

How can empowering leadership foster employee–AI collaboration? A multilevel analysis of AI trust and psychological safety

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Abstract

Purpose – The growing integration of artificial intelligence (AI) into the workplace underscores the urgent need to understand how employees collaborate effectively with AI systems. Grounded in social cognitive theory, this study investigates the impact of empowering leadership on employee–AI collaboration. Furthermore, we examine the mediating roles of psychological safety and AI trust.

Design/methodology/approach – To test the research model, we utilized a multilevel design data from 418 employees across 103 teams in AI-integrated organizations in Vietnam.

Findings – Our findings indicate that empowering leadership is positively related to employee–AI collaboration, with this relationship mediated by both psychological safety and AI trust.

Originality/value – This study contributes to the leadership and technology management literature by establishing a multilevel link between empowering leadership and employee–AI collaboration. It identifies key mediating mechanisms (AI trust and psychological safety), offering a more integrated understanding of leadership influence in AI-enabled settings. Practically, the findings offer actionable insights for practitioners navigating the dynamics of employee–AI collaboration, highlighting the importance of empowering leadership in building AI-ready workforces.

Keywords Employee–AI collaboration, Empowering leadership, Psychological safety, AI trust

Paper type Research article

1. Introduction

In recent years, organizations have increasingly integrated artificial intelligence (AI) into their operation in pursuit of greater efficiency, innovation and competitive advantage (Bankins *et al.*, 2023). Recent advances have further moved AI beyond the realm of futurology into practical application and expanded its applications' possibilities, shifting from localized pilot stages to widespread enterprise deployments (Ergün *et al.*, 2026; Mayer *et al.*, 2025). This shift is reflected in the scale of recent investment with global corporate AI investment has reached \$581.69 billion in 2025, more than doubling from the previous year (AI Index Report, 2026). Beyond investment volume, recent evidence on generative AI (GenAI) use suggests a qualitative shift in how the technology is deployed. An analysis of over 100,000 Microsoft 365 Copilot conversations found that nearly half (49%) now support higher-order cognitive work,



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including analysis, evaluation and problem-solving rather than basic information retrieval or content production (Lakhani, 2026). In the modern workplace, this practical application means AI is projected to reshape 50%–55% of all US jobs over the next two to three years alone (Emerson *et al.*, 2026). Despite these advancements, AI remains limited in its ability to interpret complex social contexts or transfer experiential knowledge across domains. Consequently, AI rarely operates independently; rather, its effectiveness depends on meaningful interaction and coordination with human employees (Marvi *et al.*, 2025; Nguyen and Elbanna, 2025). This interdependence has scholars to emphasize the concept of employee–AI collaboration, which refers to a process where employees and AI systems combine their complementary strengths to enhance learning, decision-making and task performance (Hillebrand *et al.*, 2025).

Despite this growing interest, existing research has focused more on the outcomes of employee–AI collaboration than on the conditions that enable it. Prior studies have shown that collaboration with AI can improve service performance, productivity and task efficiency (Jiang *et al.*, 2022). However, less is known about why employees become willing and able to collaborate with AI in the first place. Existing studies that examine antecedents have often emphasized individual-level factors, such as employees’ technical skills, motivations, perceptions of AI capability or readiness to use AI (Kumar *et al.*, 2025; Yin *et al.*, 2024). While valuable, this perspective risks treating employee–AI collaboration as a largely personal decision. In practice, employees do not engage with AI in isolation. Their willingness to rely on, question and adapt AI outputs is shaped by the social context in which AI use unfolds, including leadership practices, team norms and organizational expectations (Chowdhury *et al.*, 2022; Kolbjørnsrud, 2024). Thus, a fuller understanding of employee–AI collaboration requires closer attention to the social and organizational conditions that make such collaboration possible.

To address this gap, we draw on social cognitive theory (SCT) to examine how empowering leadership shapes employee–AI collaboration. SCT suggests that behaviour emerges through the interplay between environmental influences, personal appraisals and behavioural responses (Bandura, 1988). This perspective is especially relevant in AI-enabled workplaces, where employees must continuously interpret technological change, learn from social cues and adjust their behaviour through repeated interaction with AI systems (Erengin *et al.*, 2025; Makarius *et al.*, 2020). In this view, behaviour is not driven solely by external conditions but also by how individuals cognitively interpret and respond to their environment (Zhang and Zhang, 2025). This perspective is particularly relevant in AI-enabled workplaces, where emerging technologies are reshaping job roles, decision-making processes and employees’ sense of control over their work (Qin *et al.*, 2025). In such contexts, employees must continuously make sense of and adapt to these changes through ongoing social interaction and learning. On one hand, employees draw on observational learning by attending to cues from their leaders and colleagues, using these signals to understand how AI should be approached and integrated into their work (Nguyen *et al.*, 2025; Tsai *et al.*, 2022). On the other hand, employees also learn through direct interaction with AI systems, refining their behaviour through feedback, outputs and repeated use. Consistent with the principle of triadic reciprocal determinism (Bandura, 2001), these interactions reflect an ongoing process in which environmental influences (e.g. empowering leadership), cognitive evaluations (e.g. psychological safety and AI trust) and behavioural engagement with AI mutually shape one another over time.

Recent literature has increasingly underscored the pivotal role of leadership in enabling effective employee–AI collaboration (Kumar *et al.*, 2025; Tsai *et al.*, 2022). Leadership represents a particularly important environmental influence because they are expected not only to articulate strategic vision but also to cultivate an environment that instils confidence among employees to navigate AI-related changes (Bankins *et al.*, 2023). Among different leadership approaches, empowering leadership is especially relevant because it grants autonomy, encourages participation and supports self-directed action (Cheong *et al.*, 2019;

Martin *et al.*, 2013). Specifically, empowerment is relevant given that AI increasingly reshapes traditional task structures and organizational hierarchies (van Riel *et al.*, 2025). By enhancing employees' perception of autonomy and their sense of influence over work outcomes, empowering leaders motivate individuals to actively engage and leverage AI in their tasks. Through this process, employees contribute contextual knowledge and feedback that allow AI systems to adjust their outputs and reduce limitations such as hallucinations or context-insensitive recommendations (Bankins *et al.*, 2026; Chen *et al.*, 2026). In this way, empowering leadership helps create a collaborative environment in which both human expertise and AI are continuously updated through interaction.

We argue that empowering leadership promotes employee–AI collaboration through two distinct but complementary individual-level mechanisms: AI trust and psychological safety. AI trust captures the first pathway by reflecting employees' confidence in the AI system's competence, reliability and functional integrity (Chowdhury *et al.*, 2022; Kong *et al.*, 2023). We posit that AI trust is a crucial mediating mechanism that translates empowering leadership into effective collaboration with AI because empowered employees must judge whether an AI system is sufficiently capable and useful to support their work. Without this trust, they are unlikely to rely on AI-generated outputs, incorporate AI recommendations into decisions or sustain iterative exchanges with the system (van Zoonen *et al.*, 2026). However, trust in AI alone is insufficient. Even when employees trust in AI capabilities, they still worry about the personal and professional consequences of making mistakes during the collaborative process. We therefore submit that psychological safety serves as a vital parallel mediator. Psychological safety captures the second pathway via employees' perception that the team context is safe for interpersonal risk-taking, including asking questions, admitting uncertainty and learning through trial and error (Edmondson and Bransby, 2023). Without psychological safety, employees may trust AI's technical capability yet still avoid visible or exploratory AI use because they fear criticism, embarrassment or blame. By theorizing AI trust and psychological safety as parallel mediators, we develop a comprehensive sociotechnical account of how empowering leadership drives employee–AI collaboration. While AI trust ensures employees are willing to rely on AI as a work partner, psychological safety ensures they feel socially permitted to engage with AI openly and experimentally. These complementary, but distinctive, mechanisms are important because employee–AI collaboration requires both confidence in the technological system and perceived safety in the interpersonal environment surrounding its use (Bankins *et al.*, 2023; van Riel *et al.*, 2025).

