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Dynamics of user engagement: AI mastery goal and the paradox mindset in AI–employee collaboration

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ABSTRACT

Given the scarcity of previous studies on employee–AI collaboration and its impact on employee behavior and user engagement, we investigated its potential to drive user engagement using a mixed-method approach. Grounded in qualitative findings from 27 participants in a healthcare setting, we propose a robust model that emphasizes the impact of AI–employee collaboration on AI mastery goal, user engagement, and a paradox mindset, as well as the moderating role of AI empathy and technological frames. Using a quantitative method, we collected data from 452 participants in a healthcare setting across two studies. Our findings showed that AI–employee collaboration can drive AI mastery goal and a paradox mindset. We also found empirical evidence that both AI mastery goal and the paradox mindset can mediate the relationship between employee–AI collaboration and user engagement. Moreover, our findings revealed interesting moderating results across two studies. In Study 1, significant effects were found for both employee–AI collaboration and AI mastery goal at low AI empathy, but not at high levels. In Study 2, while the interaction between employee–AI collaboration and AI empathy was not significant, the influence of AI mastery goal became significant at high empathy levels, and the paradox mindset showed a significant effect only at high levels of AI empathy. These findings provide managers with valuable insights into the essential operations dynamic of employee–AI collaboration, underscoring its important role in enhancing user engagement.

1. Introduction

The dynamic interaction between employees and emerging technologies has significantly evolved in recent years (Noble & Mende, 2023). Central to this evolution is artificial intelligence (AI), which has the capacity to fundamentally change how employees work in the workplace and engage with emerging technologies (Davenport et al., 2020). The implementation of AI can enhance work efficiency and reduce costs (Kong et al., 2023), revolutionize how organizations analyze customer and market trends (Lv et al., 2022), transform innovation management (Füller et al., 2022), and, ultimately, contribute to economic growth (Huang & Rust, 2022). Further, AI's transformative impact on engagement has been notable across various sectors, such as healthcare (Panch & Bhojwani, 2021). The increasing prevalence of AI technology is driving a dynamic transformation within organizations (Kong et al., 2023).

Many organizations now focus on socio-technical systems where AI technologies are effectively integrated to transform inputs into desired and reliable outcomes. AI is widely adopted in human resource management (HRM) (Rodgers et al., 2023) due to its ability to create value for employees and firms (Chowdhury et al., 2023). For instance, in the healthcare sector, AI has the potential to unlock a significant portion of the USD one trillion improvement potential (McKinsey & Company, 2024). Further, AI technologies in healthcare are moving towards functioning independently, accurately, and efficiently (Moorman et al., 2024). In fact, it is projected that they could potentially take over the majority of the tasks performed by general practitioners (Dellaert et al., 2024).

Against this background, the collaboration between AI and employees can drive adoption (Li et al., 2024) and engagement with these technologies (Kong et al., 2023). Therefore, how AI is integrated into a firm can profoundly impact user engagement in these settings. Such practical considerations necessitate an investigation into how collaboration with AI agents affects employees' behavior and attitudes toward

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these emerging technologies (Endsley, 2023; Rai et al., 2019). Previous studies have examined the managerial and societal implications of AI (Huang & Rust, 2021; Iveson et al., 2022) and focused on improving its functional aspects to enhance adoption (Lieberman, 2021; Wang & Uysal, 2024) by applying various theoretical lenses to human–technology interaction. For instance, sociotechnical systems (STS) theory provides a holistic framework for managing AI systems by emphasizing the integration of emergent technology with employees' knowledge, capabilities, and well-being to enhance organizational effectiveness (Appelbaum, 1997). Similarly, researchers have widely applied organizational behavior models to study AI–human interaction, emphasizing psychological and social dynamics in workplace contexts (Budhwar et al., 2023; Frey & Osborne, 2017).

In line with these theoretical underpinnings, despite growing interest in AI–employee collaboration, there is still limited understanding of how employees collaborate and engage with AI systems in the workplace. While such collaboration influences employee interactions with AI systems (Li et al., 2024), the impact on engagement and the underlying theoretical mechanisms remains unclear (Yin et al., 2024a). Further, it is not yet known how employees perceive and interact with AI in such collaborative environments and how these perceptions dynamically shape their willingness to collaborate or engage with AI-driven workflows. Moreover, the psychological processes that mediate or moderate the relationship between AI collaboration and employee engagement are poorly theorized.

To bridge this gap, we propose that employee–AI collaboration plays a crucial role in enhancing user engagement by introducing a novel theoretical perspective. We specifically examine how employees collaborating with AI systems can develop psychological traits, such as an AI mastery goal or a paradox mindset, which, in turn, facilitate more engaging collaboration with AI. We argue that this collaboration fosters the development and drive of an AI mastery goal orientation and a paradox mindset, enabling employees to navigate the complexities and contradictions that arise from human–AI interactions. Furthermore, recent research has called for a deeper investigation into the moderating role of AI empathy (Huang & Rust, 2024; Liu-Thompkins et al., 2022) as well as technological frames (Ghobadi, Mathiassen, 2024). Extending this, our study explores how AI empathy moderates employees' perceptions of AI collaboration, potentially shaping their attitudes toward AI and their willingness to engage with it. Additionally, we examine the impact of technological frames within this mechanism. By integrating these elements—employee–AI collaboration, AI mastery goals, technological frames, and AI empathy—our study provides a more comprehensive understanding of how organizations can optimize employee–AI collaboration to foster meaningful user engagement.

This study makes several important contributions to the literature on AI adoption by investigating the outcomes of employee–AI collaboration. First, we expanded the existing body of knowledge by examining how AI–employee collaboration (Kong et al., 2023) influences employees' engagement with AI. While the significance of the AI mastery goal and the paradox mindset in AI adoption is well-established (Dang & Liu, 2022; Spieth et al., 2021; Yin, 2023), limited empirical research has explored the interaction of these factors within the context of employee–AI collaboration. In this regard, our study investigates how AI–employee collaboration can affect both AI mastery goal and the paradox mindset; our empirical findings indicate that such collaboration positively impacts both these factors. However, we also found that employee–AI collaboration alone is insufficient to drive user engagement with AI, and additional mechanisms are required for more effective engagement.

Second, we contributed to the body of knowledge by investigating the mediating roles of AI mastery goal and the paradox mindset in the relationship between AI–employee collaboration and user engagement. In greater detail, despite the importance of the mastery goals and the paradox mindset in driving positive employee behavior (Liu et al., 2020; Solberg et al., 2022), previous research has not investigated or analyzed their mediating roles in fostering user engagement. In this vein, we hypothesized and tested the mediating roles of AI mastery goal and the paradox mindset in the relationship between employee–AI collaboration and user engagement. Our results demonstrated that both AI mastery goal and the paradox mindset positively mediate this relationship, enhancing user engagement when employees collaborate with AI. This provides a novel theoretical explanation for how employee–AI collaboration can lead to increased user engagement.

Third, we responded to previous calls for further empirical investigations on the moderating role of AI empathy (Liu-Thompkins et al., 2022; Huang, and Rust, 2024) and technological frame (Spieth et al., 2021) in the AI context. Our findings showed that AI empathy can moderate the relationships among AI mastery goal, employee–AI collaboration, and user engagement. We further provided empirical evidence on how the technological frame can act as a moderator in such relationships. Our findings contributed empirical evidence to the literature. In Study 1, significant effects were found for employee–AI collaboration and AI mastery goals at low AI empathy level, but not at high levels. In Study 2, AI mastery goals showed significance only at high empathy level, while the paradox mindset was significant only at high AI empathy level.

Last, taken together, these findings can have important implications for business managers and provide insights into how they can incorporate AI in their business activities. These findings can provide robust support for how developing and nurturing the AI mastery goal and the paradox mindset in a firm which tries to adopt AI can enhance its user engagement. We begin with a review of the employee–AI collaboration literature. This is then followed by a preliminary qualitative study in order to develop a conceptual model in which we theorize the relationship between employee–AI collaboration and its outcomes. We proceed with the hypotheses that were tested in our primary quantitative study. We conclude our research with the discussion of the findings and the theoretical and managerial contributions of the study.

2. Literature review

2.1. Employee–AI collaboration

Although Alan Turing pioneered the field in 1950 by posing the question, "Can machines think?", it garnered little academic focus until recently. In the past few years, there has been a surge in AI-related articles, each with its own conceptual foundation, distinct objectives, and disciplinary approach. AI encompasses programs, algorithms, systems, and machines that exhibit human-like intelligence (Shankar, 2018). AI is also defined as intelligence shown by machines replicating human cognitive abilities (Huang & Rust, 2018; Syam & Sharma, 2018). Key AI technologies include machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots, and robotic process automation (Paul et al., 2024). Utilizing these technologies enables AI to accurately interpret external data, learn from them, and adapt flexibly (Kaplan & Haenlein, 2019) to address organizational needs. Practical adoption of AI in organizations involves automating processes, extracting insights from data, and engaging with customers and employees (Davenport & Ronanki, 2018; Dwivedi et al., 2023) which can enhance an organization's performance.

Given this context, organizations are increasingly integrating AI into their daily workplaces, resulting in several positive outcomes (Collins et al., 2021; Hofmann et al., 2024; Mikalef et al., 2023; Mustak et al., 2021; Samuel et al., 2022). As AI systems become more embedded within organizations, a collaborative model emerges where employees and AI systems collaborate on shared tasks (Paschen et al., 2020). Employee–AI collaboration highlights the synergistic relationship where employees and AI work together to achieve a common task (Chowdhury et al., 2023). This collaboration aims to ensure safe, seamless, and effective teamwork between employees and AI technology (Cheng et al., 2023).

AI–employee collaboration can go beyond just splitting tasks; it can also involve both parties working together on the same task. An employee may perform the task with AI providing support (Peng et al., 2022), or AI can take the lead on the task, with employee supervision or intervention when necessary (Li et al., 2024). From the organization's perspective, collaboration between AI and employees can provide a competitive edge (Huang et al., 2024). For employees, collaborating with AI systems is becoming a standard practice (Sowa et al., 2021) which helps them to become more engaged with these systems (Li et al., 2024; Foroudi et al., 2025; Marvi et al., 2019; Andriotis et al., 2021).

Previous studies have investigated employee–AI collaboration from two research streams. The first stream investigates strategies for employee–AI collaboration and their impact on organization performance outcomes (Sinha et al., 2020; Xiong et al., 2023). Studies in this research stream have also looked into the design of collaborative systems, collaborative weighting, support mechanisms, risk management strategies, and organization performance outcomes (e.g., Baird & Maruping, 2021; Endsley, 2023; Haesevoets et al., 2021). The second research stream investigates the impact of AI–employee collaboration on the responses of various stakeholders, with a particular focus on consumer responses in different contexts, such as online product recommendations (Longoni & Cian, 2022), financial services (Luo et al., 2021), and health settings (Longoni et al., 2019).

