endeavours seek information and insights beyond those obtained by traditional techniques such as surveys, focus groups, and ethnography (Yoon et al., 2012; Plassmann and Weber, 2015), to improve the accuracy of predictions of consumer preferences and behaviour when combined with traditional techniques (Venkatraman et al., 2012; Smidts et al., 2014; Boksem and Smidts, 2015). In the next three sections, we will give a brief overview of the history of marketing endeavours and how they are shaping both present and future endeavours. We specifically focus on information about the advertising strategy, the 4th P (persuasion and communication), since reviewing all four Ps in detail would go beyond the scope of this paper.

Neuromarketing *Past*

Although only gaining momentum in the past couple of decades, neuromarketing has its roots in the beginnings of marketing as a discipline. The presumed ethically problematic issues (that we will discuss in this article), arise from a shift that has happened in mainstream marketing objectives:

- **From:** "*informing people about available options*"

(informative and complementary marketing) . . .

- **To:** "*make people buy more than what they need to boost income*"

(persuasive marketing).

Where Marketing Came From

During the industrial revolution, marketing was an effort aimed at how to produce and distribute goods at the lowest possible cost and to inform people about available options. In the 20th century, the focus shifted because the market was increasingly more crowded by several producers offering similar products. Marketing became an effort aimed at persuading people that the goods of one producer were better than those of another. Today, the markets are saturated, and companies compete for customers like never before. Their effort is now to understand costumers' potential needs and to persuade customers to purchase products to fulfil these needs.

Examples of "Helping Consumers Get What They 'Need' "

Edward Bernays, a cousin of Sigmund Freund revolutionised this field. Based on the principles of psychoanalysis, Bernays presented a new vision to companies: Consumers' minds work according to unspoken (and even unconscious) feelings and desires "*that you cannot ask them about in an interview*." Hence, the science of "unlocking the consumer's unconscious mind" was born (Bernays, 1928/1955/2004).

One first landmark example of the techniques used for persuasion was the "Torches of Freedom." Edwards Bernays was hired by a tobacco company to do something about the "problem" that women were not smoking (which caused the tobacco industry to "lose out" on possible revenues). This was in the 1920s, and it was considered shameful for women to smoke in public. However, overhearing conversations of potential cigarette consumers, he understood that feminists associated (at the time) smoking with freedom, and that, for them, the cigarettes were "torches of freedom." Bernays informed newspapers that during the Easter parade of that year, a group of remarkable women would light "Torches of Freedom." To capture this event, a large number of reporters attended the occasion and captured on camera how a group of very fashionable ladies lit their cigarettes in unison. This marked a new trend: "the modern independent woman, . . .*smokes*" – wonderful PR for the cigarette: *"If you smoke, you're a free woman."* The press photographs went "viral" in terms of then, and from then on, cigarette sales increased, and, although causality is always difficult to establish in a real life context, it should be noted

TABLE 1 | The four Ps of marketing: product, price, place, and promotion (Kotler, 2003).

(1) **What?** The product. (i.e., anything that can be offered to a market from attention, to acquisition, to use or for consumption that might satisfy a want or a need (Kotler and Armstrong, 2010, p. 253).
Marketing activity: *Product design strategy* contents of the product, looks, taste, touch, sounds, wrappings, etc.
(2) **How much?** The price of the product. This is one of the most important elements of the marketing mix. If wisely chosen, it generates the turnover for the organisation (Low and Tan, 1995).
Marketing activity: *Pricing strategy* how much do people have to pay for it, etc. The price is a variable that should be set in relation to the other three Ps (Low and Tan, 1995).
(3) **Where?** The placement of the product (refers to how an organisation will distribute the product or service they are offering to the end user).
Marketing activity: *Placement strategy* where will the product be offered (what shops, online/offline), where will the product be placed on the shelf, etc (Miller and Ginter, 1979).
(4) **How?** The promotion of the product (i.e., a vital part of business, it is an integral ingredient of the total marketing process).
Marketing activity: *Advertising strategy* decisions about design of ads, videos, online/offline, posters, etc. Promotion should make potential customers aware of the available products and services (Fam and Merrilees, 1998).

Neuromarketing methods can be employed within each of these four sub-activities of marketing.

that also the prevalence for lung-cancer in women increased (Grannis, 2017).

Similar manipulations of social norms and health behaviour were performed to boost the sales of a company by Ernest Dichter in the 1950s, when instant foods started to appear on the markets. Ernest Dichter was another psychoanalyst, and he invented the "focus groups" based on the free association group sessions of psychoanalysis (Dichter, 1960/2012/2017). Eves-dropping of the target groups as they tried out new products, he understood their joys and concerns alike, and also their dilemmas. This was how a simple egg made the sales of the brand Betty Crocher Foods skyrocket. *In theory*, housewives really wanted to ease their domestic tasks, so instant products were attractive for them. However, sales didn't mirror this desire. Why? During focus groups, Dichter realised that, *in practice*, the housewives felt guilty for making their life easier by using instant products when cooking for their husbands. Although it wasn't necessary, Dichter proposed the manufacturer make it compulsory to add a fresh egg to the mixture, to return some agency of the processes to the housewives' hands, and to give them "a sense of participation" and it did the trick: sales increased dramatically. Apparently, having to add an egg to the mixture (even if that egg could, technically, have been part of the instant product already in the package) relieved the housewives of their guilt of using instant products. Sales of instant foods increased. Direct links between instant foods and obesity are still under investigation, however, based on first data, a link between high consumption of processed foods (including instant foods) and obesity is likely (Poti et al., 2017; Askari et al., 2020).

Is "Defence Breaking" Ethical?

Let us start by considering these two historical examples through the lens of the topic of this article: ethical research practices. Throughout the 20th century, experimental psychology and other behavioural/social sciences have seen dreadful examples of research misconduct that were only possible because no ethical codes were yet in place to regulate these endeavours. For example, the obedience experiments of Stanley Milgram or the Stanford Prison Experiments all had detrimental effects on research participants' mental and physical health after their participation in these. Such examples raised awareness and highlighted the need to formulate and adhere to ethical research principles to safeguard research participants, not only in medical but also in behavioural research.

In both examples from Section "Examples of "Helping Consumers Get What They 'Need'"" above, the social emotions shame and guilt (Tangney et al., 2007) were "hindering" people from purchasing the manufacturers' product (e.g., cigarettes, instant foods), and the marketing process used in both cases, removed peoples' personal defences, "helping" people to smoke and to buy instant food products. From an ethical research practices point of view, let us consider two points:

First, ever since Aristotle, emotions like shame and guilt have been mentioned as important regulators of our social behaviours within society. Modern research from psychology and affective neuroscience has illustrated how the emotions of shame and guilt are evoked when we don't act according to personal and societal values or rules. They are, thus, important regulators of our behaviour, also referred to as moral and aesthetic emotions (Tangney et al., 2007; Dempsey, 2017; Menninghaus et al., 2019). It may, therefore, be necessary to evaluate whether it is ethical to break down such natural "defences" of human cognition, effectively deceiving individuals into acting in discordance with their own values.

Second, considering what we know about human psychological and physical health *today*, neither cigarettes nor instant foods are healthy. In the beginnings of marketing as a discipline, there was little knowledge available about how smoking destroys the lungs, and about how the human brain reacts to addictive substances, and how habits and cravings develop in the brain. In the past, it was still not empirically established, how these processes stirred by marketing endeavours, boosting a business, could lead to wide-ranging negative effects for individuals' mental and physical health, for societies, e.g., due to increasing costs to health systems; exploitation of the workforce, and for the environment, e.g., due to pollution or non-sustainable use of resources.

Today, evidence with regards to such detrimental effects is accumulating. Therefore, and importantly in this piece, research that contributes to such "defence breaking" wouldn't

be in accordance with ethical research practice as it is understood today.

Neuromarketing *Present*

Current neuromarketing endeavours are based on the assumption that what one craves is also actually what one needs. This assumption is not aligned with current knowledge from affective neuroscience and psychology. Over-availability of opportunities for hedonism can corrupt our mental health and the choices we make in our life (Christensen, 2017).

In this section, we will review some ethical implications of present-day food and drink advertisement for sugary-products. Such advertisement can be one of the factors contributing to leading large segments of society into obesity-related health problems and is, therefore, an ethically-relevant issue.

The current situation is the following: Our urban visual and auditory environment is crowded with cues related to our basic and secondary needs (food, drink, sex, shelter, safety, status, etc; Maslow, 1954). Such cues remind us of hedonic experiences and, make us crave products that may give us these hedonic experiences. Thus, without any education about how our brain reacts to such cues, these can be detrimental for individual, societal and environmental health. Official health education about "pleasure" does not currently exist, nor do advertisements include disclaimers that inform consumers of these processes. Ethical research practice in neuromarketing for food advertisement must, therefore, include considerations about the possible consequences of manipulations of the human reward system can lead to detrimental effects for the individual, society and the environment.

In what follows we attempt to outline the fine line between ethical and unethical experiments in the neuromarketing realm by means of The Orange Bubble Juice Ad Dilemma. The objective of this exaggerated and provocative example is to raise awareness of potential ethically relevant issues in neuromarketing. **Box 1** and **Figure 1** set out The Orange Bubble Juice Ad Dilemma.

Is Promoting a Sugary Juice With the Help of Neuromarketing Methods Ethical?