In alignment with SCT (Bandura, 1991), this framework positions empowering leadership as a team-level environmental influence, AI trust and psychological safety as individual-level personal factors and employee–AI collaboration as the behavioural outcome. To test the proposed research model, we collected data using a survey of 418 Vietnamese employees to empirically assess our conceptual model. These employees were currently working across 103 teams in AI-integrated organizations. Using Mplus-8, we applied multi-level technique to test the direct impact of team-level empowering leadership on employee–AI collaboration, as well as the underlying mediating mechanisms of AI trust and psychological safety. Our findings make several contributions to the management literature. First, it advances the emerging literature on employee–AI collaboration by highlighting the role of empowering leadership in shaping collaborative interactions between employees and AI systems. Our research extends the fields of leadership and technological management by investigating the pivotal role of empowering leadership in shaping how employees collaborate with AI. Second, this study addresses the existing gaps in understanding the mechanisms through which empowering leadership influences employee–AI collaboration by identifying two critical mediating variables (i.e. AI trust and psychological safety). In doing so, it responds to calls for deeper theoretical exploration of how and when leadership shapes employee attitudes and behaviours toward AI use (Bankins *et al.*, 2023; Tsai *et al.*, 2022). Third, by adopting the SCT theory, this research extends existing work on AI in organizations by illustrating how the interplay between environmental influences, personal evaluations and behavioural responses

2. Literature review and hypotheses development

2.1 Social cognitive theory

We adopt SCT (Bandura, 1991) as a theoretical lens to explore the relationship between empowering leadership and employee–AI collaboration, along with its underlying mechanisms. Widely applied in organizational behaviour research, SCT provides a robust framework for understanding how individuals learn and adapt through the interaction of environmental conditions, personal factors and behavioural action (Erengin *et al.*, 2025; Zhang and Zhang, 2025). Central to this perspective is triadic reciprocal determinism, which posits that individuals do not simply respond to external conditions; rather, they interpret, learn from and act upon those conditions through their beliefs, expectations and perceptions (Bandura, 1991).

Building on this foundation, prior research has increasingly drawn on SCT to explain how leadership shapes behaviour through underlying cognitive processes across both individual and team contexts. At the individual level, evidence suggests that leadership does not influence behaviour directly; instead, it operates by shaping how employees interpret their work environment. For example, ethical and paradoxical leadership have been found to influence outcomes such as knowledge sharing and creativity by fostering cognitive states including self-efficacy and cognitive flexibility (Sun *et al.*, 2024; Zhang and Zhang, 2025). A similar pattern emerges in technology-related settings, where ethical and transformational leadership play a central role in shaping employees' cognition, such as creative self-efficacy and moral consciousness, which in turn drive their engagement with such systems (Mvondo *et al.*, 2025; Wang and Shao, 2024). At the team level, leadership shapes collective dynamics, such as reflexivity and cooperative orientation, that guide how members interpret situations and coordinate their actions (Cheong *et al.*, 2019; Leblanc *et al.*, 2022). Recent studies on human–AI teams further reinforce this point, showing that employees' engagement with AI is influenced not only by their own experiences but also by the behaviours and cues of those around them (Erengin *et al.*, 2025). Integrating these insights, we employ SCT to examine how empowering leadership, as a critical environmental catalyst, shapes personal evaluations, specifically AI trust and psychological safety, which in turn guide their collaboration with AI.

A central mechanism within SCT is observational learning, the process through which individuals acquire knowledge and behavioural strategies by observing others within their social environment (Bandura, 1991). In organizational settings, leaders serve as particularly salient role models, as their behaviours signal what is appropriate, valued and effective within a given context (Bandura, 1988). Empowering leadership is particularly well aligned with SCT because it provides employees with social cues that support autonomy, participation and self-directed action. By granting discretion, encouraging voice and expressing confidence in employees, empowering leaders signal that employees are trusted to exercise judgement and take ownership of uncertain work demands (Cheong *et al.*, 2019). These cues become especially important in contexts characterized by novelty and ambiguity, such as the increasing integration of AI into work processes, where established norms and routines are still evolving (Wang *et al.*, 2026). Through observational learning, employees look to leaders to understand how to engage with AI in ways that are both effective and aligned with organizational expectations (Sun *et al.*, 2024; Zhang and Zhang, 2025), thereby facilitating more adaptive forms of employee–AI collaboration.

Beyond learning from leaders, SCT also emphasizes that individuals adapt their behaviour through ongoing interaction with their environment (Bandura, 2001). In AI-enabled work, employees learn not only from leaders and colleagues, but also from repeated engagement with AI systems. They interpret AI outputs, test recommendations, identify limitations and adjust their behaviour through use and feedback (Bankins *et al.*, 2026). This process is not

purely technical but also social-embedded. Whether employees engage with AI in an open, sustained and adaptive manner depends on how they appraise both the AI system and the surrounding social context (Qin *et al.*, 2025). We therefore theorize AI trust and psychological safety as two individual-level mechanisms through which team-level empowering leadership is translated into employee–AI collaboration. AI trust captures employees’ technology-directed appraisal of whether the AI system is reliable, competent and useful (Erengin *et al.*, 2025; Kong *et al.*, 2023). Meanwhile, psychological safety captures employees’ socially directed appraisal of whether the team context is safe for asking questions, experimenting with AI, admitting uncertainty and learning from mistakes (Edmondson and Bransby, 2023; Newman *et al.*, 2017). Together, these mechanisms reflect SCT’s core tenet that environmental influences shape behaviour through personal appraisals. They also capture the sociotechnical nature of employee–AI collaboration, in which employees must develop confidence in the technological system and feel safe within the interpersonal context in which AI use occurs (Gong *et al.*, 2025; Makarius *et al.*, 2020).

2.2 Empowering leadership and employee–AI collaboration

The rapid advancement and adoption of AI have reshaped organization dynamics and employees’ job roles. Going beyond automation, recent developments such as GenAI extend the capabilities of intelligent systems by enabling them to analyse vast amounts of data, learn from prior interactions and generate adaptive outputs in response to user inputs (Nguyen *et al.*, 2025). As such, AI systems increasingly function as active contributors to organizational tasks, rather than merely passive technological tools. In these contexts, AI and employees jointly perform tasks by combining their distinct strengths: employees provide contextual understanding, judgement and creativity, while AI contributes computational power, pattern recognition and predictive insights (Gong *et al.*, 2025). Through these interactions, employees interpret AI-generated outputs and adjust their actions accordingly, while AI systems refine their responses based on human inputs and contextual feedback. Such iterative feedback loops enable both human and machine actors to progressively improve task performance over time (Georganta and Ulfert, 2024; Jiang *et al.*, 2022). Accordingly, employee–AI collaboration has been conceptualized as a dynamic process in which humans and intelligent systems leverage their complementary capabilities and evolve together through reciprocal learning and adaptation (Haenlein and Kaplan, 2019; Jiang *et al.*, 2022; Kong *et al.*, 2023).