Nevertheless, despite these scholarly efforts, and the benefits offered by AI systems in organizational decision making (Belizón & Kieran, 2022), most organizations have failed to experience the expected outcomes and values of integrating AI into their business processes (Economist, 2020). In this line, there is a lack of understanding regarding how organizations can integrate AI systems with their existing workforce (Makarius et al., 2020), what the best practices are for facilitating effective employee–AI collaboration (Li et al., 2024), and what underlying mechanisms drive user engagement as a result of such collaboration (Chowdhury et al., 2022; Mikalef & Gupta, 2021; Tambe et al., 2019; Marvi et al., 2023; Marvi et al., 2024). Effectively engaging employees with AI systems is essential for the successful implementation of AI–employee collaboration strategies (Yin et al., 2024a). In response to this pressing gap, we have developed and empirically tested a model that investigates how employee–AI collaboration drives user engagement, the AI mastery goal, and the paradox mindset. Table 1 shows a summary of the key issues found in the literature.

3. Research design

Using a multi-disciplinary approach, we reviewed literature from the fields of technology, management, marketing, and organization (Brakus et al., 2009; Churchill, 1979; Diamantopoulos et al., 2008; Homburg et al., 2015; Netemeyer, 2003; Schaarschmidt et al., 2021). Employing a mixed-method approach, we conducted a qualitative study (interviews) to enhance the conceptual clarity of the construct and establish a foundation for the research. We developed a questionnaire to validate the scale and the proposed model. The item measurements were based on previously validated measures, supported by the literature review and the qualitative study.

We conducted four studies over two phases. Phase 1 involved reviewing related articles on AI, employee–AI collaboration, and engagement. The validity of the findings and the questionnaire measures was enhanced by gathering data from interviews with key employees, AI practitioners, and academics in the healthcare sector (27 participants). Our qualitative stage helped to provide depth and context to the quantitative findings. It explored the underlying causal relationships between our proposed constructs observed in the quantitative data, offering a more comprehensive understanding of complex phenomena. In this line, our interviews helped to strengthen the validity of the findings and questionnaire measures by conducting interviews with 27 key healthcare sector employees, AI practitioners, and academics. This sample size ensured thematic saturation while capturing diverse perspectives. Further, these interviews revealed gaps in our initial theoretical framework and helped us to make necessary changes to our theoretical framework. Participant feedback also refined and adjusted the questionnaire's relevance. By triangulating the data (Study 1), the validity and depth of the conclusions were strengthened (Churchill, 1979; Foroudi et al., 2019; Foroudi et al., 2020). Additionally, we conducted a pre-study to assess the validity and reliability of the measurement instruments (Study 2). In this study, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to examine the dimensionality of the AI authenticity scale. In Phase 2, to enhance the generalizability of the results, we collected detailed survey data focusing on specific AI applications used by employees, particularly AI-driven Clinical Decision Support Systems (CDSS) (Study 3) and AI-enhanced Telemedicine Platforms used by employees (Study 4) (Morgan et al., 2004).

4. Study 1: perceptions and challenges of AI adoption in healthcare 4.1 overview

In Study 1, we aimed to understand how employees in the healthcare sector perceive the use of AI technologies. Specifically, this study focused on examining key constructs such as AI Adoption, AI Mastery Goal, AI-driven Clinical Decision Support Systems (CDSS), User Engagement, and the moderating effects of AI Empathy and Technological Frames (Bearden et al., 2001; Churchill, 1979; Tian et al., 2001; Zaichkowsky, 1985). To achieve this, we employed a qualitative approach, conducting 27 in-depth interviews with healthcare employees, AI practitioners, and academics. These interviews, totaling 1352 minutes with an average of 48 minutes each, were designed to explore the integration and application of AI within healthcare settings from the perspectives of those directly involved. The primary objective was to identify the perceived effectiveness, practical challenges, and areas of concern regarding AI–employee collaboration in healthcare.

4.1. Method

We employed a rigorous qualitative methodology to collect and analyze the data in alignment with the constructs and relationships outlined in our model. The interview process was guided by a semi-structured interview protocol developed through a comprehensive literature review that informed our conceptual framework (Foroudi, 2019; Churchill, 1979). Participants were carefully selected to represent a diverse range of roles within the healthcare sector, ensuring a broad spectrum of experiences and perspectives on AI use. The interviews were conducted either face-to-face or via video conferencing, depending on participant availability and preference. Each session was recorded, transcribed verbatim, and systematically analyzed using NVivo, a qualitative data analysis software. The interview data were coded according to the key constructs in our model, such as AI Adoption, AI Mastery Goal, and User Engagement. Through this process, we identified emerging themes, patterns, and key issues related to AI–employee collaboration (Hair et al., 2006). To enhance the reliability of our findings, triangulation methods were employed, including cross-verification of data from multiple sources and iterative discussions among the research team (Churchill, 1979; Foroudi et al., 2024; Foroudi et al., 2023). During the interviews, participants also provided feedback on a preliminary list of item measurements derived from the existing literature. This feedback was instrumental in refining the items and sub-constructs, ensuring that they accurately reflected the participants' experiences and perceptions within the context of our model (Bearden et al., 2001; Tian et al., 2001; Zaichkowsky, 1985).

4.2. Results

The qualitative analysis revealed several key themes related to the constructs in our model. First, participants generally acknowledged the

Table 1
Overview of prior studies on AI–human collaboration.

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
Kim et al. (2022)	Home tutoring	AI-enhanced humans	NA	Supplying human tutors with AI-generated reports can lead to improved academic performance among students.	Limited Generalizability: Findings are specific to AI applications in private in-home tutoring services in South Korea and may not apply to other countries or different home-tutoring contexts. Unique Market Context: South Korea has an unusually large private education market, requiring validation in other educational environments. Classroom Setting Exclusion: The study does not account for AI's applicability in broader classroom settings with multiple students. AI Transparency Issues: Lack of explainability in AI-generated recommendations (black-box problem) may lead to AI aversion among tutors. Human vs. AI Decision Making: Tutors may distrust AI due to a belief that humans are better at addressing emotional and contextual needs. AI Limitations in Personalization: AI struggles to recognize students' unique circumstances (e.g., illness affecting performance) compared to human tutors. Emotional Interaction Deficit: AI lacks the ability to build interpersonal relationships and provide emotional support. Lack of AI Implementation Strategies: Existing research does not rigorously address AI's impact on service outcomes or best practices for implementation. Technology Overload Focus: The study examines technology overload but does not explore other potential barriers to AI effectiveness in education.
Longoni and Cian (2022)	Recommendations	AI-enhanced humans	NA	When focused on hedonic goals, consumers are less accepting of AI recommendations but are open to human recommendations with AI assistance.	Potential Priming Effect: Drawing attention to the AI source might have unintentionally primed participants, making utilitarian attributes more salient rather than competence perceptions driving the effect. Domain-specific Variability: The word-of-machine effect may be stronger in certain product categories, particularly those where hedonic attributes are easier to assess than utilitarian ones. Transitional Nature of Lay Beliefs: Competence perceptions underlying the word-of-machine effect may change over time as AI becomes more prevalent in hedonic domains. Second-step Choice Behavior: Consumers may adjust their choices by focusing more on hedonic attributes when relying on AI recommendations for utilitarian attributes. Attenuation of Lay Beliefs: Future research should explore other factors (e.g., expertise, involvement, familiarity) that could reduce biases toward AI recommendations. Reversibility of the Effect: Investigating conditions where AI recommenders could become more persuasive than human recommenders, particularly for hedonic products. AI's Expanding Role in Consumer Behavior: More research is needed to map AI's impact across different consumption settings and its role in personalizing the consumer journey. AI-driven Customization and Data Utilization: Future research should explore

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					how AI technologies (e.g., image, text, and voice recognition, A/B testing) can optimize customer experiences. Consumer Acceptance vs. Resistance: Understanding when consumers embrace or resist AI recommendations remains a key challenge for researchers and firms.
Gonzalez et al. (2022)	Hiring practices	Augmented human intelligence	NA	Job seekers respond negatively to AI-driven hiring practices but positively to human selection processes that utilize AI.	Self-reported Measures: Susceptible to biases like social desirability (Fisher, 1993) and careless responding (Curran, 2016; Kam & Meyer, 2015). Necessary due to the perceptual nature of applicant reactions. Hypothetical scenarios and lack of sensitive questions reduced response distortion. Use of Vignettes: Participants imagined hiring situations rather than experiencing them, affecting external validity. Responses could reflect pre-existing AI perceptions rather than real-life experiences.
Oleksy et al. (2023)	Urban management	Human–AI collaboration	NA	Collaborative efforts between humans and AI enhance residents' perceptions of friendliness and control in urban environments.	Limited Sample Scope: Only participants from Warsaw were included, making results more representative of big city residents. Future studies should include participants from smaller towns. Geographical Limitation: Research was conducted only in Poland. Replication in other countries, particularly those with advanced AI-driven urban governance, is needed for validation. Third-party Perspective: Focused on individuals indirectly affected by AI rather than those directly impacted. Future research should explore perceptions of directly affected individuals. Use of Vignettes: Results may differ from real-world interactions with AI-driven decisions. Future studies should compare findings with actual AI implementation experiences. Controllability Concept: More research is needed on how people perceive control over AI in urban governance, distinguishing between authorities' and citizens' control. Perceived Influence on Decision Making: Future research should assess residents' perceived influence on urban decisions and civic participation. Individual Differences: Future studies should examine how personal attachment to a city moderates responses to AI autonomy. Types of Decisions: The study included various decision types but should expand to examine AI-driven decisions requiring individual flexibility. Experimental Limitations: Only AI autonomy was manipulated, limiting causal inference. Future studies should manipulate mediators to verify proposed relationships.
McLeay et al. (2021)	Frontline services	AI-enhanced humans	NA	A human service enhanced by AI is perceived as less innovative and holds a higher ethical/societal reputation compared to robot services.	Narrow Focus on Drivers and Barriers: The study explored only a few factors like perceived innovativeness and ethical responsibility. Future research should investigate a broader range of technology-related and customer-related drivers of and barriers to AI adoption. Need for Real-world Data: Research should be conducted once FLSRs are more commonly used, including field experiments to explore their impact on customer engagement and service

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					experiences in actual frontline service scenarios. Context of Crisis: The impact of crises, such as the coronavirus pandemic, on customer perceptions of FLSRs should be explored, especially when face-to-face interactions with human employees are restricted. Uncanny Valley and Humanoid FLSRs: The role of artificial faces and the potential negative effects of humanoid FLSRs on service experiences, as described by uncanny valley theory, needs further investigation. Longitudinal Studies: More research is needed to understand how customer perceptions of FLSRs evolve over time, as well as the long-term effects on their attitudes and behaviors. Cultural Differences: Future studies should examine how different cultural contexts (e.g., technology-affine cultures) influence customer acceptance of FLSRs, expanding the research beyond the UK. Marketing Communication: Research should focus on identifying effective methods for communicating the introduction of FLSRs to customers and addressing concerns related to substitution. Industry-specific Perceptions: The study did not delve into how perceptions of FLSRs' roles in service vary across industries, which could impact customer willingness to pay for services. Expansion of Theoretical Models: Other parts of the value creation models (e.g., network-orchestration, technology-creator) and task-based models need further empirical validation in the context of FLSRs. Level of Analysis: The study focused on customer-centric, micro-level perspectives, and future research should consider meso-, macro-, and meta-level contexts to better understand the broader impact of FLSRs in servicescapes. Scale Development: There is a need for new scales to measure perceptions related to dehumanization, privacy concerns, and FLSRs' effectiveness, as current scales are still in the early stages of development.
Gnewuch et al. (2023)	Online service encounters	Human–AI collaboration	Impression management theory	Human–AI collaboration encourages a more human-centric communication style among consumers, which can increase employee workloads.	Employee Perspective: The study focused on the customer's perspective, but future research should emphasize the employee's experience, particularly regarding the (non)disclosure of their involvement and how they cope with AI-driven decisions in hybrid service agent contexts. Human–AI Collaboration: Future work could explore the broader nature of human–AI collaboration in hybrid service agents, particularly how employees adapt to the loss of control when AI algorithms dictate their involvement. Customer Communication Behavior: The research focused on text-based communication style but should be expanded to explore other language aspects, service contexts, and communication channels (e.g., voice) to better understand how these factors influence customer interactions. Impact of Social Cues: Investigate how social cues, such as human names or humanlike chatbot appearances, affect

