



AI-driven HRM digitization in effect: Mechanisms, conditions, and employee outcomes

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ARTICLE INFO

JEL Codes:

M12
M15
O32
O33

Keywords:

AI-driven HRM digitization
tacit knowledge awareness
innovation performance
metacognitive strategies
educational innovation
self-determination theory

ABSTRACT

Artificial intelligence (AI) is increasingly used in contemporary organizations as a tool for digitizing systems and reconfiguring key functions such as human resource management (HRM). However, not all employees exposed to AI-driven HRM digitization benefit equally in their capacity to generate innovative outcomes. Drawing on self-determination theory and integrating perspectives from organizational learning, this study advances a moderated mediation model that explains how and when AI-enabled HRM digitization fosters innovation. We propose that, while AI-driven HRM practices can stimulate the metacognitive strategies of employees, the extent to which these strategies translate into enhanced innovation depends critically on their tacit knowledge awareness. In this proposal, we highlight the paradoxical nature of algorithmic systems: they may serve as autonomy-supportive tools that encourage exploration and self-directed learning or as autonomy-controlling mechanisms that intensify monitoring and reduce intrinsic motivation. Using a multi-wave, multi-source field study of Chinese employees and supervisors ($N = 347$), we found that AI-driven HRM positively predicts innovation through metacognitive strategies, but only when employees demonstrate high levels of tacit knowledge awareness. When awareness is low, AI-HRM digitization fails to enhance innovation, which reveals the limitations of digital HRM effectiveness. These findings underscore that tacit knowledge awareness fundamentally conditions how AI-driven HRM digitization supports or undermines innovation, which advances theory by extending self-determination perspectives to technology-mediated HRM. Thus, this study discusses the theoretical and practical implications for designing AI-enabled HRM systems that balance algorithmic control with employee autonomy.

Introduction

Artificial intelligence (AI) refers to a set of digital technologies, including algorithmic decision-making, machine learning, and natural language processing; these technologies enable machines to mimic human cognitive functions, including reasoning, learning, and decision-making (Jarrahi et al., 2023; Khan et al., 2024; Teng et al., 2024). As AI becomes increasingly embedded in the workplace, it reshapes job design and restructures decision-making and human capital strategies (Chen et al., 2025; Li et al., 2023; Parent-Rocheleau et al., 2024). Regarding human resource management (HRM), AI is a central driver of digital transformation, which leads to the emergence of AI-driven HRM digitization; in this process, algorithms, data analytics, and machine learning augment or reconfigure traditional HRM functions (Budhwar et al., 2023). These developments not only improve administrative

efficiency but also redefine how talent is recruited, developed, and managed (Barba et al., 2025). However, while AI-driven HRM digitization is acknowledged for enhancing efficiency, personalization, and fairness, scholars have raised concerns regarding transparency and trust and its possible facilitation of surveillance, control, and dehumanization (Charlwood & Guenole, 2022; Duggan et al., 2023). This paradox contains critical questions regarding how employees experience and respond to AI-driven HRM systems, whether as enablers of learning and innovation or as tools of constraint and compliance.

Recent research has begun exploring the role of AI in shaping HRM practices and their implications for employee behavior and organizational outcomes (Chowdhury et al., 2022; Prikshat, Malik, et al., 2023; Tambe et al., 2019). Scholars have conceptualized AI-driven HRM systems as socio-technical configurations that reshape talent acquisition, performance management, and learning and development processes

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through algorithmic personalization and data-driven insights (Tambe et al., 2019). Empirical studies have tested correlations between AI-driven HRM and outcomes such as efficiency and job satisfaction (Cheng & Hackett, 2021; Do et al., 2025; Mo et al., 2025). Notably, these studies often adopt a functionalist perspective that ignores the motivational and cognitive mechanisms through which AI systems influence employees. We acknowledge that these studies are valuable to the knowledge of the transformative role of AI-driven HRM. However, we identify a lack of theorization on how employees make sense of and navigate the paradoxes embedded in AI-driven HRM. This omission is critical given that research shows that collaboration with AI often fails because employees lack metaknowledge and awareness of their own cognitive limits, which confines productive delegation and undermines innovation potential (Fügenger et al., 2022).

Existing studies have emphasized the relevance of AI-enabled HRM systems in areas such as recruitment, training, and performance management (Allal-Chérif et al., 2021; Prikshat, Islam, et al., 2023). However, gaps remain regarding how these systems foster cognitive and psychological mechanisms in employees, such as metacognitive strategies and tacit knowledge awareness, which are essential for innovation. Organizations invest in AI technologies to remain competitive; therefore, employee innovation performance becomes a strategic imperative (Kong et al., 2024; Schweitzer & De Cremer, 2024). As such, knowledge of the paths taken by AI-driven HRM is critical to employee innovation performance. AI-driven HRM systems may support this construct by providing personalized guidance, feedback, and learning opportunities. However, these systems can also create cognitive strain or reinforce control, which depends on how employees cognitively appraise them (Zhao et al., 2025). We propose that tacit knowledge awareness is particularly relevant in this context, as it enables employees to transform intuitive and experiential knowledge into explicit forms that enhance AI collaboration and innovation (Ahn et al., 2025; Kucharska & Erickson, 2023).

To address these gaps, this study proposed two research questions. (RQ1) What role do the metacognitive strategies of employees play in mediating the correlation between AI-driven HRM digitization and their innovation? (RQ2) What factors influence the indirect effect of AI-driven HRM on the innovation performance of employees via their metacognitive strategies?

We investigated these questions by applying self-determination theory (SDT), which is a motivational framework that explains how work environments satisfy the psychological needs of individuals for autonomy, competence, and relatedness; these needs are fundamental for fostering intrinsic motivation, learning behavior, and performance (Deci et al., 2017; Ryan & Deci, 2000). From an SDT perspective, we propose that AI-driven HRM digitization can be a double-edged sword: it not only supports psychological needs and learning through intelligent guidance but also undermines them by amplifying monitoring and control (Basu et al., 2023; Charlwood & Guenole, 2022). This study suggests that AI-driven HRM practices, such as algorithmic performance appraisal and algorithmic mentoring systems, can serve as digital

affordances for these needs. As such, they encourage engagement in metacognitive strategies that foster innovation among employees. Moreover, we propose that employee tacit knowledge awareness, which indicates the extent to which an employee can consciously utilize and share ideas, skills, and intuitive knowledge gained through personal experiences (Kucharska & Erickson, 2023), moderates the influence of AI-driven HRM by strengthening its indirect effects on innovation performance. Indeed, employees who have a high level of tacit knowledge awareness are better positioned to capitalize on AI-driven HRM to improve their learning and performance (Nonaka & von Krogh, 2009; Zhao et al., 2025).