Despite these technological advances, effective employee–AI collaboration does not emerge automatically. As AI systems often rely on complex algorithms and opaque decision-making processes, the boundaries between human and machine contributions frequently become blurred (Chen *et al.*, 2026). In such contexts, employees may experience significant uncertainty regarding their role in AI-enabled work processes and the extent to which they retain control over task outcomes. Without appropriate organizational guidance and support, this role ambiguity can erode an employee’s sense of agency and reduce their willingness to actively engage with AI systems (Qin *et al.*, 2025; Wang *et al.*, 2026). Critically, although organizations may assign accountability to automated systems, responsibility ultimately requires intentional judgement and moral agency, which remain uniquely human capacities (Gong *et al.*, 2025). For employees to assume such responsibility, they need to maintain meaningful involvement and influence over the tasks, where AI is embedded. Ensuring such involvement is vital for sustaining employees as active contributors to AI-enabled work rather than mere passive operators of technological systems (Li *et al.*, 2024). In this regard, leaders who grant autonomy, encourage participation in decision-making and allow employees discretion in how technologies are applied in their work can reinforce their sense of ownership and responsibility over AI-related tasks (van Riel *et al.*, 2025). Such leadership behaviours are characteristic of empowering leadership, which emphasizes autonomy, participation and self-directed action (Cheong *et al.*, 2019; Sharma and Kirkman, 2015), making it particularly relevant for fostering effective employee–AI collaboration.

From an SCT perspective, empowering leadership represents a critical environmental catalyst that fosters employee–AI collaboration. SCT suggests that individuals learn appropriate behaviours by observing role models in their social environment, especially when navigating unfamiliar or complex situations (Bandura, 1988; Erengin *et al.*, 2025). In the context of employee–AI collaboration, where standard work practices are still evolving, employees are particularly attentive to cues from leaders regarding how AI should be interpreted and utilized (Tsai *et al.*, 2022). When leaders grant autonomy towards AI and encourage its responsible use, employees are more likely to perceive AI as a legitimate partner in decision-making and task execution rather than a mere tool (Arnold *et al.*, 2000; van Riel *et al.*, 2025). Such cues incentivize employees to actively contribute contextual knowledge and feedback necessary for AI systems to refine their outputs and reduce limitations such as algorithmic hallucinations or context-insensitive recommendations. Conversely, in the absence of empowerment, employees may become passive users of AI systems, relying on AI outputs without actively interpreting or refining them (Ahearn *et al.*, 2005; Chen *et al.*, 2022). Such limited interaction reduces the feedback and contextual input that AI systems rely on to improve their outputs, thereby constraining the adaptive learning processes that underpin effective employee–AI collaboration (Bankins *et al.*, 2026). By fostering autonomy and encouraging proactive engagement, empowering leadership therefore creates conditions that strengthen the iterative feedback loops between human expertise and machine intelligence, allowing the reciprocal interactions through which employee–AI collaboration matures and becomes more effective over time.

H1. Empowering leadership is positively related to employee–AI collaboration.

2.3 Mediating role of AI trust

AI trust can be understood through both multidimensional and unidimensional traditions in the broader trust literature. Multidimensional approaches have been useful in interpersonal settings, where trust may rest on judgements of ability, benevolence and integrity (Mayer *et al.*, 1995) or on both cognitive and affective foundations (McAllister, 1995). These distinctions are valuable in interpersonal and organizational settings, where trustees possess intentions, shared histories and the capacity to demonstrate care or moral judgement (Legood *et al.*, 2023). In the context of AI, however, the conceptual and empirical case for decomposing trust into separate dimensions becomes considerably weaker (van Zoonen *et al.*, 2026). Specifically, AI systems do not possess intentions, benevolence or integrity in the human relational sense and employees may not yet have enough experience with emerging AI systems to distinguish clearly among separate trust facets (Glikson and Woolley, 2020). Similarly, the distinction between cognitive and affective trust is less clear in human–AI interaction, as employees typically form trust based on rational evaluations of technical performance rather than genuine emotional bonds or perceived mutual empathy (Marvi *et al.*, 2025; Schuetz *et al.*, 2025; van Zoonen *et al.*, 2026). For this reason, recent AI trust research often adopts a unidimensional approach, defining AI trust as employees’ overall confidence in the system’s reliability, competence and contribution to work tasks (Chowdhury *et al.*, 2022; Kong *et al.*, 2023). This approach aligns with Rousseau *et al.* (1998, p. 395) foundational definition of trust as “a psychological state comprising the intention to accept vulnerability based on positive expectations of the intentions or behaviour of another”, which treats trust as an integrated psychological disposition rather than a composite of separable facets. This holistic view is further supported by trust-in-technology research suggesting that a unidimensional measure is appropriate when trust is examined as part of a broader nomological model and separate effects of trust facets are not theorized (Legood *et al.*, 2023; Schuetz *et al.*, 2025). Accordingly, in this study, AI trust refers to employees’ overall positive expectation that the AI system will perform reliably and contribute meaningfully to their work.

Grounded in SCT’s principle of triadic reciprocal determinism (Bandura, 1988), we posit that team-level empowering leadership functions as a critical contextual determinant of

individual-level AI trust. Empowering behaviours are often rooted in trust—leaders delegate authority and grant autonomy based on confidence in their employees' competence, judgement and integrity (Hoang *et al.*, 2021; Sharma and Kirkman, 2015). Such trust-based leadership cultivates conditions in which employees are afforded the autonomy to explore, adapt and integrate AI in ways that align with their work preferences (Georganta and Ulfert, 2024). When employees engage with AI in an autonomy and voluntary-based approach, they are more likely to develop calibrated expectations about its outputs and confidence in interpreting and applying them effectively (Glikson and Woolley, 2020; Kong *et al.*, 2024). Moreover, empowering leaders often model openness toward new technologies, which can further reinforce trust through observational learning, a key mechanism central to SCT (Bandura, 1988). By modelling AI-assisted task completion, openly sharing information about AI capabilities and limitations and affirming employees' competence in working with AI, empowering leaders provide the informational scaffold from which each individual develops calibrated cognitive judgements about the AI system's trustworthiness (Zhang *et al.*, 2026). Through these accumulated experiences, employees develop positive expectations regarding the usefulness and reliability of AI, thereby strengthening their trust in the technology (Monod *et al.*, 2024).

Additionally, we argue that AI trust predicts effective employee–AI collaboration (Kong *et al.*, 2023). When AI-generated outputs consistently meet employees' performance expectations, employees become more confident in the system and more willing to rely on its recommendations (Gkinko and Elbanna, 2023; Kong *et al.*, 2023). Such trust helps reduce initial scepticism and resistance to AI, enabling employees to incorporate AI-generated information into decision-making and ultimately engage in the interactive exchanges with AI systems (Erengin *et al.*, 2025). Beyond immediate engagement, AI trust also fosters the intrinsic motivation necessary for continuous learning and skill acquisition, promoting employees to invest effort in prompting and providing contextual feedback that enables AI systems to refine their outputs over time (Chowdhury *et al.*, 2022; Kong *et al.*, 2023). Through these interactions, human judgement and AI mutually reinforce each other, allowing both actors to contribute their respective strengths to task completion (Haenlein and Kaplan, 2019). Conversely, when trust is low, employees are more likely to ignore, override or excessively question AI outputs, limiting the sustained interaction required for meaningful employee–AI collaboration. Thus, when employees trust AI, they are more willing to rely on its outputs, engage with it interactively and treat it as a credible contributor to their work rather than merely as a peripheral tool (Georganta and Ulfert, 2024). In line with the cross-level mediation framework articulated earlier in this paper, we therefore hypothesize:

- H2. AI trust mediates the relationship between empowering leadership and employee–AI collaboration.