Of course, no university would approve an ethics application with the research objectives of the experiments outlined for our hypothetical Orange Bubble Juice example in Box 1. The obvious psychological and physical health hazards that they pose to the individual, children in this case (e.g., obesity), to society (e.g., increased cost to health services due to obesity), and to the environment (e.g., pollution through the surplus of plastic bottles) would make such research unethical from a university ethics board point of view. However, the hypothetical Orange Bubble Juice dilemma illustrates the trade-off that neuromarketers may at some point have to consider, between safeguarding individuals, society, and the environment on the one side, and of safeguarding and helping the broader economy, on the other. Therefore, let us see a brief overview of the evidence that we possess today about health hazards that the hypothetical Orange Bubble Juice would pose in these three domains.

Regarding *individual* health, the product's chemical composition (product design) induces children to ingest more sugar than what is healthy (Harris et al., 2015). As is well-known, the building blocks of adult obesity are set in childhood (Longacre et al., 2016; Hartmann et al., 2017; Rigo et al., 2018), and dental health is among the most painful and immediate consequences of surplus sugar ingestion (Duijster et al., 2015; Mela and Woolner, 2018).

Regarding the *social* consequences, both obesity and dental destruction are high costs for the health services of societies that are paid by the taxpayer. Notably, for every $1 that the World Health Organisation spends on promoting nutrition, the food industry spends $ 500 on promoting processed foods (Boyland and Halford, 2011; Wold Health Organization, 2012–2013). Besides, on a small societal scale, the tantrums at the supermarket due to the product placement are clearly antisocial for the people around and yield high levels of stress in the parent. Other societal problems that have been related to the use of brain-hack methods from the marketing realm are social exclusion, negative social comparison processes, and exploitation of the workforce in third-world countries.

Regarding *environmental* consequences, to keep costs low, the production of chemical compounds and the wrapping is often outsourced to countries where worker's rights and production laws are less stringent. This is a common societal problem of today's world (Radfar et al., 2018), but also an environmental one since it leads to pollution, e.g., in terms of miles and in terms of pollution in the country of production where environmental laws may be less strict.

The Orange Bubble Juice Ad Dilemma illustrates that the way neuroscientific methods would be used to advertise this Orange Bubble Juice would not be aligned with current understandings of how to safeguard and promote human health and cognitive functioning. Such research would, therefore, not live up to current standards of what is considered ethical research practice for the social and behavioural sciences.

THE HELSINKI DECLARATION OF EXPERIMENTATION WITH HUMAN SUBJECTS

The Helsinki Declaration of Experimentation with Human Subjects (HD) Association (1964) by the World Health Organization (WHO) sets out the ethical principles that regulate medical research, and that are based in the The Universal Declaration of Human Rights (1948). As underscored by several international directives (US Department of Health and Human Services, 1979; Iphofen, 2009; European Commission, 2018), these apply as much to medical research, as to social and behavioural research endeavours, to ensure the The Universal Declaration of Human Rights (1948) of research participants are respected and protected.

The HD was set out after the atrocities committed by "scientists" during World War 2, to avoid that, ever again, humans and animals be abused for the purposes of "science." However, some may feel uncomfortable with the fact that we are now in a situation where it has become standard practice within some segments of research, to "use" human participants

BOX 1 | Figure 1 example.

As a hypothetical dilemma that a neuromarketer may find themselves in, consider the following collaboration between marketers and neuroscientists for a new type of sparkling orange juice for children, The Orange Bubble Juice. Neuromarketing and experimental psychologists are invited as collaborators from a university to help to market this new juice in the following way, acting on all four domains of marketing outlined in Section "Marketing and Neuromarketing: Some Definitions and History").

For the *product design strategy*, the neuromarketers proceed to design two types of experiments. Experiment 1 aims to determine which chemical composition of the juice pleases children the most. For instance, from research with other drinks, it is known that high levels of sugar are very pleasing due to the reward-related activations that sugar causes in the brain, and therefore induces the person to seek to drink more of the substance (and thus, boost sales). However, through negative taste bud-brain feedback loops, the brain will usually send signals to the gut that makes us feel satiated when unhealthy levels of sugar are reached. This stops the person from drinking more, which would be "unfortunate" for sales (i.e., sales would decrease). Let us assume that previous experiments have shown that adding the right amount of CO2 (bubbles) will numb the taste buds and facilitate ingestion of sugar, also beyond healthy levels. Experiment 1 will thus find the right ratio of sugar/bubbles (Di Salle et al., 2013; Sternini, 2013). Experiment 2 builds on the research that has shown that the artificial combination of a high number of different flavours that don't exist in nature, induces strong hedonic feelings due to strong activation of the reward system of the brain. Thus, experiment 2 seeks to determine the right mix of artificial flavours that would make the Orange Bubble Juice irresistible (Flood-Obbagy and Rolls, 2009; Endrizzi et al., 2019).

For the *pricing strategy,* the neuromarketers help to find the right number combination that causes a perceptual bias in the consumer (e.g., 1.99€ instead of 2€; Sands and Sands, 2012), or deciding how to overcrowd the price tag with multiple items making it difficult to distinguish the real price of each piece (Dooley, 2011). Besides, there are additional cognitive biases in the economic domain that can be used to design the pricing strategy, such as the "*today only, two for the price of one*" -strategy.

For the *placement strategy*, research about overstimulation of the senses and ego depletion might illuminate the best placement option for the product. If we place the Orange Bubble Juice, for instance, close to the cashier, and the packaging design has been successful, children are likely to see the product while waiting with their parents at the cashier. This placement strategy might cause some temper tantrums and uncomfortable moments for the others in the queue. However, it is a useful strategy to increase sales because parents often succumb to the shameful feelings caused by the temper tantrum of their child: They buy the product just to avoid the uncomfortable situation. Several research papers analyse the behaviour of children in supermarkets and discuss it as a health-problem. For the purposes of boosting the sales of the Orange Bubble Juice, this confirms that the parents of the children in the target group are likely to succumb to the tantrum, as in e.g., O'Dougherty et al. (2006); Maubach et al. (2009), Carnell et al. (2011); Henry and Borzekowski (2011), Lesser et al. (2012); Swinburn et al. (2013), Winston et al. (2013); Haselhoff et al. (2014), Mason et al. (2014); Tipton (2014), and Rigo et al. (2018). For the placement strategy, in general, the diversity of product availability has broadened exponentially in the past decades, making choices effortful. Research shows that choices that use the body's basic energy supply can, therefore, easily be depleted (Vohs et al., 2005), a process also referred to as ego-depletion. As a result, self-control fails and decision-making is impaired (Baumeister, 2002a, 2014; Baumeister et al., 2008; Pocheptsova et al., 2009). Psychologists refer to this phenomenon as decision fatigue (Pignatiello et al., 2020), which may be an important cause of impulsive purchasing that can be followed by regret because of money spent (Baumeister, 2002b; Sharma et al., 2010). It can be exacerbated by environmental changes; for example, perceived crowding and also employee friendliness boost sales (Mattila and Wirtz, 2008), as does peer presence (Luo, 2005). The neuromarketers working on marketing the Orange Bubble Juice take all of these into account in the placement strategy, thanks to knowledge from neuroscientific and psychological research.

For the *promotion of the product*, the neuromarketers conduct experiments to find the best design of the ad, given the target group. This area of neuromarketing has expanded in the past years, with neuromarketers aiming their experiments at improving the ad design so that it stirs peoples' emotions (Folkvord et al., 2016). The most efficient marketing efforts are those that tap into our basic needs. Maslow (1954) described different levels of needs of a person, the so-called basic needs (hunger, thirst, warmth, sex, rest), needs related to the person (safety needs, esteem needs, status, accomplishment, love, friends), and higher-order needs for self-realisation (achieving full potential, do creative activities, etc.). Whenever we fulfil one of these needs, we feel pleasure, and this makes us want to repeat (Kringelbach and Berridge, 2009, 2010a,b; Kringelbach et al., 2012). Much research has shown, that when needs are not filled, we crave the items, situations, or people that can help us quash the need (hunger, thirst, sex, etc; Maslow, 1964). Here, in our hypothetical example, depending on the target group of the orange juice, the neuromarketer could consider the socio-economic status of the parents and/or developmental stage of the child, and which needs might be at the forefront of the parent's/the child's brain, in order to design the ad to tap into that specific unfulfilled need "(real or engineered)" (Cao et al., 2013; Yunus et al., 2016). From a neuro-developmental point of view, children start to perceive the world around them around the age of 5 years and start appreciating the praise of their peers (Buss et al., 1979; Tangney et al., 2007; Dempsey, 2017). Until this time, advertisement related more to basic needs and perceptual stimulation is likely to be most successful. After that, ads related to person-needs like self-esteem and friends' praise can be considered. Thus, for the promotion strategy of this hypothetical juice, experiments involve the assessment of which colours catch children's attention most, whether the ad should include some "cool peers" of the target group, and whether or not, children react more to pictures of bottles where the configuration hints at a "hot summers day" (sweaty bottle and oranges in the pictures), like adults do, or not (see Folkvord et al., 2016, p. 27 and our **Figure 1** for a short analysis). Let's ask a provocative question: Would such endeavour be ethical? See **Figure 1** for an illustration of the Hypothetical Orange Bubble Juice Dilemma.

to understand how the human brain works with regard to purchasing decisions, with the objective to boost "the economy," regardless of what negative effects there may be for us as *individuals* (McDevitt et al., 2000; Köster, 2009), our *society,* and our *environment*. For instance, the addictive nature of some devices for the human brain can result in over consumption (Duke and Montag, 2017b; van Velthoven et al., 2018; Noë et al., 2019; Yu and Sussman, 2020), and resulting e-waste can harm the environment (Needhidasan et al., 2014; Duke and Montag, 2017a; Joon et al., 2017; van Velthoven et al., 2018; Noë et al., 2019; Singh et al., 2020; Yu and Sussman, 2020).

