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Child engagement during interaction with digital and robotic activities: a systematic review

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Introduction: In the last decades we assisted in the exponential increase of information and robotic technologies for remote learning and rehabilitation. Such procedures are associated with a decrease of human interaction and "in person" control of responses, characteristics that, especially when children or youth are involved, can affect learning performances. Thus, online quantitative, and qualitative indicators of child's psychological engagement are mandatory to personalize the interaction with the technological device. According to the literature, the studies on child engagement during digitalized or robotic tasks vary in terms of underpinning constructs, technological tools, measures, and results obtained.
Methods: This systematic review was conducted with the general aim to provide a theoretical and methodological framework of children's engagement during digitalized and robotic tasks. The review included 27 studies conducted between 2014 and 2023. The sample size ranged from 5 to 299, including typically and atypically developing children, aged between 6 and 18 years.
Results: The results suggest the need for adopting a transversal approach including simultaneously emotional, behavioral and cognitive dimensions of engagement by diverse tools such as self-report questionnaires, video recordings, and eye-tracker. Although fewer studies have examined the relationship between children's engagement and task performance, existing evidence suggests a positive association between emotional, behavioral, and cognitive engagement and both task performance and skill acquisition.
Discussion: These results have implications for setting adequate protocols when using information and robotic technologies in child education and rehabilitation.
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KEYWORDS

child, engagement, learning analytics, digital task, robotic task, games, child-computer interaction

1 Introduction

Compared to previous generations, today's children demonstrate a high level of digital proficiency and knowledge: they embrace technology as a means of learning and entertainment, dedicating a substantial amount of time to technological devices (Duradoni et al., 2022). Beside the acknowledged risks associated to this prevailing trend, information and communication technology (ICTs) are demonstrating promising potential for enhancing learning (Di Lieto et al., 2021; Groccia, 2018; Ruffini et al., 2022; Stephen et al., 2008) and cognitive processes (Drigas et al., 2015; Noorhidawati et al., 2015) in children with typical development or special needs, within everyday settings such as households and schools. These contexts are particularly important since they are the places where children spend most of their time during their development phase through infancy and adolescence (Horvat, 1982; Pecini et al., 2019; Nadeau et al., 2020).

Additionally, ICTs have the potential to make the learning process easier and more enjoyable, for example by gamifying learning content (Brewer et al., 2013; De Aguilera and Mendiz, 2003). Gamifying refers to the application of game design elements—such as points, challenges, and rewards—in non-game contexts to increase motivation and engagement. This strategy has been shown to improve learning outcomes by making educational activities more interactive and rewarding (Deterding et al., 2011; Albertazzi et al., 2019). It is important to distinguish between formal game-based learning, which employs structured digital games with clear goals, rules, and feedback, and more open-ended or creative digital play activities that utilize technology in less structured ways. Such activities include exploratory, imaginative, or collaborative tasks that often emphasize creativity, social interaction, or free expression rather than competition or explicit challenges. These varied forms of digital play are widely used in educational settings and contribute differently to children's learning and development, offering benefits such as fostering creativity, problem-solving, and social skills (Clark et al., 2016). Among these, digital games stand out as a particularly influential modality due to their structured nature and strong potential for engagement. Digital games represent a fundamental and developmentally appropriate modality through which children explore, learn, and interact with the world. They possess core features, such as defined goals, rules, feedback systems, challenges, interactivity, and narrative structures that naturally support attention, emotional involvement, and intrinsic motivation. These characteristics allow digital games to create immersive and engaging learning environments where children are encouraged to participate actively, solve problems, and persist in the face of difficulty. As such, game-based activities have become increasingly relevant in educational contexts, especially those involving technology, due to their capacity to enhance engagement and promote meaningful learning experiences (Breien and Wasson, 2021). Indeed, children often lack motivation to continue learning if the process is tedious, cognitively demanding, and lacks stimulation (Dykstra Steinbrenner and Watson, 2015; Macklem, 2015). Thus, using innovative technology in learning not only enhances children's knowledge and skills but also provides enjoyable experiences through activities like gaming, fostering a sense of joy and pleasure (Hui et al., 2014). Furthermore, the concept of "fun" or "enjoyment," frequently associated with digital games and play, warrants critical consideration. While positive affect and motivation can enhance engagement and learning, effective educational experiences do not necessarily depend on constant feelings of fun. Play-based learning may also involve moments of challenge, frustration, and sustained effort, which are essential for deep learning and cognitive growth (Whitton, 2018). Therefore, the educational value of digital play lies not solely in entertainment, but in its capacity to engage learners emotionally, cognitively, and behaviorally through meaningful and sometimes demanding experiences.

Finally, the incorporation of technology within educational and intervention settings holds promising prospects even in terms of efficiency and efficacy in time and cost for families, educational and clinical institutions, and policy practitioners involved. Especially in remote format, technology can offer significant advantages by facilitating low-cost, intensive, and personalized exercises (Alexopoulou et al., 2019; Pecini et al., 2019; Rivella et al., 2023; Sandlund et al., 2009; Paneru and Paneru, 2024).

Notwithstanding, to make the use of remote ICTs services as useful and personalized as possible for students and young pupils, it is imperative to gather information concerning children's engagement during the interaction with the device, that is online quantitative and qualitative indicators of the learning process and of the child's emotional and cognitive status. Indeed, engagement research is fundamental for the creation of digital interventions (Nahum-Shani et al., 2022) and in the field of human-computer interaction (Doherty and Doherty, 2019). In this context, children's actions are strongly influenced both by situational factors, linked to the characteristics of the digital task, and by individual factors, such as personal cognitive skills, emotional needs, and motivational tendencies. The combination of these contextual and personal factors can determine different forms of engagement which then predict success in digital learning. This can be particularly important in developmental ages or in the case of neurodevelopmental disorders as they are characterized by a high intersubject variability in children's needs that can affect the successfulness of the remote intervention (Di Lieto et al., 2020). In virtual environments—particularly during play or learning activities—monitoring engagement can help address critical issues such as content personalization, improved accessibility, integration with assistive technologies, and the optimization of strategies involving augmented reality and immersive educational environments to support more effective treatment approaches. Augmented reality refers to technology that overlays digital content (such as images, sounds, or information) onto the real world, enhancing the user's perception of their environment. Immersive and interactive educational environments, on the other hand, are digitally mediated settings designed to deeply engage learners through multisensory input and real-time feedback, encouraging active participation and experiential learning. Tracking children's engagement also contributes to ensuring the reliability of data collected during interactions with robots, digital tasks, or immersive environments. This is especially important for applications involving atypical developmental conditions and for the development of algorithms for assessment and intervention (Paneru and Paneru, 2024; Paneru et al., 2024).

Nevertheless, researchers continue to face numerous challenges in understanding engagement, both due to its definition, which yields various and sometimes conflicting interpretations, and its multidimensional nature, which makes measurement challenging.

Difficulties in defining and measuring engagement can hinder the development of practical applications aimed at supporting children's learning and skill acquisition through more targeted and informed use of technology. It is therefore essential to systematize the conceptualization of the "child's engagement" within robotic and digital contexts, in order to clarify its components, identify the influencing factors, and determine the most effective methodologies for measuring it accurately and consistently. A systematic review of the existing literature can offer a theoretical framework for the construct, as well as support the identification and selection of reliable and valid tools to monitor children's engagement during interactions with digital and robotic technologies. Moreover, findings from the literature can provide valuable insights into the role of emotional, cognitive, and behavioral engagement in influencing children's performance, thereby contributing to the optimization of educational technologies in both typical and atypical development.

1.1 Engagement definition

Existing definitions of engagement vary depending on the context and the individuals involved, illustrating the lack of a universal definition (Nahum-Shani et al., 2022).

Within the frame of conversation between two agents, engagement is defined as the process through which two or more participants establish, maintain, and interrupt their perceived connection (Sidner et al., 2005). This process includes initial contact, negotiating a collaboration, verifying that the other is still taking part in the interaction, evaluating whether to remain involved, and deciding when to end the connection.

In other fields, such as education research and healthcare, engagement can be defined as the effort children devote to educationally beneficial activities to desired learning outcomes (Hu and Kuh, 2002) or as actions taken by subjects to support their health (Cunningham, 2014). Furthermore, considering adulthood, engagement can be seen also as a stable characteristic of the individual, which is based on personality traits, therefore a propensity to engage or to be engaged (Barco et al., 2014).

Nowadays, engagement can have a broader meaning if one considers a single user interacting with a screen-based interface, a technological device, or a robot. A technological device refers to an integrated hardware-software system—such as a tablet, an augmented reality headset, or an educational robot—that enables users to access, navigate, and interact with digital content or immersive environments. These devices often serve as the physical interface through which playful or learning experiences take place. In the context of social media, Jaimes et al. (2011) define engagement as the phenomenon of people being fascinated and motivated by developing a relationship with a social platform and integrating it into their lives. In human-computer interaction (HCI) it is defined as the quality of users' experiences when interacting with a digital or robotic system. This includes aspects such as challenge, positive affect, usability, attention attraction and maintenance, aesthetic and sensory appeal, feedback, variety/novelty, interactivity, and user-perceived control (O'Brien and Toms, 2008). In the definition of O'Brien and Toms, engagement is therefore a dynamic process within which four discrete events are identified: the point of involvement, the period of involvement, disengagement, and re-engagement.

Beyond defining engagement as a unitary construct, it must be acknowledged that engagement is multifaceted and can include multiple processes at different levels (Bouta and Retalis, 2013; Islas Sedano et al., 2013). In fact, although there is no consensus on which dimensions are most important in defining engagement (Lee, 2014), it is acknowledged that engagement represents the simultaneous investment of emotional, cognitive, and physical energies (Rich et al., 2010).

Definitions of emotional engagement tend to emphasize the subjective nature of the experience, including attitudes and emotions that reflect intrinsic motivation, positive affects, and a sense of pleasure and interest in the task (Fredricks et al., 2004). Cognitive engagement instead primarily refers to the appropriate use of several cognitive processes such as attention, information processing, and memory (Fredricks et al., 2004). Finally, behavioral/physical engagement implies action, participation and individual conduct during the interaction with a person or a device (Bouta and Retalis, 2013). To date there is a growing literature supporting bodily engagement in learning contexts. Proponents of "embodied cognition" in fact, agree that the way people think and reason about the world is closely related to the body's interaction with the physical environment (Lindgren et al., 2016). As a consequence, body movement can have an impact on learning processes (Goldin-Meadow et al., 2009) and on degree of engagement (Anastopoulou et al., 2011).

Considering the diverse definitions of engagement and its multifaceted underlying constructs, the first objective of this review is to describe how engagement with digital tasks is conceptualized and operationalized in the educational and intervention contexts in childhood.

1.2 Tools and procedures to measure engagement

One of the most recent approaches that attempts to measure child's engagement within the educational setting is called Learning Analytics. Learning Analytics (LA) involves the measurement, collection, analysis, and reporting of data about learners and their contexts to understand and optimize learning and its environments (LAK, 2011). It offers educators and practitioners valuable information to enhance the learning experience, improve instructional design, and support performance success. LA can supply powerful tools for teachers and researchers to improve the effectiveness and the quality of children's performance as well as inform, extract and visualize real-time data about learners' engagement and their success (Macfadyen and Dawson, 2010).

In line with the LA approach, several innovative technologies and valid and reliable tools can be used to investigate engagement in technology- or game-mediated learning experiences (Abbasi et al., 2023). Researchers have used various methods to measure it such as quantitative self-report surveys, semi-structured interviews, qualitative observation, eye-trackers, artificial intelligence (AI), video recordings, physiological measures (Crescenzi-Lanna, 2020a; Sharma et al., 2020), as reported by previous literature reviews (Boyle et al., 2012; Henrie et al., 2015; Sharma et al., 2020).

Quantitative self-report surveys, often utilizing tools like the Likert scale, have been widely employed to assess learners' engagement. Survey inquiries span from evaluating self-perceived levels of engagement (Gallini and Barron, 2001) to delving into behavioral, cognitive, and emotional aspects of engagement (Chen et al., 2010; Price et al., 2007; Yang, 2011). While surveys are valuable for older students, they may not always be suitable with younger children who may struggle to comprehend and respond to the questions directly. Additionally, data are typically collected at the end of a learning activity, and this may not be ideal for those interested in developing systems that provide researchers with real-time feedback on child engagement over the course of an activity. This need may be particularly relevant in rehabilitative contexts, when the child's response to the intervention should be constantly monitored.

The second most common approach involves qualitative measures, which include direct observations via video, capturing screenshots of children's behavior during learning, interviews or focus groups, and texting by other digital communication tools. These qualitative measures are particularly useful for exploratory studies characterized by uncertainty about how to measure or define engagement. Although qualitative methodologies offer in-depth data regarding student engagement, they are limited in their ability to generalize findings to a larger population. This lack of generalizability impedes the establishment of a common strategy for defining or assessing engagement.

Regarding quantitative observational measures, researchers use various indicators obtained through direct human observation, video recording, and computer-generated user activity data (e.g., log data). These methods have the advantage of allowing researchers to assess engagement in real time, avoiding interruptions or subsequent measurements.

Finally, another approach to measuring engagement involves the use of physiological sensors, which can detect children's physical responses during learning. Eye-tracking technologies, skin conductance sensors, blood pressure, and electrophysiological data (e.g., EEG) are used to assess the impact of various technological devices and interactive lessons on engagement and learning (Boucheix et al., 2013). Physiological sensors have the advantage to not interrupt the task, but need confirmation through self-reported data. In addition, one challenge in using physiological sensors concerns the complexity of the technology and the associated cost. Finally, it is critical to pay attention to sensor placement and to subject's limitations while conducting monitoring. To date, physiological sensor technology is advancing with simpler and more affordable options, making this type of measurement increasingly viable for studying engagement (Henrie et al., 2015).

It must be noted that a multimodal approach integrating various interaction modalities, such as verbal language, gestures, facial expression, body posture and sensory data, could provide a more complete understanding of the individual's engagement. The importance of multimodal approaches in evaluating engagement in digital tasks lies precisely in their ability to capture a wider range of behavioral and emotional signals and in providing educators with the possibility to evaluate student engagement more accurately through valuable information to adapt and optimize online learning experiences. Additionally, using advanced data analytics techniques can help identify patterns and trends in children engagement, allowing teachers to intervene in real time to improve learning. That is why the use of multimodal assessments could be widely used in learning and rehabilitation, not only because it allows for a better understanding of learning behaviors, but also because it has the potential to improve intervention and adaptation to special educational needs by supporting cognitive, affective, and metacognitive (Emerson et al., 2020; Checa Romero and Jiménez Lozano, 2025).

However, it is not always feasible to implement multiple and valid tools to study engagement in an online learning environment. Studies often measure only one dimension of engagement, or study engagement in general (without operationalize it in terms of cognitive, emotional, and behavioral components) or even within a single subject area (e.g., math; Henrie et al., 2015). Additionally, the tools mentioned above are often developed to measure students' engagement in real, face-to-face classrooms rather than the online learning environment. Most importantly, the studies reported in the previous reviews (Henrie et al., 2015) have examined engagement of university students, thus leaving school age uncovered.