2.4 Mediating role of psychological safety

In an environment entails complex interactions and carries inherent uncertainties as AI adoption, it is imperative for organizations to foster psychological safety among employees (Kumar *et al.*, 2025; Yin *et al.*, 2024). Psychological safety, originally conceptualized by Kahn (1990), refers to the belief that one can express themselves without fear of negative consequences to self-image, status or career. It is further defined as a shared perception that the work environment is conducive to interpersonal risk-taking, open dialogue and authenticity (Edmondson and Bransby, 2023). When employees feel psychologically safe, they are more likely to share ideas, admit mistakes, challenge existing assumptions and engage in collaborative learning. Prior research has consistently identified psychological safety as a critical mediator through which leadership influences various positive outcomes, including job performance, knowledge sharing, innovation and overall employee engagement (Artinger *et al.*, 2025; Newman *et al.*, 2017).

We position psychological safety as a complementary mediator alongside AI trust because the two mechanisms explain different aspects of employee–AI collaboration. While AI trust reflects a technology-directed appraisal of the AI system’s competence, reliability and functional integrity (Chowdhury *et al.*, 2022), psychological safety reflects a socially directed appraisal of whether the team context is safe for interpersonal risk-taking, such as asking questions, experimenting with AI, admitting uncertainty and learning from mistakes (Coetsee, 2019; Newman *et al.*, 2017). Put differently, AI trust concerns employees’ evaluation of the technological agent itself, whereas psychological safety concerns their appraisal of the interpersonal environment surrounding its use. This distinction matters because employees may trust AI’s technical capability but still avoid visible or exploratory engagement if they fear criticism, embarrassment or blame within the team (Erengin *et al.*, 2025). Conversely, employees who feel psychologically safe but doubt AI’s reliability may engage only cautiously, without committing to sustained, meaningful collaboration.

Within the leadership literature, empowering leadership has been identified as a key antecedent to psychological safety (Cheong *et al.*, 2019; Edmondson and Bransby, 2023). This leadership style conveys trust in employees’ capabilities, grant autonomy and encourages self-directed decision-making (Hoang *et al.*, 2021; Martin *et al.*, 2013). These behaviours signal respect, inclusion and support, thereby creating a work environment in which employees feel comfortable voicing ideas and engaging in risk-taking behaviours (Ahearne *et al.*, 2005; Zhang and Bartol, 2010). Underpinned by SCT, which emphasizes the role of environmental influences on individual cognition and behaviour, empowering leadership functions as a key contextual factor shaping how employees perceive risk, control and support in the workplace. By granting authority, offering developmental support and reinforcing employees’ agency, empowering leaders cultivate the confidence necessary for employees and help them perceive that experimentation and learning are valued rather than penalized (Arnold *et al.*, 2000; Sharma and Kirkman, 2015). We therefore posit that empowering leadership facilitates psychological safety by reinforcing beliefs in personal competence, validating employee voice and engaging in exploratory behaviours when interacting with emerging technologies such as AI.

Psychological safety is particularly relevant in high-uncertainty contexts, such as the adoption of AI, where the risks associated with failure, ambiguity or social judgment are elevated (Artinger *et al.*, 2025; Newman *et al.*, 2017). In such settings, employees must navigate unfamiliar technologies while managing shifting expectations and potential disruptions to their roles. When employees perceive a psychologically safe climate, they are more willing to engage in what Coetsee (2019, p. 319) described as “provisional tries”, which are exploratory efforts aimed at testing how emerging technologies such as AI can improve their work processes. Within this cognitive state, employees perceive that errors are tolerated, experimentation is encouraged and support systems are in place to aid their learning and adaptation. These conditions are particularly important in employee–AI collaboration, where employees must often question algorithmic outputs, raise concerns about potential errors or biases and collectively explore how AI-generated recommendations can be effectively integrated into their workflows (Chen *et al.*, 2026). Such behaviours not only help employees learn how to critically evaluate AI-generated insights but also provide valuable contextual input that enables AI systems to refine their outputs and better align with organizational needs (Jiang *et al.*, 2022). In this sense, psychological safety facilitates the open dialogue and experimentation necessary for both human and machine actors to improve their contributions to task performance. Consistent with this view, Edmondson and Bransby (2023) argue that psychological safety can buffer technology-induced stress by fostering a mindset in which employees feel confident experimenting with AI tools, even amid ambiguity, rapid change or evolving performance expectations. Conversely, when psychological safety is low, employees may hesitate to question AI outputs or voice concerns about potential limitations (van Riel *et al.*, 2025). Such reluctance reduces the feedback and contextual information that

AI systems rely on to improve their outputs, thereby limiting the iterative learning processes that underpin effective employee–AI collaboration.

Taken together, we argue that employees working in an environment created by empowering leaders are more likely to feel psychologically safe, enabling them to take interpersonal risks and express themselves openly. This heightened sense of psychological safety, in turn, fosters their willingness to engage in social risk-taking and enhances their confidence in experimenting with AI technologies, thereby promoting more effective employee–AI collaboration (see [Figure 1](#)).

- H3.* Psychological safety mediates the relationship between empowering leadership and employee–AI collaboration.

3. Methods

3.1 Research context and data sources

We chose Vietnamese companies as the empirical setting for this study for the following reasons. First, Vietnam presents an ideal setting for this study due to the government’s proactive efforts to advance the digital economy and society, wherein employee–AI collaboration plays a pivotal role ([Pham et al., 2024](#); [Vu and Nguyen, 2024](#)). Achieving this vision requires comprehensive insights into the economic, social and environmental dimensions of AI integration to inform effective policy and decision-making ([Dey et al., 2023](#)). Second, the predominance of employee–AI collaboration studies in developed nations raises the question of whether findings from such research are applicable in less explored settings like Vietnam. By conducting empirical research in Vietnam, this study addresses the call from scholars to broaden our understanding of employee–AI collaboration across diverse contexts ([Dey et al., 2023](#); [Kumar et al., 2025](#)).

To ensure a representative sample, we recruited Vietnamese companies that had integrated AI technologies into their business operations for a minimum of six months. Our sampling frame was drawn from a professional Vietnamese HR association comprising over 350 members. This network includes individuals with substantial managerial experience, notably C-level executives, business owners, vice presidents, directors and senior managers. Through this network, we invited 85 companies to participate in the study, of which 50 agreed to take part. The recruitment process was conducted between October and December 2024 and employed a combination of formal outreach methods, including phone calls, emails, virtual meetings and in-person interactions. During these engagements, CEOs or HR managers were provided with detailed participant information sheets and the full survey instrument to ensure transparency and alignment with the study’s aims. Upon receiving consent, the survey was distributed to both managers and employees across various departments.

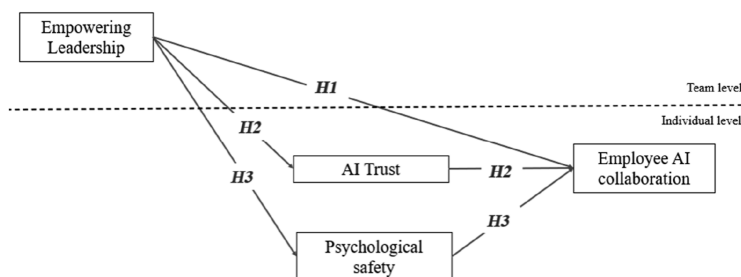


Figure 1. Proposed research model. Source(s): Authors’ own work

3.2 Participants and procedures

To optimize efficiency and accommodate participants' preferences, the survey was administered in both web-based and paper-based formats (Saunders *et al.*, 2019). The online version consisted of a self-administered questionnaire distributed via Qualtrics. Participants who consented to take part received a hyperlink directing them to access and complete the survey electronically. For those preferring a paper-based option, hard copies of the questionnaire were personally delivered and later collected in sealed envelopes to uphold participant confidentiality and data security. Each survey began with a cover letter that clearly communicated the study's objectives, its potential practical implications and assurances of participant confidentiality. To ensure the relevance and accuracy of the sample, all respondents were first provided with a clear explanation of AI and its application in workplace settings. They were then asked to indicate their level of experience using AI for job-related tasks. Respondents who reported no experience with AI were screened out and did not proceed with the remainder of the questionnaire.