The ground ethical principle of the HD is that any scientist should work to *further* individual, societal and environmental health and well-being with their work. If their findings can be used, explicitly or implicitly, for the opposite, this fact must be part of the neuromarketers' ethical considerations and risk assessment before engaging in such research. In principle, researchers are committed to minimising risks for misuse. Besides, the HD is intended to be universal and binds researchers to an ethical creed, no matter where in the world they exercise their activity. Point 9 of the HD specifically stipulates that "*No national ethical, legal or regulatory requirement should be allowed to reduce or eliminate any of the protections for human subjects set forth in this Declaration.*" Even if a neuromarketer will not be involved specifically in researching the production in a different country, this doesn't alleviate them of their responsibility to understand and question the production context of the product before agreeing to collaborate in marketing a product.



FIGURE 1 | The Orange Bubble Juice from our Hypothetical Orange Bubble Juice Dilemma. Copyright: Sina HN Yazdi.

We now discuss four aspects that researchers in neuromarketing should consider carefully before helping any entity seeking a consumer neuroscience service. These four include (i) the use of deception, (ii) individual's dignity, (iii) adequate use of methods, and (iv) effects on the environment of the (neuro)marketing effort.

Deception

Point 20 of the HD stipulates that "*The subjects must be volunteers and informed participants in the research project*." This point relates to the use of "deception" in research. Participants must be *informed,* and provide *informed consent*, if scientists are involved in the research.

An important cornerstone in the ethical considerations of any researcher undertaking experimentation is the decision about whether or not **deception** is part of the research protocol (Kim, 2012; Nijhawan et al., 2013); for discussions about this issue, see Miller and Kaptchuk (2008); Boynton et al. (2013), and Plunk and Grucza (2013). There can be research questions, where deception must be used for the results of an experiment to be useful (e.g., Bortolotti and Mameli, 2006). In such cases, however, the ethical application that will be revised by the university ethical board must include an important part that justifies this, a risk assessment, and importantly, a debrief sheet would be needed that informs the individual that they are being deceived.

An example of a blatant violation of the informed consent principle, illicit use of deception and absence of a debrief sheet, was a case where Facebook employees collaborated with academic researchers to conduct a study that intentionally manipulated nearly 700,000 users' mood states without users' consent (Kramer et al., 2014). The company received significant public backlash for not acquiring users' informed consent in advance of participating in the study (Flick, 2016).

The HD requires the experimenter to inform the research participants of the objectives of the research, and to disclose that the knowledge gathered with the evidence from their participation in this research could potentially be used to market this product in the real world and thus produce the cited negative health outcomes to those that consume the product. Point 22 of the HD stipulates: "*In any research on human beings, each potential subject must be adequately informed of the aims, methods, sources of funding, any possible conflicts of interest, institutional affiliations of the researcher, the anticipated benefits and potential risks of the study and the discomfort it may entail*." And any research, including neuromarketing research, must respect point 19 that *"[. . .] research is only justified if there is a reasonable likelihood that the populations in which the research is carried out stand to benefit from the results of the research."* The neuromarketer should ideally evaluate their contribution to a marketing effort taking into account these considerations; what is the objective of the research and are the end-users likely to benefit from this effort, or eventually be disadvantaged?

The hypothetical Orange Bubble Juice dilemma above, just as the examples of the Torches of Freedom and the "added egg" of Betty Crocher Foods instant foods, all include methods aimed at deceiving individuals into doing, thinking or feeling something that they wouldn't otherwise be doing, thinking or feeling. Brief, the strategies used (informed by psychology and neuroscientific evidence about the human brain) exploit the functioning of peoples' brain to make them consume something they otherwise wouldn't. Of course, *false* advertising is a crime, however, the boundaries between what is true and false are often blurry, which makes such laws difficult to enforce. Even so, the US Federal Trade Commission (FTC) successfully sued Lumos Labs for their misleading advertising where they claimed that their "brain training" games could prevent Alzheimer's Disease (Hufford, 2016).

If we continue with the hypothetical Bubble Orange Juice dilemma, the strategies used - hypothetically - could be seen as deceptive:

- Product design (combination of flavours, use of carbonisation, etc.) to induce individuals to ingest too

much sugar (outcome for consumer: obesity, health complications);
- Juice placement close to cashier to manipulate child into having a temper tantrum (outcome for consumer: upsetting parents and the micro-society in a supermarket with temper tantrums, harming the parent-child relationship);
- Tricks on parents to make them buy the juice through ego depletion strategies or perceptual biases regarding the pricing (outcome for consumer: making individuals act in dissonance with their own values and convictions).

As stipulated by point 14 of the HD: "*The research protocol should always contain a statement of the ethical considerations involved and should indicate that there is compliance with the principles enunciated in this Declaration.*" Thus, if this was an experiment in a psychology lab-situation, given the possibility of these negative psychological and physiological health outcomes, the experimenter would be required to debrief the participant after the session: "We have produced the juice in such a way that you couldn't stop drinking it, and a possible side-effect that we anticipated was a conflict between you and your parents." This obviously sounds rather absurd in the context of a consumerist society, however, it illustrates the ethical principles against deception that researchers may want to abide by, within or outside academia.

To illustrate this point further, in the real-life context, no researcher is standing at the exit of any shop to "debrief" consumers, telling people that their purchases were engineered, and likely biased by, e.g., perceptual biases in number perception. However, if an ethical code of conduct is to be respected, then presenting an ad that involves elements of deception, does not stop being deceptive. Besides, theoretically, wouldn't this be against the human right of self-determination (The Universal Declaration of Human Rights, 1948, article 1, 2 and chapter IX, article 55), when the same stimulus (ad) is presented in a real-life context? Conceded, this may again be a somewhat philosophical question and such an idea may seem difficult to implement in the real-life context. Nevertheless, it may still be a question we want to think about as a society.

Such "debriefing" efforts, disclaimers, or other "information signalling" are starting to emerge in some countries. For example, the European Tobacco Products Directive (2014/40/EU) imposed in 2016 that health hazards derived from smoking must be printed on cigarette packages. Examples of other initiatives include nutrition labels with a colour code indicating overall nutritional quality (e.g., red, yellow or green) (Ducrot et al., 2016), or signalling with stickers that give information about nutrient contents at a glance (Egnell et al., 2018). Awareness of the meaning of these signalling etiquettes is not always high among the most vulnerable groups such as children and adolescents (Wojcicki and Heyman, 2012a). However, such initiatives, *at least*, have the potential to inform -or, debrief- the user. If such "disclaimers" were implemented more widely, it would be in keeping with international codes of research conduct: If neuromarketing methods have been used with manipulative intent (e.g., ad and product have been designed so that they likely reduce consumers natural self-restraint; the pricing and placement of the product follow strategies from cognitive science that result in perceptual biases that cause ego depletion and, eventually, impulsive buying in the consumer, etc.), the consumer must be informed about this at purchase. Promotional ads could include a short clause, about the type of deception used in the ad. For an arguably provocative example of a disclaimer for an ad, see the lower part of **Figure 2**.

Dignity

In 1957, Vance Packard published his seminal book *The Hidden Persuaders,* and one quote from the book goes as follows: *"At one of the largest advertising agencies in America psychologists on the staff are probing sample humans in an attempt to find how to identify, and beam messages to, people of high anxiety, body consciousness, hostility, passiveness, and so on"* (Packard, 1957/2007). This quote expresses a moral outrage at a company having the objective to manipulate us into buying something we don't need, based on our personality, moods, or other characteristics. It seems incredibly naïve seen from the perspective of today. It is now a mainstream marketing effort to use personality profiles and other "psychographic" variables of the target groups (e.g., Kotler, 1965; Henriques et al., 2009; Ghosh, 2010; Cisek et al., 2014; Cai et al., 2015; Graffeo et al., 2015; Udomkun et al., 2018; Ardeshiri et al., 2019). It became even more mainstream with the launch of Google personalised ads in 2005.

With the help of psychologists and neuroscientists, marketing personnel has long realised that "*past behaviour, habit and hedonic appreciation are usually better predictors of actual food choice behaviour than psychological constructs like attitudes and intentions*" (Köster, 2009). Most of our choices are not based on rational and reasoned deliberation, and there is often an intention-behaviour gap that can be exploited to boost sales, and which is mostly grounded in personality traits and life style (Weijzen et al., 2009). These can be targetted (/exploited) quite efficiently through personalised ads.

Let us see a couple of examples. One prominent neuromarketing firm proposes the possibility to use Smart TVs in the future to provide personalised ads to TV audiences. According to their figures, the use of smart TVs increased by 12% in the past years, and they see this as a great opportunity for advertisers to target people with personalized ads while they watch TV.

Is This Ethical?