This study makes several contributions (see the theoretical model in Fig. 1). First, by integrating SDT into the AI-HRM domain, we identify metacognitive engagement among employees as a psychological mechanism that links AI-driven HRM with innovation. We argue that, when the basic psychological needs of employees are met through AI-augmented HRM practices, they are more likely to engage in intentional self-regulated learning behaviors that enhance their innovation. Second, we extend SDT by identifying tacit knowledge awareness as a key boundary condition. When tacit knowledge awareness is high, employees are more likely to feel confident, capable, and secure in deploying AI-enabled systems to enhance their job roles. This condition nurtures an environment where psychological safety supports exploration, risk-taking, and metacognitive engagement (Kucharska & Erickson, 2023; Nonaka & von Krogh, 2009), which ultimately leads to stronger innovation outcomes. Third, by linking AI-driven HRM practices to employee behaviors, this framework helps explain how digital HRM tools can cultivate specific motivational states and performance outcomes. Finally, this study offers practical implications for organizations and HRM professionals aiming to harness the full potential of AI in workforce development, specifically in creating high-involvement workplaces where learning, innovation, and adaptability thrive through digital augmentation.

Theory and hypothesis development

Self-determination theory (SDT)

We draw upon SDT (Deci et al., 2017; Deci & Ryan, 1985; Ryan & Deci, 2000) to develop our theoretical model and address the aforementioned questions. SDT provides a robust framework for explaining the influence of social and structural conditions in the workplace on the motivation of employees by supporting or thwarting their basic psychological needs (Yu et al., 2024). According to SDT (Autin et al., 2022; Gagné & Deci, 2005), when the work environment satisfies the needs for autonomy (the experience of volition and self-determination), competence (feeling effective and capable), and relatedness (feeling connected to others), employees are more likely to internalize work goals and engage in self-regulated learning and problem-solving. In the context of AI-driven HRM digitization, systems and practices that provide choice, skills development opportunities, and collaborative tools can serve as

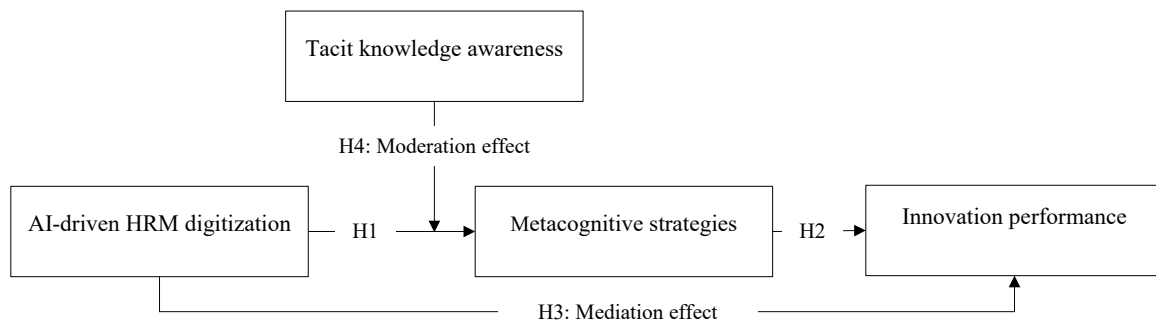


Fig. 1. Theoretical model.

“motivational affordances.” These motivational affordances fulfill these needs and encourage employees to engage in meta-cognitive strategies that generate innovative behaviors.

We also contend that AI-driven HRM introduces novel structures that SDT scholars have not fully theorized. For instance, algorithmic monitoring and appraisal may erode perceived autonomy, while personalization, intelligent feedback, and adaptive learning can enhance perceived competence; human-machine interaction can enable and displace relatedness depending on whether technology augments or replaces human connection (e.g., algorithmic appraisal vs. mentoring) (Charlwood & Guenole, 2022). A growing stream of evidence shows coexisting positive and negative outcomes from AI-HRM, which necessitates a paradox lens rather than a purely functionalist view (Basu et al., 2023). We therefore extend SDT by theorizing how AI-mediated affordances and controls re-imagine the autonomy-competence-relatedness pathways: when AI offers choice, transparency, and developmental feedback, need satisfaction rises; when AI is opaque, prescriptive, and surveillance-heavy, need frustration increases, which results in downstream cognition (e.g., metacognition) and innovation.

Notably, we argue that metacognitive strategies are central self-regulatory processes that translate the motivational benefits of AI-driven HRM digitization into enhanced innovation performance. From an SDT perspective (Do et al., 2025; Gandía et al., 2025), AI-driven HRM systems can be regarded as autonomy-supportive resources when they provide meaningful information, encourage self-initiation, and enable employees to align their work with personal values. When employees perceive such systems as supportive rather than controlling, they are more likely to engage in deeper cognitive processing, exploring new ideas, and integrating diverse sources of knowledge to produce innovative outcomes. However, if these systems are perceived as overly prescriptive or evaluative, then they may hinder motivation, which limits the potential for self-regulated learning and creativity. This conception aligns with evidence that the human-AI “division of cognitive labor” often fails without sufficient metaknowledge to judge when to rely on (or override) AI, which directly implicates metacognition as a mechanism linking AI contexts to performance (Fügener et al., 2022).

We further contend that tacit knowledge awareness is a critical personal resource that influences the response of employees to AI-driven HRM digitization. In line with the emphasis of SDT on the interaction between individual and contextual factors, employees with higher tacit knowledge awareness are better equipped to interpret and integrate the informational cues provided by AI systems into their cognitive frameworks (Zhao et al., 2025). This condition enhances the autonomy-supportive effects of systems and increases the likelihood that employees will engage in metacognitive regulation. Conversely, employees with lower tacit knowledge awareness may interact with AI-driven HRM tools more superficially and procedurally, which reduces the potential for autonomous motivation and innovation. Thus, we position tacit knowledge awareness as a “need-amplifying” resource that helps employees convert the information cues of AI into competence-building and autonomy-supportive experiences, which advances SDT in digital settings.