To address our research questions and mitigate the potential for common method variance, we implemented a multi-level, structured data collection design (Preacher *et al.*, 2010). Specifically, employees are nested within work teams supervised by a formal team leader. Each team consists of multiple employees who collaborate on shared tasks while using AI systems embedded in their workflow. These AI systems function as technological tools that support task execution rather than as formal team members with decision authority. Consistent with this structure, empowering leadership is conceptualized as a team-level contextual variable, reflecting leadership behaviours experienced collectively by team members. In contrast, AI trust, psychological safety and employee–AI collaboration are measured at the individual level, as they capture employees' personal perceptions and interactions with AI technologies. This approach aligns with prior research suggesting that employees–AI collaboration may vary within teams depending on personal evaluations and behavioural responses to AI (Kong *et al.*, 2023; Yin *et al.*, 2024). A total of 418 complete responses across 103 teams made up our final research samples, yielding response rates of 76% of the 550 questionnaires distributed. The detailed demographic information of the employees, teams and organizations participated in this study is presented in Tables 1 and 2.

3.3 Measures

All measurement scales employed in this study were adapted from previously validated instruments in the literature. As the original scales were developed in English while the survey was administered in Vietnamese, a back-translation procedure was conducted to ensure linguistic equivalence between the two versions (Brislin, 1986). All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

A five-item scale developed by Pearce and Sims (2002) was utilized to measure *empowering leadership* with a sample item being: "My team leader urges me to assume responsibilities on my own" ($\alpha = 0.853$).

AI trust was measured using a three-item scale established by Polisetty *et al.* (2023), with a sample item being: "The AI systems are trustworthy" ($\alpha = 0.737$).

Psychological safety was evaluated with a seven-item scale developed by Edmondson and Bransby (2023), with a sample item stating: "I am able to bring up problems and tough issues" ($\alpha = 0.802$).

A five-item scale developed by Kong *et al.* (2023) was utilized to gauge *employee–AI collaboration*, with a sample item being: "AI participates in my information identification and evaluation process" ($\alpha = 0.867$).

Control variables: Demographic information at the individual level (i.e. age, gender, education and tenure) was measured for employees. Meanwhile, team characteristics (i.e. team tenure and team size) were further taken as controlling variables.

Table 1. Participants' demographics

	Employee (<i>N</i> = 418) Frequency (%)	
<i>Gender</i>		
Male	193	46.2%
Female	223	53.3%
Others	2	0.5%
<i>Age</i>		
18–20 age	5	1.2%
21–30 age	265	63.4%
31–40 age	117	28.0%
41–50 age	28	6.7%
Over 51 age	3	0.7%
<i>Education</i>		
High-school or under	13	3.1%
Vocational or college	20	4.8%
University	339	81.1%
Graduate school or above	45	10.8%
Others	1	0.2%
<i>Organization tenure</i>		
Less than 1 year	124	29.7%
At least 1 but less than 3 years	143	34.2%
At least 3 but less than 5 years	61	14.6%
At least 5 but less than 8 years	46	11.0%
At least 8 years	44	10.5%
<i>Industry sector</i>		
Consulting Services	23	5.5%
Commercial Trade and Retail	70	16.7%
Financial Services	72	17.2%
IT Infrastructure	45	10.8%
IT Services	63	15.1%
Logistics and Supply Chain	45	10.8%
Software	100	23.9%
Source(s): Authors' own work		

3.4 Common method variance

To mitigate common method variance (CMV) (Podsakoff *et al.*, 2003), we carefully designed the survey instruments and implemented procedural safeguards during data collection.

First, as outlined in the survey instruments section, all questionnaire items were drawn from well-established and validated measurement scales that have been extensively tested across prior empirical studies. Utilizing these pre-validated instruments minimized the risk of measurement bias that might result from researcher-designed questions or potential influence from participating organizations (Creswell and Creswell, 2018).

Second, to address the risk of common method bias, the survey design incorporated several procedural remedies. Data collection was also conducted anonymously to reduce social desirability bias and encourage participants to respond truthfully without fear of reprisal (Creswell and Creswell, 2018; Saunders *et al.*, 2019).

Furthermore, we assessed the presence of common method bias by conducting confirmatory factor analysis (CFA) and evaluating the reliability and validity of the measurement model (Podsakoff *et al.*, 2003). Specifically, both Fornell and Larcker (1981) criterion and the heterotrait–monotrait (HTMT) ratio were applied to estimate CMV (Kline, 2023). As shown in Table 3, the square root of the AVE for each construct exceeded its inter-

Table 2. Descriptive statistics and correlation coefficient of variables

Variables	Mean	SD	1	2	3	4	5	6	7
<i>Individual level</i>									
1 Employee gender	1.54	0.51							
2 Employee age	2.42	0.69	−0.043						
3 Employee education level	3.00	0.54	0.030	0.184**					
4 Employee organizational tenure	2.39	1.30	0.053	0.489**	0.184**				
5 AI Trust	3.43	0.60	−0.032	−0.005	−0.065	−0.025	(0.81)	0.446	0.608
6 Psychological safety	3.77	0.50	−0.100*	−0.009	−0.119*	−0.049	0.343***	(0.69)	0.391
7 Employee–AI collaboration	3.51	0.68	−0.003	−0.133**	−0.030	−0.057	0.477***	0.330***	(0.80)
<i>Team level</i>									
1 Team tenure	2.51	1.03	−0.024	0.021	—				
2 Empowering leadership	3.97	0.31	−0.113*	0.127**	−0.043	(0.76)	0.043		
Note(s): $N = 103$ teams comprising of 418 workers and 103 managers. (parenthesis) = the square root of the AVE HTMT = heterotrait–monotrait ratio (in italics). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)									
Source(s): Authors' own work									

Table 3. Convergent validity of variables

Measurement items	Outer loading	Tolerance	VIF	Cronbach's alpha	AVE	CR
Empowering leadership (EPL)				0.853	0.583	0.893
EPL1	0.770	0.484	2.064			
EPL2	0.833	0.404	2.475			
EPL3	0.808	0.497	2.012			
EPL4	0.696	0.664	1.507			
EPL5	0.702	0.573	1.746			
EPL6	0.763	0.517	1.934			
AI Trust (AIT)				0.737	0.663	0.864
AIT1	0.852	0.567	1.764			
AIT2	0.867	0.550	1.819			
AIT3	0.701	0.809	1.236			
Psychological safety (PS)				0.802	0.471	0.86
PS1	0.548	0.801	1.249			
PS2	0.720	0.636	1.572			
PS3	0.684	0.654	1.530			
PS4	0.719	0.629	1.591			
PS5	0.637	0.702	1.424			
PS6	0.710	0.632	1.581			
PS7	0.760	0.571	1.752			
Employee AI collaboration (EACO)				0.858	0.639	0.898
EACO1	0.797	0.483	2.069			
EACO2	0.838	0.438	2.281			
EACO3	0.814	0.515	1.942			
EACO4	0.762	0.573	1.744			
EACO5	0.783	0.568	1.762			

Source(s): Authors' own work

construct correlations, satisfying the Fornell–Larcker criterion. Additionally, the HTMT values were well below the threshold of 0.85, indicating that all constructs are conceptually distinct. In addition, we assessed CMV by calculating the variance inflation factor (VIF). The resulting VIF ranged from 1.24 to 2.48, all below the threshold of 3.3 for CMV, as proposed by [Kock \(2015\)](#), thereby suggesting that CMV was low. Finally, we conducted CFA. The deterioration in model fit when variables were merged provided further evidence of discriminant validity ([Table 4](#)). Taken together, CMV was not a major concern in this study.