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					customer communication behavior and service encounter outcomes. Customer Perceptions of Service Encounter: Further research should explore how customers evaluate hybrid service encounters, especially the role of human involvement disclosure and whether it influences algorithm aversion or increases customer frustration with failures. Nontransparency: Investigate customer reactions to nontransparency in hybrid service encounters and how the deliberate concealment of human involvement might affect their perceptions. Advances in AI: As AI technology advances, the need for human involvement may decrease. Future research should examine the impact of chatbots powered by large language models, like ChatGPT or Bard, on customer service, including when and how human employees should intervene to verify AI-generated information. Long-term Effects of AI Advancements: As AI improves, the effects observed in this study may change. It would be useful to examine how more advanced chatbots influence employee workload and the customer experience over time.
Longoni et al. (2019)	Medical services	AI-enhanced humans	NA	Consumers show resistance to medical AI but accept physician services that incorporate AI support.	Consumer Resistance to Medical AI: Future research should explore additional factors influencing resistance to medical AI, particularly in high-stakes vs. low-stakes medical decisions, to better understand when and why consumers prefer human providers over automated ones. Theoretical Boundaries: More research is needed to map the boundaries of consumer resistance, particularly identifying additional psychological mechanisms (e.g., dehumanization, morality concerns) that may influence resistance to medical AI beyond uniqueness neglect. Uniqueness Neglect Across Domains: Future studies could examine how uniqueness neglect affects consumer preferences in non-medical domains, such as fashion, finance, and home décor, to see if similar resistance to statistical judgments exists across these areas. Curbing Resistance to Medical AI: Exploring interventions, like allowing consumers to modify AI algorithms, could help reduce resistance to medical AI by providing a sense of personalization, which may mitigate concerns about uniqueness neglect. Preference for Medical AI: Future research should investigate when consumers might prefer AI over human providers, such as in cases involving stigmatized information, affordability, or convenience. Additionally, exploring how patient-generated reviews could affect receptivity toward medical AI could offer valuable insights.
Peng et al. (2022)	Services (warmth/ competence)	AI-enhanced humans, AI supervised by humans	Concept combination theory	Consumers reject AI-only solutions and AI supervised by humans for tasks requiring high warmth, but accept human services augmented by AI.	Self-Reported Attitudes vs. Behavior: Future research should replicate findings using real-world settings to enhance external validity and better understand consumer reactions to AI services in everyday life, particularly as more AI services are introduced to the market. Required Competence and Consumer Acceptance: Further investigation is needed to explore how different types of

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					intelligence (analytical vs. intuitive) affect consumer acceptance of AI services, particularly in tasks that require creative thinking versus analytical reasoning. AI–Human Collaboration: Future studies should examine the role of human involvement in AI–human collaborations and explore how making the role of employees more salient can influence consumer acceptance of AI services. Task–AI Fit: Research should empirically test whether task-AI fit mediates the effect of AI–human collaboration types and warmth on AI acceptance. Evolving AI Capabilities: As AI progresses, especially in areas requiring emotional intelligence and warmth, future research should revisit how AI is perceived and its impact on consumer acceptance, given its potential to replace human workers in tasks requiring empathy or emotional understanding.
Luo et al. (2021)	Sales training	AI-enhanced humans	NA	AI coaches are less effective than human managers for both low- and high-performing sales agents, while humans augmented by AI perform better than either AI or human coaches alone.	Generalizability Across Settings: Future research should explore whether AI coaches produce similar effects in different industries, such as in business-to-business settings or with in-person sales. Investigating the effectiveness of AI coaches across various product types and environments will help to establish boundary conditions for the findings. Social Influence and Public Exposure: It would be valuable to examine how the public visibility of AI feedback (e.g., observable to colleagues) affects its effectiveness, as this could foster both positive cross-learning and negative impacts due to personal failures being exposed. Long-term Effects: Research should focus on the long-term impact of AI coaches on sales performance, especially regarding how quickly lower-performing agents can improve and how the adoption of AI coaches might influence recruitment and promotion strategies over time. AI Coaches in Other Training Formats: Future studies could investigate whether AI coaches perform differently in various training contexts, considering factors like social influence and exposure, to better understand their broader applicability in sales training.
Li et al. (2024)	Online service encounters	Human–AI teaming	Signalling theory	Human–AI collaboration enhances consumer acceptance of chatbots by leveraging human attributes to validate AI effectiveness. This acceptance diminishes when AI capabilities are evident or when the human service experience is negative. The study offers insights into how to optimize human involvement in AI interactions to improve consumer perceptions.	Opposing Effects on Warmth and Competence: Future research could explore how emoticons influence warmth and competence perceptions by altering the tone of communication. While emoticons may soften a message and enhance warmth, they could also make the message appear childish or unprofessional, leading to perceptions of incompetence. Social Presence and Emotional Understanding: Research should investigate how emoticons impact social presence in digital interactions. While emoticons may reduce social distance and increase perceived warmth, it remains unclear how this might simultaneously reduce perceptions of competence. Customer Inferences of Motives: Future studies should examine how customers interpret service employees' use of emoticons, whether as altruistic or egoistic motives. The perceived effectiveness of

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					emoticons could vary depending on whether customers view them as efforts to build a relationship or manipulate them, influencing perceptions of both warmth and competence.
Kong et al. (2023)	AI integration in organizations	Employee–AI collaboration	Person–environment fit theory	Trust in AI enhances employee well-being and productivity through collaboration. This relationship is stronger for employees with high protean career orientation. Two studies validated the model and developed a measure for employee–AI collaboration, highlighting practical implications for AI integration in organizations.	Cross-country Comparison: Future research should explore how AI trust impacts career sustainability in different cultural contexts, as the current study is limited to China. Cross-country studies, especially in regions like the UK and India, could enhance the generalizability of the findings. Additional Perceptions and Organizational Factors: Future studies should consider how other AI-related perceptions, such as AI understanding and perceived justice, affect employee–AI collaboration. Additionally, organizational variables like leadership and work climate may moderate the relationship between AI trust and collaboration. Employee–AI Collaboration and Skills: Future research could investigate how employee skills (low vs. high) influence the effectiveness of AI collaboration, potentially revealing differences in productivity gains. Negative and Positive Attitudes Toward AI: The mechanisms behind employees' mixed attitudes toward AI require further investigation. Understanding how managers can improve AI trust and work–life balance through proper management of AI technology is crucial. Complex Mechanisms Linking AI Trust to Outcomes: The link between AI trust and outcomes like career satisfaction and task performance may involve multiple mechanisms. Future studies should explore additional factors, such as reduced fatigue and higher employee engagement, to better understand how AI influences productivity and well-being.
Yin et al. (2024b)	Hospitality industry	Employee–AI collaboration	Protection motivation theory (PMT)	AI awareness and change-oriented leadership enhance employee collaboration with AI by influencing motivation types. The study emphasizes leadership as a coping strategy for perceived AI threats and highlights the role of AI awareness in facilitating change.	Cultural Context and Generalizability: Future research should include data from diverse countries to improve the generalizability of findings, particularly from Western cultures where change-oriented leadership might have a stronger impact on employee–AI collaboration than in China. A broader age range would also enhance the generalizability. Causal Relationships: While the two-wave survey provides insights into antecedents and mediators, longitudinal studies or field experiments in AI-integrated settings (e.g., hotels) are needed to establish stronger causal links between AI awareness, leadership, and employee–AI collaboration. Data Collection Methods: Future studies could improve reliability by using objective or observational data instead of self-reported measures, as employee evaluations of leaders can be influenced by personal biases. Additional Factors Affecting Employee–AI Interaction: Future research should explore other factors and strategies that foster positive human–AI interaction. Identifying personality traits and organizational strategies that help employees overcome AI-related fears and better adapt to AI-integrated workplaces would be valuable.

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Table 1 (*continued*)

Study	Research setting	Collaborative mode	Theoretical underpinnings	Findings	Limitations
					Broader Employee Behaviors and Industry Applications: It would be insightful to examine how AI influences other employee behaviors across different industries, expanding the scope of AI's impact on work dynamics.

potential of AI to enhance decision making and efficiency in healthcare, although they also expressed concerns about the practical challenges of integrating AI tools—particularly AI-driven Clinical Decision Support Systems (CDSS)— into their daily workflows. One participant noted, "AI can help us make more informed decisions, but it requires significant adaptation on our part to fit these tools into our existing systems". The importance of AI Mastery Goal emerged as a critical factor influencing user engagement with AI technologies. Participants emphasized the need for continuous learning and development to effectively use AI systems. As one stated, "We need to keep learning to fully harness AI's potential in our work".

The interviews also highlighted various obstacles to AI–employee collaboration, including resistance to change, lack of trust in AI outputs, and concerns about the adequacy of training provided to healthcare employees. As one interviewee remarked, "There is still a significant trust barrier—many employees are hesitant to rely on AI-driven decisions without human oversight". Additionally, the concept of the AI mastery goal emerged as a crucial factor in influencing user engagement, particularly as it relates to the moderating role of AI Empathy. One participant pointed out that "getting really good at AI is super important for us to stay competitive because it helps us use data insights to make smarter business decisions". Similarly, another participant pointed out that, "by focusing on getting really good at AI, we're investing in our future. It helps us use new tech and stay ahead of the game".

Some participants emphasized the importance of AI systems being transparent and reliable, with one stating: "For AI to be truly effective, it needs to be perceived as an empathic and reliable partner in the decision-making process". Based on the qualitative data, we refined the item measurements related to AI–employee collaboration, AI Mastery Goal, User Engagement, and the moderating factors such as AI Empathy and Technological Frames. This iterative process, guided by expert feedback, resulted in a refined set of items that were deemed representative of the core constructs (Bearden et al., 2001; Tian et al., 2001; Zaichkowsky, 1985). These findings provided critical insights into the relationships depicted in our model and informed the subsequent quantitative studies that further explored these constructs and relationships. Table 2 illustrates the examples of interview quotes.

Table 2
Examples of interview quotes.