AI-driven HRM digitization

Owing to the rapid advancement of AI technologies (Jarrahi et al., 2023), organizations are increasingly reconfiguring traditional HRM functions through the integration of AI-driven applications. Conventional HRM practices are becoming insufficient in addressing the dynamic and complex challenges of modern digital workplaces; this situation necessitates a shift toward more adaptive, intelligent, and responsive HRM systems (Basu et al., 2023). Integrating AI into HRM enables organizations to enhance operational efficiency and strategic agility, which ensures competitiveness in an era marked by digital disruption (Budhwar et al., 2023; Malik et al., 2025). AI-driven HRM has become particularly impactful in domains such as recruitment and

selection, training and development, job design, and performance management (Chen et al., 2025; Kaushal et al., 2023; Parent-Rochelleau & Parker, 2022). We argue that beyond process optimization, AI-HRM integration also plays a critical role in shaping the behaviors, knowledge, and motivation of employees toward working collaboratively with AI systems. As such, HRM serves not only as a technological enabler but also as a strategic platform for developing cognitive and metacognitive capacities among employees. In this study, we explore the contribution of AI-driven HRM digitization to enhanced innovation performance, especially when it is aligned with the tacit knowledge awareness and metacognitive strategies of employees.

Despite the growing adoption of AI-driven HRM in organizational settings, our review of the literature reveals a significant gap in understanding the effect of such digitization on the capabilities, cognitive behaviors, and ultimately, innovation outcomes of employees. While several scholars have contributed to the foundational discourse on AI in HRM, most existing works remain conceptual and lack empirical validation. For instance, Strohmeier (2020) proposed a conceptualization of AI-enhanced applications in HRM domains such as recruitment, training, performance management, and employee retention. However, existing models have been criticized for insufficient theoretical grounding (Priksat, Malik, et al., 2023). In response, Meijerink et al. (2021) introduced the notion of algorithmic HRM, which is defined as the use of software algorithms powered by digital data to support or automate HR-related decision-making. Building upon these theoretical developments, our study moves beyond broad conceptualizations by empirically examining the interaction of AI-driven HRM digitization with the tacit knowledge awareness and metacognitive strategies of employees to foster innovation performance within organizations.

Mediating role of metacognitive strategies

Metacognitive strategies involve an active monitoring and regulation of one’s cognitive processes in learning and problem-solving contexts (Flavell, 1979). In the context of AI-integrated workplaces, metacognitive strategies enable employees to plan, assess, and adjust their engagement with AI systems; these abilities improve their capacity to learn, adapt, and innovate. These strategies allow employees to reflect on their AI-related tasks, set personal goals for mastery, and refine their approaches based on feedback and results. These core processes are especially critical in technology-driven environments that demand flexibility and continuous learning (Sun et al., 2025). This study draws upon SDT to explain the facilitating effect of AI-driven HRM digitization on the development and application of metacognitive strategies. SDT posits that autonomy, competence, and relatedness are essential psychological needs that must be satisfied to foster intrinsic motivation and high-functioning self-regulation (Deci et al., 2017; Gagné & Deci, 2005). AI-driven HRM practices, such as intelligent performance feedback systems, personalized AI-supported learning platforms, and collaborative digital tools, help fulfill these needs by enabling employees to pursue their own learning paths (autonomy), improve AI-related competencies (competence), and connect meaningfully with others through AI-enabled communication and teamwork (relatedness) (Do et al., 2025).

Notably, prior research suggests that the benefits of collaboration with AI can be reaped only when individuals know their capabilities to monitor their limits and collectively analyze the value of algorithmic recommendations (Fügener et al., 2022). As such, when AI-driven HRM is need-supportive, it cultivates metacognitive regulation, which in turn enables employees to integrate machine feedback with human intuition. This ability is crucial for creative recombination and innovative outputs. Conversely, need-frustrating AI-driven HRM (surveillance-oriented) will suppress metacognitive investment, which attenuates innovation.

When employees experience supportive HRM environments, they are more likely to develop metacognitive strategies as a form of intrinsically motivated engagement (O’Donoghue & van der Werff, 2021). For

instance, digitized training platforms allow employees to reflect on their strengths and weaknesses, track their learning progress, and seek knowledge autonomously. Similarly, intelligent feedback systems offer timely and relevant insights that promote self-monitoring and performance adjustments. Employees who internalize these learning processes are more capable of managing complex AI-integrated tasks and leveraging cognitive resources effectively (Pei et al., 2024). They become more self-aware in navigating AI-supported work and more strategic in integrating digital capabilities into their roles. The use of metacognitive strategies, in turn, is strongly associated with enhanced critical thinking and the generation of creative ideas (Sun et al., 2025). Employees who actively regulate their learning and adapt to technological challenges are more likely to experiment with new solution proposals, engage in creative problem-solving, and apply novel approaches that add value to the organization. They are also more capable of bridging the gap between human intuition and AI-generated insights, which is essential for innovation in digitally transformed workplaces (Abdulmuhsin et al., 2025).

Therefore, this study proposes that AI-driven HRM digitization supports the autonomy, competence, and relatedness of employees through digitally enabled practices that foster intrinsic motivation and, consequently, promote the development of metacognitive strategies. These strategies serve as a cognitive pathway through which AI-driven HRM influences the innovation capacity of employees. Thus, the mediating role of metacognitive strategies is essential in explaining how organizations can harness AI technologies through HRM to foster innovative behavior. Accordingly, we propose the following hypotheses:

Hypothesis 1. AI-driven HRM digitization has a positive and direct effect on the metacognitive strategies of employees.

Hypothesis 2. The metacognitive strategies of employees have a positive and direct effect on their innovation performance.

Hypothesis 3. AI-driven HRM digitization has a positive and indirect effect on the innovation performance of employees via their metacognitive strategies.

Moderating role of tacit knowledge awareness

Our final consideration is the role of tacit knowledge awareness in shaping the effects of AI-driven HRM digitization. Tacit knowledge refers to deeply rooted, experience-based know-how that is difficult to formalize, codify, or communicate, but plays a critical role in practical decision-making and work performance (Polanyi, 1966). Tacit knowledge awareness, in this context, reflects the extent to which employees are consciously attuned to and capable of leveraging this form of knowledge when engaging with AI-supported HRM systems (Zhao et al., 2025). While much of the literature focuses on *explicit* knowledge acquisition in digital environments, awareness of *tacit* knowledge becomes essential in AI-integrated workplaces; in these workplaces, intuitive judgment, experiential insights, and unspoken practices must harmonize with algorithmic logic and data-driven tools (Kumar, 2025; Malik et al., 2024; Pan & Froese, 2023; Wang et al., 2024). Employees who are aware of their tacit knowledge are more likely to recognize the value of reflecting on their thinking processes and adapting their learning behaviors, which are key components of metacognitive strategies (Flavell, 1979).

