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EDITED BY
Marco De Angelis,
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REVIEWED BY
Carlos Santiago-Torner,
University of Vic - Central University of Catalonia, Spain
Fan Chuanhao,
Hohai University, China

*CORRESPONDENCE
Li Liu
✉ joyly0807@163.com

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How AI usage shapes employees' exploitative and exploratory innovation: joy as a mediator and learning goal orientation as a moderator

Li Liu[1]* and Ya Lv[2]

[1]Dhurakij Pundit University, Bangkok, Thailand, [2]Credit Approval Department, Fujian Branch, Postal Savings Bank of China, Fuzhou, Fujian, China

Introduction: Employees play a pivotal role in organizational ambidextrous innovation, yet existing studies have paid limited attention to how artificial intelligence shapes employees' exploitative and exploratory innovation. Drawing on cognitive appraisal theory and the broaden-and-build theory of positive emotions, this study identifies joy as the central emotional mechanism linking artificial intelligence usage to these two forms of innovation. As a high-arousal positive emotion grounded in person–situation fit, joy promotes active engagement, in contrast to lower-arousal emotions such as satisfaction or happiness that reflect acceptance rather than pursuit. We further examine how learning goal orientation moderates the extent to which joy translates into exploitative and exploratory innovation, thereby advancing understanding of how technological empowerment affects ambidextrous innovation.

Methods: This study draws on survey data from Chinese employees (N = 669) and employs partial least squares structural equation modeling (PLS-SEM) to examine the mediating role of joy in the relationship between artificial intelligence usage and employees' exploitative and exploratory innovation, as well as the moderating effect of learning goal orientation.

Results: Artificial intelligence usage shows small but meaningful positive effects on employee exploitative innovation (β = 0.120) and exploratory innovation (β = 0.104), with joy partially mediating the effect on exploratory innovation only (indirect β = 0.050). Moreover, joy positively predicts exploitative innovation (β = 0.182) and exploratory innovation (β = 0.206) only under high learning goal orientation.

Discussion: The findings emphasize that the role of positive emotions is not universal but rather motivation-dependent: joy mediates exploratory but not exploitative innovation, while high learning goal orientation amplifies its effects on both innovation types. These results extend emotion theories to AI-enabled work contexts and offer practical implications for fostering employees' emotions and learning motivation to achieve synergy between technological empowerment and innovation.

KEYWORDS

ambidexterity, artificial intelligence usage, employees' exploitative innovation, employees' exploratory innovation, joy, learning goal orientation, PLS-SEM, positive emotions

1 Introduction

In the context of accelerated digital and intelligent transformation, enterprises aiming for sustainable development in a dynamic competitive environment must simultaneously deepen existing capabilities (exploitative innovation) and actively explore new opportunities (exploratory innovation; Lauenstein et al., 2025). However, these two types of innovation often compete for limited resources, making it difficult to balance them effectively (Denrell et al., 2025). Prior research indicates that employees are central to both exploitative and exploratory innovation, and can foster organizational ambidextrous innovation from the bottom up by flexibly switching between the two (Boemelburg et al., 2023; Mom et al., 2019; Otto et al., 2024).

With artificial intelligence (AI) widely embedded in organizational business processes, employees' working patterns, ways of acquiring information, and role perceptions in innovation activities are undergoing profound changes (Ocal and Crowston, 2024). The usage of AI exhibits a typical "double-edged sword" effect: on the one hand, it can significantly enhance work efficiency and satisfaction, providing cognitive and resource support for employee innovation (Eshraghian et al., 2024; Noy and Zhang, 2023); on the other hand, empirical research has shown that overreliance on AI may weaken employees' autonomous thinking and deep information processing ability, thereby suppressing their innovation potential (Burton et al., 2024; Kanbach et al., 2023). Taken together, these mixed effects suggest that the consequences of AI usage cannot be fully understood solely in terms of its technical features, but also depend on how employees cognitively perceive and emotionally experience AI in their work context. Accordingly, a critical research question concerns whether and how AI usage promotes employees' exploitative innovation (EEI) and exploratory innovation (EXI).

Existing studies on ambidextrous innovation have predominantly focused on traditional resources, such as organizational support, leadership styles, and individual characteristics (Boemelburg et al., 2023; Hardy et al., 2024; Otto et al., 2024; Zhang et al., 2023). However, how AI, as an emerging digital resource, systematically shapes employees' ambidextrous innovation remains underexplored, particularly regarding the differentiated pathways through which it affects EEI and EXI. To address these gaps, drawing on prior research highlighting employees' technological perceptions and emotional responses to AI usage (Noy and Zhang, 2023), this study examines how employees' cognitive appraisals and affective processes contribute to the distinct pathways through which AI usage influences EEI and EXI.

Emotions, as critical outcomes of cognitive appraisal, are recognized to influence innovative performance through their impact on information processing (Johnson, 2020). Prior studies indicate that employees tend to hold a positive attitude toward AI usage (Guha et al., 2023; Eshraghian et al., 2024). While such positive attitudes are often associated with low-arousal positive states (e.g., satisfaction and happiness) reflecting efficiency and convenience, AI usage can also elicit high-arousal positive emotions (e.g., joy) when employees cognitively appraise it as supporting competence development and meaningful goal achievement. Accordingly, focusing on discrete positive emotions offers a theoretically informative perspective for understanding how AI usage shapes employees' ambidextrous innovation.

The broaden-and-build theory of positive emotions (BBT) proposes that high-arousal positive emotions expand individuals' cognitive structures, facilitating information integration and exploratory tendencies (Fredrickson, 2013). Cognitive appraisal theory (CAT) further underscores that various positive emotions are linked to specific appraisal patterns, which in turn elicit distinct coping tendencies (Lazarus, 1991). Among these, joy, as a high-arousal positive emotion, typically arises from a sense of accomplishment derived from the alignment between technology usage and personal goals. It broadens cognitive and behavioral repertoires, while also reinforcing psychological resilience and sustaining long-term innovative motivation (Johnson, 2020; Tan and Titova, 2024). In addition, the influence of emotions is contingent upon individual motivational traits (Smith and Lazarus, 1993), learning goal orientation (LGO), characterized by an emphasis on competence development and task mastery, may reinforce the extent to which joy facilitates both EEI and EXI (Marshall et al., 2019).