If considering point 21 of the HD, which is reminiscent of article 1 of the Charter of Human Rights ("*All human beings are born free and equal in dignity and rights*"), and of article 22 of the same Charter (which affirms each individual's economic, social and cultural rights that are indispensable for their dignity and the free development of their personality), we may question whether the above objective with Smart TVs would be considered ethical from a research ethics perspective. Point 21 of the HD posits that "*The right of research subjects to safeguard their integrity must always be respected. Every precaution should be taken to respect the privacy of the subject, the confidentiality of the patient's*



In this add we use brain-hijack methods: Choice of image gives a sense of freshness (sweating bottle, orange). Choice of colors is based on children's color preferences (catches their attention more than other colors). The product design of this juice is artificially made more pleasurable than natural foods (combination of flavours, CO2 content). Research has shown that this type of combination can cause addictive behaviours in children and cause adult obesity because the sugar intake is beyond healthy levels of sugar according to the standards of the national health guidance.

FIGURE 2 | Hypothetical debriefing, or "information signalling" on the ad of the Orange Bubble Juice of our Hypothetical Orange Bubble Juice Dilemma. This "debriefing text" is intended to be thought provoking, and maybe somewhat provocative, as is the whole thought experiment about the Hypothetical Orange Bubble Juice Dilemma. Copyright: Sina HN Yazdi.

information and to minimise the impact of the study on the subject's physical and mental integrity and on the personality of the subject." Note especially the latter part of this point. The impact of a marketing endeavour for such Smart TV, with successful product design, pricing strategy, and placement strategy, does *not* preserve the individuals' physical and mental integrity and personality, if it is aimed at conditioning our behaviour to be in a way that it wouldn't naturally occur. To cite just one example that would speak against the use of Smart TVs for personalized advertisement is that TV viewing is already heavily associated with snaking behaviour, that is, children and adults ingest quantities of unhealthy foods they otherwise wouldn't have eaten (Thomson et al., 2008; Kelly et al., 2010; Parvanta et al., 2010; Thorp et al., 2013). If university-based neuroscientific tools and evidence gathered with these contribute to individuals in some way losing control over their own actions, experience cognitive dissonance, feel upset, etc., this is in breach of the principles of ethical research. Researchers must *"[. . .] protect the life, health, privacy, and dignity of the human subject"* (HD, point 10), and make sure that *"[. . .] considerations related to the well-being of the human subject [. . .] take precedence over the interests of science and society."* (HD, point 5).

As another example, let us consider smokers who have a dependence on cigarettes. Previous research has shown that their drug dependence can be tracked with neuroimaging techniques (McClernon, 2009). Based on this knowledge, and with the help of neuromarketers in product development, cigarette manufacturers can now test groups of cigarette addicts' physiological and/or brain responses when they are presented with new varieties of cigarettes. This could help find out which designs engage brain systems associated with reward and reinforcement best, with the aim to choose those with higher addictive potential (Bates and Rowell, 2004). Wouldn't such practices be questionable ethically, for example, due to the links that we know of today, between cigarette smoking and cancer (e.g., Stanton et al., 2016), and between addictive behaviour and other negative health consequences? It is known today that addiction impairs healthy decision-making and promoting substances that may lead to addiction does not seem to be in accordance with safeguarding individuals' dignity and free development of personality.

Let us now consider several additional empirical examples as an overview, about how multisensory stimulation through the product and promotion strategy is used to target senses of consumers in an unprecedented way. There is of course, in principle, nothing wrong with accumulating knowledge about consumer behaviour. However, the education of society should go hand in hand with any such endaveours.

Vision. In the food industry, it is commonly suggested that, for unhealthy foods, ads stimulating multisensory channels "work best" (Elder and Krishna, 2010), while single-sense ads are successful to advertise healthy foods (Roose and Mulier, 2020), and that manipulation of the visual field (e.g., background/packaging/colour, dark/pale) can lead to differences in expected flavour and boost sales indirectly (Carvalho et al., 2017; Spence, 2019). Colour, shape, size, and shining transparency, reflections, and special textures can play a role in costumers' decision-making processes (Manenti, 2013). In the beauty industry, it has been shown that among alternative products having the same function and price, those that are visually more appealing are more likely to be chosen (Creusen and Schoormans, 2005; Kim, 2010), and the visual product aesthetics is used to attract the consumer (Workman and Caldwell, 2007). For example, 40 percent of all perfume purchase decisions are based on the design of the bottle (Lindstrom, 2008).

Audition. Sound manipulation includes, for example, being exposed to positive music while tasting a product (Zampini and Spence, 2012). Research has shown that, for example, music can make a beer taste more appealing and sweeter to consumers, (North, 2012; Hauck and Hecht, 2019; Reinoso-Carvalho et al., 2019). Likewise, sounds related to the packaging or pouring of the liquid, and even the sounds of carbonation of a drink in a glass influence consumer's multisensory tasting experience (Spence and Wang, 2015; Wang and Spence, 2019). In one study, participants rated their coffee taste differently when hearing the sound of a coffee maker machine versus when there was no sound (Knöferle, 2012), and ate more potato chips if the packaging was proportionate to its content's crunchy nature (Smith, 2011). The sound manipulation can also be the sound of an aerosol spray (Spence and Zampini, 2007), or the background music playing in-store. Music is also used to create a brand identity, which can evoke a sense of pleasure, familiarity, and a willingness to spend more money and time. Classical music used to be played in Victoria's Secret stores which created an atmosphere filled with

prestige (Lindstrom, 2008). Many brands including New Look, Zara (Manenti, 2013), Hollister, and Abercrombie & Fitch have their specific playlist (Clarke et al., 2012).

Smell. Smell has been shown to be an effective means of connecting people with a specific brand. For example, Women's Wear Daily reported in 2009 that Abercrombie & Fitch "ha[d] spent more than $3 million in the last two years on fragrance machines in its more than 350 stores" (Seckler et al., 2009). Several studies show that a pleasant fragrance positively influenced consumers' affective reactions, evaluations, and intentions to revisit the store (Davies et al., 2003; Bosmans, 2006; Doucé and Janssens, 2013).

Touch. Another way to attract customers to a fashion product and make it more appealing is through touch (Spence and Gallace, 2011). It's the first tool for apparel evaluation named 'tactile marketing' (Grohmann et al., 2007). It has four main characteristics: texture, hardness, temperature, and weight (Peck and Childers, 2003). In fact, the absence of tactile experience may reduce the chance of pleasurable shopping experience (e.g., online, TV). To overcome this pitfall, researchers have used sensory-enabling presentations, specifically, image zooming and rotation videos, and have measured cognitive and emotional reactions during product evaluation and purchase decision processes (Jai et al., 2014). These techniques are said to compensate for the lack of touch.

The ethical considerations for a neuromarketer approached to collaborate in experiments as in the examples above, is to determine in which cases such manipulation through the senses allows individuals to preserve their dignity and free development of their personality. Public outreach activities spearheaded by scientists from these domains may also contribute to spread the knowledge about these processes to society. This would allow individuals to make informed choices about which products to engage with.

Ethical Use of Methods

Examples continue to surface indicating that that much research in the field of neuromarketing is unfortunately based on shaky assumptions about the human mind and brain, and neuroscientific research tools are applied without sufficient knowledge and training about their correct use, and importantly, about their limitations (see Stanton et al., 2017, for a review of such examples). It is the responsibility of the neuromarketer collaborating with firms from within universities, to manage expectations about the methods and their ability to generate meaningful insights for firms. Neuroscientific research might sound very "sexy" to some. However, if methods are not applied soundly, results are, unfortunately, deprived of any scientific validity. Besides, using human participants for research that is not underlying any validated scientific methods for the question asked, is also unethical.

For instance, the HD stipulates (in point 6), that "*even the best proven interventions must be evaluated continually through research for their safety, effectiveness, efficiency, accessibility and quality*", (emphasis added by the authors). By implication, research that is not useful (i.e., without effectiveness) and not done well, i.e., done using incorrect methods (i.e., no efficiency), is unethical, as it doesn't respond to the latest quality standards of psychological or neuroscientific research. The code, furthermore, stipulates that research should be "*conducted only by individuals with the appropriate ethics and scientific education, training and qualifications*" (point 12), and "*research involving human subjects must conform to generally accepted scientific principles, be based on a thorough knowledge of the scientific literature, other relevant sources of information,* (. . .)" (point 21). Stanton et al. (2017) who we quoted in Section "Introduction" with their serious qualms about consumer neuroscience, remind us of

> "*The canonical criticisms of neuromarketing—which arose at its inception and have remained prevalent today— and which include unethical research practices, unethical applications of technology, and manipulations of consumers. Yet, despite these criticisms, the volume of academic research in neuromarketing and related areas has grown steadily and now over 200 neuromarketing research and consulting firms have been founded across the globe (Plassmann et al., 2012). With the growth of the field, criticisms and fears of neuromarketing's purported power have not yet subsided— if anything they have grown.*"

Several well-known neuromarketing firms advertise online that they are able to use psychophysiological recording methodologies to give insights about "emotions" that consumers feel while watching an ad. They openly advertise that they are able to measure neurological and biological reactions of potential consumers and tie those to the success of an ad campaign, "lifting" sales significantly.

To mention just one review from the academic literature of carefully controlled research, we recommend the paper by Professor Kreibig. Her results show that there is no specificity of affective responses to be deducted from psychophysiological reactions (e.g., heart rate, sweat, posture, facial reactions, etc.) related to any categorical emotions (Kreibig, 2010). One can say, at best, that a psychophysiological reaction in response to a particular stimulus (if that has been time-locked within the experimental paradigm), correlates with a particular heightening or lowering in physiological response. Establishing causality is an entirely different question and requires careful experimental design.