To date, although various tools can be used to measure engagement, little is known about which tools and procedures are most used to evaluate the different types of engagement, i.e., cognitive, emotional and behavioral, during childhood and adolescence. However, considering the evident benefits of utilizing technology in gathering relevant information, it is imperative to identify informative and valuable methodologies and tools to be used by practitioners and researchers with children.

Thus, the second aim of the review is to describe the tools and procedures used to measure engagement during children and adolescent activities with digital technologies and interaction with robots, through paying attention to differentiate the emotional, cognitive, and behavioral components.

1.3 Relationships between engagement, performances, and characteristics of the digital tasks

In the recent decades, there has been a growing interest in understanding the role of engagement in children's development, especially for educational special needs (Fredricks et al., 2004). Particularly, student engagement is universally recognized as one of the best indicators of success in the learning process and in personal development (Skinner et al., 2008). In the early school years engagement predicts academic achievement and test performances while subsequently it affects students' patterns of attendance, continuity, and academic resilience (Sinclair et al., 2003), creating an important gateway to better academic achievement while in school (O'Farrell and Morrison, 2003). Engagement has been also found to act as a protective factor against risky behaviors typical of adolescence, such as substance abuse, risky sexual behavior, and delinquency (Skinner et al., 2008).

Despite substantial investments in the digitization of education, which have made information and communication technologies (ICTs) an integral part of learning, current research is rather limited when considering the impact of engagement on performance during digital learning tasks (Ferrer et al., 2011). In fact, it must be noted that although it is assumed that the engagement induced by digital and game-based tasks affects positively learning and task performances in children, no systematic analysis of such a relationship has ever been explored. Moreover, it remains unclear whether different types of engagement are differently affected by the use of digital learning tasks. While emotional engagement is expected to be positively related to performance in digital tasks (Tisza et al., 2022), some hypotheses suggest that the use of technology for learning may induce cognitive fatigue, potentially negatively impacting cognitive engagement (Giannakos et al., 2020) with larger effects on accessibility to digital learning by subjects with neurodevelopmental disabilities. In addition, it is of interest to clarify which characteristics of the digital and game-based learning tasks (Crescenzi-Lanna, 2020a) favor engagement across typical and atypical developmental populations as it may have important implications for ponderated choices in the educational and interventional fields.

Given their influence on children's engagement, the design features of digital tasks deserve careful attention to ensure they effectively support motivation and learning.

Accordingly, the third aim of the review was to verify whether the degree and type of children's engagement correlated with their task performances and if it varied according to task characteristics.

2 Methods and procedure

2.1 Eligibility criteria

Studies were included if they presented the following criteria: (i) being written in English, (ii) reporting measurements of children's engagement in terms of emotion, cognition or behavior, (iii) being a peer-reviewed article, (iv) reporting on quantitative data, qualitative data or mixed-method study designs were included, (v) having a sample between 0 and 18 years old, (vi) having children completing a digital task, (vii) being published between 2000 and 2024.

2.2 Search methodology

The review was conducted in accordance with the recommendations of the Preferred Items for Reporting of Systematic Reviews and Meta-Analyses (PRISMA) to organize all the data retrieved from possible eligible studies (Page et al., 2021). Electronic bibliographic databases including the PsycINFO, PubMED, and Scopus were searched up to January 2024 using the following full string:

child* AND engage* AND ((“learning analytics” OR “embodied learning” OR “immersive learning”) AND (“game*” OR “computer*”OR “robot*” OR “digital*” OR “tablet” OR “multimod*” OR “educational technology”)).

The search strategy string was informed by previous literature on children's engagement and utilizing commonly used key terms pertaining to each of the three categories of engagement (e.g., Crescenzi-Lanna, 2020b; Lee-Cultura et al., 2021; Kosmas et al., 2019). Population was identified by the keyword “child*,” thus including typical and atypical development; the keyword “engage*” defined the variable of interest; the keywords “learning analytics,” “embodied learning,” and “immersive learning” were used to target the procedures used to measure engagement; the keywords “game*,” “computer*,” “robot*,” “digital*,” “tablet,” “multimod*,” and “educational technology” were used to define the type of task within which engagement was measured.

Filters were applied to include only English. The reference lists of all studies included were screened to identify additional citations of interest.

2.3 Review process

Papers were screened according to the following procedure: the principal reviewer (XX) fully compiled a list of all the papers obtained through the keywords and selected them as eligible based on the reading of the abstracts. A second reviewer (XX) independently carried out the same task and reported which papers were deemed eligible according to them based on their abstracts. A third reviewer (XX) intervened if there were any discrepancies in selecting a paper between the two other reviewers.

2.4 Data extraction

Data extracted were also in duplicate by two independent reviewers (XX, XX). The following information was reported for each of the included papers: reference, journal, main aim and scope, study methods, populations characteristics, intervention setting, tools used and main findings.

2.5 Study collection

Four thousands abstracts were screened to assess the potential eligibility of the studies to be included in the systematic review. During this process of screening, 89 papers were accepted based on their titles and abstracts only and were thus read in full-text. Seventy-five papers were removed because they did not meet the eligibility criteria, specifically 8 presented a sample of either university students or of adult people, 24 did not present any empirical data, 40 did not focus on evaluating emotional, behavioral, or cognitive engagement, and 3 did not present any digital task. As a result, 17 papers were included through this process. References were also analyzed through other sources (e.g., forward citation searches, contact with authors) to find potentially eligible studies. A total of 13 references were screened and 10 papers were added in the end. Finally, 27 papers were deemed eligible for this PRISMA systematic review (Figure 1).

2.6 Quality assessment

A risk of bias assessment was conducted independently by two reviewers (XX, XX) using a quality appraisal tool, the Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018), which has been validated and tested on different methodologies including quantitative, qualitative, and mixed-methods study designs. The tool consists of two screening

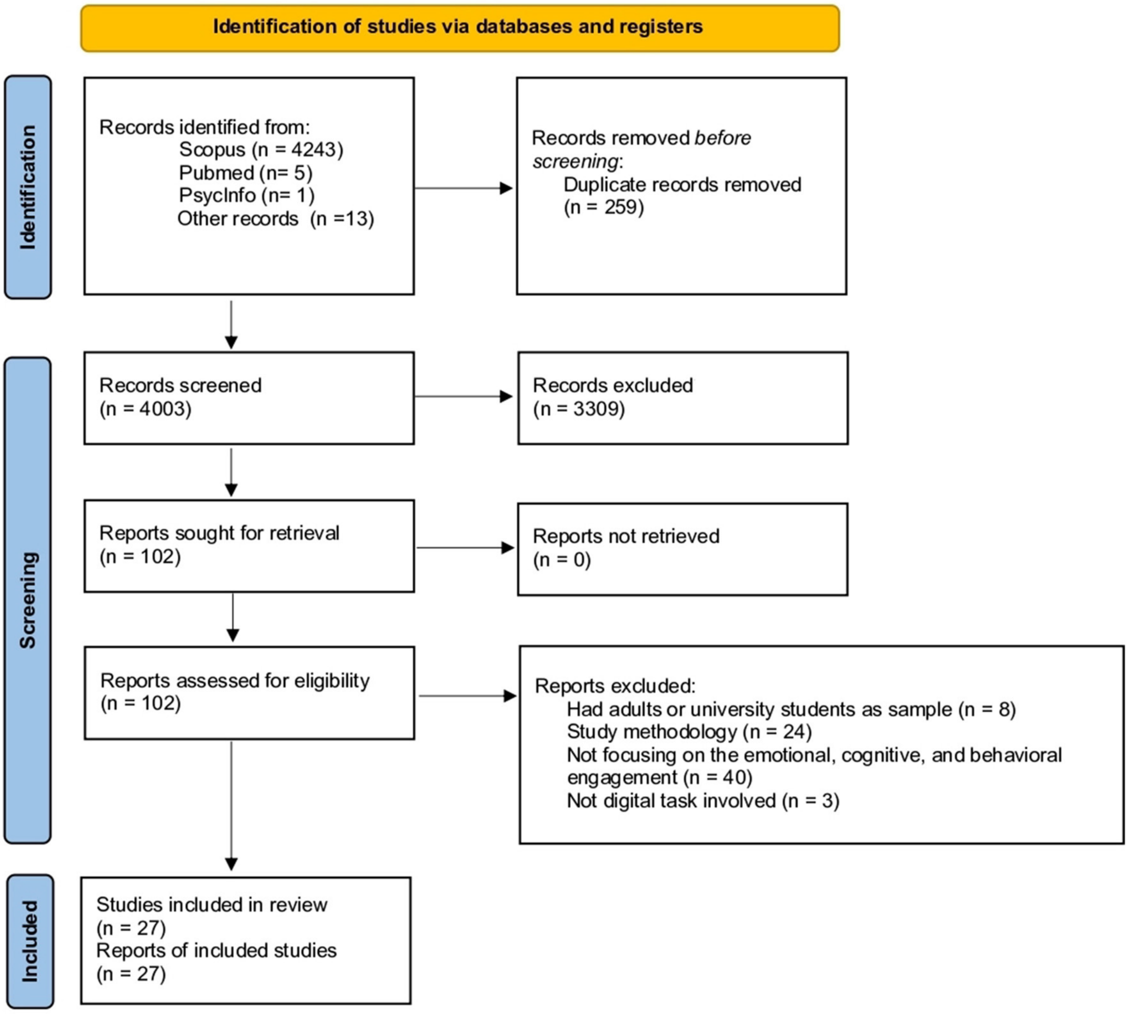

FIGURE 1
Flow diagram showing the search methodology to identify papers about the engagement of children and instruments used to assess it.

questions (i.e., "Are there clear research questions?" and "Do the collected data allow for addressing the research questions?"). If both questions receive affirmative responses, five additional questions are posed regarding sample characteristics, study design, measurement efficacy, statistical analysis, and outcome data. These five questions vary based on the study design: qualitative, quantitative, or mixed methods. For mixed-method studies, all types of questions are utilized, totaling 15 questions. Total scores are computed as the percentage of MMAT criteria met, ranging from 0% (indicating no quality) to 20% (very low quality), 40% (low quality), 60% (moderate quality), 80% (good quality), and 100% (very high quality).

3 Results

3.1 Studies' setting

This systematic review synthesizes data from 27 studies on the assessment of children's emotional, cognitive, and behavioral engagement during the completion of digital activities. A brief summary with reference numbers used in the Section 3 of the included studies is provided in Tables 1, 2.

All studies were published between 2014 and 2023. Studies were cross-sectional in nature and most of them were conducted within the school setting. Specifically, 22 were carried out inside a school context, 2 were carried out in a university lab [12, 19], 1 was in a home setting [7], and 1 in a therapeutic center [27]. One paper did not provide any setting details [24]. Additionally, 2 papers used a double setting by carrying the experiments in a school and in a museum room [3, 13]. By location studies were conducted in Norway ($n = 6$) [2, 3, 8, 12, 13, 18], followed by Cyprus ($n = 3$) [6, 17, 20], United States ($n = 1$) [25], the Netherlands ($n = 2$) [4, 9], United Kingdom ($n = 1$) [22], China ($n = 2$) [1, 7], Brazil ($n = 1$) [11], Morocco ($n = 1$) [18], Singapore ($n = 2$) [14, 21], Greece ($n = 1$) [23], Canada ($n = 1$) [24], Finland ($n = 1$) [26], Croatia ($n = 1$) [5], German ($n = 2$) [10, 15], and Italy ($n = 2$) [16, 27].

3.1.1 Studies' participants

Sample sizes ranged from 5 to 299. In total, across the 27 studies there were 1,666 participants. Twenty five studies included primary

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TABLE 1 Main characteristics of the studies included: APA reference, sample size, and its characteristics; type of task; type of engagement measured and the tool/technology used in the studies.

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
1.	Zhang et al. (2023)	80	42 M 38 F	Not given 12–13 y/o	Typically developed	Engagement as embodied learning. Embodied learning highlights active engagement between body and environment in cognition, enhancing education through inspiration and empowerment	A programmable robot (LEGO Mindstorms EV3) focused on computer programming EL-CP vs. control group C-CP; 2 session of 40 min	**Emotional** Questionnaire items not given **Cognitive** Questionnaire items not given **Behavioral** Questionnaire items not given	**Emotional** A self-report questionnaire **Cognitive** A self-report questionnaire **Behavioral** A self-report questionnaire
2.	Lee-Cultura et al. (2022)	26	16 M 10 F	M = 10.95, sd = 0.21 10–12 y/o	Typically developed	Engagement as embodied learning. Embodied learning highlights active engagement between body and environment in cognition, enhancing education through inspiration and empowerment	A Kinect game ("Marvy Learns"—focused on math skills); 3 sessions of 8 min	**Emotional** Playfulness: facial expression qualitatively coded by two coders Stress (mean Heart Rate) and arousal (Heartbeat; Electrodermal) Activity (phasic EDA; n° of EDA peaks) **Cognitive** Cognitive load (pupillary activity) Perceived difficulty (saccade speed) Information processing index (global = short fixation and long saccades; local = long fixation and short saccades) **Behavioral** Physical activity and social interaction with the research team qualitatively coded by two coders	**Emotional** Empatica E4 wristband Video recordings **Cognitive** Tobii eye tracker (glasses) **Behavioral** Video recordings Kinect
3.	Sharma et al. (2022)	40	14 M 26 F	M = 10.9, sd = 1.09 9–12 y/o	Typically developed	Engagement is related to a person's level of involvement and absorption into an activity and it represents a fundamental component of the person's experience with that activity	2 Kinect games ("Suffiz" focused English grammar, "Sea Formuli"—focused on algebra skills); 3 consecutive sessions Each game followed the same structure (a) question reading phase (b) move phase—move the body to give the answer; (c) answers giving phase	**Emotional** Stress (mean of Heartbeat; n° of EDA peaks) Arousal (phasic EDA) **Cognitive** Cognitive load (pupillary activity) Perceived difficulty (saccade velocity) Information processing (analysis of AOI where they analyzed the gaze to see the information processing)	**Emotional** Empatica E4 wristband **Cognitive** Tobii eye tracker (glasses) video recordings

(Continued)

TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
4.	Tisza et al. (2022)	53	27 M 26 F	M = 10.13, sd = 1.103 8–12 y/o	Typically developed	Engagement as enjoyment related to fun activities. Enjoyment is an affective state during which one feels in control, loses perception of time and space, abandons social inhibitions, encounters the appropriate level of challenge	A 2 h coding tasks in small groups; 90 min in total	**Emotional** (a) Enjoyment through a self-report questionnaire (b) Facial expressions (c) Transition of each affective state Stress (Heartbeat increase) Arousal (phasic EDA)	**Emotional** Empatica E4 wristband Video recordings OpenFace AI + FACS taxonomy (video analysis for facial expression and emotions) Self-reports
5.	Drljević et al. (2024)	35	Not given	Not given 6–8 y/o	Typically developed	Engagement in an educational context has a dual definition: it can be defined as engagement with the school experience or engagement with schoolwork during a lesson	Digital lessons (SCOLLAm platform) with augmented reality platform (ARLE); 9 lessons of 45 min	**Emotion** Engagement with fellow students or teachers, positive reactions to school works **Cognitive** Showing intent to understand the task given and to master it **Behavioral** Active participation in the learning experience	**Emotion** Video-recordings of the ARLE with two cameras **Cognitive** Video-recordings of the ARLE with two cameras **Behavioral** Video-recordings of the ARLE with two cameras
6.	Georgiou et al. (2021)	31	14 M 17 F	M = 8.9, sd = 0.63; 7–10 y/o	Typically developed	Engagement as embodied learning. Embodied learning highlights active engagement between body and environment in cognition, enhancing education through inspiration and empowerment	Math game ("AngleMakers"—aimed at improving math skill); traditional math class; 2 consecutive days of 1 h	**Cognitive** Cognitive load	**Cognitive** Self reports