AI Mastery goal	Getting a handle on AI helps us find new opportunities, make things run smoother, and boost our overall performance…and perhaps it can make everyone more engaged. Focusing on getting good at AI helps us keep learning and adapting, which is really important in today's fast-moving world. When employees team up with AI, it helps us get better at it faster because they learn from the tech, and the tech learns from them. Working with AI helps employees really get the hang of things, which makes it way easier for us to ace our AI skills.
Paradox mindset	Being open-minded helps us see that AI can make our work simpler and more complicated at the same time, which keeps us on our toes to keep innovating and adapting. Having a flexible mindset in AI helps us see challenges as chances to learn; the trickier the problem, the more we can grow. Having an open mindset in AI means being cool with contradictions, like using machines while still trusting our gut, which helps us get better results. Working with AI helps us realize that we sometimes have to lean on data while still going with our gut, which builds a better mindset for handling contradictions.
User engagement	When employees work alongside AI, they can respond faster and more accurately to user questions, which really boosts engagement. Collaborating with AI helps employees focus on what matters—building relationships with users and making their experience better. The teamwork between employees and AI gives us deeper insights into what users want, driving up engagement and loyalty.
AI empathy	AI understanding acts more like a bridge, helping create a more understanding vibe between tech and users When AI shows higher level of compassion, it makes users feel more connected and appreciated during their interactions.
Technological frame	How we view tech really affects how we team up with AI, impacting everything from design to user experience. Understanding the tech frame lets us tweak our processes and strategies, making our interactions with AI way more effective.

5. Hypothesis development

5.1. Employee AI collaboration and AI mastery goal

A mastery goal orientation refers to an employee's focus on developing competence through learning, problem-solving, and skill refinement rather than prioritizing external validation or performance outcomes (Howarth et al., 2017). In AI-augmented workplaces, employees with this orientation engage deeply (Musarra et al., 2023) with AI systems by actively seeking to understand their underlying mechanisms (e.g., analyzing algorithmic logic) and experimenting with AI tools to expand their expertise. As such, mastery goal orientation can drive employees to engage more in deep learning and possess a greater sense of self-efficacy (Dang & Liu, 2022; Mora & González, 2016).

Mastery goals motivate employees to develop new abilities through learning and acquiring new knowledge, while performance goals push individuals to showcase their existing abilities (Hohenberg & Homburg, 2019). Technological advancements influence changes in job requirements, necessitating that employees broaden their skill sets and improve their collaboration with AI (Kase et al., 2022; Sowa et al., 2021). As AI becomes an integral part of the workplace, the nature of tasks evolves, demanding more sophisticated interaction with AI systems. Employees must invest time and effort to complete tasks within set time frames to gain the necessary knowledge and skills, and increased collaboration with AI can lead to more frequent use (Huang & Rust, 2022). With frequent use, employees recognize the importance of learning opportunities when collaborating with AI (Della Corte et al., 2023; Vrontis et al., 2022), acquiring new knowledge and skills, and thereby preferring to learn and master the use of AI. This was highlighted by one of the participants who mentioned: "Working with AI regularly makes employees realize how important it is to learn and pick up new skills". In a similar line, a manager highlighted that "Many of our employees actually prefer diving into AI tools and mastering them, as it opens up new opportunities for their career growth".

Moreover, the collaborative process itself reinforces mastery goals.

When employees engage with AI, they are often presented with novel problems and tasks that require innovative solutions and a deeper understanding of AI capabilities (Cheng et al., 2023). This iterative learning process, facilitated by AI, fosters an environment where mastery goals can thrive. For instance, as employees encounter AI's problem-solving approaches, they are prompted to refine their skills and knowledge, aligning with the essence of mastery goals (To et al., 2020). This continuous engagement with AI systems ensures that employees are not merely using AI as a tool but are also evolving alongside it, enhancing their expertise and proficiency. This was highlighted by one of the participants who stated that, "By continuously working with AI, employees aren't just using it as a tool—they're growing with it (AI), building their expertise and getting better at what they do".

Viewed from a different angle, how people perceive the intelligence and emotional capabilities of AI affects how they interact with it. Human interactions with AI can encompass elements of both competition and cooperation, which, in turn shape their goal-setting. Performance goals linked to competitive perceptions are often about seeking approval for one's competence, whereas mastery goals focus on enhancing one's competence. When AI is seen as competitive, it tends to generate more negative emotions towards robots, whereas if AI is perceived as cooperative, it fosters more positive and willing interactions. Individuals with malleable mindsets see collaborating with others as an efficient way to make advancements and tackle obstacles. Dang and Liu (2022) demonstrated that a malleable theory of the human mind was positively linked to mastery goals, leading to positive predictions of cooperative interactions with robots. Employees striving for mastery goals tend to view AI robots as more cooperative, resulting in increased engagement with them. Thus, AI mastery goal is positively associated with employee engagement.

User engagement, defined as the experiential flow of behavior that users undergo, is characterized by its independence from deliberate mindsets such as control, attention, curiosity, focus, or intrinsic interest. It manifests as a positive and fulfilling mental state characterized by energy, involvement, and effectiveness, encapsulated through three aspects—vigor, absorption, and dedication (Owens et al., 2016). Vigor denotes high levels of energy and mental resilience while using a system, a readiness to exert effort in its use, and the persistence to overcome challenges encountered during AI collaboration (Auh et al., 2016). Dedication reflects the enthusiasm, inspiration, pride, and sense of challenge that users derive from collaborating with the AI system (Byrne et al., 2016). Absorption signifies deep immersion and concentration in collaborating with AI (Menguc et al., 2017).

In this line, AI systems are designed to perform tasks consistently and reliably with minimal error, which can build user trust over time (Bauer et al., 2023). Users rely on AI outputs to consistently deliver accurate information (Davenport et al., 2020) and perform tasks efficiently, enhancing their trust in the AI when collaborating with it (Pereira et al., 2023). When employees trust AI systems during collaboration, they are open to following the systems' advice (Hughes et al., 2019). Such favorable attitudes towards AI enhance user engagement (Prentice et al., 2023), encouraging employees to proactively engage with AI in their work as a result of reliable collaboration with AI. One of our participants highlighted this by stating: "When employees trust AI, they're more likely to follow its advice, which really ramps up their engagement." In a similar vein, one manager suggested: "They (employees) get more involved with using AI in their work because they see it as a reliable partner that keeps them proactive and engaged".

A paradox mindset is defined as an individual's capacity to embrace, cognitively reframe, and derive energy from competing demands or contradictions (e.g., automation vs. human agency) rather than viewing them as irreconcilable threats. Rooted in cognitive–behavioral frameworks (Miron-Spektor et al., 2018), it functions as a mental tool that enables employees to navigate tensions inherent in AI–human collaboration—such as balancing AI's analytical precision with human intuition—by interpreting these conflicts as opportunities for innovation. Unlike a paradox itself (an inherent contradiction), the mindset is a strategic *framework* (Klein et al., 2024) that fosters adaptive responses to opposing priorities, allowing individuals to sustain engagement, experiment with hybrid solutions (e.g., integrating AI insights into human decision making), and reframe challenges as catalysts for growth (Miron-Spektor, Gino, & Argote, 2011). In AI-augmented collaboration, a paradox mindset enables employees to leverage paradoxical dynamics rather than resist them, thus transforming friction into collaboration and value creation with AI (Miron-Spektor et al., 2018).

The paradox mindset fosters the creation of innovative solutions to conflicts that employees might face when collaborating with AI (Moschko et al., 2023). The paradox mindset can aid employees in managing the uncertainty of collaborating with AI (Batool et al., 2023). Conversely, this mindset enables employees to grasp competing demands more deeply, facilitating acceptance of the tensions of collaborating with AI (Sleesman, 2019). In this vein, one employee suggested: "This mindset lets employees really get what's going on with competing demands, making it easier for them to deal with the challenges that pop up when they're working with AI". When employees collaborate with AI, they are more likely to be exposed to challenges and tasks which comprise managing multiple contradictory elements (Anthony et al., 2023). One manager highlighted this by saying that, "when employees work with AI, they usually end up dealing with challenges that require them to juggle a lot of conflicting stuff". Similarly, one employee stated: "When we collaborate with AI, we have to manage a mix of different, sometimes clashing tasks, which can get pretty tricky". Therefore, exposure to collaborating with AI can encourage employees to develop a paradox mindset and embrace the tensions inherent in AI collaboration as learning opportunities. Against this background, grounded on the above discussion, we propose the following hypotheses:

H1: Employee–AI collaboration can positively influence (H1a) AI mastery goal, (H1b) user engagement, and (H1c) the paradox mindset.

5.2. AI mastery goal and user engagement

Mastery goals signify the aspiration to acquire knowledge and skills through training participation (Musarra et al., 2023). Employees focused on mastery goals prioritize comprehending the content domain over merely completing training for credit (Humborstad & Dysvik, 2016). Their approach to acquiring new skills training emphasizes skill acquisition, effort exertion, persistence, and enjoyment of the learning challenges involved (Guarino et al., 2017; Schmidt and Ford, 2003) which reflects an adaptive self-regulation strategy and acts as instinctive motivation. Such instinctive motivation can make the process of learning and collaborating with AI more pleasant, which can deepen the user engagement. Furthermore, mastery goals encourage employees to adopt a growth mindset (Guo et al., 2022). Employees with a mastery goal orientation typically aim for personal development and growth, leading to behavior focused on achievement and active engagement in tasks (Adriaenssens et al., 2015). As such, employees with a more positive approach towards learning from collaborating with AI are expected to stay more engaged and motivated during this collaboration. This was reflected by one of the interview participants: "Employees who are excited about learning from working with AI usually stay more pumped and involved when they're collaborating with it". Aligned with this, another participant mentioned that "employees who have a mastery goal orientation usually focus on personal growth and development, which drives them to engage actively in tasks and strive for achievement". Moreover, employees with a mastery goal mindset are more likely to grow their confidence in using AI as they acquire increasing skills (Pee et al., 2018; Yi et al., 2020). Such growth in competence and confidence in using and collaborating with AI can help employees to tackle the challenges that they face when collaborating with AI, as well as keeping employees engaged in the long term. One participant explained: "Getting better and more confident with AI helps us (employees) handle the challenges that pop up, keeping us (employees) interested and in the game for the long haul". Against this background, we propose the following hypotheses:

H2: Mastery goals (H2a) can positively impact user engagement, and (H2b) can mediate the relationship between employee–AI collaboration and user engagement.

5.3. *The paradox mindset and user engagement*

Employees equipped with a paradox mindset typically exhibit optimism when navigating the tensions inherent in complex scenarios—such as collaborating with AI systems. This resilience often translates into persistence, even in challenging or failing situations, offering opportunities for enhanced learning and discovery (Liu et al., 2020; Sleesman, 2019). Such experiences encourage employees to explore new ways to manage and improve their self-efficacy, aligning with findings from Smith and Besharov (2019) and Vedula et al. (2022) which suggest that individuals are more likely to engage in efforts to progress and discover new methods for handling complexities when collaborating with AI. Furthermore, the paradox mindset bolsters employees' resilience (Zheng et al., 2018); it helps them to manage tensions and predicts an employee's tendency to seek challenges. This was stated by one of the interview participants: "The paradox mindset totally amps up employees' resilience, helping them deal with tensions and making them more likely to go after challenges". Similarly, another participant mentioned that "our people (employees) are more likely to jump in and figure out how to tackle tricky stuff and keep moving forward". This positive effect on accepting tensions and encouraging proactive behavior subsequently drives their engagement with AI systems. Personal investments in resilience and self-efficacy, thus, enable employees to effectively manage the challenges that they encounter when collaborating with AI, thereby enhancing their engagement with AI systems.