We consider other moderators (e.g., digital literacy, organizational culture) but argue that tacit knowledge awareness is more proximal to the human–AI cognitive boundary: (i) Delegation calibration hinges on recognizing what one knows (and does not)—a metaknowledge function central to productive human–AI teaming (Fügener et al., 2022); (ii) Creativity under AI-enabled non-routinization is amplified when tacit knowledge awareness triggers challenge (vs. hindrance) appraisals, which directly moderates cognition–innovation links (Zhao et al., 2025);

(iii) Algorithmic management affects perceived autonomy/complexity at the task interface, where tacit knowledge awareness, not generic literacy, helps employees translate lived, experiential know-how into choices regarding when and how to rely on algorithms (Meijerink & Bondarouk, 2023; Parent-Rocheleau et al., 2024). Digital literacy and culture matter, but they operate at infrastructure and context levels; tacit knowledge awareness operates at the cognitive junction where SDT-need signals are interpreted and converted into metacognitive effort.

Drawing from SDT (Deci et al., 2017; Ryan & Deci, 2000), we argue that tacit knowledge awareness enhances the fulfillment of the basic psychological needs, autonomy, competence, and relatedness of employees, by enabling them to apply their internalized experiential knowledge with greater intentionality. This deepened self-awareness fosters intrinsic motivation to think critically, self-monitor, and evaluate their learning within AI-enhanced HRM environments (Plant & Ryan, 1985). When employees are attuned to their tacit capabilities, they are more likely to engage with AI systems reflectively and effectively (Zhao et al., 2025), which maximizes the benefits of AI-driven HRM digitization for their metacognitive development. As a result, employees with higher levels of tacit knowledge awareness are more likely to adopt and use metacognitive strategies in response to AI-driven HRM interventions. They are more capable of reconciling automated guidance with personal insight. They also assess when to rely on human intuition versus machine-generated outputs, which enhances their capacity for innovation by promoting adaptive, self-regulated behavior in complex and evolving work contexts.

By contrast, employees with lower tacit knowledge awareness may struggle to integrate internalized experience with external technological inputs, which reduces the likelihood of engaging in metacognitive behaviors that fuel innovation. Therefore, tacit knowledge awareness is proposed to strengthen the pathway between AI-driven HRM digitization and the utilization of metacognitive strategy. Thus, we propose **Hypothesis 4**:

Hypothesis 4. Tacit knowledge awareness moderates the mediated relationship between AI-driven HRM digitization and innovation performance, such that the relationship is stronger when the level of tacit knowledge awareness among employees is high, and vice versa when it is low.

Method

Sample and procedure

We collected data from employees in a large company located in China. The target company has a digitized HRM system using AI tools. China provides a suitable context to test our model due to the following reasons. First, companies across Chinese industries are widely transforming their HRM systems through AI technologies (Mo et al., 2025). As such, Chinese employees broadly interact with AI-driven HRM systems in a rich empirical setting. Second, the cultural context amplifies the relevance of studying employee cognition and motivation under AI-HRM. For instance, in contrast to the monitoring and evaluation practices in collectivistic societies, those in high power-distance societies such as China are more likely to be perceived as legitimate and aligned with organizational authority (Charlwood & Guenole, 2022; Pan & Froese, 2023). Therefore, the target employees are relevant for testing our hypothesized model. Furthermore, to ensure employees are aware of the AI-driven HRM system, we conducted interviews with 10 employees before conducting the surveys. The survey included consent for voluntary participation and assured that the collected data would be used solely for the current study and not shared with anyone.

Data were collected in three phases, with a two-week gap in each survey. This approach helps eliminate common method bias (Podsakoff et al., 2003). In Phase 1, among the 530 shared questionnaires, 437 participants reported their perceptions of AI-driven HRM digitization,

tacit knowledge awareness, AI trust, AI transparency, and demographic variables. In Phase 2 (two weeks later), 359 participants reported their metacognitive strategies. In Phase 3 (two weeks later), supervisors evaluated the innovation performance of their subordinates. After excluding the participants who did not respond to all questions, the final sample consisted of 347 participants (a 66 % response rate).

The sample composition was 61.40 % male. Among the respondents, 34.70 % held a bachelor's degree and 44.7 % had a master's degree. The average age of participants was 34.59 years, and a majority of respondents (71.80 %) were in their current job for up to 10 years.

While our response rate (66 %) is comparable to or higher than those reported in prior field studies (e.g., Cai et al., 2018), attrition across the three survey waves may still raise concerns regarding non-response bias. Therefore, we used the Chi-square difference test to compare early and later respondents on randomly selected variables (Armstrong & Overton, 1977). We found no significant difference between the two groups, which suggests that non-response bias is not an issue in our data.

Measures

All measures were translated into Chinese following the back-translation approach of Brislin (1980). Unless otherwise stated, employees indicated their responses using a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree).

AI-Driven HRM digitization

Based on our theorization, we assessed AI-driven HRM digitization using a seven-item scale ($\alpha = 0.98$). The instrument captures the algorithmic recording and appraisal (Deng et al., 2024). This scale was used to assess the perception of employees on the use of AI-based tools by the company to monitor and appraise their performance, identify training and development needs, determine rewards and punishments, and make job design decisions.

Metacognitive strategies

We used an eight-item scale developed by Chen et al. (2020) to measure metacognitive strategies ($\alpha = 0.89$). This scale reflects the extent to which employees reflect on, plan, and monitor their tasks. Scholars have validated this measure in the AI context (Sun et al., 2025).

Tacit knowledge awareness

The four-item scale developed by Kucharska and Erickson (2023) was adopted to measure tacit knowledge awareness ($\alpha = 0.87$). This measure is validated in the AI context (Zhao et al., 2025). The items assess the ability of employees to express or articulate experiential knowledge.

Innovation performance

Innovation was assessed using a six-item scale adopted from Ali-Hassan et al. (2015) ($\alpha = 0.86$). Direct supervisors evaluated employees by indicating how frequently each employee engaged in innovative behaviors, such as "Generate original solutions to problems."