Stanton et al. (2017), furthermore, argue that researchers in academia and neuromarketing have very different goals and approaches to collect the data and then interpret the result:

> "(1) *Scientific results are worthwhile only if the methods used to collect the data are sound. Yet, industry clients who hire neuromarketing firms are not likely to have sufficient background knowledge to evaluate the methods used to collect and analyse neuroscientific data.*
> (2) *Neuromarketing firms are incentivized to exaggerate their capabilities and potential deliverables to attract clients. Unlike the academic world, neuromarketing firms lack peer review when they report results to clients, and peer review protects against the risk of overstating results. For instance, the "case reports" that are often included on the web pages of such companies, are more often than not "internal reports" that have not passed by any quality filter, such as peer review.*

(3) *Moreover, neuromarketing firms tend to maintain proprietary control of data they collect. Neuromarketing firms also do not tend to publish or share their data collection protocols. This opacity means that the extent to which neuromarketing companies' data are valid, or in correspondence with their promotional claims, remains unclear. In contrast, academic science utilizes peer review as a self-correcting feature.*"

Stanton and colleagues conclude that due to the sophistication and lack of tractability of neuromarketing research methods, compared to traditional marketing research, third-party evaluation agents, such as the Advertising Research Foundation (ARF), could be organised with the goal of delivering a quality certification. This would allow consumers of neuromarketing research to make a more informed choice regarding the product that they are purchasing from neuromarketing companies. See Venkatraman et al. (2015) for an example of such endeavour.

Another problem for companies interested in purchasing a neuromarketing service, is that when used properly, neuroscientific methods often do not show anything that the marketer didn't already know (Harrison, 2008), which doesn't justify the high costs of using neuroscientific methods.

See **Figure 3** for an example of an old joke regarding the power of neuromarketing to tell marketers anything that they didn't already know.

Environment

When research is conducted in collaboration with academic staff from publicly funded universities, universities require researchers to give some prior consideration to the potential misuse of research results, and they are asked to write a risk assessment. This includes potential harm or risks to individuals, societies, and the environment. In the case of neuromarketing research, this may include considerations about how to safeguard the latter three from these potential harms and risks. For this, three points of the HD are noteworthy: "*It is the duty of the [researcher] to promote and safeguard the health, well-being, and rights of [individuals], including those who are involved in [the] research. The [researcher's] knowledge and conscience are dedicated to the fulfilment of this duty"* (point 4), and "*research should be conducted in a manner that minimises possible harm to the environment*" (point 11), and "*appropriate caution must be exercised in the conduct of research which may affect the environment, and the welfare of animals used for research must be respected*" (point 12).

Societies are increasingly consumerist, and this has a negative impact on individuals, societies, and the environment (Seiffert and Loch, 2005; Ghosh et al., 2016; Aschemann-Witzel et al., 2017; Rohm et al., 2017; Janssens et al., 2019). Several international bodies and associations have highlighted that we need a sustainable consumption strategy (Ellen, 1994). At the World Economic Forum (2012) it was emphasised that businesses might need support to reshape demand to promote sustainable consumption (Kaufmann and Panni, 2017). Neuroscientific knowledge about behavioural change can be useful to help businesses change the "fast consumption" mindset to a "sustainable consumption" mindset, such as, for instance, the promotion of a circular economic model (Milios, 2018; Ruiz-Real et al., 2018; Moraga et al., 2019), or emphasise the possibility of developing sharing economies (Querbes, 2018; Sands et al., 2020). However, if neuromarketers collaborate for the opposite to help increase consumerist behaviour, this should potentially be considered as violating the HD in terms of working to safeguard our environment.

FUTURE NEUROMARKETING?

One argument put forward by companies using persuasive advertisement is that we are all free to choose to purchase the products, services, experiences, etc., that they promote, or not. The companies do not oblige or coerce anyone into consuming.

And, that's the crux of the problem:

Are we free, and do we choose what we *do* and *don't do* at our own *free will*? Am I the *true* agent of my actions?

The Free Will debate has a long tradition within philosophy. The view that we have a "Free Will" (Dennett, 2003, 2004) is counterposed to deterministic views (Caruso, 2012, 2018). The deterministic, or, consequentialist view contends that our present behaviour is conditioned by previous events, and thus our actions are not entirely *free*, they are pre-*determined*. Events that happened in the past *cause* us to act in a particular way in the present. Notably, this view has received some backing from research in cognitive neuroscience. One seminal study by Libet and colleagues showed that research participants' brain activity suggested that there was an activation pattern of action preparation, measurable in the motor cortices of the brain, milliseconds *before* the individual *was aware* of wanting to perform that action (Libet et al., 1983). This finding has been confirmed repeatedly ever since, and it implies that we are not entirely the conscious agents of our actions, as we like to think (Haggard et al., 2002; Engbert et al., 2008; Filevich et al., 2013).

In Section "Dignity," we outlined examples of how specific variations in perceptual features (vision, audition, touch, smell, etc.) increased purchasing behaviour. Were these consumers entirely "free" when choosing? If it is true that "*past behaviour, habit, and hedonic appreciation are better predictors of actual food choice behaviour than psychological constructs like attitudes and intentions*" (Köster, 2009), then it would be recommendable that neuromarketing endeavours underlie ethical research codes to safeguard individuals (Dennett, 2010; Klemm, 2010; Brembs, 2011; Pereboom and Caruso, 2018).

The dilemma is outlined in **Table 2**. Situations A and B are the same in terms of the intention of the person, "*I'll go to the show and buy X."* The question is whether their purchase decision will be different, depending on situation A or B, in terms of the ultimately chosen product to purchase, number and types of



FIGURE 3 | Illustration inspired by a well-known joke in neuromarketing. Copyright of the illustration within this paper: Sina HN Yazdi.

additional products purchased (that were not part of the initial intention), etc.

We can say that it is, *theoretically,* correct that people are free to choose, whether or not they buy a product. Freedom of choice is a basic human right, we are free; Article 1 of the The Universal Declaration of Human Rights (1948). However, considering what we know about human cognition today in the realm of consumer behaviour, we may doubt that our decisions are entirely "free" (e.g., Berthoud, 2007). This implies that we need (1) to safeguard individuals against manipulation that can lead to detrimental effects of the individual, societies, or the environment, (2) to regulate persuasive advertisement, and (3) to educate ourselves as consumers about how our brain can be manipulated during a purchase decision.

Empirical research shows that very often our choices and behaviours during purchasing decisions are, at least in part, determined by three main processes:

(1) *habit loops* (especially those related to basic need satisfaction);
(2) *elicitation of aesthetic emotions* (e.g., being moved, awed, attracted, made curious, impressed, etc.);
(3) *perceptual and cognitive biases* (e.g., number biases, and the distancing bias).

As we will see in the next sections, these three processes modulate our decisions. We will briefly review how (1) *habit loops* (Section "Habit Loops"), *aesthetic emotions* (Section "Move Me! Move Me to Act. . . Aesthetic Emotions"), and (3) *perceptual*

TABLE 2 | Illustration of two possible situations, outlining the dilemma of the effect of the presence of persuasive advertisement on ultimate purchase decisions.

Intention				
Situation		**Persuasive advertisement on the way / in the shop?**		**Purchase decision**
A	"I'll go to the shop and buy X"	➡ ✓ ➡		?
B	"I'll go to the shop and buy X"	➡ ✗ ➡		?
		Time		

biases (Section "Perceptual and Cognitive Biases") condition our purchasing behaviour.

When is it ethical, and when is it not?

Habit Loops

Is neuromarketing research simply aimed at benefitting the individual and society, by giving individuals and societies "*what they want and truly desire*" (Bernays, 1928/1955/2004; Dichter, 1960/2012/2017; Papakonstantinou, 2019)**?** In keeping with the idea set out above, that our decisions to purchase a product are not entirely free if persuasive advertising is used, the answer to this question is "no." What we think we "need" and what the human body and brain actually need from a psychological and physiological health perspective, is not always aligned if persuasive ads target the habit loops of our brain.

Habit loops are learned cue-reactivities of our brain. Stimuli related to our basic needs (food, drink, shelter, sex, sleep; Maslow, 1943) trigger strong activations of the reward systems of the brain and strong subjective hedonic reactions (Kringelbach and Berridge, 2009, 2010b). Receiving "pleasure" causes us as individuals to develop a strong motivation to repeat the behaviour that led to this pleasure also in the future. As the contingency between stimulus and pleasure becomes stronger ("*if I do Z, I will feel pleasure*"), the organism is *learning*. This means that circuits in the brain become optimised into motivational loops that aid the execution of the behaviour in the future without much conscious effort. The basic principle at play here is known as operant conditioning in psychology, a basic principle of learning (Skinner, 1937, 1938, 1966, 1986). Thus, habits are learned behaviours (i.e., outcome/contingency-based learning) that require little conscious effort. This is basically a way to save energy resources for the brain (Knowlton et al., 1996; Shohamy et al., 2004; Bayley et al., 2005; Ashby et al., 2010).

The ability to develop habits is a very adaptive feature of the human brain, allowing optimisation of resources, and ultimately, optimisation of behaviour. It is helpful not having to plan out every sequence of behaviours that leads to a goal.