In summary, drawing on CAT and the BBT, this study develops a moderated mediation model of "AI usage - joy - EEI/EXI." Accordingly, this study pursues two specific research objectives: (1) to examine whether and how joy mediates the relationship between AI usage and EEI/EXI, and (2) to investigate whether LGO moderates the effects of joy on EEI and EXI. By elucidating the synergistic mechanism between positive emotions and motivational dispositions, this study contributes to advancing theoretical insights into human–machine collaboration and ambidextrous innovation, and provides practical implications for enterprises in designing targeted strategies for AI deployment and human resource management to achieve a dynamic balance between technological empowerment and innovation outcomes.

2 Literature review and hypothesis development

AI refers to technologies that mimic human intelligence by replicating cognitive functions to accomplish complex tasks (Davenport et al., 2020). AI usage refers to the extent to which employees integrate AI systems or tools into their work processes, thereby facilitating information processing, knowledge creation, and decision-making (Man Tang et al., 2022).

Existing research generally affirms the value of AI in enhancing organizational efficiency and stimulating innovation; however, the mechanisms by which AI shapes employee-level innovation remain contested (Liu et al., 2024; Mithas et al., 2022). Importantly, organizational ambidexterity arises from balancing exploitative and exploratory innovation, yet the resource competition between these two activities makes their simultaneous pursuit inherently challenging (Mom et al., 2019). Although structural separation across organizational units or temporal sequencing has been proposed as a solution, such arrangements are often difficult to implement in resource-constrained small and medium-sized enterprises (Boemelburg et al., 2023). Consequently, an increasing body of research emphasizes the critical role of employees in enacting ambidexterity from the bottom up. By exercising autonomous judgment in their work, employees flexibly allocate attention and effort between refining existing practices and experimenting with new approaches, which constitutes the microfoundations of organizational ambidextrous innovation (Otto et al., 2024). Accordingly, understanding how AI usage shapes EEI and EXI becomes critical for explaining how digital technologies contribute to organizational ambidexterity.

While concerns persist that excessive reliance on AI usage may dampen employees' willingness and capacity to innovate (Burton et al., 2024), growing evidence highlights its benefits in enhancing knowledge sharing, autonomy, and information processing (Jia et al., 2023; Malik et al., 2021). Notably, these existing studies adopt a unidimensional view of innovation, overlooking the distinct cognitive and resource demands of EEI and EXI. As a result, the mechanisms by which AI usage differentially influences the two forms of innovation remain largely underexplored (Hwang and Wu, 2025). Given the fundamental distinction between process optimization and disruptive breakthroughs, treating innovation as unidimensional fails to capture AI's functional role across diverse forms of innovation (Boemelburg et al., 2023; Mom et al., 2019).

Positive emotions have been shown to enhance individuals' cognitive flexibility and creative potential, thereby providing essential psychological resources for innovation (Fredrickson, 2013). However, positive emotions differ in their arousal level and functional implications (Keltner et al., 2019). Low-arousal positive states such as happiness or satisfaction tend to signal comfort and acceptance of current conditions, whereas joy, as a high-arousal positive emotion, reflects an activated appraisal of person-situation fit that mobilizes approach-oriented motivation and innovation-oriented effort (Arnett, 2023; Tan and Titova, 2024). Accordingly, joy is particularly relevant for understanding different forms of innovation. AI usage can evoke joy by alleviating cognitive load, enhancing perceived control, and improving efficiency, which in turn fosters EEI and EXI (Eshraghian et al., 2024). However, research has largely focused on positive emotions in general, paying little attention to how joy—as a discrete emotion—differentially influences EEI and EXI (Eshraghian et al., 2024; Lin and Chen, 2024). For example, joy may foster EEI through efficiency and task engagement, while facilitating EXI through cognitive flexibility, resource accumulation, and psychological resilience.

2.1 Theoretical background

According to CAT, positive emotions originate from individuals' primary appraisals of a situation as favorable to their goal attainment and are subsequently refined into distinct types of positive emotions through secondary appraisals, such as responsibility attribution, coping potential, and future expectations (Lazarus, 1991). Among them, joy is characterized as a high-arousal state driven by goal congruence and a sense of accomplishment, manifested through excitement and vitality, with its core rooted in the perceived fit between the individual and the situation (Johnson, 2020). In contrast to happiness (enduring and stable), satisfaction (low-arousal fulfillment), gratitude (externally triggered), or schadenfreude (marked by moral undertones), joy is immediate, motivation-driven, and socially meaningful (Arnett, 2023). Accordingly, joy is not merely a positive affective state but also a dynamic interaction between individuals and their environment, which motivates the pursuit of further goal-congruent experiences and thus demonstrates unique research value in the context of innovation (Tan and Titova, 2024).

The BBT delineates two core functions of positive emotions (Fredrickson, 2001). First, positive emotions broaden individuals' momentary attentional and cognitive scope, stimulating a wider range of thought patterns and action possibilities and thereby fostering flexible cognition and the capacity to integrate diverse information and materials. Second, positive emotions build enduring personal resources that span psychological, cognitive, and social domains and persist beyond the emotional episode, thereby strengthening resilience and supporting long-term adaptive functioning, including sustained innovative potential (Fredrickson, 2013; Lin and Chen, 2024).

The integration of these two theories provides a systematic account of how AI usage promotes EEI and EXI through joy. Specifically, CAT explains that employees are more likely to experience joy when they cognitively appraise AI usage as reshaping task characteristics by enhancing task controllability and feedback clarity, thereby increasing goal congruence and perceived controllability. Building on this emotional response, the BBT clarifies that joy facilitates innovation through two complementary functions. First, joy broadens attentional and cognitive scope, enhancing flexible information processing and integration, which supports the efficiency-oriented refinement and improvement characteristic of EEI. Second, joy builds enduring personal resources that strengthen resilience and sustain adaptive functioning over time, thereby enabling continued engagement with EXI. Moreover, LGO, as a motivational trait, may amplify the positive effect of joy on EEI and EXI, underscoring individual motivation as a critical boundary condition in the emotion–innovation pathway.