Control variables

Several control variables were included to account for alternative explanations: AI trust, AI transparency, task complexity, and demographic factors (employee gender, education, and organizational tenure). AI-trust was evaluated using three items adapted from Venkatesh et al. (2016) ($\alpha = 0.95$). AI transparency was captured through four items drawing on Welch et al. (2005) and Venkatesh et al. (2016) ($\alpha = 0.78$). Finally, employees rated the complexity of their tasks in three items adapted from Venkataramani and Tang (2024) ($\alpha = 0.85$).

Analysis and results

Measurement models

To assess the distinctiveness of our key constructs (AI-driven HRM, metacognitive strategies, tacit knowledge awareness, innovative performance, AI trust, AI transparency, and task complexity), we conducted a set of confirmatory factor analyses using AMOS (Hu & Bentler, 1999). Table 1 illustrates that the seven-factor model demonstrated a good fit to the data ($\chi^2/df = 668.33/539$, CFI = 0.98, SRMR = 0.04, RMSEA = 0.03). This baseline model outperformed all alternative models, which confirms the discriminant validity of our constructs.

Table 2 shows the correlations, means, standard deviations, and reliability statistics of the data. The values in the table suggest that the AI-driven HRM digitization in the study positively correlated with metacognitive strategies ($r = 0.27$, $p < 0.001$). Moreover, the metacognitive strategies were positively related to innovation performance ($r = 0.36$, $p < 0.001$). These correlations provide initial support for our model.

Hypothesis testing

To test our hypothesized model, we employed the PROCESS macro in SPSS (Hayes et al., 2017), which allows for simultaneous testing of mediation, moderation, and moderated mediation using bootstrapping with 10,000 resamples to compute 95 % confidence intervals (CIs). This approach offers a robust test beyond traditional significance testing (Preacher et al., 2007). In addition, following guidelines from prior studies, we calculated the effect size of the overall models (Cohen, 1992; Lorah, 2018; Selya et al., 2012).

We controlled for demographic variables (i.e., employee gender, education, and experience) and AI-trust, AI-transparency, and task complexity in the hypothesis analysis. We first examined Hypothesis 1, which proposed that AI-driven HRM would positively predict the metacognitive strategies of employees. Supporting this hypothesis, the results in Table 3 revealed a significant positive relationship between AI-driven HRM and metacognitive strategies ($\beta = 0.28$, $SE = 0.05$, $p < 0.001$). The results also show that the model explained 16 % of the variance ($R^2 = 0.16$), with a small-to-medium effect size ($f^2 = 0.19$). Hypothesis 2 suggested that metacognitive strategies would be positively associated with innovative performance. Results supported this hypothesis, which show significant paths from metacognitive strategies to innovative performance ($\beta = 0.26$, $SE = 0.05$, $p < 0.001$). This model explained 16.3 % of the variance ($R^2 = 0.18$) with a small-to-medium

Table 1
Alternative model comparison.

Model	χ^2	df	CFI	SRMR	RMSEA
1-Seven-factor model	698.33	539	0.98	0.04	0.03
1-Six-factor model	1,347.08	545	0.91	0.07	0.07
2-Five-factor model	2,447.99	550	0.80	0.13	0.10
3-Four-factor model	3,185.25	554	0.69	0.15	0.12
4-Three-factor model	4,200.17	557	0.58	0.16	0.14
5-Two-factor model	4,617.74	559	0.53	0.17	0.15
6-Single-factor model	5,052.51	560	0.48	0.18	0.15

Note: N = 347; Seven-factor model = AI-driven HRM digitization, tacit knowledge awareness, metacognitive strategies, innovation performance, AI-trust, AI-transparency, and task complexity; Six-factor model = combined tacit knowledge awareness and metacognitive strategies; Five-factor model = AI-driven HRM digitization, tacit knowledge awareness and metacognitive strategies combined; Four-factor model = Combined AI-driven HRM digitization, tacit knowledge awareness, metacognitive strategies, and innovation performance; Three-factor model = Combined AI-driven HRM digitization, tacit knowledge awareness, metacognitive strategies, AI-trust, and innovation performance; Two-factor model = Combined AI-driven HRM digitization, tacit knowledge awareness, metacognitive strategies, AI-trust, AI-transparency, and innovation performance; Single-factor model = combined all variables.

Table 2
Correlations, means, standards deviations, and validities.

Variables	Mean	Std. Deviation	1	2	3	4	5	6	7	8	9	10
1. Gender	0.61	0.49										
2. Education	2.54	0.83	-0.01	0.00								
3. Experience	2.03	0.98	-0.03	0.08	0.00							
4. AI-trust	4.05	1.05	-0.06	0.03	-0.02	0.95						
5. AI-Transparency	3.28	0.76	-0.01	0.07	0.16**	-0.04	0.80					
6. Task complexity	4.72	1.29	0.01	0.04	-0.06	0.02	-0.02	0.85				
7. AI-driven HRM digitization	3.68	1.16	0.00	0.09	0.04	0.04	0.01	0.14**	0.98			
8. Metacognitive strategies	4.14	1.04	-0.02	0.14**	-0.01	0.13*	-0.02	0.18**	0.35**	0.89		
9. Tacit knowledge awareness	2.64	0.99	0.07	-0.05	-0.09	0.11*	-0.10	-0.03	0.08	0.13*	0.87	
10. Innovation performance	4.34	1.03	0.00	0.10	-0.01	0.11	0.05	0.21**	0.27**	0.36**	0.06	0.86

Note: N = 347, *p < 0.05, **p < 0.01, Cronbach’s alpha values bold in diagonal cells.

Table 3
Hypothesis testing.