Table 4. Measurement models

Model	χ^2	df	CFI	TLI	RMSEA	SRMR for individual level	SRMR for team level	AIC	BIC
Hypothesized four-factor model	232.521	9	0.998	1.000	0.037	0.002	0.057	2020.619	2093.257
Three-factor model: (AIT and PS combined)	232.521	9	0.489	0.080	0.234	0.037	0.595	2056.211	2108.672
Two-factor model: (AIT, PS and EACO combined)	232.521	9	0.334	0.000	0.267	0.269	0.448	2164.038	2216.499
All combined	330.718	5	0.000	0.000	0.395	0.269	0.414	2230.776	2291.309

Source(s): Authors' own work

3.5 Aggregation

The present study calculated the R_{wg} , ICC(1) and ICC(2) statistics for empowering leadership to assess the degree of agreement among group members in rating their supervisor's empowering behaviours. R_{wg} values above 0.70 are deemed acceptable (Humphrey and LeBreton, 2019). The within-group agreement value was $R_{wg} = 0.839$, which indicates strong consensus among raters. The intraclass correlation values were ICC(1) = 0.05 and ICC(2) = 0.16. While these values are lower than those typically reported in some multilevel research, such results are not uncommon in research with relatively small team sizes and a limited number of raters per group – factors that inherently reduce between-group variance and attenuate reliability estimates (Humphrey and LeBreton, 2019). Critically, ICC(1) values around 0.05 are often considered sufficient to justify multilevel modelling because they indicate that a statistically meaningful proportion of variance resides between groups (Bliese, 1998; Humphrey and LeBreton, 2019). In addition, recent methodological literature cautions against placing undue emphasis on ICC(2), noting that high values are not a strict prerequisite for detecting emergent multilevel effects (Bliese *et al.*, 2018).

In light of this, we acknowledge that team-level measure of empowering leadership may reflect lower levels of consistency and consensus among members within teams in this study. This is theoretically plausible because leadership behaviours, although enacted at the team level, may be experienced differently by individual employees depending on their roles, interactions with the leader and task responsibilities (Tsai *et al.*, 2022). Nonetheless, empowering leadership is conceptually defined as a team-level leadership style enacted by a formal leader toward the entire team and prior multilevel leadership studies commonly model such constructs at the team level even when within-team variability exists (Humphrey and LeBreton, 2019; Lin *et al.*, 2020; Tsai *et al.*, 2022).

To further address this issue, we conducted a robustness check using a disaggregated model, in which empowering leadership was analysed at the individual level rather than aggregated to the team level. This robustness test suggests that our findings are not driven by the level of aggregation and provides additional confidence in the interpretation of empowering leadership as a contextual team-level influence in the present study. Further details can be found in Section 4.4.

3.6 Analytical strategy

The hypotheses were quantitatively tested using Mplus (version 8.0). The software was employed for initial data screening, the computation of descriptive statistics and preliminary analyses, including evaluations of correlations, normality and reliability. Multilevel structural equation modelling (MSEM) was then performed, encompassing multilevel CFA to assess convergent and discriminant validity and path analysis to test the hypotheses. MSEM is particularly well suited for the present study, which involves hierarchically structured data and includes mediating variables within its hypothesized model (Eid *et al.*, 2024; Zhang *et al.*, 2009). The present study adopts a multilevel modelling approach, comprising two levels of data: the individual level (Level 1) and the team level (Level 2). In this hierarchical structure, individual-level data are nested within team-level units.

Following the methodological guidance of Preacher *et al.* (2010), a Monte Carlo simulation with 20,000 replications was employed to generate 95% bias-corrected confidence intervals (CIs) for the assessment of cross-level mediation effects. All analyses were conducted using Mplus 8.0 (Muthén and Muthén, 1998–2017), applying the robust maximum likelihood (MLR) estimation. Model fit was evaluated using several indices, including the comparative fit index (CFI), Tucker–Lewis Index (TLI), root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) for the within-level (individual-level) and for the between-level (team-level). In comparing alternative multilevel models, scaled chi-square difference testing was conducted, in accordance with the recommendations of Kline (2023).

4. Results

4.1 Descriptive statistics

Table 2 shows the correlations, the HTMT values, means and standard deviations of the study variables. All HTMT values are below the recommended threshold, supporting discriminant validity and confirming the suitability of the data for further analysis.

As shown in Table 3, all CR values exceeded 0.70, and all AVE values were above the 0.50 threshold (Hair *et al.*, 2019), indicating satisfactory convergent validity.

4.2 Confirmatory factor analysis

A multilevel CFA was conducted with three individual-level variables (i.e. AI trust, psychological safety and employee–AI collaboration) and a group-level variables (i.e. empowering leadership). Results as shown in Table 4 revealed the 4-factor model to have good fit ($\chi^2 = 232.521$, $df = 9$; CFI = 0.998, TLI = 1.000, RMSEA = 0.037, SRMR for individual level = 0.002, SRMR for team level = 0.057).

This hypothesized model fits the data better than other alternative models (refer to Table 4). Since the model fit worsened as more variables were combined, discriminant validity was also confirmed.

4.3 Hypothesis testing

Hypothesis 1 proposes that empowering leadership is positively related to employee AI collaboration. As shown in Table 5, the relationship between empowering leadership and employee–AI collaboration was positive and significant ($\gamma = 0.390$, $SE = 0.148$, $p = 0.009$). Thus, Hypothesis 1 was supported.

Hypothesis 2 proposes that AI trust mediates the relationship between empowering leadership and employee–AI collaboration. As shown in Table 5, empowering leadership was positively and significantly related to AI trust ($\gamma = 0.244$, $SE = 0.076$, $p = 0.001$) and AI trust was positively and significantly related to employee–AI collaboration ($\gamma = 0.460$, $SE = 0.053$, $p = 0.000$). Furthermore, we conducted a bootstrapping test to examine the indirect effect of empowering leadership on employee–AI collaboration through AI trust. The result in Table 6, based on Monte Carlo bootstrap simulation with 20,000 replications, showed that the estimate of the indirect effect was 0.112 ($SE = 0.037$, $p = 0.002$, 95% CI = [0.041, 0.184]). Since the confidence interval did not include zero, a mediating effect of AI trust was confirmed. Thus, Hypothesis 2 was supported.