2.2 AI usage and employees' exploitative innovation

EEI primarily relies on existing knowledge and resources to improve established capabilities or processes in order to enhance efficiency. Compared with exploratory innovation, it entails relatively lower difficulty and risk and requires less complex knowledge structures (Boemelburg et al., 2023; Mom et al., 2019). AI usage plays a pivotal role in this process by streamlining routine and programmed tasks, thereby freeing employees' time and energy to focus on core activities and strengthening their capacity for knowledge-based improvements (Zhou et al., 2023). Moreover, by simulating human cognitive functions, AI helps employees identify suboptimal processes and propose improvements, reducing cognitive load and enhancing the efficiency of process optimization and product refinement (Dennis et al., 2023). In addition, AI's ability to store and integrate vast amounts of data facilitates the recombination of existing knowledge, ultimately boosting both productivity and creativity (Lee and Chung, 2024; Peres et al., 2023).

Drawing on CAT and the BBT, employees are likely to appraise the functional benefits of AI usage as enhancing task controllability and goal attainment, which broadens their momentary cognitive scope and supports the efficient refinement of existing knowledge and routines, thereby creating favorable psychological and cognitive foundations for exploitative innovation. Accordingly, we propose the following hypothesis:

> *H*1: AI usage positively influences EEI.

2.3 AI usage and employees' exploratory innovation

EXI centers on the creation of new knowledge, opportunities, and technologies. It is inherently uncertain, difficult, and risky, requiring employees to mobilize stronger intrinsic motivation and more diverse knowledge structures. Despite these challenges, it delivers substantial benefits and supports the achievement of long-term organizational goals (Boemelburg et al., 2023; Mom et al., 2019). AI usage, with its vast data pools, cross-domain knowledge bases, and advanced algorithms, contributes to EXI in several parallel ways. First, it equips employees with novel analytical insights, extends professional expertise, and unlocks creativity and decision-making capacity (Kanbach et al., 2023; Spring et al., 2022). Second,it enhances motivation and confidence to pursue new solutions by automating routine tasks and supporting complex activities (Malik et al., 2023). Third, AI applications in personalized knowledge management and digital learning strengthen employees' skills and engagement, thereby fostering innovative thinking (Jatobá et al., 2023; Verma and Singh, 2022). Finally, AI usage stimulates employees' proactive engagement by enabling high-complexity and specialized tasks that create challenging environments, while its data-driven decision-making and information-processing capabilities facilitate the emergence of new technologies and products (Jia et al., 2023).

Integrating CAT and the BBT, employees are likely to appraise AI usage in uncertain and complex tasks as enhancing coping potential, competence development, and future opportunities, which broadens their cognitive and attentional scope and facilitates the accumulation of enduring cognitive and psychological resources, thereby creating favorable conditions for sustained engagement in exploratory innovation. Accordingly, we propose the following hypothesis:

> *H*2: AI usage positively influences EXI.

2.4 Joy as a mediator

Joy is a high-arousal positive emotion that evokes experiences of ease and freedom, broadens attention and thought processes, and thereby enhances creativity and cognitive flexibility (Johnson, 2020). According to CAT, joy emerges from individuals' holistic evaluations of goal congruence, responsibility attribution, coping potential, and future expectations within a given situation (Lazarus, 1991). When employees perceive that AI usage enhances efficiency, facilitates knowledge acquisition, and improves performance, and attribute this achievement to their effective mastery of AI, joy is more likely to be evoked (Luo et al., 2021; Shao et al., 2024). Moreover, the continuous advancement of AI's analytical and predictive capabilities reinforces employees' positive expectations of its future value, thereby amplifying the experience of joy.

The BBT further elucidates how joy exerts differentiated effects on distinct forms of innovation through its emotional functions. With respect to EEI, joy broadens individuals' momentary thought–action repertoires, providing immediate cognitive benefits (Fredrickson, 2001, 2013). This momentary broadening facilitates the integration of diverse information into existing knowledge frameworks and supports efficiency-oriented refinement and optimization of processes and products (Forgas and George, 2001; King, 2020). However, because EEI largely relies on established routines, procedural knowledge, and incremental improvements aimed at short-term efficiency gains (Boemelburg et al., 2023), its implementation is less dependent on sustained emotional arousal.

In contrast, EXI requires employees to move beyond existing frameworks and pursue novel directions, involving sustained resource investment and exposure to high levels of uncertainty and risk (Boemelburg et al., 2023). Although joy is inherently transient, its broadening effects promote open and flexible thinking and facilitate the accumulation of psychological resources, thereby enhancing resilience, risk tolerance, and sustained engagement under uncertain conditions (Fredrickson, 2001, 2013). Through these processes, joy supports employees in deriving positive meaning from setbacks and persisting in the pursuit of long-term goals such as exploratory innovation (Johnson, 2020; Tan and Titova, 2024; Welpe et al., 2012).

Taken together, joy functions as a positive emotional mechanism linking AI usage to employee innovation, but its functional significance differs across innovation types. Whereas joy provides supplementary cognitive support for EEI, it constitutes a more fundamental psychological resource for sustaining long-term engagement in EXI. Accordingly, we propose the following hypothesis:

> *H*3: Joy mediates the relationship between AI usage and EEI.
>
> *H*4: Joy mediates the relationship between AI usage and EXI.

2.5 Learning goal orientation as a moderator

LGO reflects an individual's inclination to enhance personal competence and to understand or master new tasks. As a key motivational construct, it fosters learning, knowledge acquisition, and creativity (Dweck and Leggett, 1988). From the perspective of CAT, emotional responses arise from individuals' subjective evaluations of situational events, and this appraisal process is shaped not only by external task characteristics but also by internal motivational orientations, goals, and cognitive capacities (Schwarz, 2012; Smith and Lazarus, 1993). Accordingly, individual differences such as LGO play a central role in shaping how employees interpret AI-enabled work contexts and the meaning they assign to emotional experiences such as joy. Compared with alternative motivational orientations that emphasize outcome validation or risk avoidance, LGO is especially well suited to AI-enabled work because it supports autonomous judgment regarding when to refine existing practices and when to pursue novel solutions, thereby strengthening the translation of joy into both exploitative and exploratory innovation (Boemelburg et al., 2023).

In particular, employees with high LGO prioritize capability development, willingly embrace challenging goals, and exhibit strong motivation and autonomy (Marshall et al., 2019). From the BBT, such individuals are more likely to use joy elicited in AI-enabled work to broaden their momentary cognitive scope and actively engage with task demands, thereby strengthening perceived task control and deepening involvement in process optimization and improvement, which facilitates exploitative innovation (Da Motta Veiga and Turban, 2014). Furthermore, high LGO individuals tend to engage in deep processing and continuous learning, which allows them to convert the broadening effects of joy into enduring cognitive and psychological resources, such as persistence, confidence, and resilience. These built resources sustain engagement with complex and unfamiliar tasks, fostering perseverance and creativity in exploratory innovation (Da Motta Veiga and Turban, 2014; To et al., 2015). By contrast, employees with low LGO are inclined to settle for the status quo, relying on the convenience of AI to complete basic tasks and avoid risks. Without a strong mastery-oriented motivation, joy is less likely to be transformed into broadened cognition or accumulated resources, thereby constraining its positive influence on both exploitative and exploratory innovation (Lench et al., 2016).