Outcome variable	Metacognitive strategies			Innovation performance			Metacognitive strategies		
	β	SE	t	β	SE	t	β	SE	t
Gender	-0.03	0.11	-0.27	0.01	0.10	0.14	-0.04	0.10	-0.40
Education	0.13	0.06	2.13*	0.05	0.06	0.74	0.15	0.06	2.44*
Experience	-0.02	0.05	-0.36	-0.02	0.05	-0.39	0.02	0.05	0.35
AI-trust	0.11	0.05	2.20*	0.06	0.05	1.28	0.10	0.05	2.12*
AI-Transparency	-0.03	0.07	-0.47	0.08	0.07	1.25	-0.02	0.07	-0.34
Task complexity	0.11	0.04	2.63**	0.11	0.04	2.71**	0.10	0.04	2.56**
AI-driven HRM digitization	0.28	0.05	6.24***	0.13	0.05	2.87**	0.26	0.04	5.88***
Metacognitive strategies				0.26	0.05	4.93***			
Tacit knowledge awareness							0.06	0.05	1.17
Interaction							0.20	0.04	4.75***
R ²		0.16***			0.18***			0.23***	
f ²		0.19			0.22			0.30	
Mediation effect of metacognitive strategies	Effect	SE	LLCI	ULCI					
	0.07	0.02	0.04	0.11					

Note: N = 347, *p < 0.05, **p < 0.01, ***p < 0.001, Cronbach’s alpha values bold in diagonal cells.

effect size ($f^2 = 0.22$). **Hypothesis 3** posited that metacognitive strategies would mediate the relationship between AI-driven HRM and innovative performance. Bootstrapping mediation analysis shows that metacognitive strategies mediated the indirect relationship between AI-driven HRM digitization and innovation performance (indirect effect = 0.07, SE = 0.02, 95 % CI [0.04, 0.11]). Thus, **Hypothesis 3** was supported.

Hypothesis 4 predicted that tacit knowledge awareness would moderate the mediated relationship between AI-driven HRM and innovation performance via metacognitive strategies. In support of this

hypothesis, the interaction term between AI-driven HRM and tacit knowledge awareness significantly predicted metacognitive strategies ($\beta = 0.20$, SE = 0.05, $p < 0.001$, **Table 3**). The results reveal that the moderation effect explained 23 % of the variance ($R^2 = .23$), which yielded a medium effect size ($f^2 = 0.30$). **Fig. 2** illustrates the interaction effect. In particular, AI-driven HRM digitization was positively related to metacognitive strategies when tacit knowledge awareness was high (effect = 0.46, SE = 0.06, $p < 0.001$) than when it was low (effect = 0.06, SE = 0.06, not supported). **Table 4** presents the moderated mediation models. Results revealed that the indirect impact of AI-driven

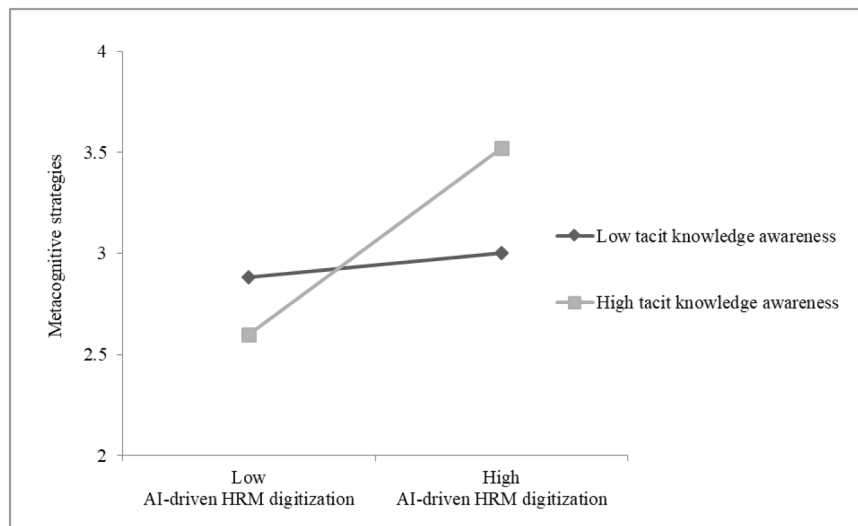


Fig. 2. Interaction effect of AI-driven HRM digitization and tacit knowledge awareness on metacognitive strategies.

Table 4
Conditional indirect effect of AI-driven HRM digitization on innovation performance via metacognitive strategies at levels of tacit knowledge awareness.

Mediator	Tacit knowledge awareness	Effect	SE	LLCI	ULCI
Metacognitive strategies	−SD	0.02	0.02	−0.02	0.05
Metacognitive strategies	Mean	0.07	0.02	0.04	0.11
Metacognitive strategies	+SD	0.12	0.03	0.07	0.18

HRM on innovative performance via metacognitive strategies was more substantial at high levels of tacit knowledge awareness (conditional indirect effect = 0.12, 95 % CI [0.07, 0.18]). By contrast, the AI-driven HRM digitization effect was weak and became insignificant on innovation performance via metacognitive strategies when tacit knowledge awareness was lower (conditional indirect effect = 0.05, 95 % CI [−0.02, 0.09]). These results show that AI-driven HRM digitization provides more benefits to employee innovation performance via metacognitive strategies when employees possess tacit knowledge awareness. Thus, [Hypothesis 4](#) was supported.

Discussion, implications, and conclusion

Discussion

Our study examined the relationship between AI-driven HRM digitization and employee innovation based on SDT. Exploration was considered a mediating mechanism, and tacit knowledge awareness was used as a moderating factor. Using a multi-source, multi-wave dataset collected from employees in China, our results suggest that the influence of AI-driven HRM on innovation outcomes is not uniform across employees: it depends on underlying cognitive and motivational processes. Specifically, the results reveal that AI-driven HRM was positively associated with the metacognitive strategies of employees ($\beta = .28, p < .001$). Therefore, when algorithmic systems offer developmental feedback, personalization, and adaptive learning opportunities, they encourage employees to plan, monitor, and regulate their cognitive efforts more deliberately. Such findings echo arguments that digital tools, when thoughtfully designed, can act as “motivational affordances” that stimulate adaptive learning behaviors (Do et al., 2025; Pan & Froese, 2023).

In line with [Hypothesis 2](#), our results reveal that metacognitive strategies significantly predict innovation performance ($\beta = .26, p < .001$). In line with [Sun et al. \(2025\)](#), these results suggest that employees who actively evaluate and adjust their problem-solving approaches have better ability to integrate diverse information sources, recombine knowledge, and produce creative solutions. Our study extends findings of earlier studies to AI-driven HRM contexts. By doing so, this study clarifies that metacognitive regulation serves as a bridge between digital feedback systems and innovative behaviors; it helps resolve inconsistent findings in earlier research that questioned whether algorithmic tools genuinely foster creativity (Fügener et al., 2022). In addition, bootstrapping analyses supported [Hypothesis 3](#) and indicated that AI-driven HRM enhances innovation indirectly through metacognitive strategies (indirect effect = .07, 95 % CI [.04, .11]). Therefore, AI-based HRM does not generate innovation through efficiency gains alone but by deepening the cognitive engagement among employees. This mediating pathway helps reconcile inconsistent findings in earlier studies, where algorithmic tools spurred creativity in some cases, but produced compliance without innovation in other settings (Fügener et al., 2022).