However, habits also leave a gap in our awareness. Therefore, it is important to supervise wisely which habits we develop. Considering that habits are behaviours that we *do,* that occur without much awareness, it is clear how habits can be dysfunctional for our health.

An example for a positive habit could be: **Cue** → "*going to bed*"; **behaviour associated with that cue** → "*brush your teeth*"; **reward associated with the behaviour:** "*fresh clean feeling in the mouth, no plaque.*"

An example of a habit that has negative consequences for our health could be: **Cue** → "*I feel nervous when I am with other people*"; **behaviour associated with that cue** → "*I grab a cigarette*"; **reward associated with the behaviour:** "*calm feeling, nervousness is gone*" (e.g., see Naqvi et al., 2007 for the social aspect of smoking addiction).

Some techniques from the (neuro-) marketing industry are directly aimed at bridging this habit-gap of our awareness to drive individuals toward purchase, irrespectively of any negative consequences for the individual, society or environment. The example of a habit with negative consequences above illustrates this. In this gap lies the challenge for the (neuro-) marketer of the future, to align their activity with current understandings of ethical research, and knowledge about the human brain. To put it slightly provocative: People don't *need* the amounts of sugar that soft drinks contain, even if they *want* them. They also don't *need* a smartphone of the newest generation whose expense sends their bank account into bankruptcy, even if they *want* it. And people also don't *need* burgers that have a too low nutrient content for the amount of fat that they contain, even if they say that they really *want* that burger (Roos and Wndel, 2005; Zheng and Berthoud, 2007; Berridge et al., 2010).

Enjoying pleasure requires the right education (Christensen, 2017). The reason why people might be convinced that they *need* these things is because their brain has developed a habit and craves these items like a drug addict craves a drug (Köster, 2009). The same goes for other types of products, like downloadable music, games, or artworks. Even the pleasure that we feel from higher-order pleasures like music and arts, rely on the exact same neural substrates as drugs and addiction to drugs (Kringelbach and Berridge, 2009, 2010a,b). Hence, anything that leads to overuse of these products that can stimulate the reward circuitries and induce *craving* deprives us of our healthy decision-making behaviour. This can make our behaviour shift from being a conscious action to a bad habit, and from there to becoming a compulsion (Frijda, 1987; Delgado et al., 2005; Everitt and Robbins, 2005).

For example, high-calorie food cues in ads (designed with the help of neuromarketing efforts?) trigger our sugar habits and make us crave, just like a drug addict craves their drug. Research shows that if such potent habits are learned in early childhood, a high reactivity of the reward system to high-calorie food cues will never subside. This makes the development of obesity highly likely (Birch et al., 2007; Biro and Wien, 2010; Craigie et al., 2011; Movassagh et al., 2017).

Another aspect of a food/drink product that can induce such habits is another aspect of the product's composition. The "bliss point" in food design refers to the perfect mix of sweet, fat and salty in a product, and is the result of a neuromarketing effort, aimed at finding the most hedonic mix of ingredients to make the product highly hedonic, provoke a strong pleasure response that will increase the motivation of the individual to ingest the juice again, each time a cue related to the juice appears. Such mixture, however, increases ghrelin (a so-called hunger hormone) concentration in blood, inducing hunger feelings in the individuals. In principle, this process is good, since it starts off digestion (saliva and gastrointestinal systems are set to be ready for digestion). However, these processes also initiate if the nutrient content of the food is zero, which is the case with junk food, that is deprived of nutrients (vitamins, minerals, fibres, etc.). The body, ready for digestion, will keep sending signals to the brain to ingest more, even if the caloric intake (calorie intake is not the same as nutrient intake) already surpasses healthy levels (Flood-Obbagy and Rolls, 2009; Halford and Harrold, 2012; Van Kleef et al., 2012; Moss, 2013), the result of this is overeating, and eventually, obesity.

Already in 1957, Packard expressed his concern in relation to the overuse of advertising, highlighting the risk of manipulating

customers into over-consuming (Packard, 1957/2007), and puzzlingly, today, the food industry is still allowed to target children with persuasive advertising for products like sugary drinks.

To give one beat more detail of what we know today about sugary drinks' effect on the body: From a nutritional point of view, there is absolutely no reason for a child to ingest sugar, considering current knowledge about the effects of sugar on the consumer's brain and, subsequently, on their body, and then, subsequently, on the societies' economic burden due to ill health and dysfunctional behavioural patterns. Besides, studies show that no level of processed fruit (juice, puree or juice with fibres) has the same effect on satiety as a real fruit (Wojcicki and Heyman, 2012a,b). In one study, participants were given a processed fruit serving or a real fruit to eat 15 minutes before a meal. After the meal, the group of people that had eaten the real fruit felt more satiated and felt fuller than any of the groups that had consumed processed options (Flood-Obbagy and Rolls, 2009). One study showed that serving fruit juice to children should potentially be questioned altogether, given the adverse health effects (Wojcicki and Heyman, 2012b).

This is a clear example where what people want and desire (more sweet juice), is not what they (their body) really need. And the reason why they "want" it, is the presence of cues related to the juice and the pleasure that is expected, which triggers the habit (behaviour) to ingest it. The same goes, for many other things that we may engage with, including products related to social media, films, music, gaming, pornography, etc. (Kalivas and Volkow, 2005; Grant et al., 2010; Freimuth et al., 2011; Gearhardt et al., 2011; Olsen, 2011; Alavi et al., 2012).

We may find the fine line that differentiates a healthy product or service from an unhealthy one by asking ourselves a question: Is the content of the product or service that the neuromarketer is hired to investigate junk or genuine? "Genuine" content is content that is ethical from the standpoint of today's knowledge about the human brain, our societies, and our environment. This implies that the content, the advertising, the sales strategies etc., don't hamper individuals', societies', and environmental health. By implication, the use of neuromarketing methods to boost sales with persuasive ads is not in itself bad. Let us end this section with some examples where knowledge about how the brain reacts to a conditioned cue has produced positive outcomes for individuals, as well as for industry.

First, persuasive advertising for toothpaste. In the 1950s, toothpaste manufacturers were not very successful in marketing their products, until they used knowledge about how attention to sensory cues can drive behavioural change, and even form "good habits." "The sense of freshness with mint" became the cue that everyone could feel through brushing their teeth. The sensory cue that the persuasive ads proposed to get rid of it was: plaque (Fischman, 1997; Miskell, 2004; Aunger, 2007). Now, every time that consumers would identify "plaque" with their tongue on their teeth, they would know what to do: brush their teeth to get the taste of mint that is "so fresh" and "clean" (Hopkins, 1998; Hujoel, 2019). This boosted the sales numbers of the companies involved, increased individual health (because the use of toothpaste resulted in better dental health), and lessened the economic burden of the society due to ill dental health burden on the health services.

Second, resealable packages for a better self-regulation are another example (Plassmann et al., 2008; Reimann et al., 2010). Optimal food packaging strategies (with the right cues!) can help consumer self-regulation. One study found that if an energy-dense food product is offered in a resealable package, this helps consumers self-regulate their consumption and thus eat less palatable foods (De Bondt et al., 2017).

Third, reduce ad volume (Stallen et al., 2010). Ad volume is in itself a problem due to the sensory overstimulation that it entails for us in our everyday lives (Baumeister et al., 2008; Baumeister, 2014). Targetting segments of consumers more directly and selectively may help to reduce ad volume be the way forward more directly and selectively (Venkatraman et al., 2012), reducing ad volume. This is not an invitation to personalized ads regardless, but for ethically designed personalized ad procedures.

Fourth, neuroscientific techniques can also help gain deeper insights into the neurobiological mechanisms of compulsive purchasing, and then assist the development of awareness campaigns, e.g., in collaboration with policymakers and other stakeholders in the domain of health promotion (Black et al., 2000; Fortunato et al., 2014).

Move Me! Move Me to Act. . . Aesthetic Emotions

Aesthetic emotions are another set of potent drivers of consumers' choices. Aesthetic emotions are emotions that we feel in the everyday context, for example, in response to artworks, films, music, dances, architecture, nature scenes, etc., and also when faced with a product, service, person or idea that is being marketed. Aesthetic emotions include (but are not limited to), *being moved*, feeling *awe*, *fascination*, *surprize*, *suspense*, *elation*, *caring*, *tenderness*, *pity*, *shock*, *fear*, *guilt*, *shame*, *outrage*, *disgust*, etc, and they cause an affective reaction in us (Menninghaus et al., 2019). For empirically grounded theoretical stances about aesthetic emotions, see, e.g., the Multicomponent Model of Aesthetic Emotions (Menninghaus et al., 2019), or the Vienna Models of Aesthetic Appreciation (Leder et al., 2004; Pelowski and Akiba, 2011; Pelowski et al., 2016, 2017) and see also (Chatterjee, 2003, 2011) for the framework behind neuroaesthetics as a discipline. Physiological responses that occur when we have an aesthetic episode include, but are not limited to, unspecific activation patterns of the autonomic nervous system (measurable as changes in heart rate, galvanic skin response, pupillary responses, etc.), chills/goosebumps, tears, shivers (Pelowski and Akiba, 2011; Pelowski, 2015; Pelowski et al., 2016; Tinio and Gartus, 2018), that are likely related to the subjective experience of an emotional reaction to what is being perceived. Besides, aesthetic emotions may implicitly stir a call to action in us (Keltner and Haidt, 2003; Konecni, 2005; Markovic, 2010; Pelowski, 2015).