Taken together, learning goal orientation shapes how employees interpret and utilize joyful experiences elicited by AI usage, thereby influencing the extent to which joy can be translated into exploitative and exploratory innovation. Accordingly, we propose the following hypothesis:

> *H5*: LGO positively moderates the relationship between joy and EEI, such that the effect of joy on EEI is stronger when LGO is higher.
>
> *H6*: LGO positively moderates the relationship between joy and EXI, such that the effect of joy on EXI is stronger when LGO is higher.

The research model is depicted in Figure 1.

3 Methods

3.1 Data collection

To examine the proposed hypotheses, this study employed a quantitative research design, distributing questionnaires both online and offline. Data were collected between January and May 2025 from full-time employees who used AI tools in their daily work.

To enhance methodological rigor, a clear definition of AI usage was provided at the beginning of the questionnaire. AI was defined as digital systems or tools used by employees to support their work, including content generation, problem solving, decision support, or innovation-related tasks, and may involve technologies such as machine learning, natural language processing, image recognition, knowledge-based systems, robotic process automation, or generative AI.

Respondents were then presented with a screening item indicating whether they primarily used AI to support problem solving, task automation, content generation, or other innovation-related activities, or whether they mainly relied on other software tools (e.g., Excel, Photoshop, or traditional information systems) to support their work. Only respondents who selected the former option were allowed to proceed to the main questionnaire, whereas those selecting the latter option were automatically screened out. This screening item was used solely for sample selection purposes and was not treated as a latent construct in the analytical model.

Notably, this study did not differentiate between specific AI types, as the focus was on employees' functional use of AI as a work-enabling resource rather than on technical distinctions among AI systems. Respondents also indicated their daily AI usage time using predefined time categories, which was used to describe AI usage intensity in the sample.

The survey was conducted in Suzhou and Shanghai, regions in China where AI adoption is relatively advanced. Target enterprises were identified through company websites to ensure that participating organizations had implemented AI in work processes. After obtaining informed consent, questionnaire links were distributed to employees. The incentives consisted of small gifts valued at approximately RMB 30 and were provided solely to encourage participation and voluntary referrals, independent of respondents' answers or survey completion. Given that the survey was anonymous and posed minimal risk, formal ethical approval was exempted under the institutional guidelines. The study was conducted in accordance with generally accepted ethical principles for research involving human participants.

Following established practices for detecting careless responses in survey research (Meade and Craig, 2012), multiple data screening criteria were applied. Responses with completion times of less than 2 min were excluded, whereas responses exceeding 15 min were

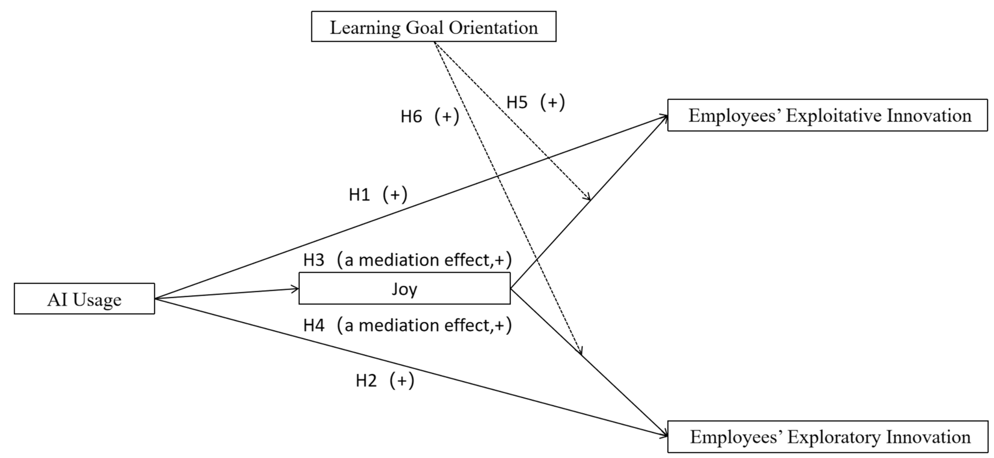

FIGURE 1
Hypothesized research model.

treated as missing. Cases showing largely uniform response patterns or clear cross-item inconsistencies between reported daily AI usage time categories and AI usage frequency were removed. After screening, 669 valid responses were retained for further analysis, yielding an effective response rate of 87.64%.

Table 1 presents the sample characteristics, indicating that the respondents' demographic attributes are broadly representative of the target population. Of the 669 respondents, the gender distribution was nearly balanced (51.6% male; 48.4% female). The majority were born after 2000 (46.5%) or after 1990 (45.0%), reflecting the age profile typical of emerging technology users. Most participants held a bachelor's degree (61.4%), had 2–5 years of work experience (65.6%), and were employed in IT (28.8%), finance (21.8%), or film/media (19.6%). Frontline employees comprised the majority (81.6%), with relatively few in managerial positions. AI usage intensity was high, with 49.0% using AI 4–8 h daily and 25.4% using it more than 8 h.

TABLE 1 Participant characteristics.

Characteristic	Variables	n	%
Gender	Male	345	51.6
	Female	324	48.4
Age	Born after 2000	311	46.5
	Born after 1990	301	45.0
	Born after 1980	46	6.9
	Born after 1970	9	1.3
	Born after 1960	2	0.3
Education	Associate degree	98	14.6
	Bachelor's degree	411	61.4
	Master's degree	118	17.6
	Doctoral degree or above	42	6.3
Work experience	≤ 1 year	53	7.9
	2–5 years	439	65.6
	5–10 years	81	12.1
	≥ 10 years	96	14.3
Industry	Manufacturing	17	2.5
	Finance	146	21.8
	Services	29	4.3
	IT	193	28.8
	Advertising & Marketing	40	6.0
	Film & Media	131	19.6
	Gaming	103	15.4
	Other industries	10	1.5
Position	Frontline employees	546	81.6
	Frontline managers	95	14.2
	Middle managers	12	1.8
	Senior managers	16	2.4
Daily AI usage time	Less than 1 h	50	7.5
	1–4 h	121	18.1
	4–8 h	328	49.0
	More than 8 h	170	25.4

Although respondents may be nested within organizations, the present study focuses on individual-level cognitive and emotional processes. All focal constructs were conceptualized and measured at the individual level; accordingly, following established practices in management research (Hitt et al., 2007), single-level analysis was adopted.