The unpredictably dynamic environment of AI collaboration pushes employees to challenge the status quo, actively shaping their job roles (Shin and Jung, 2021). Employees who embrace challenges often recraft their roles and alter their work practices and methods (Grant & Parker, 2009), behaviors that encourage individual 'unlearning', which involves questioning fundamental knowledge and skills (Hislop et al., 2014). Both role recrafting and unlearning have been found to enhance engagement (Matsuo, 2019). In light of the growing complexity of our world, paradoxical tensions critically arise at both the individual and team levels, presenting challenges across work and family, learning and performing, and collaborating and competing. These tensions act as the micro-foundations for higher-level organizational paradoxes (Waldman et al., 2019). Paradox theory, which addresses conflicting objectives and competing demands in complex settings, suggests that paradoxes are contradictory yet interrelated elements that exist simultaneously, persist over time, and make sense (Smith & Lewis, 2011). For example, Murphy (2012) noted that the 'great societies' that have profoundly influenced the history of civilization were founded on paradox.

Organizations that successfully adopt a paradoxical orientation often demonstrate improved long-term performance and sustainability. Leaders play a crucial role in influencing followers' paradox mindset through cognitive and behavioral aspects, fostering a learn-by-doing approach that enhances effectiveness (Boemelburg et al., 2023). Effective employee engagement requires consistently managing complexity, juggling competing demands, and navigating tensions (Klein et al., 2024; Moschko et al., 2023). This was confirmed by one of the participants: "To keep them (employees) really engaged, you've got to handle the complexity, juggle all the competing demands, and navigate the tough spots on the regular basis". The paradox mindset, characterized by enactive cognition, involves both and thinking, which encompasses the cognitive juxtaposition of competing demands to leverage tensions for achieving beneficial outcomes. This mindset encourages individuals to seek diverse solutions, embrace cognitive complexity, and remain open to ambiguity and multiple experiences, allowing them to develop innovative strategies to manage and navigate tensions effectively (Waldman et al., 2019). One manager stated: "I think this mindset [paradox mindset] pushes our people [employees] to look for different solutions, embrace complexity, and stay open to ambiguity, which helps them come up with creative ways to handle and navigate tensions". Based on these insights, we propose the following hypotheses:

H3: The paradox mindset (H3a) can positively impact on user engagement and (H3b) can mediate the relationship between employee–AI collaboration and user engagement.

5.4. *Moderating role of AI empathy*

Empathy, defined as the emotional capacity to understand and respond to another's emotional state (Eisenberg and Strayer, 1990), plays a foundational role in human social interactions. In the context of AI, artificial empathy extends this concept to computational systems, enabling machines to simulate cognitive and emotional empathy through advanced models (Concannon & Tomalin, 2023; Zhu & Luo, 2024). This involves embedding empathetic traits into AI agents, allowing them to recognize and adapt to users' emotional and situational needs (Asada, 2015). Drawing from interpersonal relationship theories, empathy is critical for fostering trust, satisfaction, and sustained engagement between individuals (Wieseke et al., 2012). Similarly, in human–AI interactions, recent research underscores that users' perceptions of an AI's empathetic capabilities significantly shape the quality of these interactions (Meier et al., 2024).

Recent studies indicate that the employee's perception of an AI's empathy also significantly influences between AI systems and humans (Meier et al., 2024). In the same way that empathetic human employees enhance satisfaction and relationship quality (Aw et al., 2020; Joireman et al., 2006), higher empathy in interactions between AI devices and users can foster acceptance and trust towards AI, driving user engagement. AI systems that address users' unique needs demonstrate higher empathy (Cheng et al., 2021). This mirrors the supportive behaviors of more empathetic human colleagues, fostering psychological safety and trust (Huang & Rust, 2024). In this line, higher levels of AI empathy positively moderate the relationship between employee–AI collaboration and user engagement by enabling AI systems to address users' unique needs more efficiently (Cheng et al., 2021), thereby mirroring the supportive, personalized behaviors of empathetic human colleagues. This fosters psychological safety and trust (Huang & Rust, 2024), as employees perceive the AI as a relational partner rather than a transactional tool. When AI demonstrates higher level of empathy, it strengthens the collaboration–engagement link by creating emotional resonance alongside functional utility. Drawing on social exchange theory, trust and reciprocity drive users to invest more deeply in the relationship,. Consequently, employees are more likely to proactively use AI, experiment with its features, and sustain engagement over time, as the collaboration evolves from purely task-focused to emotionally aligned, engagement-based synergy.

Higher levels of AI empathy positively moderate the relationship between AI mastery orientation and user engagement by creating a supportive environment where users perceive their goals and efforts as understood and validated. When AI systems demonstrate higher levels of empathy, they mimic the role of a supportive collaborator, which can foster a sense of psychological safety (Pentina et al., 2023; Zhou, Liu, & Feng, 2025). This was echoed by an employee stating that "it's like having a supportive coach cheering me on". This higher level of empathetic alignment reduces apprehension and boosts intrinsic motivation, as users feel empowered to pursue mastery goals through collaboration with AI systems (Pentina et al., 2023). This was echoed by one of the employees: "If the AI understands my needs and goals, I'm much more likely to dive in and use it. Empathy makes it feel like a true partner in my journey". Users' unique AI empathy transforms transactional interactions into relational exchanges where employees view the AI as a "true collaborator" in their growth journey (Cheng et al., 2021). This was highlighted by one of our interview participants who stated: "When I feel like the AI gets me and my goals, I'm way more inclined to use it. It's like having a supportive coach cheering me on". This emotional resonance amplifies effort investment (Liu et al., 2024), as employees engage more deeply with AI tools to refine skills, experiment, and achieve outcomes, knowing that their progress is met with adaptive, empathetic support.

Furthermore, when AI demonstrates a higher level of empathy, it can help employees to navigate tensions and complexities in paradoxical situations (Chaturvedi et al., 2024; Coker & Thakur, 2024) during their collaboration with AI, thereby making users feel more appreciated and valued. Therefore, this empathetic feature can enhance user trust in the AI's ability to effectively navigate paradoxical challenges in AI–employee collaboration (Bove, 2019; Pelau et al., 2021), making them feel more valued and understood, thereby increasing user engagement. This was highlighted by a number of participants: "When employee see AI as empathetic, they're way more likely to trust its recommendations, especially when things get tricky and human intuition might not cut it". Similarly, one employee stated that, "in those times when priorities clash, an empathetic AI can really help sort things out. It feels like the AI is in my corner, helping me find a balance instead of just throwing data at me". Against this background, we propose the following hypotheses:

H4: AI empathy can moderate the relationship between (H4a) AI mastery goal, (H4b) employee–AI collaboration, (H4c) the paradox mindset, and user engagement.

5.5. Moderating role of technological frame

AI systems introduce significant complexity by augmenting physical objects with intangible, abstract functions, thereby fostering new methods of collaboration between employees (Bailey et al., 2010; Nambisan et al., 2017). To concentrate on the pertinent features of these technologies, assess their value, and make decisions, employees depend on their cognitive interpretive frameworks, also known as 'technological frames' (Gray et al., 2015; Samuel et al., 2022). Technological frames refer to the beliefs, anticipations, and understanding that an employee or group employ to interpret the use and implications of an AI within a specific situation (Spieth et al., 2021). Since an individual's technological frame influences how they perceive changes brought about by technology, this frame is likely to impact their attitude toward those changes (Spieth et al., 2021) introduced by integrating AI into their work activities.

If an individual's interpretation is positive, they are likely to acknowledge the benefits of the technology and feel more confident and optimistic about the ensuing organizational changes (Klos and Spieth, 2021). This was mentioned by one employee: "When I see technology as a good thing, it makes me excited about the changes coming to the company. I feel like we're heading in a great direction". Therefore, a higher level of technological frame can lead employees to view a digital technology as beneficial and potentially useful for their daily working tasks (Minkkinen et al., 2023). This was suggested by another employee: "When I see technology as a good thing, it makes me excited about the changes coming to the organization. I feel like we're heading in a great direction". Technological frames act as interpretive tools that help employees to simplify the complexity of AI and focus on its key aspects, such as its empathic traits and responses (Kaplan & Tripsas, 2008). Consequently, these frames influence the level of empathic traits that an employee attributes to a particular technology—such as AI systems (Plambeck & Weber, 2010). Furthermore, a higher level of technological frame can encourage employees to more willingly embrace mastering AI system capabilities and utilize the AI's empathic features to enhance their engagement (Hsu et al., 2014). One manager stated that, "when our employees interpret the technology positively, it feels like our company is on the brink of something awesome. I can't help but feel optimistic about what's ahead".

Employees with a higher level of technological frame can also help others to benefit more from empathic features, facilitating effective collaboration between AI and employees, which, in turn, can drive user engagement (Engås et al., 2023). Individuals with a higher technological frame are better equipped to navigate paradoxes or conflicting challenges that occur when working (Frennert et al., 2021) with AI systems. Grounded on social exchange theory, trust and reciprocity drive engagement, and, as translators, tech-savvy employees (Annosi et al., 2024) foster this exchange by leveraging AI's empathetic tools, creating a cycle of mutual benefit. In this line, employees with higher levels of technological frame tend to ensure that AI's empathetic features are effectively utilized, thus enabling smoother interactions (Annosi et al., 2024). Subsequently, employees with higher level of technological frame tend to leverage AI's empathetic capabilities, and create a positive feedback loop of trust and engagement (Spieth et al., 2021). For instance, when employees experience AI as empathic and supportive, they are more likely to feel comfortable using it, resulting in stronger collaboration. Grounded on social exchange theory, this fosters mutual benefit, as AI helps employees to perform tasks more efficiently, while their feedback and engagement help refine the system's responses. Ultimately, this cycle strengthens both employee engagement and AI system performance.

One participant mentioned that, "when you have a strong grasp of technology, you can approach those conflicting issues with AI more easily. It's like having a toolkit ready for whatever comes up". Further, when users have a higher level of technological frame and view AI as an empathetic and supportive tool, they are more likely to embrace its capabilities, which can enhance engagement (Ghobadi & Mathiassen, 2024), even in the face of paradoxes or conflicting expectations. In contrast, if users have a lower level of technological frame, perceiving AI as complex or impersonal, their paradox mindset may impede engagement as they may struggle to reconcile conflicting demands or expectations (Liu & Zhang, 2022; Yin, 2023). Hence, employees with a higher level of technological frame are expected to better understand how to utilize AI's empathic features to effectively resolve challenges and paradoxes during collaboration with AI, thereby potentially enhancing engagement (Fig. 1). Against this background, we propose the following hypotheses:

H5: The technological frame can moderate the moderating effect of AI empathy on the relationships between (H5a) AI mastery goal, (H5b) employee–AI collaboration, (H5c) the paradox mindset, and user engagement.