There are several aspects of a product or service that have the potential to elicit aesthetic emotions. As examples, take a look at the orangutan commercial and the MR W commercial, that induce us to reconsider the use of products that contain palm-oil, and to choose wind-energy if we can. Or, consider, this deeply *moving* commercial for a soap.

Anything that stirs our emotions can induce basic tendencies to approach or to withdraw in us – in terms of consumerism: to purchase or not. Emotions generally trigger two basic behavioural tendencies (pleasure and displeasure) that motivate individuals to either approach (and wish to move toward/possess), or withdraw from (and avoid/wish to discard) the stimulus or situation that is causing the affective reaction in us. Basic theories of motivation and emotion suggest that this affective reaction primes our behaviour (approach or avoid) (for a review, see Harmon-Jones et al., 2017). Such behavioural approach-avoid tendencies are also extensively studied with regards to food cues in the lab, as a measure of implicit bias toward certain foods, for instance, evidenced with push-pull (withdraw-approach) kind of experimental paradigms (Werthmann et al., 2014; Lender et al., 2018; Meule et al., 2019a,b). These findings provide insight into the biases in our choices that occur as a consequence of the emotional states that are evoked in us through a marketing effort (be it in product design or the promotion strategy).

Commercials that use strategies to trigger aesthetic emotions can change our behaviour for the better ("better" here meaning "enhancing" for individual, societal and environmental health). However, some other commercials give a different flavour, when the product itself is ethically questionable, for instance, due to its contents, or due to the way it is produced (respecting or not workers' rights and environmental sustainability in the country and location of production).

Let us consider the following examples where consumers' aesthetic emotions of curiosity, surprize, outrage, being shocked, and beauty are being used both to bond them to a product/brand but is at the same time used to reinforce racist or religious stereotypes:

For example, this clothing commercial, this beer commercial, and this detergent commercial. These campaigns thankfully stirred important social backlash. As did this other soap commercial for being racist (Simms, 2017; Wootson, 2017).

For the neuromarketer the basic question here is: the aesthetic emotions that I'm helping to trigger (e.g., awe, surprize, outrage, etc.), what are they for? Can they be harmful for consumers psychologically, or physically (Murray, 2013). It is important to ensure that Article 2 of the Charter of Human Rights is respected:

> "*Everyone is entitled to all the rights and freedoms set forth in this Declaration, without distinction of any kind, such as race, colour, sex, language, religion, political or other opinion, national or social origin, property, birth or other status. [. . .].*" (United Nations, 1948, Article 2)

We experience aesthetic emotions in response to stimuli that reach our senses (vision, hearing, touch, smell, taste). They have the potential to motivate us in one direction or another. We may feel change of mindset and want to improve something in our life after an aesthetic episode, like after a movie, a dance, a piece of music, or after having seen the commercial with Mister W. These emotions can, however, also be misused (like making people feel admiration for the ladies carrying the "torches of freedom" alluded to in Section "Examples of "Helping Consumers Get What They 'Need' "". Spectators were induced to feel admiration and a drive to be like these "free" women with the Torches of Freedom, and therefore, to smoke).

Perceptual and Cognitive Biases

In the hypothetical dilemma of the Orange Bubble Juice (in Section "Neuromarketing Present"), we mentioned the cognitive and perceptual biases that are being triggered wilfully, using the knowledge about biases of the human brain to condition consumer choices, especially, in the pricing and placement strategy of the product, including the use of ego-depletion strategies, number biases, etc.

Human choices are invariably infused by perceptual and cognitive biases. A long research tradition in psychology, and, more recently in cognitive neuroscience studies these irrational determinants of human choices (Tversky and Kahneman, 1981; Harmon-Jones and Mills, 1999; Kahneman and Tversky, 2000; De Martino et al., 2006; Santos and Rosati, 2015; Linares et al., 2019). Research in experimental psychology and cognitive neuroscience shows that repeatedly resisting temptations in an environment scattered with cues promising pleasure, where we must repeatedly regulate our affect and control our behavior, can deplete cognitive resources (Muraven and Baumeister, 2000; Saleh, 2012; Hirt et al., 2016; Martela et al., 2016), and affect the body's basic energy supply (Vohs et al., 2005). When this resource is depleted, self-control may fail and decision making is impaired (Baumeister, 2002a, 2014; Baumeister et al., 2008; Pocheptsova et al., 2009). Some research links ego deplesion to impulsive purchasing (Baumeister, 2002b; Sharma et al., 2010). Nevertheless, such an overcrowded visual field is approved, in every supermarket, everywhere in the world.

Another important cognitive bias is brought to our brain by celebrity endorsement. One study conducted in India showed that celebrity credibility has a significant impact on consumers' attitudes toward the brand and advertisement, and on purchase intention (Singh and Banerjee, 2018). On the other hand, followers in social media may be connected emotionally to influencers which may increase the chance of behavioural inclination to accept the influencer's endorsement (Bragg et al., 2016; Cuevas et al., 2020). Unfortunately, many such endorsements are for products that probably would not meet the criteria of being healthy (Zhou et al., 2019).

The question for the neuromarketer is always *why* they wish to trigger a perceptual or cognitive bias during the marketing process, and for *which* product, idea, person or service that they are being asked to assist a marketing endeavour. What is the final outcome and what it does to people ethical from the point of view of the Helsinki Declaration for Experimentation with Human Subjects?

THE DILEMMA

It has been argued that if purchase behaviour of consumers in the market is left unprotected, it will ultimately become a catalyst for unscrupulous and unethical business practices (Titus and Bradford, 1996). This could lead even consumers that commit to ethical consumerism into a deep attitude-behaviour gap, where expressed attitudes (intention to be an ethical consumer) are not matched in behaviour (purchase decisions) (Chatzidakis et al., 2007). However, if policy makers propose regulations of the market, voices are very fast to say that this might put the economy at risk. Puzzlingly, by implication this means that the industry acknowledges that the strategies used are aimed at enticing consumers to over-consume. Detrimental effects on individual, societal and environmental health are discounted as "side-effects," according to the utilitarian moral philosophy. The "Greater Good" here is the "health" of the economy, according to the consumerist economic model (Boström, 2005).

The type of threats that come from the industry toward policy makers were exemplified in July 2020 where the United Kingdom was to introduce a ban on sugary food ads before 9PM because a clear positive relationship between obesity and Covid-19 had been found. The proposal to ban certain ads before 9PM came from the United Kingdom Prime Minister.

Economists were fast to condem this intention to ban such ads as "dangerous." One article warned that the predicted cost to the United Kingdom's economy of the ad ban would be around $1.3 billion, and that this ban would probably lead to a raise in prices for consumers (Morales and Swint, 2020). It was summarised by the chief operating officer at the Food and Drink Federation, as *"[. . .] new restrictions on promoting and advertising everyday food and drink will increase the price of food, reduce consumer choice and threaten jobs across the U.K."*. A different outlet read "*The government's new obesity strategy for England will raise prices, reduce consumer choice, threaten jobs and stifle innovation. And all to save 17 calories a day*" (Morrison, 2020); using "ridiculing" to take credibility from the proposal (i.e., "17" calories doesn't seem much making the possible gains of the proposal seem insignificant, on the expense of a great cost).

Let us consider this dilemma that the Prime Minister now faced through the lens of research on moral judgement (for a review, see Christensen and Gomila, 2012). The prime minister stood before this choice:

(A) ban ads before 9pm and risk jobs,

vs.

(B) allow the ads before 9PM and risk an obesity pandemic on top of the Covid pandemic.

In moral judgement research, a dilemma is a hypothetical situation where two different chains of events are possible. Each chain of events leads to some type of harm. These are different types of harm, but harm nonetheless. Research participants are then asked to, hypothetically, *choose* which of the proposed chains of events they prefer. For example: do you pull a switch to redirect a trolley so that it changes its course and kills one person instead of five people that would die if you don't intervene? (Foot, 1978; Thompson et al., 1981; Greene et al., 2001). Similarly, the Prime Minister faced a dilemma about who to save (children or jobs?), and who to sacrifice (children or jobs?). See **Figure 4**.