(Continued)

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TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
7.	Gong et al. (2021)	36	18 M 18 F	M = 7.06; sd = not given 6–8 y/o	Typically developed	Engagement is viewed from a multi-componential perspective, and person-oriented engagement has been operationalized in terms of affective, cognitive, and behavioral states	Holoboard session with a VR focused on school program teaching content; normal lesson; 70 min in total	**Emotional** Arousal (valence; positive or negative emotions) Qualitative speech analysis (i.e., exclamations or out loud speech/affirmations) **Cognitive** Reasoning (i.e., remembering, understanding, applying rules, analyzing, evaluation; qualitative video analysis) Reasoning (speech analysis) (i.e., loudness and frequency of exclamation while reasoning) **Behavioral** Classroom behavior (positive—e.g., leaning forward, normal—e.g., neutral stance or misbehavior—e.g., making noises) Posture (close, neutral)	**Emotional** Video recordings Audio recordings **Behavioral** Video recordings **Cognitive** Video recordings Audio recordings
8.	Lee-Cultura et al. (2021)	26	16 M 10 F	M = 10.95, sd = 0.21 Not given	Typically developed	Engagement as embodied learning. Embodied learning highlights active engagement between body and environment in cognition, enhancing education through inspiration and empowerment	Kinect game ("Marvey Learns" focused on math); 3 sessions of 8 min	**Emotional** Emotional regulation (HRV index and peaks) Stress and engagement (Heartbeat; Electrodermal activity (phasic EDA); beat per second (BVP); n° of EDA peaks) **Cognitive** Cognitive load (pupil diameter) Perceived difficulty (saccades speed/time) **Behavioral** Behavioral enjoyment (e.g., jumping, dancing, celebratory movements)	**Emotional** Empatica E4 wristband **Cognitive** Tobii eye tracker (glasses) **Behavioral** Video recordings
9.	Tisza and Markopoulos (2021)	82	45 M 37 F	M = 10.35, sd = 0.743 9–12 y/o	Typically developed	Engaging activities correspond to fun activities. Enjoyment is an affective state during which one feels in control, loses perception of time and space, abandons social inhibitions, encounters the appropriate level of challenge	Programming task for 2 h	**Emotional** Overall enjoyment	**Emotional** Self report

(Continued)

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TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
10.	Reinhold et al. (2021)	27	13 M 14 F	Not given 11 y/o	Typically developed	Person × Situation translates into individual forms of emotional and behavioral engagement which in turn predict success after the lesson. This approach considers individual prerequisites as a relevant predictor of learning success	e-textbook (ALICE), a way of introducing fractions; 15 lessons in 4 weeks	**Emotional** Perceived intrinsic motivation, competence and autonomy support, situational interest, and perceived demand **Behavioral** Task count and exercise count, time measure, problem solving time	**Emotional** Self report **Behavioral** Process data of the e-textbook
11.	Crescenzi-Lanna (2020a)	12	Not given	M = 4.6 sd = n.g 4–5 y/o	Typically developed	Engagement as a mediator of learning that influences students' cognitive engagement through affective mediation ("Cognitive-affective theory of learning with media")	15 educational apps on tablet, 23 sessions of 45 min	**Emotional** (a) Facial expressions (b) Vocal expression of enjoyment, surprise, enthusiasm, surprise, frustration, anxiety and boredom **Behavioral** Time spent with the games (minutes and days/week) **Cognitive** Private speech involvement (e.g., putting effort, determined, persistent, paying attention)	**Emotional** Video recordings observationally coded **Behavioral** Data from the platform
12.	Giannakos et al. (2020)	44	32 M 16 F	M = 12.50, sd = 2.8 8–17 y/o	Typically developed	Learning activities for children include rich interactions with peers, tutors, and learning materials (in digital or physical format). During such activities, children acquire new knowledge and master their skills	Robot programming in small groups of 2/3 participants; 4/5 h in total	**Cognitive** Cognitive load (pupil diameter) Attention (fixation) Anticipation (saccade velocity) Fatigue (Blink rate) Joint attention of all children **Behavioral** Off task activity (Time spent not looking at the screen)	**Cognitive and behavioral** Tobii eye tracker (glasses)

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TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
13.	Lee-Cultura et al. (2020)	46	18 M 28 F	M = 10.3, sd = 1.32 8–12 y/o	Typically developed	Engagement as embodied learning. Embodied learning highlights active engagement between body and environment in cognition, enhancing education through inspiration and empowerment	3 Kinect games (kinems: “Marvy Learns”—focused on English or Math—or “Suffiz” focused English grammar, “Sea Formuli”—focused on algebra skills); 3 consecutive sessions	**Emotional** Facial expression Stress (Heartbeat; Electrodermal activity; phasic EDA; beat per second, BVP; n° of EDA, peaks) Arousal (EDA slope) **Cognitive** Cognitive load (pupil diameter, saccade speed and fixation) Visual focus (long and short fixation and saccades velocity/time) Anticipation (skewness of the saccade velocity) **Behavioral** On task ratio (ratio between the time gaze on screen and off screen)	**Emotional** Video recordings OpenFace web-based AI Empatica E4 wristband **Cognitive** Tobii eye tracker (glasses) **Behavioral** Tobii eye tracker (glasses) Kinect
14.	Wen (2021)	53	Not given	Not given 8–9 y/o	Typically developed	Students’ cognitive engagement is analyzed in terms of ICAP (Interactive, Constructive, Active, or Passive) framework which helps to analyze cognitive engagement with behavioral metrics	Augmented reality interface (ARC&S game) for vocabulary learning; similar activities without ARC&s; 3 rounds of 60 min lessons	**Cognitive** ICAP framework (interactive, constructive, active or passive)	**Cognitive** Two video cameras (face to face interactions with peers and interactions with the app) Discourses recorded by Ipad’s screen recording
15.	Reinhold et al. (2020)	253	143 M 110 F	Not given 11 y/o	Typically developed	Classroom engagement is a complex multifaceted construct, consisting of behavioral, cognitive, and emotional facets	e-textbook (ALICE), a way of introducing fractions; 15 lessons in 4 weeks	**Cognitive** Text length (the word count of students’ written responses in writing-to-learn activities) **Behavioral** Time on task (the amount of time during which students are actively engaged with writing-to-learn activities)	**Cognitive** Process data obtained from the electronic textbook **Behavioral** Process data obtained from the electronic textbook

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TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
16.	Barana and Marchisio (2020)	299	Not given	Not given 8 y/o	Typically developed	Student engagement in technology-enhanced learning environments includes any student interaction with instructors, peers, or learning content through the use of ICT	Interactive worksheets with real-life mathematical problems, (Advanced Computing Environment ACE); 6 months	**Emotional** Items aimed at investigate the extent to which students are interested in and value Mathematics **Cognitive** Items related to the perceived control of success, self-regulation and openness to problem solving **Behavioral** Items on students' effort and completion of work, perseverance and participation to school and social related activities	**Emotional** Online self-questionnaire **Cognitive** Online self-questionnaire **Behavioral** Online self-questionnaire
17.	Kosmas et al. (2019)	52	Not given	Not given 7–10 y/o	Typically developed	Engagement as embodied cognition. Embodied cognition theory has brought to light the involvement of the physical body in the learning process, changing the learning environment, altering the design of learning, and generating questions about the nature of the relationship between body and mind (cognition)	2 Kinect games ("Unboxit"—focused on short memory or "Lexis" focused on vocabulary and linguistic development); 13 sessions (45 min)	**Emotional** Children's overall appreciation	**Emotional** Video recordings coded by teachers
18.	Ouherrou et al. (2019)	42	24 M 18 F	M = 9.57, sd: 1.08–1.17 7–11 y/o	14 with specific learning disabilities 28 typically developed	Emotions and motivation have an impact on the process and outcome of learning: they are essential and inseparable. Emotions influence motivational processes which include intrinsic task motivation and extrinsic task motivation	One educational game focused on learning	**Emotional** Facial expression	**Emotional** Video recordings Artificial intelligence to detect emotions
19.	Sharma et al. (2019)	105	69 M 36 F	M = 14.55, sd = 0.650 13–16 y/o	Typically developed	The study of emotions in education holds great promise when it comes to informing understanding of teaching, motivation, and self-regulated learning. Emotions play a central role in teaching, motivation and particularly in the context of self-regulated learning	game programming in small groups of 2/3 participants; 4 h per 3 sessions	**Emotional** Facial expressions: (a) Emotion type proportion/time (b) Emotional consistency/time (c) Participants joint emotional state	**Emotional** Video recordings OpenFace AI and FACS taxonomy Qualitative field notes

(Continued)

TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
20.	Kosmas et al. (2018)	31	21 M 10 F	Not given 6–12 y/o	Special Educational Needs and Disabilities (SEND)	Engagement as embodied cognition. Embodied cognition (EC) and embodied learning show promising effects of bodily engagement and movement on children's cognitive and academic outcomes	2 Kinect games ("Unboxit"—focused on short memory, and "Melody Tree"—focused on visual memory, attention and concentration); 2 sessions of 40 min per week	**Emotional** Children's overall appreciation **Behavioral** Time spent on the game; n° of time the game was completed; game completion speed n° of errors	**Emotional** Teachers' and researchers' field notes **Behavioral** Kinect
21.	Sridhar et al. (2018)	15	9 M 6 F	M = 5.23, sd = 0.73 4–6 y/o	Typically developed	Engagement as affective states that occur during a task. In theories of motivation it is important to integrate the affective and cognitive components	Computerized task on memory and executive functions	**Emotional** Affective State (Skin Conductance Responses; heart rate and heart rate variability) Facial expressions	**Emotional** Empatica E4 wristband Video recordings Consensys Shimmer3 GSR Microsoft Emotion API Video recordings coded by researchers
22.	Grawemeyer et al. (2017)	77	Not given	Not given 8–10 y/o	Typically developed	Engagement as an affective-cognitive state that influences the learning process	A game learning environment (called "FractionsLab," game: Whizz Maths) focused on math skills	**Emotional** Affective State	**Emotional** Data from the platform Speech analysis Qualitative field notes
23.	Kourakli et al. (2017)	20	17 M 3 F	M = 8.91, sd = 1.72 6–11 y/o	Special Educational Needs and Disabilities (SEND)	Engagement as embodied learning. The use of game-based activities has a positive impact in order to accelerate learning processes and promote different cognitive abilities of children with SEN	3 Kinect games ("Unboxit"—focusing on visual memory; "Melody tree"—focused on attention and math skills, "Farm walks"—focused on math skills and motor skills); 8-week intervention	**Emotional** Overall enjoyment **Behavioral** N° of times they played the game	**Emotional** Field notes Qualitative interviews with parents and teachers **Behavioral** data from the platform
24.	Martinovic et al. (2016)	45	21 M 20 F	Not given 7–12 y/o	Typically developed	Player engagement is an experience influenced by "challenge, positive affect, bearability, aesthetic and sensory appeal, attentiveness, feedback, variety/novelty, interactivity, and perceived user control." Engagement in gaming may depend on various personal traits	15 commercial games for 3 trials in one session (1.5–2.5 h)	**Emotional** Overall frustration/enjoyment **Cognitive** Pays attention, gets distracted, has troubles understanding **Behavioral** Needs encouragement puts effort	**Emotional, cognitive and behavioral** Observational scale filled by researchers during video game activity

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TABLE 1 (Continued)

No.	References	Sample size	Gender distribution	Age mean/ age range	Children development	Engagement underpinning construct	Task	Engagement measure	Tool/technology used
25.	Bhattacharya et al. (2015)	18	Not given	$M_1 = 9.8$, $sd_1 = 1.7$ $M_2 = 11.3$, $sd_2 = 2.1$ $M_3 = 16.6$, $sd_3 = 2.1$ 8–19 y/o	Autism spectrum disorder	Engagement as embodied learning. Individuals with autism may find the multisensory nature of social interactions overwhelming. Sharing a virtual space with a peer can be particularly effective in strengthening interactions in autism	A game (name not specified) played during lessons focusing on self-awareness, imitation, communication; few time a week per 9 months	**Emotional** Overall enjoyment	**Emotional** Video recordings Qualitative field notes by teachers
26.	Ronimus et al. (2014)	138	82 M 56 F	M = 7.36, sd = not given 6.82–10.01	30.4% had learning or developmental problems (SEND)	Engagement as intrinsic motivation. Intrinsic motivation refers to a situation in which actions are performed in the absence of any apparent external contingency	A game ("GraphoGame"—focused on reading and language skills), twice a week for 10–15 min per 8 weeks	**Emotional** Overall enjoyment **Cognitive** Concentration **Behavioral** Motivation	**Emotional** Self-report question during game based activity **Cognitive and behavioral** Parents' reports
27.	Bartoli et al. (2013)	5	Not given	Not given 10–12 y/o	Autism spectrum disorder	Engagement as embodied learning. Motion-based touchless interaction is ergonomic, mimics natural human gestures, enhances engagement, and removes physical contact, improving user experience	4 Kinect games ("Bump Bash," "Body Ball," "Pin Rush," "Target Kick") and 1 Rabbids Alive and Kicking ("It's not what you think! Honest!") all focused on attention; 45 min week sessions (for a total of 3 h and 40 min) for 2 months	**Emotional** Facial expression **Behavioral** Distress Loss of interest Loss of attention	**Emotional and behavioral** Video recordings Therapists' field notes

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TABLE 2 Methods used for each engagement category.