Hypothesis 3 proposes that psychological safety mediates the relationship between empowering leadership and employee–AI collaboration. As shown in Table 5, empowering leadership was positively and significantly related to psychological safety ($\gamma = 0.520$, $SE = 0.063$, $p = 0.000$) and psychological safety was positively and significantly related to employee–AI collaboration ($\gamma = 0.208$, $SE = 0.081$, $p = 0.010$). In addition, we conducted a

Table 5. Tests of direct relationships

Path	Estimates	S.E.	Status
Empowering leadership → Employee–AI collaboration	0.390**	0.148	Supported
Empowering leadership → AI trust	0.244**	0.076	Supported
AI trust → Employee–AI collaboration	0.460***	0.053	Supported
Empowering leadership → Psychological safety	0.520***	0.063	Supported
Psychological safety → Employee–AI collaboration	0.208**	0.081	Supported

Note(s): For direct relationships and indirect relationships, unstandardized estimates are reported. CI = confidence interval. Significant direct and indirect effects using Monte Carlo confidence intervals.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)

Source(s): Authors' own work

Table 6. Tests of indirect relationships

Path	Estimates	S.E.	Lower and upper 95% CI limits
Empowering leadership → AI trust → Employee AI collaboration	0.112**	0.037	[0.041, 0.184]
Empowering leadership → Psychological safety → Employee AI collaboration	0.108**	0.045	[0.020, 0.224]

Note(s): For direct and indirect relationships, unstandardized estimates are reported. CI = confidence interval. Significant direct and indirect effects using Monte Carlo confidence intervals. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)

Source(s): Authors' own work

bootstrapping test to examine the indirect effect of empowering leadership on employee–AI collaboration through psychological safety. The result in Table 6, based on Monte Carlo bootstrap simulation with 20,000 replications, showed that the estimate of the indirect effect was 0.108 (SE = 0.045, $p = 0.016$, 95% CI = [0.020, 0.224]. Since the confidence interval did not include zero, a mediating effect of psychological safety was confirmed. Thus, Hypothesis 3 was supported.

4.4 Post-hoc analysis

Given the relatively low ICC values for empowering leadership, we conducted additional robustness checks to ensure that our findings were not sensitive to the aggregation of empowering leadership to the team level. Specifically, we estimated an alternative model in which empowering leadership was analysed at the individual level rather than aggregated to the team level, while retaining the same model specification and control variables. The results of this individual-level analysis were substantively consistent with those of the multilevel analysis (see Table 7). Empowering leadership remained positively and significantly associated with AI trust, psychological safety and employee–AI collaboration. Importantly, the path coefficients for empowering leadership on AI trust ($\beta = 0.216$, $p < 0.001$), psychological safety ($\beta = 0.436$, $p < [0.001]$) and employee–AI collaboration ($\beta = 0.155$, $p < 0.01$) remained in the same direction and were of comparable magnitude to those obtained in the team-level model. The indirect effects through AI trust and psychological safety also remained significant, indicating that both mediating mechanisms were robust to the alternative operationalization of empowering leadership (Table 7).

Table 7. Robustness check

Path	Estimates	S.E.	Status
Empowering leadership → Employee–AI collaboration	0.155**	0.056	Supported
Empowering leadership → AI trust	0.216***	0.050	Supported
AI trust → Employee–AI collaboration	0.457***	0.050	Supported
Empowering leadership → Psychological safety	0.436***	0.036	Supported
Psychological safety → Employee–AI collaboration	0.167**	0.056	Supported
Empowering leadership → AI trust → Employee AI collaboration	0.099***	0.025	[0.013, 0.132]
Empowering leadership → Psychological safety → Employee AI collaboration	0.073**	0.030	[0.049, 0.148]

Note(s): For direct and indirect relationships, unstandardized estimates are reported. CI = confidence interval. Significant direct and indirect effects using Monte Carlo confidence intervals. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)

Source(s): Authors' own work

Overall, these supplemental analyses suggest that the hypothesized relationships are not an artefact of aggregating empowering leadership to the team level. Rather, the pattern of results remains stable when empowering leadership is examined at the individual level. These findings provide additional confidence in the robustness of our conclusions while preserving the theoretical interpretation of empowering leadership as a contextual team-level influence in the main model.

5. Discussion

Utilizing a multilevel research design, this study examines how team-level empowering leadership fosters employee–AI collaboration, as well as the mediating mechanisms that underly this relationship. The findings indicate that empowering leadership is positively associated with employee–AI collaboration, and this relationship is mediated by both AI trust and psychological safety. These mediators suggest that empowering leaders foster an environment in which employees feel psychologically secure and develop AI trust, thereby enhancing their willingness and capacity to collaborate with AI.

5.1 Theoretical implications

First, this study responds to recent calls in the leadership literature to understand better how leaders enable employees to collaborate effectively with AI technologies (Tsai *et al.*, 2022; Yin *et al.*, 2024). Moving beyond prior work that has largely treated leadership as a moderating condition (Luo *et al.*, 2025), we adopt a multilevel perspective and position empowering leadership as a key environmental antecedent of employee–AI collaboration. Drawing on SCT (Bandura, 1991), our findings highlight how leadership shapes employees' personal evaluations, which in turn guide their engagement with AI. Importantly, we extend SCT to AI-enabled work contexts by showing that employee–AI collaboration is shaped not only through observational learning from leaders, but also through ongoing interaction with AI systems, where employees interpret and refine AI outputs through feedback and use. This dual process underscores the dynamic nature of collaboration in which leadership and technology jointly shape employee behaviour.

Second, this study advances the literature by specifying the parallel mediating mechanisms through which empowering leadership fosters effective employee–AI collaboration. By positioning AI trust and psychological safety as parallel mediators, we move beyond single-channel explanations of employee–AI collaboration to show that effective collaboration requires both a technology-directed appraisal of the AI system and a social-directed appraisal of the work context (Makarius *et al.*, 2020). These distinctive, but complementary, mechanisms are important because employees may trust an AI system yet remain reluctant to use it visibly within the team; conversely, they may feel psychologically safe within the team yet remain hesitant to rely on AI-generated outputs. In doing so, we respond to calls for a more fine-grained account of how employees navigate the challenges of AI integration, shifting theoretical focus from mere risk avoidance to proactive, adaptive engagement (Bankins *et al.*, 2023; Wang *et al.*, 2026).

Furthermore, this study refines the role of AI trust by conceptualizing it not merely as an initial boundary condition (Erengin *et al.*, 2025), but as an ongoing personal driver of deeper employee–AI collaboration. While prior research often positions trust as an antecedent to technology adoption or baseline usage, this view offers a limited account of how employees interact with AI once it becomes deeply embedded in everyday tasks (van Zoonen *et al.*, 2026). In our theorization, AI trust reflects employees' overall confidence in the AI system's reliability, competence and task contribution. This conceptualization is especially salient in GenAI-enabled work contexts, where outputs are probabilistic, context-sensitive and cannot be accepted passively; instead, they require continuous human judgement, interpretation and refinement (Nguyen *et al.*, 2025; Schuetz *et al.*, 2025). Our findings therefore suggest that AI

trust serves as the cognitive foundation that enables employees to critically evaluate AI outputs, calibrate their reliance and engage with AI in a more adaptive manner. Importantly, this points to the concept of calibrated trust, which refers to the dynamic, task-sensitive adjustment of reliance on AI based on ongoing assessment of system performance and contextual fit—as a more nuanced and practically meaningful goal than the simple accumulation of trust (Erengin *et al.*, 2025; Vössing *et al.*, 2022). In GenAI-enabled work, where system outputs vary in quality, reliability and contextual appropriateness, calibrated trust can help employees to adjust their reliance on AI selectively and reflectively. It is a core competency to derive value from AI collaboration while avoiding the risks of over-reliance or uncritical acceptance.

In parallel, our study highlights the role of psychological safety as a complementary condition that shapes how employees approach AI in their daily work. Specifically, employees are more willing to experiment with AI, question its outputs and adjust their behaviours when they believe that doing so will not result in negative consequences (van Riel *et al.*, 2025). This is particularly relevant in AI-enabled environments, where ambiguity and uncertainty make it necessary to move beyond routine use and engage in more exploratory forms of interaction. Our findings indicate that when employees feel psychologically safe, they are more likely to approach AI with a learning-oriented mindset, which supports experimentation, refinement and ongoing adjustment. These mechanisms reframe employee–AI collaboration as a mutually shaping process and open avenues for future research to examine additional cognitive pathways, such as learning orientation or role identity (Qin *et al.*, 2025), that may further explain how employees engage with AI across contexts.