Perhaps the most interesting finding of this study is related to [Hypothesis 4](#), which demonstrated that the indirect effect of AI-driven HRM on innovation is conditioned by tacit knowledge awareness. The interaction between AI-driven HRM and tacit knowledge awareness was

significant ($\beta = .20, p < .001$). Specifically, employees with higher tacit knowledge awareness translated AI-enabled HRM into metacognitive engagement and innovative performance more effectively (conditional indirect effect = .12, 95 % CI [.07, .18]). By contrast, those with low tacit knowledge awareness had negligible gains (conditional indirect effect = .05, 95 % CI [−.02, .09]). This finding contrasts with those in earlier works that assumed digital HRM effects were relatively uniform across employees (Do et al., 2025); these studies provided a critical boundary condition and showed instead that digitization may fail to improve innovation unless employees can recognize, integrate, and apply their experiential knowledge alongside algorithmic recommendations (Zhao et al., 2025).

Beyond these empirical findings, our results underscore that digital HRM cannot be understood only as a functional efficiency tool. Instead, it must be framed through a paradox lens in which algorithmic affordances (e.g., personalization, developmental feedback, and intelligent learning support) coexist with algorithmic controls (e.g., monitoring, opaque scoring, and prescriptive nudging). This paradox explains why AI-driven HRM is simultaneously praised for efficiency and fairness, but criticized for surveillance and dehumanization (Basu et al., 2023; Charwood & Guenole, 2022). Our evidence clarifies that whether employees perceive these systems as empowering or alienating depends on the interplay between design features and their own cognitive resources, particularly tacit knowledge awareness and metacognition. We discuss how our study contributes to theory on digital HRM and innovation, and SDT in the following sections.

Theoretical implications

This study offers significant theoretical contributions. First, this study applied SDT into the domains of AI and HRM by demonstrating that AI-driven HRM digitization can serve as a contextual enabler of psychological need satisfaction. While previous studies have begun to explore the role of AI in HRM (Do et al., 2025; Pan & Froese, 2023; Prikshat et al., 2023), they often fall short in capturing the influence of AI-driven HRM interventions on cognitive, motivational, and behavioral outcomes among employees. Specifically, the study shows how AI-enhanced HRM practices, such as AI-supported feedback systems, intelligent learning platforms, and data-driven decision aids, can promote the feelings of autonomy, competence, and relatedness among employees, which are central to intrinsic motivation as outlined in SDT (Deci et al., 2017; Deci & Ryan, 1985; Ryan & Deci, 2000). This study represents a theoretical advance, as much of the prior SDT literature has focused on traditional HRM systems or non-digital environments (Laguerre & Barnes-Farrell, 2025; Rahaman et al., 2023) and has not yet fully addressed how algorithmic and intelligent systems contribute to or hinder psychological need satisfaction. By incorporating algorithmic affordances and constraints, we argue that SDT requires new boundary conditions when applied to digital HRM, given that the experience of autonomy, competence, and relatedness is dynamically shaped by system transparency, explainability, and monitoring intensity. This re-routing of autonomy, competence, and relatedness is a distinct theoretical move beyond conventional, non-digital contexts.

Second, we identify metacognitive engagement among employees (the use of reflective, self-regulatory learning strategies) as a central psychological mechanism linking AI-driven HRM practices to innovation performance. Although SDT has been used to explain broad motivational and behavioral outcomes (Laguerre & Barnes-Farrell, 2025; Li et al., 2022), this study contributes by showing how SDT-driven need fulfillment translates into specific cognitive strategies that are critical for innovation and adaptability in the digital workplace. Metacognitive strategies, including self-monitoring, evaluation, and goal-setting, allow employees to respond effectively to the complexity and uncertainty inherent in AI-mediated environments. By positioning metacognitive engagement as an outcome of need-supportive HRM practices, we provide a more granular and cognitive-focused extension of SDT. This

theoretical contribution explains inconsistent findings in prior AI-related studies, where the same digital systems promoted learning and innovation in some cases but triggered resistance or disengagement in other settings (Deng et al., 2024; Juquelier et al., 2025; Liang et al., 2022). Metacognition clarifies these discrepancies by serving as the “switch” that channels motivational affordances into innovative outcomes.

Third, this study introduces tacit knowledge awareness as a novel boundary condition that moderates the effect of AI-HRM digitization on metacognitive engagement. The findings align with those of Zhao et al. (2025). These previous authors suggested that employees who are aware of their tacit knowledge, their intuitive, experience-based insights, are better equipped to reconcile AI-generated outputs with their internal expertise. Thus, these employees engage more deeply in reflective and adaptive learning behaviors. This understanding contributes to SDT by highlighting how cognitive readiness and knowledge awareness interact with need-supportive environments to influence motivational outcomes (Deci et al., 2017; Deci & Ryan, 1985; Ryan & Deci, 2000). Thus, we argue that tacit knowledge awareness deserves special emphasis over alternative moderators such as digital literacy or organizational culture because it is located at the cognitive interface of human–AI collaboration. Employees high in tacit knowledge awareness are better positioned to calibrate delegation, override inappropriate recommendations, and combine experiential know-how with algorithmic insights. This capability reshapes autonomy in digital contexts, which transforms algorithmic oversight into developmental support and makes it a critical extension of SDT in AI-driven HRM.

Finally, although considerable research has applied SDT in organizational behavior and management studies (Deci et al., 2017; Deci & Ryan, 1985; Ryan & Deci, 2000), most have focused on workplace factors and examined how supportive contexts facilitate basic psychological need satisfaction to enhance motivation, performance, and well-being (Autin et al., 2022; Baard et al., 2004; Do et al., 2025). This study extends the literature by finding that psychological need satisfaction also plays a critical role in the influence of AI-driven HRM digitization on the innovation performance of employees. This finding is consistent with the core proposition of SDT that autonomy, competence, and relatedness satisfaction are essential for fostering autonomous motivation and optimal functioning. It also provides evidence for the applicability of SDT in understanding technology-driven HRM practices. By identifying tacit knowledge awareness as a “need-amplifying” personal resource, we extend SDT into a new terrain. Specifically, we show how individual cognitive capabilities interact with digital contexts to shape motivational outcomes. This integration of SDT with organizational learning and knowledge management advances the theoretical conversation on how employees navigate paradoxical digital environments.