3.2 Statistical procedure

Partial least squares structural equation modeling (PLS-SEM) was employed to test the proposed model. This approach was appropriate given the presence of multiple latent constructs, mediating and moderating relationships, and a complex path structure, as well as its robustness to potential deviations from multivariate normality (Hair et al., 2019).

Following established PLS-SEM guidelines, we adopted a two-stage analytical procedure. The measurement model was first evaluated in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity to ensure that the constructs were measured appropriately before interpreting structural relationships. Subsequently, the structural model was assessed to test the hypothesized direct, indirect, and moderating relationships among constructs. Given that PLS-SEM does not rely on distributional assumptions, the significance of these effects was examined using a non-parametric bootstrapping procedure with 5,000 resamples, which provides empirical standard errors and confidence intervals for parameter estimates, with *p*-values reported as complementary information to facilitate interpretation.

In addition, supplementary robustness analyses were conducted to assess the stability of the results across alternative analytical specifications. These analyses are reported in a later section of the manuscript and are intended to examine whether the main findings are sensitive to model assumptions.

3.3 Measurement

The measurement instruments for this study were developed from well-established scales that have been widely adopted in leading journals and repeatedly validated, ensuring strong reliability and validity. To align with the research context, the measures for AI usage, EEI, EXI, joy, and LGO were carefully adapted. All items were translated using a back-translation procedure to ensure semantic equivalence and were reviewed by academic experts to enhance clarity and contextual relevance. In addition, a pilot test was conducted to assess item comprehensibility and refine wording where necessary. Each construct was measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

In line with the data collection procedure, only respondents who reported active use of AI tools in their work were included in the analysis. The screening item used to identify eligible respondents was employed solely for sample selection and was not specified as a construct in the analytical model.

AI usage: This construct was measured with a three-item scale adapted from Man Tang et al. (2022). A sample item is, "*I use artificial intelligence to accomplish most of my work tasks*" (Cronbach's $\alpha = 0.803$).

Joy: This construct was measured with a seven-item unidimensional scale adapted from Sun et al. (2022), which was originally derived from the emotion dimension scale of Clark and Watson (1994). Despite some linguistic overlap with general positive affect (e.g., happiness), the inclusion of activation-related items (e.g., excited, enthusiastic, lively, energetic) captures high-arousal joy. Thus, joy reflects an activated emotional state elicited by AI usage in this study (Cronbach's α = 0.890).

Employees' exploitative and exploratory innovation: EEI and EXI represent the two key dimensions of ambidextrous innovation as conceptualized by Mom et al. (2019). EEI was measured with seven items adapted from Mom et al. (2019); a sample item is, "*I have optimized existing processes based on my prior work experience*" (Cronbach's $\alpha = 0.887$). EXI was measured with seven items from the same source; a sample item is, "*I search for possibilities of new services, products, processes, or markets*" (Cronbach's α = 0.888).

Learning goal orientation: This construct was measured with a six-item scale developed by VandeWalle (1997). A sample item is, "*I often read materials related to my work to improve my competence*" (Cronbach's α = 0.887).

Control variables: To reduce potential confounding effects and enhance the robustness of model estimation, this study controlled for variables commonly included in prior research on AI usage and employee innovation, following Man Tang et al. (2022) and Bernerth and Aguinis (2016), including gender, age, education level, and work experience. In addition, industry type, job position, and daily AI usage time were controlled to account for potential contextual influences. All control variables were measured using single-item indicators and incorporated as exogenous control variables in the analytical model.

3.4 Common method bias

Given that the data were collected using a cross-sectional, self-report survey, common method bias (CMB) may represent a potential concern. Following the recommendations of Podsakoff et al. (2003), this study addressed potential common method bias through both procedural remedies and an additional statistical diagnostic.

With respect to procedural remedies, anonymity and confidentiality were emphasized in the questionnaire instructions, and respondents were informed that there were no right or wrong answers to reduce evaluation apprehension and social desirability bias. In addition, survey items were refined through expert review and pilot testing, and items measuring different constructs were presented in a mixed order rather than grouped by construct to reduce respondents' ability to infer hypothesized relationships.

As a statistical diagnostic, Harman's single-factor test was conducted. The results indicated that no single factor accounted for the majority of the variance, with the first factor explaining 32.51% of the total variance, which is below commonly accepted thresholds. These findings suggest that common method bias is unlikely to substantially bias the results.

4 Results

4.1 Reliability and validity test

This study employed SmartPLS 4 and Mplus 8 for data analysis. As shown in Tables 2, 3, all constructs exhibited acceptable reliability and validity (Cronbach's $\alpha > 0.80$, $CR > 0.70$, $AVE > 0.50$). Confirmatory Factor Analysis (CFA) results indicated a good fit for the five-factor model ($\chi^2/df = 1.050$, $CFI = 0.998$, $TLI = 0.998$, $RMSEA = 0.009$, $SRMR = 0.026$), supporting discriminant validity (Williams et al., 2010).

4.2 Research model test

The results of the partial least squares structural equation modeling (PLS-SEM) analysis are presented in Table 4. Overall, the findings provide partial support for the proposed hypotheses.

Regarding the main effects, AI usage exerted a significant positive impact on both EEI (H1: $\beta = 0.120$, $p < 0.01$) and EXI (H2: $\beta = 0.104$, $p < 0.05$). Although these effects are modest in magnitude, they indicate that AI usage contributes incrementally to both forms of innovation, explaining approximately 11.4% of the variance in EEI and 11.6% in EXI.

With respect to the mediating role of joy, the indirect effect of AI usage on EXI was statistically significant (H4: $\beta = 0.050$, $p < 0.05$). For EEI, although the bootstrap confidence interval suggested statistical significance, the effect size was small and the p value was marginal (H3: $\beta = 0.041$, $p > 0.05$). Consistent with the recommendations of Hair et al. (2019), this indirect effect was therefore interpreted as statistically weak and lacking substantive relevance, and was not regarded as evidence of a supported mediation.