Finally, our findings underscore the importance of cultural context as a boundary condition. Conducted in Vietnam – a context where collectivist values and moderate power distance remain influential (Hofstede, 2001) – the effects of empowering leadership may be amplified by the relative salience of autonomy and voice in more hierarchical environments (Cheong *et al.*, 2019). This suggests that the strength and potentially the mechanisms of empowering leadership may not be uniform across contexts. In more individualistic settings, where autonomy is more taken for granted, empowering leadership may exert weaker effects or operate through different pathways (Zhang and Bartol, 2010). By highlighting these contextual contingencies, our study not only strengthens the external validity of the findings but also points to the need for more comparative, cross-cultural research on employee–AI collaboration.

5.2 Practical implications

Our findings suggest three actionable strategies for day-to-day management to promote effective collaboration in AI-integrated work environments. First, this study underscores empowering leadership as a critical organizational lever for fostering employee–AI collaboration. Organizations should therefore invest in targeted leadership development initiatives that equip managers with the skills and mindsets needed to promote autonomy, support employee growth and delegate meaningful responsibility. These principles should be integrated into leadership development frameworks to ensure that managers embed empowering behaviours in their daily practices (Chen *et al.*, 2026). For instance, rather than maintaining rigid top-down control, leaders might delegate tasks such as refining AI-generated chatbot scripts or co-designing decision rules with experienced team members, while providing constructive feedback and guidance. Such practices not only enhance employees' confidence and self-efficacy in working with AI but also strengthen their AI trust, as the technology evolves through their direct input (Georganta and Ulfert, 2024; van Riel *et al.*, 2025). However, it is equally important to ensure that leaders themselves are supported through adequate organizational resources, clear expectations and ongoing coaching. Without such structural and psychological support, leaders may face increased strain, which can ultimately diminish their ability to empower others effectively (Cheong *et al.*, 2019).

Second, our finding that AI trust is a critical mediating mechanism emphasizes the importance of actively fostering trust systems. Simply cultivating high levels of trust in AI is insufficient and may itself become counterproductive if it leads employees to over-rely on AI-generated outputs without adequate critical evaluation. Organizations can foster calibrated trust by training employees to recognize the boundaries and limitations of AI, creating opportunities for them to gain hands-on experience with AI tools and creating opportunities to compare AI outputs with their own expert judgements (Erengin *et al.*, 2025). In AI-enabled contexts where outputs are probabilistic and context-sensitive, the ultimate goal of trust management is not to maximize employees' confidence in AI but to ensure that their reliance on it is appropriately calibrated to the demands of each situation (Glikson and Woolley, 2020; Kong *et al.*, 2024). This includes affirming employees' sense of value and professional identity, helping them view AI not as a threat, but as a tool for collaboration and growth (Hillebrand *et al.*, 2025). Furthermore, giving employees a voice in refining AI systems also reinforces their belief that the technology serves their work goals rather than undermining them.

Third, organizations should invest in practices that strengthen psychological safety. Organizations can provide training programmes that incorporate emotional regulation skills to help employees reframe challenging situations and manage uncertainty in a constructive manner (Luo *et al.*, 2025). Further, comprehensive learning and development initiatives should not only build technical competence but also promote creativity and innovative problem-solving skills to work with AI. By fostering an environment where employees feel safe to speak up, share ideas and experiment with new technologies without fear of negative repercussions, organizations can reinforce employees' adaptability and engagement (Artinger *et al.*, 2025). This is particularly important as AI continues to reshape tasks and roles, requiring employees to continually update their skills and mindsets.

6. Limitations and future research directions

While this study offers meaningful contributions, several limitations provide avenues for future research. First, the findings are based on a specific context and may not fully generalize across cultures. Prior research suggests that attitudes and behaviours toward AI can vary significantly across cultural settings (Chowdhury *et al.*, 2022; Pham *et al.*, 2024). As such, the dynamics of employee–AI collaboration may differ substantially depending on cultural context. Future studies should therefore replicate this research in diverse national contexts to examine the robustness of the observed relationships.

Second, this study focuses on empowering leadership as the primary leadership approach. Future research could extend this by examining alternative leadership styles such as transformational, servant or entrepreneurial leadership that may also shape employee–AI collaboration (Tsai *et al.*, 2022). Moreover, our model examines employee–AI collaboration as a focused outcome, but employees may respond to AI in a wider range of adaptive ways. Future research could examine related outcomes such as employee–AI empathy (Marvi *et al.*, 2025) and employee–AI crafting (Li *et al.*, 2024). Scholars could also investigate boundary conditions that may shape the strength of these relationships, including potential moderators such as task complexity, employees' baseline GenAI experience and whether AI use is voluntary or mandated. Examining these additional leadership approaches, outcomes and contingencies would provide a more comprehensive understanding of how leadership enables employees to collaborate with AI across different organizational contexts.

Third, while we employed established scales of employee–AI collaboration and AI trust from prior research (Kong *et al.*, 2023; Polisetty *et al.*, 2023), both constructs may require further refinement as AI-enabled work becomes more complex. The employee–AI collaboration measure used in this study primarily captures employees' behavioural engagement with AI systems. As such, it may reflect AI participation in work processes rather than fully capturing deeper, reciprocal forms of complementary or mutually enhancing employee–AI collaboration.

Future research could develop more refined measures that distinguish among varying levels of collaboration and better capture how human expertise and AI capabilities jointly contribute to task performance. In addition, our measure of AI trust is consistent with our theoretical focus on unidimensional perspective (Legood *et al.*, 2023). Although this approach is appropriate for examining AI trust within our parallel mediation model, it may not capture the full complexity of trust in AI-enabled work. Future research could adopt multidimensional measures that distinguish functional confidence from related dimensions such as affective comfort, perceived transparency, ethical assurance and behavioural willingness to rely on AI (Erengin *et al.*, 2025). Such work would help clarify whether different facets of AI trust have distinct or asymmetrical implications for employee–AI collaboration.

Fourth, although this study draws on SCT to explain how leadership influences employee–AI collaboration, it does not directly test key learning mechanisms emphasized by this theory, such as observational learning and reciprocal learning processes (Bandura, 2001). In this study, these mechanisms serve as underlying theoretical explanations for how employees interpret leadership cues and adapt their behaviour when interacting with AI systems. Given that SCT's triadic reciprocal determinism (Bandura, 2018) suggests that collaborative behaviour itself is likely to provide feedback and progressively reshape both AI trust and psychological safety, tracing feedback loops empirically would significantly deepen our understanding of how employee–AI collaboration stabilizes over time. Future research could examine these processes more explicitly through longitudinal designs that can capture how employees learn AI-related behaviours from leaders or peers or how the dynamic, recursive relationships theorized here unfold over time.

Finally, the aggregation of empowering leadership to the team level should be interpreted with caution. Although within-team agreement supported aggregation, the relatively low ICC values indicate that perceptions of empowering leadership may vary within teams, suggesting that leadership is not experienced uniformly. Future research could address this by adopting designs that better capture the dynamic and differentiated interactions between leaders and team members in AI-enabled work environments. In particular, examining how shared team contexts interact with leadership and individual cognition would offer a more nuanced understanding of employee–AI collaboration.

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