No.	References	Cognitive	Emotional	Behavioral
1.	Zhang et al. (2023)	Self-report questionnaire	Self-report questionnaire	Self-report questionnaire
2.	Lee-Cultura et al. (2022)	Eye movement correlates	Video recordings qualitatively coded Physiological indexes	Video recordings qualitatively coded
3.	Sharma et al. (2022)	Eye movements correlates Video recordings	Physiological indexes	–
4.	Tisza et al. (2022)	–	Artificial intelligence Video recordings coded by AI Self-report questionnaire Physiological indexes	–
5.	Drljević et al. (2024)	Video recordings with 2 cameras	Video recordings with 2 cameras	Video recordings with 2 cameras
6.	Georgiou et al. (2021)	Self-report questionnaire	–	–
7.	Gong et al. (2021)	Video qualitatively coded Audio recordings quantitatively and qualitatively coded	Video and audio recordings qualitatively coded	Video recordings qualitatively coded
8.	Lee-Cultura et al. (2021)	Eye movements correlates	Physiological indexes	Video recordings qualitatively coded
9.	Tisza and Markopoulos (2021)	–	Self-report questionnaire	–
10.	Reinhold et al. (2021)	–	Self report questionnaire	Process data of e-textbook
11.	Crescenzi-Lanna (2020a)	Video recordings qualitatively coded	Video recordings qualitatively coded	Data from the game platform
12.	Giannakos et al. (2020)	Eye movements correlates	–	Eye correlates
13.	Lee-Cultura et al. (2020)	Eye movements correlates	Video recordings coded by AI Physiological indexes	Eye correlates
14.	Wen (2021)	Video recordings Discourses recordings	–	–
15.	Reinhold et al. (2020)		Process data from the e-book	Process data from the e-book
16.	Barana and Marchisio (2020)	Online self report questionnaire	Online self report questionnaire	Online self report questionnaire
17.	Kosmas et al. (2019)	–	Video recordings qualitatively coded	–
18.	Ouherrou et al. (2019)	–	Video recordings coded by AI	–
19.	Sharma et al. (2019)	–	Video recordings coded by AI Qualitative field notes	–
20.	Kosmas et al. (2018)	–	Qualitative field notes	Kinect data
21.	Sridhar et al. (2018)	–	Video recordings coded by AI and Qualitatively coded Physiological indexes	–
22.	Grawemeyer et al. (2017)	–	Data from the platform Speech analysis Qualitative field notes	–
23.	Kourakli et al. (2017)	–	Qualitative interviews	Data from the game platform
24.	Martinovic et al. (2016)	Observational scale	Observational scale	Observational scale
25.	Bhattacharya et al. (2015)	–	Video recordings qualitatively coded Qualitative field notes	–
26.	Ronimus et al. (2014)	Parents' reports	Self-report question inside the game	Parents' reports
27.	Bartoli et al. (2013)	–	Video recordings qualitatively coded Therapist qualitative field notes	Video recordings qualitatively coded Therapist qualitative field notes

and middle school children with the age varying from 6 to 18 years old. Only two studies had a sample of preschool children, aged between 4 and 6 years old [11, 21]. Twenty-four studies included children with typical development, whereas two included children with Autism Spectrum Disorder (ASD) [25, 27], three focused exclusively on children with Special Educational Needs or Disabilities (SEND) [20, 23, 26], and one study included both typically and atypically develop children (i.e., Learning Disabilities)

[18]. In most studies children were predominantly White whereas one study conducted in Morocco [18] and another in China [7]. As per gender distributions, most samples comprised over 50% male children. Gender was not reported in seven studies [5, 11, 14, 17, 22, 25, 27].

3.1.2 Description of the digital, game-based, and robotic tasks

All studies engaged students in a digital task, through a game, a robot, or a computer to complete an activity (Figure 2). In particular, nine papers used educational games or digital exercises, whose purpose was to gamify the school learning content and make the learning process easier for the student. The game content among studies was broad, touching different topics such as math [i.e., 6] and language [i.e., 21]. Two studies [5, 14] used augmented reality (AR) technology for creating and presenting digital lessons to students and for promoting vocabulary learning in young children. One study used robot interactions [1] through a learning instrument called LEGO Mindstorms EV3, a combination of physical robot and a computer programming environment, including LEGO building blocks, sensors, and programmable hardware.

Game-based tasks typically rely on software interfaces emphasizing goal-oriented play and feedback. Differently, robotic tasks engage users through embodied, multimodal human-robot interaction and involve physical interaction, sensorimotor feedback, and a richer multisensory engagement, differentiating it from purely screen-based or software-driven learning experiences.

Eight papers used Kinect games, also called "kinems." Kinems are motion-based games that can empower a variety of learning skills such as math (i.e., "Sea Formuli," [13]), second language (i.e., "Suffiz," [13]), memory (i.e., "Melody Tree," [20]), and attention (i.e., "Body Ball," [27]). Kinect uses a camera and sensors to detect the actions carried out by the participants in order to interact with the games. The platform can also register data about joints movements, the jerks and even descriptive data such as time spent playing. The gameplay activity usually varies based on the type of game whereas the difficulty can be determined by the player or the researcher, making the games self-adaptive according to children's needs.

In four studies children were asked to complete a coding task within small groups of 2/3 people [4, 9, 12, 19]. During this activity, children were expected to use the Arduino platform and upon watching a tutorial to code on a computer with the aim of crafting a small robot or creating a game. In one study children attended a lesson designed with VR technology [7]. During the study children were presented with a giant board that could project holograms and with which they could interact through the VR visor. Two studies [10, 15] used an e-book platform (i.e., ALCE). Lastly, one study used a simple computerized task on memory and executive functions [21].

3.2 Study findings

3.2.1 Engagement: definitions and construct

Through careful examination of studies, a diverse range of interpretations and conceptualizations of engagement in digital contexts have been identified. A summary of the definitions used in each study is reported in Table 1.

Specifically, 12 studies [1, 2, 3, 6, 8, 13, 16, 17, 20, 23, 25, 27] define engagement as linked to the concept of "embodied cognition" or "embodied learning," that is, as mentioned in

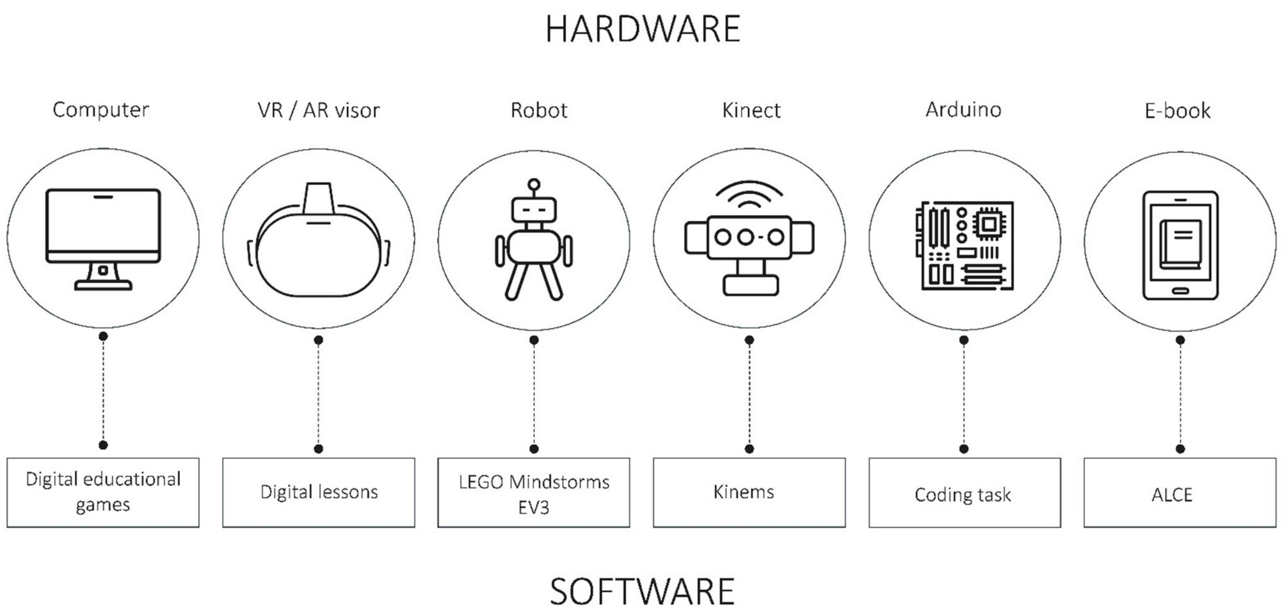

FIGURE 2
Graphical representation of task types categorized by associated hardware and software components used across the reviewed studies+. "Other" records: forward citation searches, contact with authors.

the introduction, an educational approach that emphasizes the importance of physical experience in learning, where active and bodily participation becomes fundamental.

Two studies [4, 9] define engagement as enjoyment, an affective state during which the user feels in control, loses perception of time and space, abandons social inhibition, and encounters the appropriate level of challenge.

In five studies [11, 18, 19, 21, 22] engagement is represented by all emotions and affective states an individual experiences during the task, including enjoyment, boredom, happiness, anger, and excitement.

One study [5] states that in the educational context, engagement includes a wide range of different dimensions including behaviors (such as perseverance, commitment, attention, and participation in challenging courses), emotions (such as interest, pride in success), and cognitive processes (such as problem solving, use of metacognitive strategies).

Two studies [7, 15], defined engagement by distinguishing the behavioral (i.e., as active participation and involvement in activities), emotional (i.e., as positive reactions and feelings toward teachers and work), and cognitive dimension (i.e., as effort and concentration on completing work).

One study [14] focuses on the cognitive engagement through defining it in terms four subject's modes: Interactive, Constructive, Active, and Passive (i.e., ICAP framework).

One study [24] used O'Brien and Toms (2008) definition that, as described in the introduction, postulates engagement as the quality of subject experiences when interacting with a digital or robotic system.

Finally, one study implies that engagement is the intrinsic motivation of an individual interacting with a specific device [26]. Intrinsic motivation refers to situations in which actions are undertaken without any perceivable external influence. For example, an intrinsically motivated individual derives satisfaction from the activity itself and does not anticipate specific gains, such as extrinsic rewards.

In sum, conceptualizations vary greatly, ranging from affective states and emotions experienced during interaction with digital content, to active participation, embodied learning, enjoyment, and intrinsic motivation in completing digital tasks.

3.2.2 Tools and procedures

Tools and procedures have been gathered according to the type of engagement, specifically emotional, behavioral, and cognitive. No studies directly compared the results obtained by different methodologies as most of them used one tool at time for different emotional, cognitive, and behavioral aspects.

A detailed description of the tools used in each of the three categories is provided in the following sections and is reported in Tables 1, 2.

3.2.2.1 Emotional/affective engagement

Studies evaluating children's emotional engagement gathered data on the affective state of the children during the completion of a digital task. Overall, emotional engagement was assessed by 22 papers, making it the most thoroughly explored category. All included studies focused on measuring a wide range of positive and negative affective states (e.g., boredom, happiness, anger, excitement, etc.). Nine studies measured emotional engagement through qualitative notes [2, 5, 7, 11, 17, 20, 21, 25, 27], five used video recording analysis through Artificial Intelligence [4, 13, 18, 19, 21], two speech analysis [22, 26], six self-report methods [1, 4, 9, 10, 16, 26], six physiological indexes [2, 3, 4, 8, 13, 21], one semi structured interview [23], one observational scale [24], and one log data gathered directly from the platform [22].

Video recordings focused on children's facial expressions, verbal cues (e.g., laughing, smiling), and body movements through qualitative analysis of the notes reported by researchers and teachers, AI (e.g., trained by the Facial Action Coding System taxonomy FACS; Cohn et al., 2007).

Self-reports consisted of Likert-based questionnaires or surveys referring to children's or parents' perceptions during the game-based learning activity. They were administered after completing the activity or online, while the child was playing the game or after each play session. The FunQ questionnaire (Tisza and Markopoulos, 2023) consists of 18-items gathered in six dimensions: (a) autonomy (i.e., experiencing control over the activity), (b) challenge (i.e., feeling challenged by the activity), (c) delight (i.e., experiencing positive emotions), (d) immersion (i.e., feeling immersed in it and lost the sense of time and space), (e) loss of social barriers (i.e., socially connectivity), and (f) stress (i.e., experiencing negative emotions during the activity). The questionnaire used by Reinhold et al. (2021, [10]) investigated perceived intrinsic motivation, competence support and autonomy, situational interest, and perceived demand.

In the study by Barana and Marchisio (2020, [16]) the questionnaire was composed of 35 questions inspired by the Pisa 2012 student questionnaire, including items investigating the emotional engagement on specific school topics (e.g., "I like lectures about Mathematics.").

Finally, Ronimus et al. (2014, [26]) asked the parents to complete online a single quantitative item about the children's motivation in doing the task (i.e., "How eagerly did the child play the GraphoGame during the study?").

Physiological indexes were used to measure children's stress and arousal (e.g., heart beat and rate and the electrodermal activity); they were collected by Empatica E4 wristband [2, 3, 4, 8, 13, 21] or the Consensys Shimmer 3 GSR [21]. The Empatica E4 wristband is an unobtrusive bracelet that can be worn by children while they are completing the task. The Shimmer, it is composed of electrodes that must be worn its along with a few probes and a sensor.

Qualitative field notes were collected from teachers, experienced therapists or researchers who were instructed to provide an overall evaluation of children's enjoyment or to focus on children's facial expressions and emotions [20, 25, 27]. Notes could be time-sampled (e.g., Baker-Rodrigo Ocumpaugh Monitoring Protocol method, BROMP, Ocumpaugh, 2012) and computer-assisted (e.g., Human Affect Recording Tool, HART; Ocumpaugh, 2012).

Semi structured interviews were used with teachers and the parents to verify the enjoyment experienced by children in using the intervention Kinems [23].

Speech analysis was used by two studies [22, 26] to evaluate the emotional characteristics of the interaction with the digital task, platform or robot provided. The affective states were analyzed through specific keywords pronounced by the children and prosodic signals that were then clustered by an algorithm in the different categories (i.e., frustration, in flow, boredom, confusion and surprise).

An **observational scale,** used by Martinovic et al. (2016, [24]), was compiled by the researchers to assess emotional engagement during digital tasks. The items assessed whether the child showed amusement (i.e., laughing or smiling), frustration (i.e., sighing, groaning) or anxiety and nervousness during the task.

Log data were acquired by Grawemeyer et al. (2017, [26]) to infer emotional engagement on the base of the interaction of the child with the digital platform (e.g., explore the functions of the platform to find a solution, stop without interacting with the platform to think about what to do).

3.2.2.2 Behavioral engagement

Behavioral engagement was explored by 16 studies, making it the second most thoroughly investigated category. Considering the fact that the reviewed studies analyzed diverse types of behavioral signs to determine behavioral engagement, results in this category are heterogeneous.

Precisely, the behavioral signs indicating engagement that were included in this category were as follows: the time spent looking and not looking at the screen [12, 13]; time spent on the activity and other information related to it (e.g., errors, speed, completion time; [10, 11, 15, 16, 20, 23]); socially interacting and being physically active while performing the task [2, 5, 8]; behavioral reactions (e.g., making noise in the classroom) and somatic posture while completing the task (e.g., leaning forward or keeping a neutral stand; [7]); behavioral distress [27]; behavioral signs of loss of attention [27]; and behavioral signs of loss of interest [27].

The most common methodologies to assess behavioral engagement were video recordings analyzed through qualitative notes [2, 5, 7, 8, 27] and log data acquired from the digital platform [10, 11, 15, 20, 23]. Other methods included eye correlates [12, 13], qualitative notes [27], a single quantitative item [27], observational scales [24], and self-report questionnaires [1, 16].