Regarding the moderating effect, results showed that the interaction between joy and LGO was significant for both EEI (H5: $\beta = 0.089$, $p < 0.05$) and EXI (H6: $\beta = 0.092$, $p < 0.05$). The subsequent simple slope analyses showed that joy promoted both forms of innovation at high levels of LGO (EEI: $\beta = 0.182$, $p < 0.01$; EXI: $\beta = 0.206$, $p < 0.01$), but not at low levels (EEI: $\beta = 0.004$, $p > 0.05$; EXI: $\beta = 0.022$, $p > 0.05$).

For a more intuitive demonstration of the moderating effect of LGO, this study employed simple slope analysis, plotting graphs at the mean (M), −1 SD, and +1 SD to represent average, low, and high values of the variable. The graphs illustrate how employees with high versus low LGO differ in exploitative and exploratory innovation (see Figures 2, 3).

4.3 Robustness checks

To assess the robustness of the main findings, this study re-estimated the structural model by including daily AI usage time as a control variable. As shown in Table 5, the hypothesized relationships remain substantively unchanged. Although the indirect effect of AI

TABLE 2 Measurement model results.

Variables	Cronbach's α	M	SD	CR	AVE	R2
AIS	0.803	3.911	0.998	0.884	0.718	–
JOY	0.890	3.923	0.878	0.912	0.603	0.191
EEI	0.887	3.942	0.849	0.912	0.596	0.114
EXI	0.888	3.940	0.863	0.914	0.598	0.116
LGO	0.887	3.828	0.959	0.914	0.639	–

AIS, AI usage; M, mean; SD, Standard deviation; CR, Composite reliability; AVE, Average variance extracted; R2, adjusted R-square.

TABLE 3 Confirmatory factor analysis results for discriminant validity.

Model	χ^2	df	χ^2 / df	RMSEA	CFI	TLI	SRMR
Five-factor model	414.672	395	1.050	0.009	0.998	0.998	0.026
Four-factor model	2066.609	399	5.179	0.079	0.826	0.810	0.110
Three-factor model	2089.368	402	5.197	0.079	0.823	0.809	0.114
Two-factor model	3991.257	404	9.879	0.115	0.625	0.596	0.152
One-factor model	4509.610	405	11.135	0.123	0.571	0.539	0.155

The four-factor model combines EXI and LGO into one factor; the three-factor model combines EEI, EXI and LGO into one factor; the two-factor model combines joy, EEI, EXI and LGO into one factor; the one-factor model combines all constructs into one factor.

TABLE 4 Results of the hypothesis tests.

Path	Coef.	Mean	SD	*t*-value	*p*-value	95%CI	VAF	Results
AIS → EEI	0.120	0.121	0.042	2.836**	0.005	[0.037,0.204]	–	Supported
AIS → EXI	0.104	0.105	0.044	2.393*	0.017	[0.018,0.190]	–	Supported
AIS → Joy → EEI	0.041	0.041	0.021	1.934	0.053	[0.001,0.084]	25.6%	Not supported
AIS → Joy → EXI	0.050	0.050	0.022	2.285*	0.022	[0.009,0.095]	32.5%	Supported
Joy * LGO → EEI	0.089	0.091	0.038	2.366*	0.018	[0.016,0.163]	–	Supported
Joy * LGO → EXI	0.092	0.093	0.039	2.340*	0.019	[0.013,0.167]	–	Supported
Joy → EEI (LGO = +1 SD)	0.182	0.185	0.066	2.746**	0.006	[0.059,0.319]	–	–
Joy - > EXI (LGO = +1 SD)	0.206	0.207	0.068	3.020**	0.003	[0.080,0.348]	–	–
Joy → EEI (LGO = −1 SD)	0.004	0.004	0.054	0.068	0.946	[−0.102,0.111]	–	–
Joy → EXI (LGO = −1 SD)	0.022	0.022	0.057	0.386	0.699	[−0.091,0.136]	–	–

Paths correspond to Hypotheses H1–H6 as specified in Section 2.2–2.5. Simple slope results are reported for illustrative purposes. VAF, variance accounted for; CI, confidence interval. Bootstrapping was performed with 5,000 resamples. Effects are considered statistically significant when the 95% confidence interval does not include zero. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

usage on EEI becomes marginally significant after controlling for daily AI usage time, the effect size is small and the significance is sensitive to model specification, and is therefore not interpreted as robust. Moreover, daily AI usage time does not exhibit significant direct or indirect effects, suggesting that the main findings are not driven by differences in AI usage intensity.

5 Discussion

5.1 Findings

This study examines how AI usage shapes EEI and EXI by integrating the mediating role of joy and the moderating role of LGO. Overall, the findings reveal the differentiated emotional pathways through which AI usage influences distinct forms of innovation, highlighting how the effects of positive emotions depend on task characteristics and individual motivational orientations in AI-enabled work contexts.

The results demonstrate that AI usage significantly promotes both EEI and EXI, suggesting that AI supports employees not only in refining existing processes and resources but also in pursuing new methods and opportunities. These findings align with prior research indicating that AI usage facilitates incremental improvements while simultaneously enabling the generation of novel knowledge through human–AI collaboration (Einola and Khoreva, 2023; Lee and Chung, 2024). Moreover, the results indicate that AI usage contributes to EEI and EXI alongside other individual and contextual factors, consistent with the multi-resource nature of ambidextrous innovation (Boemelburg et al., 2023).

Importantly, the mediating role of joy differs across innovation types. Joy mediates the relationship between AI usage and EXI, but not between AI usage and EEI. This divergence can be understood through the functional alignment between emotional processes and task characteristics. Drawing on the BBT, high-arousal positive emotions such as joy broaden individuals' momentary thought–action repertoires and facilitate the accumulation of enduring psychological resources over time (Fredrickson, 2001). These functions are especially relevant for EXI, which involves experimentation, novelty seeking, and sustained engagement under conditions of uncertainty and risk (Boemelburg et al., 2023; Mom et al., 2015).