6. Study 2: quantitative analysis of ai-driven clinical decision support systems in employee engagement

6.1. Overview

This phase of the research was informed by the qualitative findings

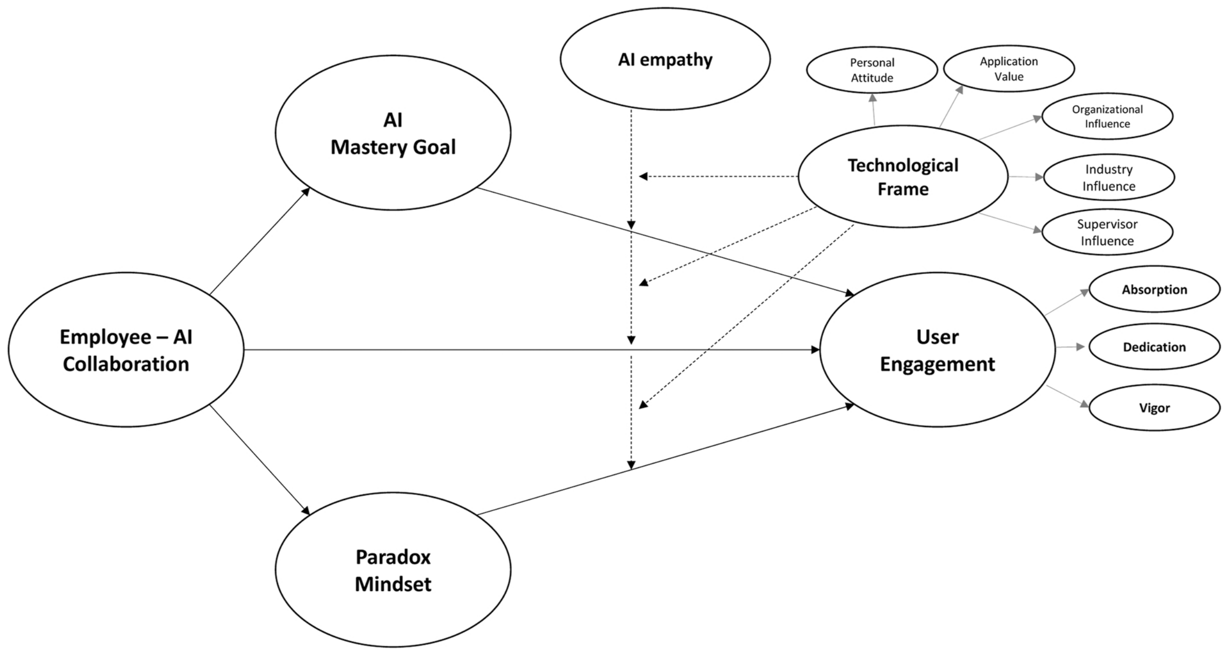

Fig. 1. Conceptual model.

from Study 1, which highlighted the need for a deeper understanding of how specific AI applications, particularly AI-driven Clinical Decision Support Systems (CDSS), impact user engagement, AI mastery goal, and the paradox mindset among employees. To explore these dynamics quantitatively, we conducted a detailed survey targeting a global employee base. The survey collected extensive data on the aforementioned constructs, aiming to uncover the factors influencing AI adoption and usage in the healthcare sector. The company employed both convenience and purposive sampling strategies—the former to access readily available data and the latter to focus on data subsets that were deemed essential by the researchers and aligned with the study's goals.

6.2. Method

The survey data were analyzed using SPSS for descriptive statistics and reliability assessments, while AMOS was utilized for confirmatory factor analysis (CFA) to ensure the robustness of our measurement models (Foroudi, 2023). This multi-method approach provided a comprehensive understanding of the employees' perspectives on AI, facilitating a nuanced analysis of the factors influencing AI adoption and usage in the health sector.

We utilized two distinct samples, and, after a thorough screening process that assessed responses to specific system-related questions, we excluded 26 data points in Study 1, and, in Study 2, we removed 12 data points based on an informant competency check conducted after the survey, resulting in a final dataset of 452 and 207 valid responses, respectively. The survey was divided into two sections: (1) demographic information and (2) a seven-point Likert-type scale (1 = strongly disagree, 7 = strongly agree), with items derived from established academic literature and tailored to our specific context. A detailed list of items and their original sources is presented in Appendix Table 1. The majority of participants in Study 1 were male (52.2 %), had postgraduate education or higher (53.8 %), and were primarily aged 35–44 (37.0 %) and 45–54 (35.7 %), as detailed in Appendix Table 2. In Study 2, the participant demographics were similar, with the majority also being male (50.2 %). Most participants in Study 2 had postgraduate education or higher (53.6 %) and were primarily aged 35–44 (37.7 %) and 45–54 (35.7 %).

6.3. Results

6.3.1. Data analysis

We began our analysis by performing descriptive statistics on the entire sample using SPSS (Statistical Package for the Social Sciences). The reliability of the constructs was assessed using Cronbach's alpha, which produced high reliability scores, aligning with the high validity criteria established by Aaker , Churchill (1979), Foroudi (2020) and Foroudi & Dennis (2023). To address potential common method variance, we conducted Harman's single-factor test, as recommended by Lindell and Whitney (2001), and Podsakoff et al. (2003). This included a Chi-square difference test between the original model and a fully constrained model across all four datasets, which identified distinct variances among the models, thereby alleviating concerns about common method variance. Additionally, we adhered to Podsakoff et al. (2003) by utilizing four distinct classifications of common method variance sources. To investigate potential non-response bias, a Mann–Whitney *U* test was conducted, comparing the first 50 respondents with the last 50, which revealed no significant differences. Thus, non-response bias was not a concern for our study, allowing for model measurement without considering method bias.

6.3.2. Confirmatory factor analysis (CFA)

To validate the measurement model, we utilized AMOS (Analysis of Moment Structures) to evaluate discriminant validity and the overall quality of the model. We assessed composite reliability (CR) and average variance extracted (AVE) for reliability and convergent validity, respectively, as shown in Appendix Table 3a, Table 3b. The AVE values ranged from 0.703 to 0.888 (Study 1) and 0.744 and 0.854 (Study 2), demonstrating satisfactory convergent validity. Composite reliability for all constructs exceeded 0.899 (Study 1) and 0.887 (Study 2), confirming that respondents could distinctly recognize the constructs under investigation. After excluding overlapping constructs, the CFA results indicated a good model fit with Chi-square (Study 1 = 272.123; Study 2 = 143.542), Degrees of freedom (Study 1 =137; Study 2: 104), RMSEA (Study 1 = 0.052; Study 2: 0.43), CFI (Study 1 = 0.977; Study 2:.987), TLI (Study 1 = 0.972; Study 2: 0.983), NFI (Study 1 = 0.956; Study 2: 0.955), IFI (Study 1 =0.978; Study 2: 0.987), and RFI (Study 1 = 0.945; Study 2: 0.941) in accordance with the good fit standards proposed by Hair et al. (2006).

6.3.3. Evaluation of hypotheses

For hypothesis testing, we employed the PROCESS bootstrapping method described by Preacher and Hayes (2008), using 5000 bootstrapped samples with bias-corrected percentile confidence intervals. This was supplemented by regression analysis in SPSS to evaluate the main effects model. A significant advantage of these bootstrapping techniques is their independence from traditional distributional assumptions required for inferential analyses, as emphasized by Preacher, and Hayes (2008). The detailed results of our model investigation are shown in Appendix Table 4.

The analysis of the direct impacts of employee–AI collaboration on different outcomes revealed that employee–AI collaboration had a significant positive influence on AI mastery goal (Study 1: $b = 0.20$, $t = 3.15$, $p < 0.01$; Study 2: $b = 0.40$, $t = 4.46$) and the paradox mindset (Study 1: $b = 0.30$, $t = 5.66$, $p < 0.01$; Study 2: $b = 0.43$, $t = 488$, $p < 0.01$). This was aligned with our qualitative findings where one participant mentioned that "collaborating with AI makes employees eager to sharpen their skills, leading them to focus on mastering the technology". In similar fashion, another participant highlighted that "working alongside AI really pushes employees to level up their skills, helping them focus on mastering those tools and technologies". Contradictory to this, AI–collaboration impact on user engagement was not significant in either dataset (Study 1: $b = 0.05$, $t = 1.33$, $p = 0.18$; Study 2: $b = 0.09$, $t = 1.41$, $p = 0.15$), suggesting that collaboration alone might not suffice to enhance user engagement without other moderating factors. Although this was not found in our qualitative results, one employee pointed out that, "if they (employees) perceive AI systems as a burden or are hesitant to rely on it, collaboration might not yield positive outcomes". Similarly, another participants pointed out that "collaboration between humans and AI works best when there's mutual understanding and trust; without it, AI can be seen as an obstacle, not an asset". Without mutual understanding, users struggled to interpret AI's role, seeing it as an obstacle, especially when technical proficiency was needed. Further, a lack of empathy in AI systems led to disengagement, as collaboration felt transactional. Employees need emotional reassurance, like empathy, to feel valued. Social Exchange Theory highlights that engagement thrives on reciprocity, with users expecting both functional and emotional benefits.

Further analysis indicated that AI mastery goal significantly impacted user engagement (Study 1: $b = 0.06$, $t = 1.93$, $p = 0.05$; Study 2: $b = 0.18$, $t = 3.77$, $p = 0.00$) and that the paradox mindset had a significant positive effect on user engagement (Study 1: $b = 0.13$, $t = 3.37$, $p < 0.01$; Study 2: $b = 0.27$, $t = 5.17$, $p < 0.00$). This was aligned with our qualitative findings as one participant mentioned that, "when employees chase mastery goals that align with the organization's objectives, it gives their work purpose and boosts their engagement by showing how their efforts contribute to the bigger picture". Similarly, one manager pointed out that this mindset (paradox mindset) "fosters openness to diverse perspectives and innovative solutions, enhancing collaboration and creative problem solving in the workplace". Top of FormBottom of Form

6.3.4. Mediation and interaction effects

The mediation analysis using Hayes' PROCESS macro revealed that the impact of employee–AI collaboration on user engagement through AI mastery goal was not significant (Study 1: $b = 0.03$, 95 % CI [-0.3060, 0.2247]; Study 2: $b = 0.09$, 95 % CI [-.0068.2173]), indicating that the pathway from collaboration to user engagement via AI mastery goal lacks substantial impact. Conversely, the mediation effect through the paradox mindset was significant (Study 1: $b = 0.08$, 95 % CI [0.1325, 0.3656]; Study 2: $b = 0.08$, 95 % CI [.0490.3672]), suggesting that a paradox mindset serves as a critical mediator in enhancing user engagement.

The interaction effects were assessed at different levels of AI empathy and technological frame using Hayes' PROCESS macro. For the interaction between employee–AI collaboration and AI empathy on user engagement, the effect was significant at low levels of AI empathy in Study 1 ($b = 0.62$, $t = 2.22$, $p = 0.02$) but not at high levels ($b = -0.03$, $t = -0.35$, $p = 0.72$). In Study 2, the interaction was not significant at either low ($b = -0.03$, $t = -0.32$, $p = 0.7461$) or high levels ($b = 0.06$, $t = 0.29$, $p = 0.7739$), suggesting that high AI empathy might overshadow the benefits of collaboration. Similarly, the interaction between AI mastery goal and AI empathy was significant at low levels of AI empathy in Study 1 ($b = 0.62$, $t = 2.22$, $p = 0.02$) but not at high levels ($b = -0.03$, $t = -0.35$, $p = 0.72$). In Study 2, the interaction effect was not significant at low levels ($b = -0.03$, $t = -0.61$, $p = 0.5424$) but became significant at high levels ($b = 0.18$, $t = 2.01$, $p = 0.0459$), indicating that the influence of mastery goals diminishes when AI empathy is high. The interaction effect between the paradox mindset and AI empathy was not significant in either study at low levels (Study 1: $b = -0.04$, $t = -0.23$, $p = 0.81$; Study 2: $b = -0.08$, $t = -1.68$, $p = 0.0938$) but was significant at high levels in Study 2 ($b = 0.20$, $t = 4.34$, $p = 0.0000$), suggesting that the paradox mindset may play a stronger role when AI empathy is elevated.