Video recordings were used to explore diverse signs of behavioral engagement such as: how much the children moved during the activity (e.g., too much, not at all, lazily) and whether they autonomously sought for social interaction with the researchers to also engage them in that activity [2]; specific behaviors, such as jumping, dancing, and making celebratory movements [8]; purposed and intentional movements toward the device or to reach the next goal [5]; overall behavior during virtual reality sessions (i.e., positive, normal or misbehavior) as well as children posture while [7]. The only study with children with Autism Spectrum Disorder [27] measured behavioral distress (e.g., clothing manipulation, teeth grinding, wobbling), loss of interest (e.g., verbal manifestation of tiredness), and loss of attention (e.g., child overstimulation—loss of movement control).

Log data from the digital platforms were collected automatically by the games and included the time spent playing on the platform, the number of mistakes, and the speed of completion of the game [10, 11, 15, 20, 23].

Eye correlates were measured by the Tobii eye-tracker device [12, 13]; the skewness of saccade velocity and the blink rate was used to calculate the level of anticipation and the tiredness.

Qualitative therapist notes were used in children with Autism Specter Disorders to record the presence of inappropriate movements (i.e., genital manipulation, clothing manipulation, teeth grinding, running in place, wobbling, putting hands on the mouth) [27].

Observational scales filled in by the researchers were used to evaluate whether the child was distracted by looking around or eating while carrying out the task [25].

Self-reported questionnaires were used by Barana and Marchisio (2020, [16]) and include items on students' effort, completion of work, perseverance, participation in school and social related activities.

3.2.2.3 Cognitive engagement

The "cognitive engagement" category refers to all those studies that tried to assess diverse cognitive aspects of the participating children, such as attention or cognitive load, while they were completing the digital task. Overall, 14 studies evaluated cognitive engagement. Majority of the studies assessed more than one cognitive aspect: seven papers assessed cognitive load [1, 2, 3, 6, 8, 12, 13, 15], three attention/focus [12, 13, 24], three perceived difficulty [2, 3, 8], two information processing (global and local) [2, 3], two anticipation of the task (i.e., anticipation of the stimuli's appearance during the task) [12, 13], two reasoning processes (e.g., remembering, understanding, analyzing, doing evaluations) [5, 7], one private speech (i.e., language directed to oneself that guides the cognitive execution) (Zivin, 1979) [11], one fatigue [12], one joint attention of all children [12], one ICAP framework (interactive, constructive, active or passive) [14], one perceived control of success and self-regulation [15], and one concentration [26].

The methods used to evaluate cognitive engagement included eye correlates and movements ($n = 5$) [2, 3, 8, 12, 13], questionnaires and self-reports ($n = 5$) [1, 6, 16, 24, 26], video recordings of each game session ($n = 5$) [3, 5, 7, 11, 14], and speech analysis [15].

Eye correlates were detected through Tobii eye-tracking glasses that are an unobtrusive support tool that are considered reliable to obtain a wider and more precise range of the eye data (Tobii, 2023). Several eye-tracker metrics were used to evaluate specific aspects of cognitive engagement: pupil diameter for cognitive load [2, 3, 8, 12, 13]; saccades velocity for perceived difficulty [2, 8, 12] and cognitive anticipation [12, 13]; fixations and saccades velocity for distinguish between global and local information processing [2, 3]; blink rate for cognitive fatigue [12]; simultaneous gazing for joint attention [12].

Self- reported questionnaires were used by three studies [1, 6, 16] to evaluate through Likert scales (e.g., 1 = extremely easy to 7 = extremely difficult) or direct questions (e.g., "How difficult was it for you to successfully accomplish the activity?") the perceived cognitive load and students' effort in completing the task [16].

Parents' reports requested to rank children's concentration on a Likert scale and a final overall question (i.e., "How well did the child concentrate while playing the GraphoGame?") [26].

Observational scale was used by one study [24] to assess comprehension of the game instruction and attention/distraction to the gameplay.

Video recordings were conducted by one [3] or more devices (e.g., one device to record the entire body of the children, one a mirror in front of the children and another through the tablet camera, [11]). Movements and postures were used to analyze the intent to understand the task given and to master it, as careful reading of instructions, reasoning, actively attempting to solve problems presented in the digital lesson, trying to understand task-related issues in discussion with fellow students or teachers and similar [5, 7]. In the study by Wen (2021, [14]) the researchers used video recordings to see whether the children displayed passive behavior (e.g., listening to the lecture but not taking notes), active behavior (e.g., turning or inspecting objects), constructive behavior (e.g., generating new ideas) or interactive behavior (e.g., interacting with the platform).

Speech and discourse analysis were used in three studies: audio recordings, exclamations and other phrases related to cognitive reasoning [7]; private speech as representative of language directed to oneself to guide cognitive execution and regulates social behavior [11]; e-text length (i.e., the word count of students' written responses in writing-to-learn activities) was used as an operationalization of cognitive effort exerted [15].

Figure 3 provides an illustrative overview of the various engagement measures during a child-robot interaction.

3.2.3 Does engagement predict performances and vary according to digital tasks?

Through different study design and methodologies, including qualitative, quantitative (mainly descriptive analyses) and mixed methods studies, it has been possible to evaluate the presence of a relationship between engagement and task performance.

Out of the 22 studies that evaluated emotional engagement, only a minority concentrated on examining this correlation. Through data obtained from self-report questionnaires, the results of a study [4] indicate that there is a link between the fun that children experienced during the digital task and their learning outcomes. Indeed, the FunQ questionnaire total score correlated significantly with learning to code, suggesting that having fun while completing a digital task contributes to learning outcomes. Similarly, two studies [17, 20] suggested that the pleasure of embodied learning, through the use of motion-based educational games, can help to improve children's short-term memory. Another study [10] found that emotional engagement, measured with a self-report questionnaire, could be a unique predictor in explaining a substantial portion of the variance in cognitive learning outcomes. Furthermore, through the use of an observational scale, Martinovic et al. (2016, [24]) demonstrated that children performed better in games in which they show higher levels of fun (e.g., smiling, verbal expression of enjoyment).

Many other studies did not investigate learning improvements, but, however, they analyzed the link between digital games characteristics and emotional engagement, suggesting that the use of digital tasks or robotic activities in comparison to traditional tasks can favor positive emotions [7], reduce stress levels [3, 4, 8], and boredom [7, 20, 22, 27]. Moreover, Zhang et al. (2023, [1]) found that average emotional engagement scores in embodied learning contexts are higher than those obtained in non-embodied learning contexts. Two studies reported that children tend to feel more frustrated when digital activity is too easy or too difficult [11, 24]. Three studies showed that tailoring the characteristics of an intervention to children's preference improves their emotional engagement [20, 22, 25]. One study [13], examined the effect of different modes of self-representation of avatars on children's participation and another study [18] analyzed emotional engagement in children typically developing and those with learning disabilities; neither study found differences between conditions in terms of emotional engagement.

Considering the high level of heterogeneity, studies on behavioral engagement have reported different conclusions. Specifically, only five studies [10, 12, 15, 24, 27] investigated the relationship between behavioral engagement and cognitive performance. Through data obtained from digital platforms, three studies found that the interaction time with the screen [10, 12] or the time on the task [15] predicted student learning and their academic performance. Lastly, through data obtained from video recordings and qualitative notes, Bartoli et al. (2013, [27]) observed that children with ASD tended to reduce their repetitive behaviors associated with discomfort, loss of attention and concentration when playing Kinect games [27].

Nevertheless, most studies have not analyzed this relation but investigated the link between digital task characteristics and behavioral engagement. Gong et al. (2021, [7]) reported that students participating in the digital activity were more behaviorally engaged when there was a positive class behavior and a closer posture to the device. Similarly, Lee-Cultura et al. (2021, [8]) and Lee-Cultura et al. (2020, [13]) found that when children enjoyed the activity they tended to move more. Barana and Marchisio (2020, [16]) reported that the digital learning environment had a strong impact on the behavioral engagement's levels of initially poorly engaged students. Kosmas et al. (2018, [20]) and Kourakli et al. (2017, [23]) found that embodied Kinect game lessons, which involve motor movements during the completion of the task, were in general enjoyable for children. Finally, five studies that utilized data as acquired automatically by the digital platform [10, 11, 20, 23] or a single quantitative item [26] found that if digital activities are well-liked by children, they tend to play more and express the desire to repeat the experience [11, 20, 23, 26].

Considering the 14 studies assessing children's cognitive engagement (i.e., putting effort in remembering and applying the activity rules), those studies that investigated the relationship between cognitive engagement and task performance used eye tracker data (saccade speed, fixation time, pupil diameter) to assess cognitive load, perceived difficulty and anticipation. Two studies [2, 3] found that saccade speed was negatively associated with children's task performance. Three studies found that the cognitive load, measured by pupil diameter and fixation time, was positively associated with children's performance, with higher cognitive load to be related to an overall better performance in the digital task [2, 8, 13]. Lastly, Giannakos et al. (2020, [12]) suggested that anticipation and attention levels, measured by fixation time and saccade speed, had a high predictive value of performances. Regarding the use of self-report questionnaires and observational scale, Georgiou et al. (2021, [6]) found that students who participated in the digital intervention outperformed those who participated in the non-digital intervention in terms of cognitive load and Martinovic

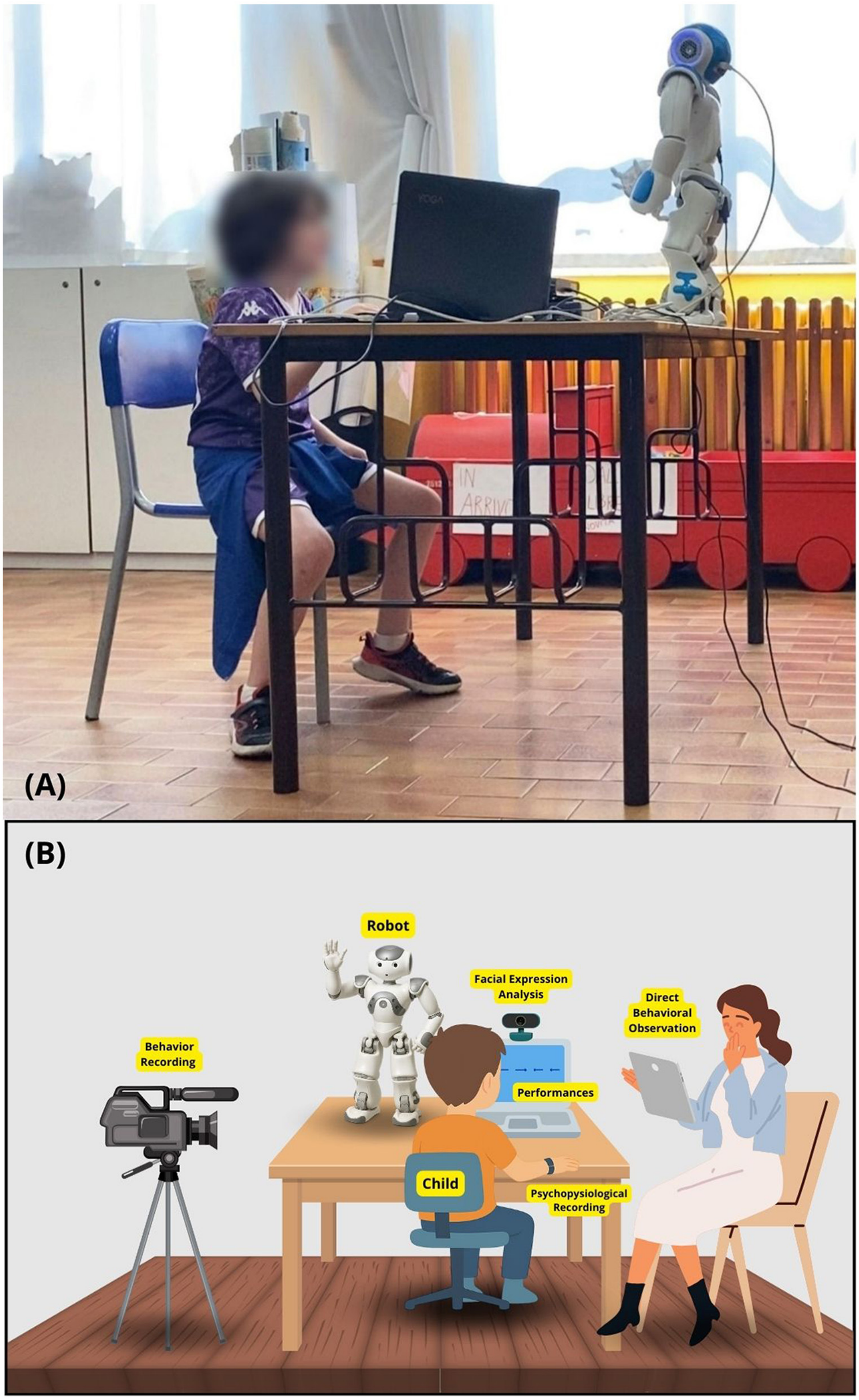

FIGURE 3
Example setting of **(A)** a child interacting with robot and **(B)** procedure and tools used to measure different dimensions of engagement.

et al. (2016, [24]) found that an increased cognitive engagement (e.g., paying attention and putting effort) was related to better performance in computer games. Finally, Barana and Marchisio (2020, [16]) found that cognitive engagement, measured by self-reported questionnaire, is linked to self-regulation and persistence with schoolwork and cognitively engaged students are less likely to give up their learning and more likely to keep engaged with school.

3.3 Methodological quality of the studies, limitations, and risk of biases

The methodological quality assessment of the included studies was carried out through the MMAT instruction. Table 3 depicts the MMAT analysis of each study included in full detail.

Fifteen studies out of 27 obtained high quality MMAT scores. Those studies show several characteristics to be considered reliable and valid, such as appropriate research designs to answer the research question, well-defined and representative sample populations, adequate control of confounding factors and analysis methodologies. Besides, eight studies obtained MMAT scores of some concerns, as they present some characteristics of the best research studies, but also show some limitations or weaknesses that distinguish them from high-quality ones (e.g., the study design is adequate but not optimal, the population is representative but the sample size is small, the data have been collected with methods that are not entirely appropriate, the results are presented in an incomplete or complete but not exhaustive manner). Finally, four studies were of low quality as they exhibited characteristics such as: weak or inappropriate study designs, non-representative populations, unreliable data collection methods, failure to control for confounding factors, inappropriate statistical analysis, and incomplete presentation of results.

The most common limitations of the aforementioned studies included having a cross-sectional study design. Almost all papers, except one, had a relatively small sample size. Furthermore, studies that used self-reported methodologies acknowledged that these methods can be affected by social desirability or other individual variables. Six studies reported that findings may differ based on children's age, thereby older or younger participants could have yielded different results [2, 3, 8, 11, 12, 13]. Five studies also noted that using a different methodology could have given different findings [3, 8, 12, 13, 26]. Notably, five studies recognized that many of the technical tools used (e.g., AI, Empatica E4) were not designed for children and thus findings may have been impacted because of this [4, 8, 13, 18, 22]. Carrying the intervention within the school setting provided high ecological validity to the findings, yet external variables were less monitorable [4, 8, 9, 12, 18, 20] whereas the implementation of the intervention tools within school could sometimes be challenging [7, 23].