Practical implications

Our findings offer practical guidance for organizations seeking to leverage AI-driven HRM digitization to enhance innovation performance. First, organizations should recognize that algorithmic systems are not neutral but actively shape motivation and cognition among employees. Managers should ensure that AI-driven HRM practices are implemented in ways that maximize transparency and explainability. Explainable dashboards, recourse options, and opportunities for employees to provide feedback on system recommendations can reduce alienation and strengthen perceptions of autonomy and competence (Parent-Rochelleau & Parker, 2022). Second, AI-driven HR systems should balance algorithmic control with autonomy-supportive design. For example, organizations can design monitoring functions as a source of developmental feedback rather than surveillance. This initiative can be achieved by embedding growth-oriented metrics, learning goals, and adjustable feedback frequency. This design allows employees to tailor algorithmic inputs to their needs. By combining structure with choice,

organizations can transform control mechanisms into supports that facilitate self-regulation rather than diminish autonomy.

Third, we show that AI-enabled HRM systems can foster innovation by stimulating the metacognitive strategies of employees, which suggests that organizations should design and implement these systems to support the capacity of employees for self-monitoring, self-regulation, and adaptive problem-solving. Critically, our results highlight the enabling role of tacit knowledge awareness in strengthening the effect of AI-driven HRM digitization on metacognitive strategies. Organizations should therefore assess and develop the tacit knowledge awareness of employees when introducing AI-driven HRM tools. Importantly, tacit knowledge awareness and metacognitive strategy, while viewed as stable traits in some cases, can be cultivated through targeted interventions (Nonaka & von Krogh, 2009; Sun et al., 2025). Such interventions range from brief awareness-building exercises and digital tool use simulations to extended learning programs embedded in HRM systems (Bell & Kozlowski, 2008; Sun et al., 2025). Research has demonstrated that training combining metacognitive instruction and reflective error management significantly enhanced adaptive thinking, while similar methods could be adapted to raise tacit knowledge awareness (Keith & Frese, 2005). Depending on budget and priorities, organizations may opt for short-form workshops, embedded digital learning modules, or longer-term development programs, which are potentially combined with selective hiring for high-awareness candidates where feasible.

Finally, AI-driven HRM digitization plays a vital role in providing trusted and transparent systems to employees. Similarly, prior research has suggested that the physical workplace also plays a critical role in providing an environment that facilitates the adaptation of employees to job demands and increases their well-being (Reijula et al., 2011). For instance, intelligent building management systems are likely to provide real-time comfort, safety, and energy efficiency to employees and the organization, especially when combined with AI-driven HRM digitization. These may also provide a favorable environment for employees to better focus on obtaining benefits from AI-driven HRM digitization. Thus, based on the findings of previous research, we suggest that organizations implement AI-driven HRM digitization while incorporating intelligent building management systems to transform workplaces into adaptive, supportive, and innovation-enabling ecosystems.

Limitations and future research directions

This study has several limitations that offer opportunities for future research. First, we used multi-wave and multi-source data to avoid the potential effect of common method bias (Podsakoff et al., 2003). However, such an approach may not completely mitigate the concerns. Thus, we invite future scholars to use objective data for AI-driven HRM digitization and employee outcomes. Second, while time-lagged data increase the robustness of the empirical findings, they do not account for causality. In such a scenario, we invite scholars to use experimental design to test the model. Nevertheless, our model is grounded in strong theoretical reasoning from SDT, which we view as a strength. Third, our data were collected in a single cultural and organizational context in China. Chinese cultural characteristics such as collectivism, respect for hierarchy, and varying attitudes toward algorithmic monitoring may shape how employees interpret and respond to AI-driven HRM practices (Dorfman & Howell, 1988; Pan & Froese, 2023). Moreover, although our target company provides a suitable context to test our model, it may differ in organizational motivation toward AI from other organizations across industries. We therefore caution readers that generalizing our findings to Western or different cultural contexts should be done carefully. Moreover, we invite future studies to replicate these findings across diverse institutional environments. Finally, while our focus on tacit knowledge awareness provides an interesting moderating condition, other factors, such as psychological capital (Pang, 2019), organizational learning climate, or digital literacy (Yi-No Kang et al., 2023;

Zhu et al., 2019), could further explain the variability in the effectiveness of AI-driven HRM digitization. Examining these factors would deepen understanding of the boundary conditions for enhancing innovation performance.

Conclusion

This study investigated a mediated model linking AI-driven HRM digitization to innovation performance through metacognitive strategies. We found empirical support for a moderating effect of tacit knowledge awareness on the link between AI-driven HRM digitization and metacognitive strategies. As a result, the association for employees with higher tacit knowledge awareness was stronger. By reframing SDT for digital contexts, we argue that algorithmic HRM introduces new boundary conditions that reshape how autonomy, competence, and relatedness are experienced. Our findings provide compelling evidence that AI-driven HRM digitization can be a valuable resource for stimulating innovation. Moreover, the extent to which employees can effectively leverage these systems depends on their awareness of tacit knowledge. Therefore, digital transformation alone is insufficient: organizations that cultivate tacit knowledge awareness, design autonomy-supportive HRM systems, and balance algorithmic control with developmental affordances will be best positioned to unlock innovation in digitally transformed workplaces.

Declarations

Ethics approval and consent to participate: This study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of our institute. Informed consent was obtained from all employees who participated in this study.

Availability of data and material: Data generated and used in this study is available from corresponding author on a reasonable request.

Funding statement: This research was supported by National Natural Science Foundation of China grant number W2433182.

Guarantor: Not applicable

CRedit authorship contribution statement

Ahsan Ali: Writing – original draft, Project administration, Supervision, Methodology, Formal analysis, Conceptualization. **Dariusz Cichon:** Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Asad Abbas:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Acknowledgements

The authors acknowledge the financial and technical support of the Writing Lab, Institute for the Future of Education, Tecnologico de Monterrey, Mexico, in the production of this work. The authors also acknowledge the Research Group "Engaging and Motivating Learning Models," in which the corresponding author (Asad Abbas) is a member.

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