In addition, another ingredient that we know from moral judgement research was present in the prime minister's dilemma: our own relationship to the saved or to be "sacrificed" individuals, is a factor that has been called "Benefit Recipient" in moral

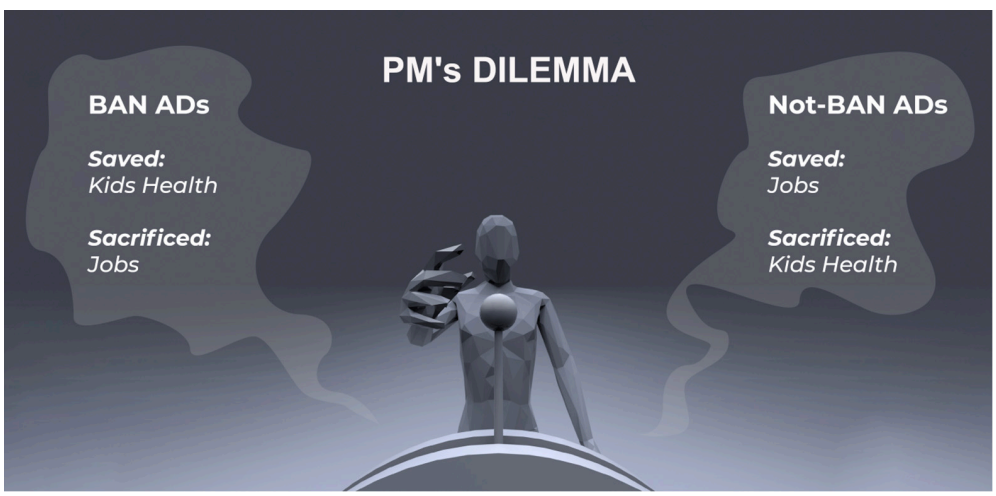


FIGURE 4 | The moral dilemma faced by the UK Prime Minister. Observe the two possible judgements about this dilemma: we can choose to refrain from acting (and cause harm by omission we don't act, or we can choose to act (and cause harm by commission this will save people (because they don't get obese in the first place), but harm people that will lose their jobs until the economy has restructured itself. Designed by all authors. Illustration by Sina HN Yazdi.

judgement research (Christensen et al., 2014). The background at the time was that the Prime Minister had just recovered from a serious Covid-19 episode, that likely had been exacerbated by his own high BMI, and he had become a father to a baby-son. Thus, his choice was suddenly not only a dilemma between jobs and health, but also a very personally relevant moral dilemma. The dilemma had now become a type of dilemma, where the outcome, if the agent choose to act (i.e., here: ban ads for unhealthy foods before 9PM), would be a "self-beneficial" outcome, because it would be benefical to the agent themselves or their kin. The individuals to save, by imposing an ad-ban of this kind, are in this case himself and his baby-son. As evidenced by the research on moral judgement, it is always easier to consent harm (in this case to "the economy"), if the harm produced is "self-beneficial," i.e., relevant to our own benefit.

At present, the above example of a successful ban for palatable drinks ads is rather unusual. The most common situation is that there are stark warnings from potent stakeholders that "overregulating" food, drink and cigarette markets would be turning countries into "nanny-states" that will feel patronising for citizens (Rouch et al., 2010; Wheeler, 2018; Nanny State Index, 2019). For sure, European countries like the United Kingdom are considered among the most patronising in this respect, and European countries like Germany among the least so (Austin, 2016; Nanny State Index, 2019). Generally, citizens dislike a state that aims to "protect" them from themselves' (Kwon et al., 2019), for instance, in terms of food policies to promote healthy diets (Kwon et al., 2019), and it is true that more regulation isn't always the best solution (Peters et al., 2013).

However, from a different point of view, "*The nanny state critique is ultimately a call for the state to be agnostic about the health of citizens, allowing market forces to dominate*" (Magnusson, 2015, p. 1). Besides, as reviewed above, also research in cognitive neuroscience shows that the story isn't as easy as that, that we are not as free as we think we are, when we choose to purchase something that is detrimental to our health. Therefore, adopting a view that sees "*legislation* [as a way that] *brings about changes that individuals on their own cannot, and sets new standards for the public good. Rather than condemning such activity as 'nanny statist', it might be more appropriate to view it as a form of 'stewardship'*" (Jochelson, 2006, p. 1), which seems more adequate. Such legislation might be informed, among other factors, by what we know about the human psyche and brain at present from psychology and neuroscience.

On a very basic level, legislating neuromarketing research practice following the principles set forth in the Helsinki Declaration for Experimentation with Human Subjects would be a first important step. Then the point would be about identifying, via democratic processes, what basic liberties a society can agree on with regards to (neuro-)marketing endeavours, and which then should be protected by law. This is a different form of freedom than leaving citizens to their own fate, full well *knowing* that this will contribute, for instance, to the global social and economic burden of poor health (Pettit, 2015; Kwon et al., 2019).

FINAL CONSIDERATIONS

On the basis of our non-exhaustive analysis of available literature in this domain throughout this article, we propose several take-home messages:

(1) ***Scientists/academics at universities and research institutions working with industry:***
- Read the Helsinki Declaration of Helsinki for Medical Research Involving Human Subjects, especially regarding the points (i) use of deception, (ii) how to safeguard individuals' dignity, (iii) adequate use of methods, and (iv) how to safeguard effects on the environment.
- Perform a proper risk assessment prior to any research activity (as is costumery within academic research), specifically regarding whether the evidence that would be gathered with this research could be misused to exploit individual, societal and the environmental health to favour financial gains of a small number of individuals. And, work minimise any such risk.

(2) ***Companies, classical marketers, producers of ads, artists working in the marketing business, etc.*:**
- Consult professionals that have a scientific background and who are trained in applying ethical research practices.
- Collaborate only with adequately trained scientists who are able to apply the right methods, and at the same time can contribute to elaborate cost-benefit plans as well as risk assessments regarding potential risks to individuals, society and environment, while keeping the potential benefits for the company in mind.

(3) ***Policy makers, individuals working in NGOs, etc*:**
- Evaluate the potential impact of certain neuromarketing practices for individual, societal and the environmental health and wellbeing, with the help of adequately trained scientists.
- Undertake risk assessments to inform whether regulatory endeavours are needed to safeguard individuals, the society and/or the environmental from some neuromarketing practices.
- Contribute to the discussion about *whether* and *which* risk-signalling endeavours might be useful on packaging etc., to inform consumers, and societies of potential risk (e.g., as proposed as a "disclaimer" in our provocative Hypothetical Orange Juice Dilemma example).

(4) ***Individuals*:**
- Educate oneself regarding the effects of persuasive advertising on our body and brain, and ultimately on our decision making in the consumer choice domain.
- Avoid exposing ourselves to potential manipulation of persuasive ads (e.g., switch off TV during ad blocks, instal ad blocker in computer browser, etc.).
- Educate children as much about the risks of too much fat and sugar intake, as of the hazards of succumbing to a persuasive advertisement.

Conclusions

The Helsinki Declaration (1964) is inspired by the The Universal Declaration of Human Rights (1948). It was brought forward after the turmoil of the Second World War, to prevent that, ever again, research should be carried out that fails to safeguard individual, societal and environmental health and wellbeing. It has been endorsed additionally by several international directives since then (US Department of Health and Human Services, 1979; Iphofen, 2009; European Commission, 2018), and it has been clearly stated that these apply as much to medical research, as to social and behavioural research endeavours. This means, these guidelines for ethical research also apply, in their entirety, to the domain of Neuromarketing research.

We have outlined that both individuals as consumers, and policy makers assuming stewardship, can assist the neuromarketing researcher to move toward an ethical research practice in this domain.

Limitations

Individuals (consumers), the neuromarketer and the steward face important obstacles. The consumer, due to the biases of our human brain, the neuromarketer due to pressures from industry and the need to earn a living, and the policy maker, due to the warnings and threats from the industry of job losses and economic hardship if the marketing effort is regulated.

Outlook

The Neuromarketing Science and Business Association (NMSBA) has provided a Code of Ethics, that members can sign up to voluntarily. This code takes into account precisely the important ethical guidelines that should govern any research with human subjects. Such self-regulatory efforts should be promoted extensively. The most important step for neuromarketers of the future, as much as for companies working in the marketing business in general, is to familiarize themselves with the available ethical guidelines that regulate research with human participants in general, and then apply these to the (neuro)marketing domain. The Code of Ethics of the NMSBA provides a useful starting point.

AUTHOR CONTRIBUTIONS

JC: conceptualisation, literature search, main responsible for providing drafts and revisions of the manuscript. FF: conceptualisation, literature search, provided revisions of drafts, and lead discussion rounds. MV: literature search, provided critical revisions of manuscript drafts, content check, and reference management. SY: conceptualisation of summary figures, critical revisions of manuscript drafts, and content check. All authors contributed to the article and approved the submitted version.

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Conflict of Interest: FF and SY were employed by 3Fish Corporate Filmmaking, Tehran, Iran.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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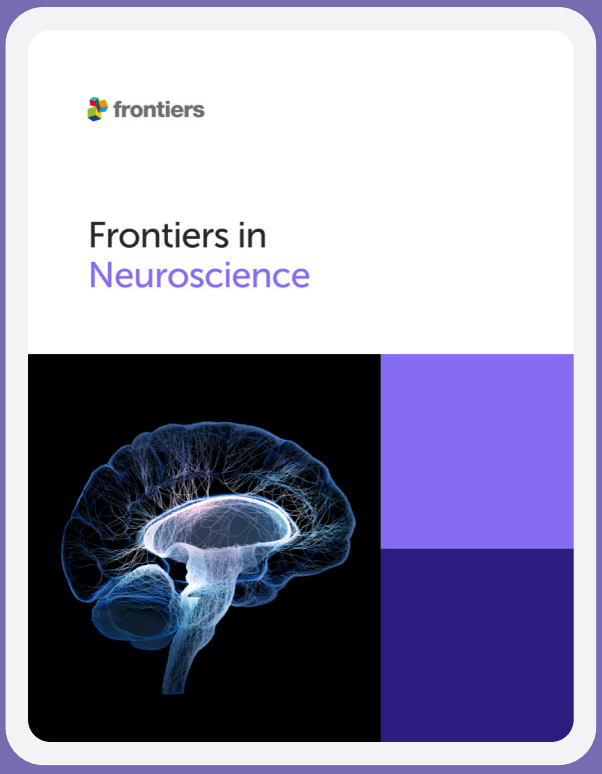
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