In two studies the authors stated that quantitative data should be paired up with qualitative data to provide more in-depth findings concerning engagement [4, 19].

Overall, majority of studies were affected by the following risk biases: (a) potential sampling bias due to the relatively small sample sizes as children from the same country and often the same school setting were recruited, thereby making findings less generalizable; (b) response bias due to the self-report measures used; (c) measurement bias due to the fact that the digital tools used (e.g., AIs, Empatica E4) were not designed or adapted for children. More specific details about limitations and risks of biases are reported in Table 4.

4 Discussion

The main research objectives of this systematic review were: (1) to describe the most commonly used conceptualizations of children engagement in digital and robotic contexts; (2) to understand which tools and procedures are widely used to measure three main types of engagement, that is emotional, behavioral and cognitive, in children and adolescents performing digital and robotic tasks; (3) to investigate the relationship between engagement, children's performances, and task characteristics.

Thorough selection process conducted according to the PRISMA method 27 studies were deemed eligible.

The review includes a diverse selection of studies from different continents, albeit mainly Europe: America ($n = 3$), Asia ($n = 4$), Africa ($n = 1$), and Europe ($n = 19$). Except for Norway, which accommodates 6 of the 27 studies considered, the countries distribution is quite even but there are few studies from each one.

Regarding the population included in the selected studies, the review examined a wide age range, from 6 to 18 years, while only two studies (Crescenzi-Lanna, 2020a; Sridhar et al., 2018) had a sample of preschool children (4–6 years). While no study has investigated the effect of age on the results obtained, such a wide age range may prevent the generalization of the findings to different developmental periods. Indeed, both the conceptualization of engagement and the tools and methodologies used to measure it may vary between preschoolers or school-age children and adolescents, thus not being uniformly adaptable to all ages included in the review. Additionally, most of the studies focused on typically developing children, with only a few considering children with atypical development (Bartoli et al., 2013; Bhattacharya et al., 2015; Ouherrou et al., 2019; Ronimus et al., 2014), leaving open the issue of whether the engagement conceptualization and measures are suitable also for different needs. Future studies should include a larger number of children with atypical development. In fact, with the advancements in ICTs, tele-intervention, tele-assessment, and tools like AI or sensors, it is now possible to gather more information about these children's level of engagement and improve their accessibility and training. Another important consideration is that most of the tools used in these studies were not specifically designed for children (Grawemeyer et al., 2017; Lee-Cultura et al., 2020, 2021; Ouherrou et al., 2019; Tisza et al., 2022). This could have impacted the quality of the data and the suitability of the tools for assessing engagement in children. Future research should focus on developing and utilizing tools that are specifically tailored to the needs, characteristics, and different ages of children.

Additionally, none of the included studies compared different settings, as most of these were conducted in schools. Despite the high ecological validity of carrying the studies in such settings, the children's engagement might have been influenced by external factors, such as environmental noise or unexpected events (Giannakos et al., 2020; Lee-Cultura et al., 2021; Ouherrou et al.,

TABLE 3 Methodological quality for the included studies as conducted with the Mixed Methods Appraisal Tool (Version 2018).

No.	References	Score		Qualitative					Quantitative RCT					Quantitative non-RCT					Quantitative descriptive					Mixed methods					Total
		S1	S2	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5	3.1	3.2	3.3	3.4	3.5	4.1	4.2	4.3	4.4	4.5	5.1	5.2	5.3	5.4	5.5	
1.	Zhang et al. (2023)	Y	Y						Y	Y	Y	N	Y																Some concerns
2.	Lee-Cultura et al. (2022)	Y	Y	Y	Y	Y	Y	Y						Y	Y	Y	CT	Y						Y	Y	Y	Y	Y	High
3.	Sharma et al. (2022)	Y	Y											Y	Y	Y	CT	Y											High
4.	Tisza et al. (2022)	Y	Y											Y	Y	Y	Y	Y											High
5.	Drljević et al. (2024)	Y	Y	Y	Y	CT	CT	Y																					Some concerns
6.	Georgiou et al. (2021)	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y											Y	Y	Y	CT	CT	Some Concerns
7.	Gong et al. (2021)	Y	Y	Y	Y	CT	CT	N						Y	Y	Y	N	Y						Y	Y	CT	CT	N	Low
8.	Lee-Cultura et al. (2021)	Y	Y	Y	Y	Y	CT	CT						Y	Y	Y	CT	Y						Y	Y	Y	Y	CT	Some concerns
9.	Tisza and Markopoulos (2021)	Y	Y											Y	Y	Y	Y	Y											High
10.	Reinhold et al. (2021)	Y	Y											Y	Y	Y	N	Y											Some concerns
11.	Crescenzi-Lanna (2020a)	Y	Y	Y	Y	Y	CT	CT						Y	Y	Y	Y	Y						Y	Y	Y	Y	Y	Some concerns
12.	Giannakos et al. (2020)	Y	Y											Y	Y	Y	Y	Y											High
13.	Lee-Cultura et al. (2020)	Y	Y											Y	Y	Y	CT	Y											High
14.	Wen (2021)	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N	Y											Y	Y	Y	N	CT	Low
15.	Reinhold et al. (2020)	Y	Y											Y	Y	Y	N	Y											Some concerns
16.	Barana and Marchisio (2020)	Y	Y																					Y	Y	Y	Y	Y	High
17.	Kosmas et al. (2019)	Y	Y	Y	Y	Y	Y	Y						Y	Y	Y	Y	Y						Y	Y	Y	Y	Y	High
18.	Ouherrou et al. (2019)	Y	Y											Y	Y	Y	Y	Y											High
19.	Sharma et al. (2019)	Y	Y											Y	Y	Y	Y	Y											High
20.	Kosmas et al. (2018)	Y	Y	Y	N	N	Y	CT						Y	Y	Y	CT	Y						Y	Y	N	CT	N	Low
21.	Sridhar et al. (2018)	Y	Y	Y	Y	Y	Y	Y						Y	Y	Y	Y	Y						Y	Y	Y	CT	Y	High
22.	Grawemeyer et al. (2017)	Y	Y						Y	Y	Y	Y	Y																High
23.	Kourakli et al. (2017)	Y	Y	Y	N	N	Y	Y						Y	Y	Y	Y	Y						Y	Y	Y	CT	N	Low
24.	Martinovic et al. (2016)	Y	Y	Y	Y	Y	Y	Y						Y	Y	Y	Y	Y						Y	Y	Y	Y	Y	High
25.	Bhattacharya et al. (2015)	Y	Y	Y	Y	Y	Y	Y																					High
26.	Ronimus et al. (2014)	Y	Y											Y	Y	Y	Y	Y											High
27.	Bartoli et al. (2013)	Y	Y	Y	Y	Y	Y	Y											Y	Y	Y	Y	N	Y	Y	CT	Y	CT	Some concerns

TABLE 4 Main findings, study limitations, and risk of biases of the papers included in the review.

No.	References	Main findings	Study limitations	Risk of biases
1.	Zhang et al. (2023)	The experimental group scored higher in either overall or subcategories (i.e., cognitive, behavioral, and emotional) of learning engagement than the control group, implying that the EL-CP approach could better facilitate students' learning engagement than the C-CP approach	Limited sample scale; limited intervention duration in this study; low control the possible factors that might affect the outcome variables; there isn't a different embodied learning taxonomies or combine different teaching strategies to support students' learning in robotics courses; there aren't different educational robots to design learning activities	Sampling bias (the children came all from one country and one specific school)
2.	Lee-Cultura et al. (2022)	Saccade speed is negatively associated with children's task performance, so high speed is associated with difficulties in the task; cognitive load is positively associated with the children's performance; lower levels of Heart Rate are associated with lack of engagement; global information processing indicates that children are assessing and comparing different options prior to selecting their answers	The participants' age may impact the results because younger children may play more than older ones	Sampling bias (the children came all from one country and one specific school); measurement bias (tools are not designed for children)
3.	Sharma et al. (2022)	For both games, cognitive load, information processing, saccade velocity, mean of heart rate (HR), n° of EDA peaks and mean phasic EDA have a significant relationship with students' performance; saccade velocity was higher for the interactions associated with wrong responses than for the interactions associated with right responses and it is positively associated with higher perceived difficulty. A significantly higher information processing index associated with wrong responses means that global processing is higher when the students meet a difficult problem to solve; mean HR was higher for wrong responses and it indicates higher stress level. If students were highly stressed, the n° of errors increased; n° of EDA peaks and mean of phasic EDA level were higher in cases of wrong answers. Higher n° of EDA peaks and higher levels of phasic EDA are associated with higher emotional arousal and are negatively associated with the students' performances	Authors are not sure if cognitive load or stress originated from the problem solving task or the novelty of the modality; the problem content was altered to be aligned with the students' projected abilities, thus a different age range may have yielded different results; even though the measurements used are widely used and known, other methodological decision could give different results	Sampling bias (the children came all from one country and one specific school); measurement bias (tools are not designed for children)
4.	Tisza et al. (2022)	Children's average FunQ score was quite high (71.55; sd = 9.756); arousal and the transition between happiness and surprise was a positive predictor of relative learning gain (RLG), while sadness, anger, stress and transition between sadness and anger contributed negatively to the students' RLG; physiological data could not predict the level of fun that the children experienced; FunQ total score positively correlates with RLG; physiological affective states of sadness, anger, stress and the transition between sadness and anger contribute positively to stress, while happiness and surprise contribute negatively; higher level of physiological arousal indicate higher level of engagement	Practical difficulties involved in collecting physiological response data from the children as these technologies are designed for adults; the coding activity was designed as a non-curricular activity, but in a classroom setting, thus it could have been perceived by the children as school activity and autonomy might have been affected; only quantitative data were gathered	Sampling bias (the children came all from one country); response bias (self-report questionnaires can be affected by social desirability) Measurement bias (tools are not designed for children)
5.	Drljević et al. (2024)	The ARLE methodology allows for the systematic coding of student actions to enable analysis of engagement, from which it emerges that students start out being highly engaged with a drop off as the lesson progresses	Additional cameras (i.e., rear cameras in the class) would provide an incremental improvement; the ARLE field is not yet mature; sensors could be inserted to obtain more information	Sampling bias (the children came all from one class and one country)
6.	Georgiou et al. (2021)	Students who participated in the digital intervention outperformed their counterparts who participated in the non-digital intervention in terms of cognitive engagement; the experience cognitive load was higher for students who participated in the non-digital intervention, even though the difference between the two groups was not significant	The sample was small and drawn from a population of convenience; the study relied on self-reported and retrospective measures: Findings are strictly related to the game played in the intervention ("Angle-Makers") as a specific motion-based application for Kinect	Sampling bias (the children came all from one country and school, group was small and they were a group of convenience); response bias (self-report questionnaires can be affected by social desirability)

(Continued)

TABLE 4 (Continued)

No.	References	Main findings	Study limitations	Risk of biases
7.	Gong et al. (2021)	Students in the HoloBoard setting were more engaged behaviorally than those in the normal group, with a more close posture and a more positive class behavior; students in the HoloBoard setting exhibited higher levels of emotional engagement, which was demonstrated by more emotion that has high arousal and positive valence; students in the HoloBoard setting showed more signs of cognitive engagement, with more contribution to the class as well as more responses in the remembering and understanding levels	The experimental setting with the HoloBoard system is not easy to implement and not all the functions of it were used; the study design of comparing students' interaction during the two classes cannot help in estimating possible novelty effects	Sampling bias (the children came all from one country); measurement bias (tool was created *ad hoc* by the researchers)
8.	Lee-Cultura et al. (2021)	Children's physiological stress, cognitive load and emotional regulation were higher during the problem solving phase; there is no connection between the guessing phase and the children's lack of engagement; children experience the lowest stress, cognitive load and emotional regulation during the play phase; children's fatigue was significantly higher during episodes of play than during problem solving, in fact children physically moved more during the former phase	The age of the children represent an adequate population for the intended task, but younger or older children might produce different results; data obtained exhibit high ecological validity, but they are vulnerable to potential disruptions since they were collected in an isolated room of the school; sensor based measurements involve inference and thus have a higher degree of error; different methodological decisions might have yielded different results; the study is cross-sectional	Sampling bias (the children came all from one country); measurement bias (tools can be subjected to errors due to the context)
9.	Tisza and Markopoulos (2021)	Experienced fun has no direct influence on the reported learning; indirect effect of fun on learning across the attitude and the total effect of fun on learning are significant	Authors cannot be sure of what type of learning students considered when responding to the question (e.g., knowledge acquisition, learning new skills, etc.), and the time constraints of the workshop could have played a role in the depth and extent of learning; single-item measures were used; most of the participants were novices, thus novelty might have played a role in the aspects investigated	Sampling bias (the children came all from one country); response bias (self-report item could have been affected by social desirability) Measurement bias (single item cannot investigate the phenomena as deeply as a multidimensional instruments)
10.	Reinhold et al. (2021)	Emotional and behavioral engagement can be considered two distinct predictors for achievement besides prior knowledge. Students' engagement could explain a substantial part of the variance in their cognitive learning outcome, after controlling for prior knowledge. It is noteworthy that while emotional engagement has shown to be a unique predictor, the interaction of behavioral engagement and prior knowledge was predictive for achievement, i.e., higher behavioral engagement was more beneficial for students who had higher prior knowledge of fractions before the intervention	As all 27 students were taught by the same teacher, we cannot answer questions regarding the specific role of the teacher on students emotional and behavioral engagement during the intervention. Limited sample size and lack of a control group	Sampling bias (the children came all from one country, small sample)
11.	Crescenzi-Lanna (2020a)	Enthusiasm and enjoyment were the emotions most often observed; there were no significant differences between the sample of apps in terms of frustration, generally they showed it when the app was very simple or very complex; very few negative emotions were recorded; there were any significant difference between the apps and private speech	Limited sample size of both children and apps, which affects the statistical power; the study of emotions is difficult with pre-school participants since it can provide imprecise or partial information	Sampling bias (the children came all from one country, small sample); reporting bias (one case was not included); measurement bias (Artificial intelligence are not trained with children)
12.	Giannakos et al. (2020)	The best predictors for children's learning were: anticipation, interaction time with the screen and the level of focus; the weakest predictors were: child looking somewhere else other than the AOIs, the interaction time with the robot *per se* and the children's transition from something to someone (child or tutor)	Younger or older population might produce slightly different results while using the eye tracking glasses; generalizability of the findings can be constrained by the design of the activity; only pre- and posttest were used, but other assessment techniques such as interaction analysis or think-aloud could have allowed to have more information about the cognitive process	Sampling bias (the children came all from one country); measurement bias (Eye tracker may yield different results with children)

(Continued)

TABLE 4 (Continued)