Taken together, these findings show that AI empathy moderates the relationship between employee–AI collaboration, AI mastery goals, and user engagement. This is aligned with social exchange theory by framing human–AI collaboration as a relationship governed by reciprocity, where users subconsciously weigh the benefits and costs of engagement. When AI demonstrates empathy, it signals a *relational investment*, akin to an empathic human colleague providing support. Users interpret this empathy as a benefit triggering a psychological obligation to reciprocate through increased effort, trust, and sustained engagement. For instance, an employee striving to master AI tools will invest more time experimenting with features if the AI empathetically adjusts its feedback to their skill level, reducing the perceived cost of learning (e.g., frustration) while amplifying benefits (e.g., skill growth).

6.3.5. Three-Way Interactions

Such interactions involving AI empathy and technological frame were also assessed using Hayes' PROCESS macro. The interaction between employee–AI collaboration, AI empathy, and technological frame on user engagement was not significant at low levels of technological frame (Study 1: $b = 0.03$, 95 % CI [-0.0276, 0.1034]; Study 2: $b = -0.05$, $t = -0.75$, $p = 0.4522$) but became significant at high levels in Study 2 ($b = 0.17$, $t = 2.59$, $p = 0.0103$). This underscores the importance of a supportive technological frame for collaboration and empathy to enhance user engagement. This was pointed out by one participant: "Honestly, without the right tech setup and personal mindset, even the best collaboration and empathy just don't cut it in boosting engagement. It's like trying to run a marathon in flip-flops". Similarly, another participant highlighted the importance of a supportive technological frame by stating that, "Honestly, without the right tech setup, even the best collaboration and empathy just don't cut it in boosting engagement. It's like trying to run a marathon in flip-flops". Despite this, technological frame was significant at high levels (b = 0.09, 95 % CI [0.0265, 0.1594]), indicating that a strong technological frame can amplify the positive effects of collaboration and empathy on user engagement. One participant stated: "Having a strong technological mindset really cranks up the benefits of teamwork and understanding of AI systems. It's a game changer for user engagement". In greater detail, when users possess a strong technological frame, they better recognize AI's empathetic adaptations and perceive these features as collaborative tools to achieve mastery. This alignment amplifies the positive moderating effect of AI empathy on the link between mastery goals and engagement, as tech-savvy users trust and anthropomorphize the AI, thus driving user engagement. Conversely, a weak technological frame diminishes this moderating effect. Users may overlook AI's empathetic cues due to discomfort or misunderstanding, causing engagement to stagnate despite high AI empathy.

The interaction between AI mastery goal, AI empathy, and technological frame on user engagement was not significant at low levels of technological frame in either study (b = −0.01, 95 % CI [-0.0567, 0.0706]) but became significant at high levels in Study 2 (b = 0.09, t = 1.85, p = 0.0663), albeit marginally. This finding suggests that a robust technological frame is necessary for maximizing the benefits of mastery goals. This was aligned with qualitative findings,as one participant explained that, "when the tech mindset is lacking, it's like we're running in quicksand; those interactions just don't make a splash in user engagement. But when the tech is solid, it really lights up the room!". In detail, a strong technological frame acts as a catalytic boundary condition, enabling users to decode AI's empathetic adaptations as intentional support, thereby amplifying mastery goals into dynamic engagement. Tech-savvy users anthropomorphize AI, perceiving it as a collaborator that aligns with their growth journey, fostering trust and engagement. Conversely, low-tech users, despite encountering empathetic AI, remain trapped in static engagement where they cannot translate AI's cues into actionable collaboration.

Finally, the interaction between the paradox mindset, AI empathy, and technological frame on user engagement was not significant at low levels of technological frame in either study (Study 1: b = 0.08, 95 % CI [-0.1325, 0.3656]; Study 2: b = −0.00, t = -0.07, p = 0.9408) and remained insignificant at high levels in Study 2 (b = 0.21, t = 1.18, p = 0.2404), indicating that the paradox mindset requires additional factors to significantly influence user engagement. This was reflected in our findings where one manager stated that, "when the tech mindset isn't strong, it's like trying to make a great cocktail without the right mixers; the impact of the paradox mindset and empathy just falls flat. But when you boost that tech mindset, everything starts to gel!". The lack of moderation by technological frame between the paradox mindset and user engagement stems from the theoretical disconnect between cognitive tech proficiency and paradox resolution. While a robust technological frame enables employees to operate AI systems, it does not inherently equip them to resolve the competing demands central to a paradox mindset (e.g., balancing innovation and efficiency). Engagement in paradox-driven contexts requires AI systems to explicitly mediate tensions, which technological frame alone cannot substitute for. For example, even tech-savvy users may disengage if AI tools improve efficiency but limit creativity. The situation is paradoxical because, while AI tools enhance efficiency, which users typically value, they simultaneously restrict creativity, which users also need for problem solving. This creates a conflict, where the tool's benefits in one area (efficiency) are undermined by its limitations in another (creativity).

7. Discussion

The advancements in technology brought by artificial intelligence are reshaping the nature of AI–employee collaboration. Previous studies (e.g., Baruch & Sullivan, 2022; Nakra & Kashyap, 2023) have mainly focused on how adoption of AI can impact developing career skills, employee's adaptability, and unexpected changes. Furthermore, prior studies have predominantly highlighted the negative impact of AI adoption on employees' behavior, including anxiety (Zhou et al., 2023), role identity (Strich et al., 2021), and job insecurity (Koo et al., 2021).

We extended prior research on employee–AI collaboration in marketing and management. While earlier studies (e.g., Kong et al., 2023; Yin et al., 2024a) explored its impact on various job aspects, limited empirical work has examined its effects on employee mastery goals, the paradox mindset, and user engagement. Combining qualitative insights with quantitative analysis, we provided empirical evidence on the diverse outcomes of employee–AI collaboration. The qualitative phase informed our theory and hypothesis development, while the quantitative phase, using a positivist approach, enhanced the validity, reliability, and generalizability of our findings (Bryman, 2006; Foroudi et al., 2021). The proposed framework, informed by qualitative insights, explores how employee–AI collaboration influences psychological and behavioral outcomes such as mastery goals, user engagement, and the paradox mindset. We investigated the mediating roles of AI mastery goals and the paradox mindset in linking collaboration to engagement, and the moderating effects of AI empathy and technological frames. Taken together, our findings highlight how collaboration with AI shapes employees' perceptions of AI systems.

7.1. Theoretical contributions

Our study makes several theoretical contributions. First, we extend the current research on employee–AI collaboration in marketing and management by addressing a gap in empirical evidence on its impact on mastery goals, the paradox mindset, and user engagement. Unlike prior studies (e.g., Kong et al., 2023; Yin et al., 2024a), we provide a nuanced understanding and empirical validation of these relationships, highlighting how employee–AI collaboration fosters mastery-oriented learning and a paradox mindset. Second, our mixed-methods approach, combining qualitative insights with robust quantitative analysis, provides a holistic and validated understanding of AI integration in the workplace. This enables us to explore both strategic and psychological outcomes of employee–AI collaboration, broadening theoretical contributions. While prior research often frames AI as a replacement with adverse effects (e.g., Brougham & Haar, 2018; Kong et al., 2021), recent studies highlight positive human–AI interactions (e.g., Chowdhury et al., 2022). Aligning with this, our findings show that employee–AI collaboration fosters eagerness to learn and a paradox mindset, emphasizing its potential for positive outcomes.

Overall, we found that employee–AI collaboration positively influences AI mastery goals and a paradox mindset. Consistent with prior research (e.g., Huang et al., 2024), AI aids employees in analyzing large datasets and uncovering creative solutions, encouraging them to learn more about AI's capabilities. For instance, one employee noted: "Seeing how AI helps me at work makes me want to learn more—it's like unlocking a new skill set". Another shared: "When the workplace embraces AI, it sparks my curiosity, making me eager to explore its features and use it effectively". Collaborating with AI can foster a paradox mindset by requiring employees to embrace uncertainty in AI outputs. However, our findings reveal that collaboration alone does not drive user engagement, as employees value human connection, especially for complex tasks. Consistent with recent studies (e.g., Liu-Thompkins et al., 2022; Pentina et al., 2023), AI struggles to replicate empathy, a key driver of engagement. As one participant noted, “AI provides fast solutions, but employees need a human touch to stay engaged”. Another added that, “without meaningful interaction or outcomes, my interest fades quickly—it has to be more than just a task”.

Third, we contribute to the literature by empirically showing that AI mastery goals and a paradox mindset drive user engagement with AI. Consistent with prior studies (e.g., Yi et al., 2020), as employees become proficient with AI, they experience a sense of achievement which, in turn, fosters motivation and engagement. As one participant noted, “solving challenges with AI gives me a sense of accomplishment, motivating me to learn more”. Another added: “Small wins with AI make me more invested—it’s a snowball effect where success boosts motivation to engage”. Users with mastery goals are more likely to invest time in learning AI systems to enhance their skills (Adriaenssens et al., 2015), driving further engagement. Similarly, employees with a paradox mindset tend to view AI positively and optimistically, fostering greater engagement (e.g., Evanschitzky et al., 2015; Yin et al., 2024a). As one employee noted, “a positive view of AI makes me use it more often—optimism drives engagement.” A manager added that “the paradox mindset helps me appreciate AI’s complexities, making me curious and willing to engage, even when challenges arise”. Another participant shared: “Feeling motivated to learn about AI makes me see it as a valuable asset, keeping me engaged and excited about its potential”.

Fourth, while AI empathy is emphasized in the literature, few studies have empirically examined its moderating impact on employee perceptions of AI systems (Huang & Rust, 2024). We explored how AI empathy moderates the relationship between employee–AI collaboration, AI mastery goals, the paradox mindset, and user engagement. Our findings revealed that AI empathy moderates the link between AI mastery goals and engagement. In Study 1, collaboration significantly boosted engagement at low AI empathy level but not at high levels. In Study 2, no significant effect was observed, suggesting that high AI empathy may diminish the impact of collaboration. As Liu et al. (2020) noted, a paradox mindset helps employees to navigate AI complexities. When AI demonstrates empathy, it adapts to user needs, thus enhancing engagement. For example, one participant said: “If AI adapts to my feedback, it shows it cares, keeping me engaged”. Another noted: “Empathetic AI builds trust, making me feel understood and valued”.

Our findings revealed intriguing insights about AI empathy across studies. In Study 1, employee–AI collaboration significantly increased user engagement at low levels of AI empathy but not at high levels. In Study 2, no significant effect was observed at either level, indicating that high AI empathy might diminish the benefits of collaboration. Notably, higher AI empathy in Study 1 overshadowed the advantages of a paradox mindset, reducing the impact of collaboration on engagement. This may occur because overly empathetic AI responses could shift focus from achieving reliable results to providing emotional support, potentially undermining the primary goal of AI integration in firms. As one manager noted: “When AI is too focused on empathy, we lose sight of real goals. Support is great, but results matter”. Another added: “If AI becomes too emotional and not practical, I disengage. I need it to help me achieve goals, not just offer comfort.” Our results showed that AI empathy moderates the paradox mindset–engagement relationship in Study 2 but not in Study 1. A paradox mindset influences how users perceive and engage with AI systems, independent of AI empathy. Employees with this mindset engage based on their evaluation of AI’s complexity, not its empathic responses. As one employee noted, “I judge AI based on its complexity, not empathy—engagement depends on my interpretation”. Another added that “a paradox mindset lets me see AI’s potential and challenges. My engagement hinges on functionality, not emotional responses”.