In contrast, EEI involves structured and incremental refinement within established routines, placing relatively weaker demands on emotional arousal (Boemelburg et al., 2023; Mom et al., 2015). In AI-enabled work settings, the functional features of AI, including the recombination of existing process knowledge, can directly support EEI (Scarbrough et al., 2024). Consequently, joy operates as a

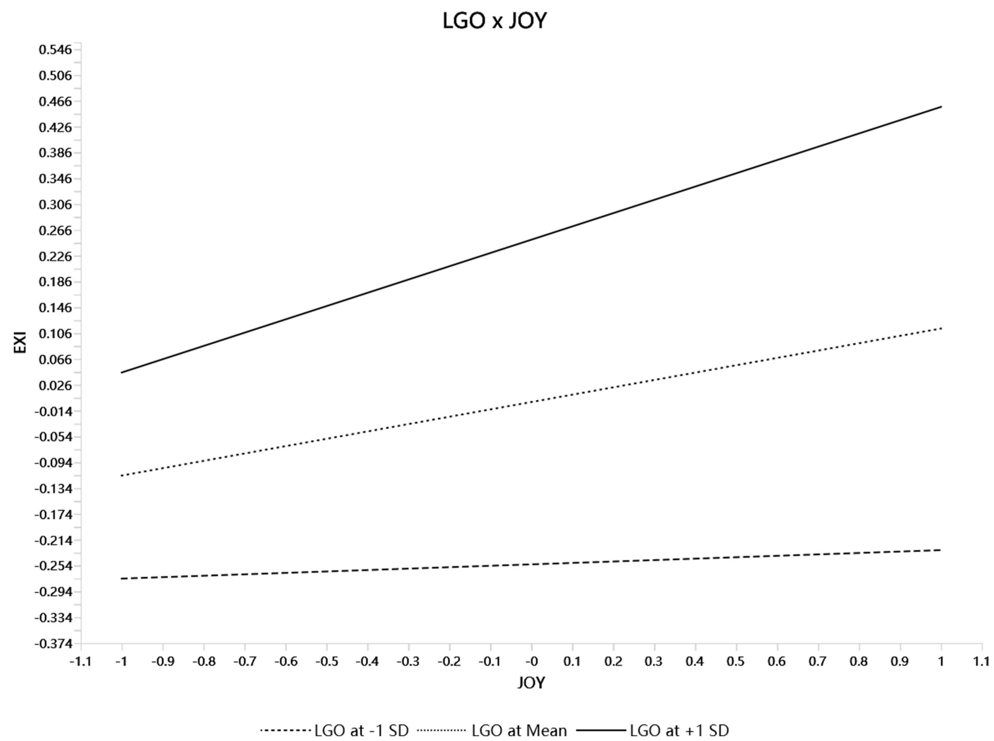

FIGURE 2
Moderating effect of LGO on joy and EEI.

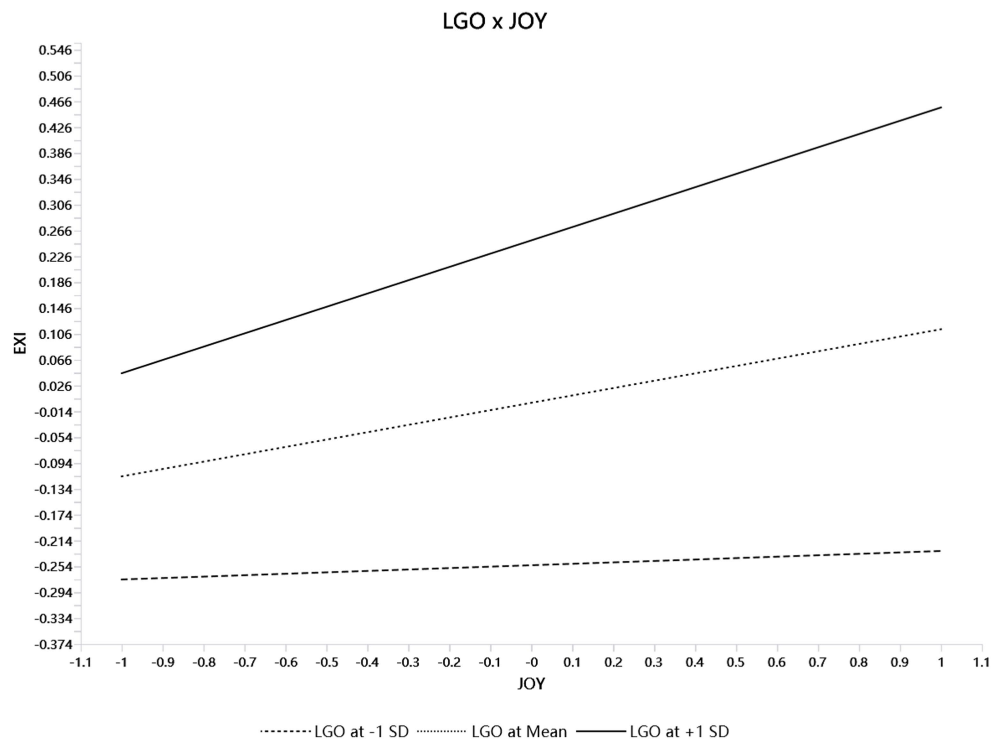

FIGURE 3
Moderating effect of LGO on joy and EXI.

TABLE 5 Robustness checks with daily AI usage time as a control variable.

Hypothesized path	Baseline model β (p)	With AI Time β (p)	Robustness
AIS → EEI (H1)	0.120 (0.005)	0.118 (0.005)	Robust
AIS → EXI (H2)	0.104 (0.017)	0.103 (0.019)	Robust
AIS → Joy → EEI (H3)	0.041 (0.053)	0.042 (0.049)	Not robust
AIS → Joy → EXI (H4)	0.050 (0.022)	0.051 (0.021)	Robust
Joy * LGO → EEI (H5)	0.089 (0.018)	0.091 (0.016)	Robust
Joy * LGO → EXI (H6)	0.092 (0.019)	0.093 (0.018)	Robust

Values are standardized path coefficients with *p*-values in parentheses; the baseline model refers to the main model without control variables; the robustness model includes daily AI usage time as a control variable; robustness indicates whether the direction and statistical significance of the hypothesized relationships remain unchanged.

supplementary rather than a central psychological mechanism in translating AI usage into EEI.