No.	References	Main findings	Study limitations	Risk of biases
13.	Lee-Cultura et al. (2020)	Children felt the highest stress when they played with the low avatar self-representation (e.g., just an icon moving on the screen, ASR); high ASR (e.g., avatar was human realistic and moving according to the real movements of the children) was the most arousing; children's cognitive load was higher when they played with the High ASR; high ASR also yields the most local processing (e.g., a specific area or argument); there was no significant difference between the focus for moderate and low ASRs; moderate ASR (e.g., icon is more realistic and it moves with a little delay) corresponded to the most behavioral engagement, followed by high ASR; using low ASR was associated with the least fatigue; there were no statistical significant difference in anticipation levels, on-task ration, emotions and hand movements	The participants of the study were 8–12 years old, but younger or older populations might produce different results; the data were collected *in-situ*, so they have high ecological validity, but they are vulnerable to potential disruptions and noise; different methodological reasons (e.g., different settings, different tools) might have yielded different results; the study is cross-sectional	Sampling bias (the children came all from one country); measurement bias (the validity could have be affected by possible external factors)
14.	Wen (2021)	Students' high levels of cognitive engagement have been evident through the quantified qualitative data of their learning processes with AR. The results show an obvious improvement of the ARC&S class in the activities of creating artifacts and sharing, though not only the experimental class but also the control class were actively engaged in the designed activities	The study was only conducted in two classes across three lessons; the learning process data were only collected from two target groups in each class	Sampling bias (the children came all from the same class, one country, small sample)
15.	Reinhold et al. (2020)	The findings confirm the link between students' active engagement during classroom instruction and their academic outcomes	It is not possible to know from the data whether engagement is a rather stable construct of engagement or a very specific construct of engagement that might vary across a school year; lack of control group	Sampling bias (the children came all from one country)
16.	Barana and Marchisio (2020)	The biggest increase in the engagement level was observed in the students who started the path from the lowest levels of engagement. Moreover, belonging to a lower social class did not influenced the increase in the engagement levels, except for cognitive engagement, for which it is related to the biggest increases	Some non-relevant items in the questionnaire related to the age; performance evaluation related to participation	Sampling bias (the children came all from one country and same school)
17.	Kosmas et al. (2019)	The qualitative note written by the teachers reported high levels of enjoyment of the task; there were progressive improvements in cognitive and academic skills across time	The study was conducted with a small sample; the study is cross-sectional; the game used was commercial; group control was not present so causal effects could not be found	Sampling bias (the children came all from one country, small sample)
18.	Ouherrou et al. (2019)	There were no statistical difference in emotions between children with learning disabilities and peers with no learning disabilities in virtual learning environments	Emotion data were gathered only by using Artificial Intelligence, which might not provide efficient results about the actual learner's emotional state; children could have been influenced by social pressure of playing in a natural environment classroom	Sampling bias (the children came all from one country, small sample); measurement bias (AIs are not trained to analyze children's facial expressions and their emotions)
19.	Sharma et al. (2019)	Emotions, such as happiness and contempt co-occur with higher perceived effectiveness and high satisfaction from the task; negative emotions co-occur with low perceived effectiveness and low satisfaction from the task; emotional togetherness was higher for the groups with high perceived effectiveness and high satisfaction than groups with low perceived effectiveness and low satisfaction; high perceived effectiveness and high satisfaction are positively correlated with the emotional consistency and negatively correlated with the emotional entropy	The study is cross-sectional; the study lacks qualitative data to empower the quantitative ones	Sampling bias (the children came all from one country, small sample); measurement bias (AIs are not trained to analyze children's facial expressions and their emotions)
20.	Kosmas et al. (2018)	Embodied learning showed higher level of enjoyment and appreciations, leading to improvements on short term memory, with significant difference in pre and posttest; qualitative data reported that the experience was fully appreciated by the participants. Most thought that the lesson was more enjoyable; teachers reported that children increased in self-confidence, showed joy, enthusiasm, calmness and motivation to participate	Results might have been affected by the novelty of the situation; data about consecutive sessions were lackings; the study does not cluster students based on their special needs due to small sample size; the study was carried out in mainstream schools with or without special units	Sampling bias (the children came all from one country, small sample)

(Continued)

TABLE 4 (Continued)

No.	References	Main findings	Study limitations	Risk of biases
21.	Sridhar et al. (2018)	Each observations was proved to be useful in understanding the learning method of each child; there were interindividual difference in emotions response to the task depending on the child	Small sample of children; triangulations methods requires longer analysis	Sampling bias (the children came all from one country, small sample); measurement bias (tools can be subjected to errors due to the context)
22.	Grawemeyer et al. (2017)	Students in the affect condition (e.g., students received a customized feedback based on their speech analyzed in real time) were less bored than students in the non-affect condition (e.g., feedback is technical and not based on the speech analysis); if the feedback is not adapted based on a student's affective state, there is a risk that the feedback gets ignored; students in the affect condition were less off-task than students in the non-affect condition; student's knowledge improved in both conditions, but the difference between the conditions was not statistically significant	Emotions were detected only through speech and data from the platform; validity and reliability issues because they relied on humans annotations as well; the second condition, the non-affect one, restricted other interactive aspects of the system; novelty might have influenced the results	Sampling bias (the children came all from one country); measurement bias (instruments used were *ad hoc*)
23.	Kourakli et al. (2017)	The teachers appreciated the positive influence of the Kinems-based intervention because it strengthens the confidence and the enjoyment of the children; parents reported that: children were enthusiastic of the intervention program; children were highly motivated; children had the desire to keep playing even at home	Sample was small; the implementation of the kinems can be hard for some schools; these intervention works best with high functioning SEN children	Sampling bias (the children came all from one country and sample was small)
24.	Martinovic et al. (2016)	Increased engagement was related to better performance in computer games for 13 out of 15 games; as their aged increased, players had less difficulty understanding 6 games out of 15 and they put more effort into these games; 3 games revealed significant correlations between player's age and their observed enjoyment; children seemed to enjoy games containing clear and concise instructions, goals that matched the player's skill level, immediate feedback and opportunities for success; children did not enjoy games that were too simple or too difficult	Sample size was small; sessions were lengthy and some children were tired by the time they played the computer games; several participants experienced technical difficulties during gameplay, which disrupted the order of the games and may have prevented them from fully engaging; participants identified some games as too confusing, too easy or too difficult; games were not classified by game genre as specifically as in other research; correlations do not imply causal inferences	Sampling bias (children all come from the same country; sample of convenience); measurement bias (tool was built *ad hoc* for the experiment)
25.	Bhattacharya et al. (2015)	Motion-based activities have a positive impact on students' engagement; the combination of a fun activity tailored to students' preferences and interests, the embodied nature of the interaction and the facilitative role played by the teacher all contributed	The school in which the intervention took place was already used to technology inside classroom, thus students might not find this intervention as something novel or peculiar; since teachers were asked to video record the children, recording of each child across both early/later and one/two player sessions are missing; novelty may have played an effect	Sampling bias (sample all came from the same country; sample of convenience)
26.	Ronimus et al. (2014)	Children's initial level of enjoyment was high and no significant change in the level of enjoyment occurred during the training period; according to the parents; the children playing with the reward system were concentrating better than the children without; children's own ratings of enjoyment were not affected by game features or the passing of time; the children motivation to play the GraphoGame was high	The study was conducted online which may have affected the assessment method; the enjoyment is strictly related to the GraphoGame environment; answers might have been different if they had been obtained by more traditional methods; it was not possible to monitor how well the children understood the instructions and the questions presented by the game; the surveys were short	Sampling bias (sample of convenience); response bias (self-report item could have been affected by social desirability)
27.	Bartoli et al. (2013)	As the game experience proceeded, stronger positive emotions were triggered and distress tended to decrease, moderating the negative effects that "breaks of routine" normally induce on autistic children	Since data were gathered in a therapeutic setting, it is not possible to know how the results can be translated to other contexts; causality of the improvements is hard to define since not all variables could be isolated; some benefits might have been due to the motion-based game condition; other activities outside of the intervention could have influenced the evaluation; the sample was really small	Sampling bias (sample of convenience coming from one country and really small)

2019; Tisza and Markopoulos, 2021; Tisza et al., 2022). Participants from different regions and age groups might produce different research results, therefore it is important to consider and control these external factors to obtain more reliable and valid data.

In the future, more specific studies focusing on interindividual differences or different subgroups might help implement engagement measurements that are customizable to each individual child.

The review also encompasses four studies classified as low quality (Gong et al., 2021; Wen, 2021; Kosmas et al., 2018; Kourakli et al., 2017), thus, their results being poorly interpretable due to methodological limitations.

4.1 Engagement conceptualizations

The first research question focused on analyzing the conceptualization of engagement, with particular attention to the developmental age, a period in which the concept of engagement may have different facets compared to adulthood.

The presence of multiple interpretations has highlighted numerous theories and approaches that analyze different aspects of the same construct. This variety of perspectives and theoretical approaches provides a rich and complex framework for understanding the nature and the importance of engagement in different digital contexts, thus contributing to a deeper and more articulate view of this fundamental phenomenon in educational dynamics.

Although there are many approaches used, it is important to note that there is no theory of engagement that is universally recognized as the most effective. The complexity of the phenomenon requires a more transversal exploration that takes into account numerous factors and should be able to capture the complexity of interactions between children and digital platforms. Engagement is a polyhedral multicomponential construct, which means that it involves different dimensions and manifestations, therefore, to fully understand it we cannot limit it to a single perspective or a single aspect (Tisza et al., 2022; Ronimus et al., 2014).

As represented in Figure 4, the constructs utilized in the selected studies can be conceptualized through three main components of engagement.

The first component is the emotional engagement (Tisza et al., 2022; Drljević et al., 2024; Tisza and Markopoulos, 2021; Crescenzi-Lanna, 2020a; Reinhold et al., 2020; Ouherrou et al., 2019; Sharma et al., 2019; Sridhar et al., 2018; Grawemeyer et al., 2017). It regards the emotions perceived by children while they are performing a task and interacting with a device or at the end of the interaction. It must include both positive and negative emotions, such as sadness, happiness, fear, surprise, anger, and disgust, and other affective states, such as enjoyment, fun, boredom, frustration, and motivation. Measuring emotional engagement during interaction with digital tasks and robotics can be particularly important in children, for whom, unlike adults who generally have clear goals they want to achieve and therefore own motivation to perform tasks, emotional activation represents a driving factor in exercise and learning (Tisza et al., 2022). In fact, positive emotions are an essential feature to promote engagement and they are also essential in how children and adolescents imagine goals and challenges, guide their behavior, and shape group dynamics and interactions (Sharma et al., 2019). Therefore, when designing effective interventions aimed to promote engagement and improve children's experiences it is important to consider the role of affective state.

The second dimension is the behavioral/bodily engagement (i.e., Barana and Marchisio, 2020; Bartoli et al., 2013; Bhattacharya et al., 2015; Drljević et al., 2024; Georgiou et al., 2021; Kosmas et al., 2019; Lee-Cultura et al., 2020, 2021, 2022; Reinhold et al., 2021; Sharma et al., 2022; Zhang et al., 2023). It refers to the physical actions and active participation of the child during the activity. It includes time spent in front of the screen or the robot, the interaction time with the task, the posture (e.g., closeness to the device), the verbal expressions used, the movements frequency, the actions used. As illustrated by some studies (Bartoli et al., 2013; Giannakos et al., 2020; Reinhold et al., 2021), while log data can be indicators of this type of engagement in both adults and children, in the latter movements during task performance could be as well a positive indicator of engagement and promote learning through processes of embodied cognition.

Lastly, the third fundamental aspect of engagement is the cognitive dimension, which focuses on mental processing and understanding the task (Drljević et al., 2024; Martinovic et al., 2016; Reinhold et al., 2020). Cognitive engagement implies attentional aspects, which goes beyond simple superficial participation, and it translates into the ability to analyze, synthesize and apply information in a meaningful way. Digital and robotic environments could induce higher levels of cognitive engagement (such as attention and cognitive load), essential to promote a real acquisition of knowledge and skills, allowing individuals to develop critical thinking and problem solving skills that are essential for learning. However, in the developmental age, the appropriateness of using digital tools and robotics for learning and intervention, given the cognitive immaturity of individuals such as children, is still a debated issue (Vedechkina and Borgonovi, 2021). Although none of the included studies assessed the effects of age on different dimensions of cognitive engagement, such as attentional engagement and cognitive fatigue, the results of selected studies emphasize the importance of measuring cognitive engagement during children's interaction with digital tools and robotics.

As suggested by the model proposed in Figure 4 it is important to note that these three main dimensions of engagement are all relevant in childhood, as they can interact dynamically and influence each other as well as the child's overall level of engagement.

4.2 Tools and procedures to measure engagement in childhood

The second research question focuses on the evaluation of the tools used to measure the three main components of engagement. In this analysis, a dual approach was adopted. First, we evaluated how much the tools were a direct and sensitive measure of engagement, with particular attention to the interpretability of the

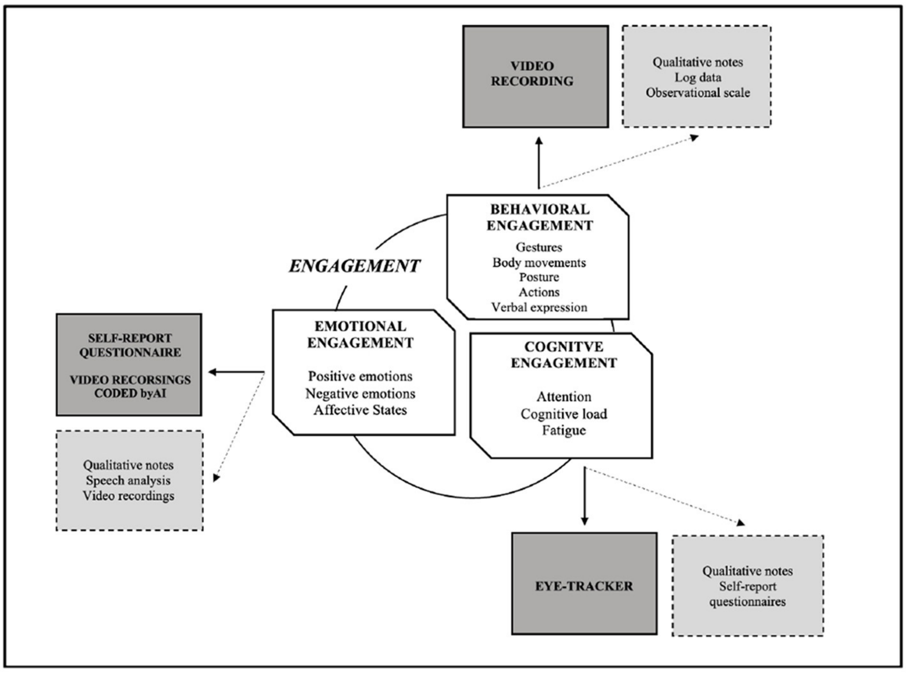

FIGURE 4
A three-dimension model of engagement and the respective measurement tools. Solid arrows indicate the most frequent and evidence-based measures.

results. Subsequently, we considered feasibility by examining the ease of use with children of different ages.

The model represented in Figure 4, alongside the visual depiction of the three components of the engagement that have been described in the section above, offers a comprehensive overview of the most commonly used tools and measures for each component.

In terms of the emotional dimension, there is a widely accepted consensus and understanding regarding the tools and methodologies mainly used to measure it. Indeed, the operationalization of emotions is firmly established, as emotions like joy or sadness, have clear definitions and known behaviors indicators (e.g., smiling, laughing). The majority of the studies (Barana and Marchisio, 2020; Lee-Cultura et al., 2020; Ouherrou et al., 2019; Reinhold et al., 2021; Ronimus et al., 2014; Sharma et al., 2019; Sridhar et al., 2018; Tisza et al., 2022; Tisza and Markopoulos, 2021; Zhang et al., 2023) used self-reports questionnaires or video-recordings coded by AI to measure the emotions and/or facial expressions the children experimented with during the execution of the digital tasks.

Self-report questionnaires offer children the opportunity to directly express their perceptions and communicate autonomously, without external interpretation. Furthermore, by completing the questionnaires, children are encouraged to reflect on their educational experiences, preferred learning methods and any obstacles encountered. Even from a usability point of view, self-report questionnaires represent a particularly suitable option for children as they are easy to use and understand. Their intuitive structure and clear questions make them accessible even to younger children or those with limited language skills. Furthermore, visual formats with images or smileys are often used, which further simplify the compilation and encourage active participation of all children.

Video-recording coded by AI that allows for codification of children's facial expressions associated with the emotions they feel (Lee-Cultura et al., 2020; Ouherrou et al., 2019; Sharma et al., 2019; Tisza et al., 2022). The use of facial detection systems provides continuous monitoring of emotional state with real-time feedback. Furthermore, these tools only require the child to be present and visible to the camera and there is no need to integrate them with sensors. Lastly, they can be configured to respect children's privacy. This is achieved by not storing or recording facial images and processing data anonymously or pseudonymously.

In addition to self-report questionnaires and video-recordings coded by AI, there are other tools used to assess emotional engagement, such as speech analysis, observational scales, and qualitative notes (Bartoli et al., 2013; Crescenzi-Lanna, 2020a; Drljević et al., 2024; Grawemeyer et al., 2017; Kosmas et al., 2019; Lee-Cultura et al., 2022; Martinovic et al., 2016; Sharma et al., 2019; Sridhar et al., 2018). These tools provide valuable information on the child's facial and verbal expression but require a certain level of expertise and preparation by researchers and the interpretation of the information collected can be influenced by their perspective. They can therefore be considered tools to be used in combination with self-report questionnaires or video recordings to provide a more complete and in-depth view of children's emotional engagement (see Figure 4).

Finally, physiological tools, although they offer an innovative approach to assessing engagement in children, present significant challenges related to their complexity of use. Furthermore, the interpretation of physiological data can be subjective and vary based on different factors. For instance, the study by Sharma et al. (2022) suggested that higher arousal is associated with greater stress, while another (Tisza et al., 2022) that higher arousal is associated with a higher level of engagement. Therefore, despite their potential to provide detailed information about children's emotional engagement, physiological tools are often considered more complex to use and require more attention to interpreting results.

Although a few of the selected studies involved children with special educational needs, the mentioned tools could be particularly useful to measure emotional engagement in those children with emotional dysregulation for whom the use of digital or robotic devices for learning could be highly challenging (Paneru and Paneru, 2024; Ribeiro Silva et al., 2024).

In terms of behavioral engagement, researchers collected heterogeneous data by assessing different behaviors based on the digital tasks used. Indeed, in contrast to the standardized operationalization of emotional engagement, there is a lack of consensus in the literature that pertains to the optimal motor or bodily indicators of behavioral engagement in childhood. The most commonly used tool in this category is video recording (Bartoli et al., 2013; Drljević et al., 2024; Lee-Cultura et al., 2021, 2022), which accurately and comprehensively records children's interactions with the digital environment, capturing gestures, body movements, reactions, verbal expressions, and postures. Thanks to its ability to capture a wide range of behaviors, video recording could be a valuable tool for understanding children's behavioral engagement and interactive dynamics with digital and robotic devices. From a usability point of view, it offers direct and non-invasive observation of children's actions, and it allows researchers to analyze the behaviors both during interaction with digital devices and at a later time.

In addition, there are other important methodologies that, although less direct, can provide valuable insights into children's behavioral engagement in digital contexts. These tools include observational scales, qualitative therapist notes, and log data and they could be used in combination with video-recordings to get a complete measure (see Figure 4). Among those studies which analyze data from digital platforms (Reinhold et al., 2020, 2021), some take into consideration the execution time, while others the number of tasks completed, the number of exercises carried out and the time to resolve the problem.

As well as for the emotional engagement, most of the studies demonstrated a shared consensus regarding cognitive engagement's definition and operationalization, as well as its associated indicators, such as attention, cognitive load, and fatigue (e.g., Lee-Cultura et al., 2022; Giannakos et al., 2020; Sharma et al., 2022).

The most used tool in this type of engagement was the eye-tracker, which allowed the collection of data on fixation time, saccade speed and pupil diameter (Giannakos et al., 2020; Lee-Cultura et al., 2020, 2021, 2022; Sharma et al., 2022). This tool provides objective and quantitative measurements of children's eye movements as they engage in digital tasks. It collects accurate data on the child's attention and fatigue and allows researchers to assess children's cognitive engagement in real time. By analyzing the fixation and saccade patterns of the eyes, it is possible to identify which elements of the digital interface capture the child's attention the most and which may be less stimulating or engaging. Modern eye trackers are also designed to be non-invasive and easy to use. They can be integrated into devices, allowing children to naturally engage in tasks without feeling disturbed or restrictive. They can be used with children of different ages and needs.

Additionally, besides the eye tracker, other tools are used to evaluate cognitive engagement in children, such as self-report questionnaires and qualitative notes (Barana and Marchisio, 2020; Georgiou et al., 2021; Martinovic et al., 2016; Zhang et al., 2023). Self-report questionnaires can be easily administered to children in formats suited to their age and level of understanding. However, it is important to note that these tools are based on subjectivity responses and depend on children's ability, which could vary based on age and individual experiences. Therefore, integrating the use of these questionnaires with objective tools, such as the eye tracker, can provide a more complete and accurate assessment of cognitive engagement in children during digital tasks (see Figure 4).

4.3 Engagement-performances relationship

Regarding the relationship between engagement measures and task performance the literature reviewed was scarce and thus, despite its critical role on the construct, limited conclusions can be drawn. The digital and robotic tasks used in the selected studies were developed primarily to entertain and amuse players, with an emphasis placed on immersion and enjoyment rather than on learning and performance. Few studies have shown that being emotionally, behaviorally, and cognitively engaged during a digital activity can lead to an improvement in children's performance or in a certain area of interest (Bartoli et al., 2013; Giannakos et al., 2020; Kosmas et al., 2019; Lee-Cultura et al., 2020, 2021, 2022; Martinovic et al., 2016; Reinhold et al., 2020, 2021; Sharma et al., 2022; Tisza et al., 2022). However, due to the limited amount of findings available on the topic, it is not currently possible to draw definitive conclusions about this relationship. Therefore, although games and activities with robots can be effective in promoting engagement and maintaining children's interest during learning activities, it is important to critically evaluate how they can be integrated into educational contexts to maximize their impact on learning. This requires careful design to ensure that digital games are used effectively as tools to support learning.

This gap in research presents an opportunity for future investigation. Indeed, it would be beneficial to have a better understanding of how engagement affects learning and, to personalize the digital or robotic activity to the diverse child's individual characteristics, how different engagement's components correlates with performance. Furthermore, better understanding this link could provide important information to optimize the design of digital tasks and improve the overall user experience.

The characteristics of the digital task can play a significant role in influencing children's engagement, and many studies have analyzed this aspect (Grawemeyer et al., 2017; Lee-Cultura et al., 2021; Sharma et al., 2022; Tisza et al., 2022). It turns out that, compared with non-digital environments, children who interact with digital and robotic tasks tend to show more positive emotions, greater enjoyment, and a lower propensity for boredom. In agreement with the framework of embedded cognition, games that require more physical and bodily activation were more engaged from the behavioral point of view (Lee-Cultura et al., 2020, 2021). This underlines the importance of actively engaging the body and the mind in educational experiences, not only influencing engagement during the activity but also motivation to participate in the future and enthusiasm to repeat the experience.

Lastly, in relation to the characteristics of digital games, one study highlighted that children liked games more that contained clear and concise instructions, objectives that corresponded to the player's skill level, appropriate use of sound and color, increasingly challenging gameplay, and pleasantly frustrating, immediate feedback, and opportunity for success (Martinovic et al., 2016).

In summary, the characteristics of the digital task can have a significant impact on children's engagement during the activity, highlighting the importance of carefully considering the design of digital environments to maximize engagement and improve the overall user experience.

4.4 Potential implications and impact

To our knowledge, this is one of the first systematic reviews that synthesizes evidence on the conceptualizations and existing tools, measures, and variables used to measure emotional, behavioral, and cognitive engagement during children's performance on a digital task or robotic activity. Previous reviews have focused more on specific approaches to explore children's engagement, such as multimodal data (Crescenzi-Lanna, 2020b; Sharma and Giannakos, 2020), or explored engagement as a general construct without focusing on the different types and aspects of it (Mangaroska and Giannakos, 2018; Sharma and Giannakos, 2020). Conversely, the comprehensive nature of the current systematic review extends beyond the mere documentation of assessment methodologies to encompass an exploration of the wide array of variables considered in evaluating emotional (e.g., facial expression), cognitive (e.g., cognitive load, focused attention), and behavioral (e.g., motor movements) engagement. This synthesis holds substantial value, as it equips different stakeholders, including policy practitioners, researchers, and educators, with rich evidence on the methodologies that can be directly applied. Additionally, this synthesis highlights the importance of a multidimensional approach to engagement assessment (e.g., Fiorini et al., 2024), promoting a holistic understanding of the diverse ways that each type of engagement can be assessed and providing evidence for the development of more nuanced interventions tailored to children's needs.

The findings of the present review hold promise for facilitating future advancements, not only within the realm of research but also at a practical level, by supporting the development of tailored educational tools and interventions When applied in a coordinated and synergic manner, technologies can provide immersive, interactive and adaptive environments that meet the specific cognitive and sensory needs of each child, thus enhancing language acquisition, promote social interaction and increase engagement during interventions, while ensuring accessibility and usability (Bhattacharya et al., 2015; Grawemeyer et al., 2017; Sridhar et al., 2018; Paneru and Paneru, 2024). Considering the interindividual differences in children's development, not all digital and robotic tolls could be effective for everyone. Consequently, selecting adequate tools to gain insight into specific elements that decrease motivation, elicit fatigue, as well as distracting factors during digital tasks, can prove valuable to personalize ICT and robotic tools to children's needs as much as possible.

Given this heterogeneity in the effectiveness of the tools, the use and development of cutting-edge technologies and Generative AI algorithms could prove particularly useful for the automated processing of large datasets and for identifying functioning clusters, thus enabling the identification of more appropriate measures of children's engagement, an essential aspect to ensure the reliability of the collected data.

It is thereby of the utmost importance for clinicians and researchers to pay attention to make treatments for children with special educational needs more enjoyable and sustainable over the long period. In fact, such information can find application in tele-assessment or tele-intervention settings enabling enhanced comprehension of children's behavior observed through webcams or during virtual interactions (Kheirollahzadeh et al., 2024). Despite promising initial findings, further research is needed to address challenges such as content customization, interface accessibility, and seamless technological integration. Optimizing these aspects may significantly improve the effectiveness of digital interventions and contribute to better developmental outcomes and overall quality of life for children with neurodevelopmental conditions (Paneru and Paneru, 2024).

Finally, It is worth noting that, although not directly investigated in the present review, the adoption of emerging technologies such as augmented reality (AR), virtual reality (VR), and generative artificial intelligence (AI) is transforming early childhood education by offering innovative tools to enhance learning, motivation, and personalization.

For example, AR applications can support language acquisition and increase engagement in young children through multisensory interaction (Demirdağ et al., 2024). Similarly, the structured use of these technologies in educational settings has been shown to foster deeper learning and improve perceived learning effectiveness (Demirdağ et al., 2024).

Nonetheless, it remains essential to address issues of accessibility and inclusive design (Ahmed, 2021), as well as to ensure the ethical and safe implementation of such technologies. The integration of comprehensive engagement monitoring measures may contribute significantly to achieving these goals, assuring as well the reliability of data processed by AI based algorithms.

4.5 Limitations and future studies

Despite its strengths, the current review has several limitations that need to be acknowledged. Firstly, there is high heterogeneity across the reviewed studies, with each intervention targeting different objectives or learning outcomes (e.g., language, memory).

This heterogeneity poses challenges in providing a cohesive analysis and synthesis of the reviewed findings. Secondly, as previously mentioned, the broad age range of the children in the reviewed studies, including adolescents, may introduce additional variability and affect the generalizability of the findings. Furthermore, there are no comparative studies across the different types of engagement and the methods most suitable to assess each of them. Another significant limitation is the limited number of studies that specifically investigate the relationship between engagement, performance, and task characteristics. This lack of research hinders the ability to draw solid, generalizable conclusions about the effect of engagement on performance. Lastly, there is a need for further research that includes children with atypical development, utilizes tools designed specifically for children, explores different settings, and focuses on customizable engagement measurements for more effective interventions and understanding of individual differences.

To address these needs, it is crucial to conduct more studies and research specifically focused on children with special needs or atypical neurodevelopment. This will provide a better understanding of their engagement patterns and enable the development of tailored interventions for these types of populations. In addition, increasing the sample size in future quantitative and mixed method studies is important to enhance the generalizability of findings and to capture a wider range of individual differences. Comparisons between different settings, such as laboratory settings and more ecologically valid environments (e.g., classrooms), should be conducted to examine the impact of external variables on engagement results in ecological settings. This will help determine the extent to which engagement measures are influenced by specific contextual factors and provide insights into the ecological validity of the findings. Furthermore, using a variety of instruments and measures to collect data on engagement will provide a more comprehensive assessment. Instead of focusing solely on one aspect of engagement, incorporating multiple dimensions and perspectives will contribute to a richer understanding of children's engagement experiences.

In this context, future reviews should consider studies that incorporate the latest advancements in technology, including AR, VR and generative AI-based approaches. These emerging technologies are significantly reshaping the environments in which children develop, presenting new opportunities for enhancing educational engagement, therapeutic interventions, and promoting social inclusion. By facilitating more immersive, adaptive, and individualized experiences, these technologies have considerable potential to support the development of both typically developing children and those with special educational needs. It will be essential to integrate these innovations into future research to comprehensively capture the evolving landscape of child-technology interactions and to inform the design of advanced measurement tools and interventions (Neugnot-Cerioli and Laurenty, 2024).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

VM: Writing – original draft, Writing – review & editing. AM: Writing – original draft, Writing – review & editing. EB: Writing – original draft, Writing – review & editing. DG: Writing – original draft, Writing – review & editing. SS: Writing – original draft, Writing – review & editing. AG: Writing – original draft, Writing – review & editing. CP: Writing – original draft, Writing – review & editing.

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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.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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