The significant interaction between joy and LGO further clarifies the contingent role of joy in EEI. Joy predicts EEI only among employees with high LGO, indicating that positive affect is more likely to be mobilized into process-focused improvement behaviors when individuals cognitively appraise AI usage as an opportunity for skill development and mastery (Solberg et al., 2022). Under such conditions, joyful experiences associated with AI use may be interpreted as signals of learning progress, thereby sustaining incremental refinement efforts. By contrast, for employees with low LGO, joy is more likely to remain a transient experiential state that does not translate into sustained EEI. This divergence helps explain why the indirect effect of joy in the AI usage–EEI relationship is not significant at the aggregate level.

Taken together, these findings suggest that joy does not function as a universal emotional mechanism linking AI usage to all forms of employee innovation. Instead, its role is contingent on the alignment between emotional functions and task characteristics, as well as on individual motivational orientations. Whereas joy constitutes a core psychological resource for sustaining exploratory innovation, its influence on EEI is conditional and becomes salient only under specific motivational conditions. This pattern is consistent with CAT, which suggests that the implications of emotions for action tendencies vary depending on how individuals appraise situational demands and goal relevance (Lazarus, 1991; So et al., 2015; Tan and Titova, 2024).

5.2 Theoretical and practical implications

5.2.1 Theoretical implications

By addressing two core research objectives, this study advances CAT and the BBT in explaining employee innovation in AI-enabled work contexts.

Objective 1 was to examine whether and how AI usage influences EEI and EXI through discrete positive emotions. The findings show that joy mediates the relationship between AI usage and EXI, but not between AI usage and EEI. This result extends the application of CAT in innovation research by demonstrating that, in AI-enabled contexts, the innovation-enhancing role of joy is contingent on task demands, such that the same emotional experience serves different functions in EEI and EXI. At the same time, this finding refines the BBT by indicating that the broadening potential of positive emotions is not uniformly translated into all forms of innovation. By conceptualizing joy as a discrete positive emotion, the results advance the discrete emotions literature by showing that even high-arousal positive emotions may exert differentiated effects across innovation outcomes.

Objective 2 was to examine when joy translates into EEI and EXI by considering individual motivational orientations. The findings indicate that LGO constitutes a critical boundary condition for the innovation-enhancing role of joy, such that positive emotional experiences are converted into innovative outcomes only under high levels of LGO. This result advances understanding of emotion-innovation linkages by highlighting that the functional consequences of joy depend not only on task demands but also on individuals' motivational orientations.

Collectively, these findings underscore the interactive roles of cognitive appraisal, discrete emotions, and individual traits in shaping how AI usage translates into employee innovation. By empirically integrating CAT and BBT in an AI-related context, this study provides a more fine-grained theoretical framework for understanding ambidextrous innovation and lays a foundation for future research to explore the differentiated roles of other discrete positive emotions across diverse forms of innovation.

5.2.2 Practical implications

This study offers several theory-informed managerial implications for guiding AI adoption and innovation management.

First, the findings suggest that organizations may benefit from moving beyond a narrow focus on efficiency gains and tool value by designing AI systems and training programs that support learning-oriented experiences rather than solely emphasizing task automation. Specifically, managers may emphasize features such as transparent AI feedback, opportunities for experimentation, and user control over AI-assisted outputs. Prior research suggests that such design choices can help position AI usage as a source of perceived competence development and engagement, which may facilitate the conversion of positive emotional experiences into innovative outcomes.

Second, drawing on prior literature on automation reliance and human-AI interaction, organizations may need to remain attentive to the potential risk of employees' overreliance on AI in routine and procedural tasks, which has been suggested to undermine active engagement in exploitative innovation. Prior research indicates that reduced initiative in process improvement, weakened task ownership, or uncritical acceptance of AI-generated outputs

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may signal overreliance. Managers may help ensure that AI functions as an enabling tool rather than a substitute for employees' problem-solving efforts by adopting practices such as human-in-the-loop designs, reflective review sessions, and accountability mechanisms.

Third, the findings underscore the relevance of LGO, suggesting that AI training and development practices may benefit from differentiation according to employees' motivational profiles. For employees with high LGO, training programs may place greater emphasis on advanced AI functionalities, exploratory use cases, and open-ended problem-solving tasks that reinforce joy as a signal of learning progress. For employees with low LGO, more structured training approaches, guided learning paths, and targeted feedback may help translate positive affect into sustained innovative behavior. Overall, aligning AI implementation with individual motivational orientations may increase the likelihood of fostering synergy between technological empowerment and employee innovation.

Taken together, these implications should be viewed as plausible and theory-consistent extensions of the findings rather than direct causal conclusions, given the study's cross-sectional design and modest effect sizes.

5.3 Limitations and directions for future research

This study has several limitations that provide avenues for future research. First, its cross-sectional design restricts the ability to draw strong causal inferences. Future studies could adopt longitudinal designs to better capture the dynamic evolution of AI usage and ambidextrous innovation over time, and conduct experimental studies that manipulate AI-related features (e.g., feedback transparency or autonomy) to strengthen causal inference.

Second, the analysis focused solely on joy as a discrete positive emotion, which may limit the comprehensiveness of the emotional mechanisms examined. Moreover, although joy is conceptually distinct from more stable evaluative states such as job satisfaction in terms of arousal and temporal dynamics, the use of AI as a work tool may blur this distinction in practice. Future studies could therefore explicitly distinguish discrete emotions from general attitudinal constructs, or examine their joint effects, to further clarify the unique role of joy in AI-enabled innovation processes.

Finally, the data were collected primarily from Chinese enterprises, which may constrain the cross-cultural generalizability of the findings. Replications across cultural contexts and multilevel designs examining how organizational AI strategies interact with individual emotions and motivational orientations would further strengthen and extend the present findings.

6 Conclusion

This study investigates the role of discrete emotional and motivational mechanisms in linking AI usage to EEI and EXI. By integrating CAT and the BBT, the findings indicate that joy functions as a differentiated emotional pathway rather than a uniform driver across innovation types. In addition, the study identifies LGO as a critical boundary condition that shapes when joy translates into innovation. Taken together, the findings underscore that the innovation-related consequences of AI usage depend not only on technological features, but also on how employees cognitively appraise AI-enabled work and how emotional experiences interact with individual motivational orientations, offering a key takeaway for research on digital work and AI-enabled innovation.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The requirement of ethical approval was waived by Institutional Review Board, Dhurakij Pundit University, Thailand for the studies involving humans because Institutional Review Board, Dhurakij Pundit University, Thailand. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

LL: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. YL: Conceptualization, Formal analysis, Methodology, Writing – review & editing.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fhumd.2026.1695355/full#supplementary-material

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