Fifth, while the technological frame is crucial in shaping how employees interpret and collaborate with AI, few studies have explored its moderating role in employee–AI collaboration (Samuel et al., 2022; Spieth et al., 2021). We examined how the technological frame interacts with AI empathy in moderating the relationships between AI mastery goals, collaboration, the paradox mindset, and engagement. Our findings show that a stronger technological frame positively influences these relationships, simplifying the challenges of learning and collaborating with AI. As one employee noted, “a solid tech background helps me navigate AI’s complexities—it’s like having a map in a maze”. Another added: “With a good grasp of technology, I find it easier to collaborate with AI, boosting my confidence”. Consistent with prior research (e.g., Engås et al., 2023; Minkkinen et al., 2023), employees with a stronger technological frame are better equipped to leverage AI’s empathic features, enhancing collaboration and engagement. Last, we contributed empirical evidence showing that, while employee–AI collaboration alone does not drive user engagement, AI mastery goals and a paradox mindset mediate this relationship in both studies. These traits enhance engagement by helping employees to view AI more favorably and fostering optimism about its capabilities, aligning with prior research (e.g., Liu et al., 2020; Liu & Zhang, 2022). This mediation highlights their role in promoting engagement with AI.

7.2. Managerial implications

These findings can have significant implications for managers aiming to foster employee engagement in collaborating with AI. Based on our findings, managers should enhance the AI mastery goal and the paradox mindset for their employees in order to encourage them to engage with AI systems. This aligned with one of our participant’s views: “By offering targeted professional training, we can make the technology seem more relevant and appealing, which in turn helps encourage employees to engage with it”. Therefore, practitioners can create interventions, such as professional training programs, to increase the appeal of a technology or to effectively encourage employees to become engaged with it. For example, offering workshops that demonstrate how AI can streamline workflows or enhance decision making can help employees to feel more confident and engaged. In healthcare settings, interactive workshops could showcase how AI-powered clinical documentation tools automatically transcribe patient–provider conversations into structured electronic health records (EHRs), reducing time spent on manual data entry and minimizing errors. Workshops could also highlight predictive analytics tools that forecast patient deterioration by synthesizing real-time data from wearables or bedside monitors, allowing nurses to intervene proactively. Additionally, training on AI-enhanced workflow platforms could show how algorithms optimize staff scheduling, inventory management, or operating room utilization, thus alleviating administrative burdens and driving user engagement with AI systems.

Similarly, in healthcare settings, allowing time for staff to explore how AI can predict patient outcomes could lead to new ways to improve treatment plans. For instance, staff training workshops could involve hands-on sessions where clinicians interact with AI-driven Clinical Decision Support Systems tools that generate real-time risk scores or flag high-risk patients based on predictive algorithms, enabling proactive interventions. Workshops might simulate scenarios where providers input patient data into the system, review AI-generated predictions, and discuss how to balance these insights with clinical judgment. Emphasizing transparency in how models are trained (e.g., using diverse datasets to minimize bias) and fostering interdisciplinary collaboration between clinicians and data teams could address scepticism and improve technological frame. By creating structured opportunities for staff to test these tools in controlled environments, healthcare organizations can demystify AI's role, highlight its value in collaborating with—not replacing—clinical expertise, and cultivate trust in its ability to enhance precision and efficiency in patient care.

Further, since collaborating with AI can be inherently paradoxical for employees, we invite managers to support both and thinking within their workforce to help them accept and understand, and navigate the tensions that arise during these changes. This was raised by one employee who stated: "Collaborating with AI is complex, so inviting managers to foster both/and thinking can really help employees understand and accept those contradictions". As such, we highly recommend to managers that they need to be focused on emphasizing the development of the paradox mindset among their employees.

Firms can facilitate the paradox mindset by external intervention. For instance, workshops encourage employees to engage by influencing their mindset. Further, it might be useful for managers and key decision makers to provide additional information on the importance of the implications of collaboration with AI in the organization. One manager + *highlighted this: "By emphasizing the importance of AI collaboration, managers can help everyone see how it impacts the firm positively, making it easier to get on board". Similarly, another manager pointed out that, "if we (managers) take the time to explain the significance of collaborating with AI, it can motivate our employees to engage more actively and understand its benefits". This could be a crucial strategy for minimizing potential tensions among those who do not adopt a paradox mindset, as changes occur in employees' work routines when collaborating with AI.

8. Limitations and research directions

As with any studies, our study is subject to a number of limitations. The current study has been conducted in a developed market where, more than at any time, firms have started to adopt AI in their business activities. However, whether carrying out this study in an emerging market would exhibit similar findings to those of our current study remains uncertain and should be subject to future investigation. Accordingly, we invite researchers to carry out studies in less developed or emerging markets and compare their findings with those of the current study. Another limitation is the setting of our study. Our current study is also conducted in the healthcare setting. Future studies are invited to see how employee–AI collaboration in other business domains can impact on, and complement, our findings.

Further, conducting both parts of our study within the healthcare setting can limit the generalizability of our qualitative findings to other sectors. Future scholars are invited to include a qualitative method in other diverse settings like retail, education, or finance to explore how the dynamics of AI–employee collaboration may differ in these contexts. In details, while the proposed model was rigorously examined within healthcare settings—a context rich with high-stakes decision making, ethical complexity, and regulatory constraints, its broader applicability remains underexplored, representing a key limitation of this study. Restricting the analysis to healthcare may obscure insights into how the framework performs in industries with distinct operational dynamics, such as finance, or retail. For instance, in finance, AI-enhanced tools like robo-advisors operate in environments where trust hinges on algorithmic transparency, risk tolerance, and real-time market responsiveness, contrasting with healthcare's focus on patient outcomes and ethical safeguards. Similarly, retail applications—such as AI-driven personalized marketing—rely on consumer behavior analytics and emotional engagement strategies that differ starkly from clinical decision-making processes. Testing the model in these domains could reveal whether core constructs like user trust, engagement, and perceived utility generalize across sectors or are context dependent.

Additionally, gaps in the interview data may exist due to the limited scope of questions or the specific context of the healthcare setting. Future research could address these limitations by incorporating triangulation methods, such as combining interviews with focus groups or observational data, to enrich the findings. Furthermore, the cross-sectional nature of this study cannot fully capture the dynamic evaluation of user engagement and the impact of AI–employee collaboration on the AI mastery goal and the paradox mindset over time. Therefore, future researchers should consider longitudinal studies, allowing for more robust findings on how collaborating with AI can impact on the employee–AI mastery goal and develop their paradox mindset. Such findings can provide more robust results into how training programs can be effective in developing both the AI mastery goal and the paradox mindset. Appendix Table 5 summarizes the potential research questions.

9. Conclusion

In light of the scarcity of research on employee–AI collaboration and its impact on user engagement, our study explores how this collaboration can enhance user engagement. We develop a model based on qualitative insights from 27 healthcare participants and quantitative data from 452 participants, highlighting the roles of AI mastery goal, user engagement, and the paradox mindset. Our findings demonstrate that employee–AI collaboration positively influences these factors, with AI empathy and technological frames acting as key moderators. This research offers valuable managerial insights, emphasizing the importance of AI–employee collaboration in driving user engagement.

CRediT authorship contribution statement

Forouudi Pantea: Writing – original draft, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marvi Reza:** Writing – original draft, Investigation, Conceptualization. **AmirDadbar Najla:** Writing – original draft, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest. The research was conducted independently without any influence or support from any commercial entity that could benefit from the results of this study. All procedures performed in this study involving human participants were in accordance with ethical standards and approved by the appropriate ethics committee.

Appendix

Table 1
Item measurement and reliability

Construct	Sub-construct	Item measurements	Factor Loading	Mean	Std. Deviation	Factor Loading	Mean	Std. Deviation
			Study 1			**Study 2**		
Employee–AI Collaboration Kong et al. (2023)			**Cronbach @ = .927**			**Cronbach @ = .896**		
Definition: Human–AI collaboration highlights the synergistic partnership where humans and AI join forces to achieve collaborative intelligence (Kong et al. 2023; Wilson, and Daugherty, 2018)			Removed			Removed		
EAC1		AI participates in my firm's decision-making process.	Removed			Removed		
EAC2		AI participates in my firm's prediction process.	Removed			Removed		
EAC3		AI participates in my firm's problem-solving process.	.818	5.4054	1.36665			
EAC4		AI participates in my firm's information identification and evaluation process.				.863	5.7633	1.09589
EAC5		AI participates in my firm's problems, opportunities, or risk recognition process.	.865	5.2541	1.55837	Removed		
EAC6		AI participates in my firm's learning and development process.	.868	5.2243	1.53935	.781	5.6570	1.13344
EAC7		AI participates in my firm's knowledge acquisition and accumulation process.	Removed			.869	5.7101	1.12907
EAC8		AI participates in my firm's mistake reduction process.	Removed			Removed		
EAC9		AI participates in my firm's knowledge-sharing process.	.855	5.3270	1.54554	Removed		
EAC10		AI participates in my firm's communication process.				Removed		
AI Mastery Goal Dang and Liu (2022)			**Cronbach @ = .912**			**Cronbach @ = .934**		
Definition: To improve competence in using AI (Dang& Liu, 2022)								
AMG1		In the era of global advances in AI, my aim is to do better than AI robots.	.898	5.5135	1.56904	.901	5.7005	1.49665
AMG2		In the era of global advances in AI, I am striving to do well compared to AI robots.	Removed			Removed		
AMG3		In the era of global advances in AI, my goal is to perform better than AI robots.	Removed			Removed		
AMG4		In the era of global advances in AI, my aim is to avoid doing worse than AI robots.	.923	5.5459	1.54755	Removed		
AMG5		In the era of global advances in AI, I am striving to avoid performing worse than AI robots.	.846	5.6730	1.61751	.871	5.6763	1.53173
AMG6		In the era of global advances in AI, my goal is to avoid performing poorly compared to AI robots.	Removed			.837	5.7729	1.53650

(*continued on next page*)

Table 1 (*continued*)

Construct	Sub-construct	Item measurements	Factor Loading	Mean	Std. Deviation	Factor Loading	Mean	Std. Deviation
AMG7		In the era of global advances in AI, my aim is to master more new skills.	Removed					
AMG8		In the era of global advances in AI, I am striving to improve my capabilities.	Removed					
AMG9		In the era of global advances in AI, my goal is to learn as much as possible.	Removed					
User Engagement Chandra et al. (2022)			Removed			Removed		
Definition: An Experiential Flow of Behavior Characterized by Absorption, Dedication, and Vigor Independent of Deliberate Mindsets (Chandra et al., 2022)			Removed			Removed		
	Absorption		**Cronbach @ = .888**			**Cronbach @ = .916**		
UEA1		Time flew when I was using the chatbot.	.766	5.7108	1.33745	.812	5.6908	1.44513
UEA2		Using chatbot was so absorbing that I forgot about everything else.	.906	5.8865	1.20211	.856	5.7343	1.39065
UEA3		I was immersed in the chatbot.	.920	5.8216	1.26473	.871	5.6618	1.40445
	Dedication		**Cronbach @ = .957**			**Cronbach @ = .946**		
UED1		I was enthusiastic in using the chatbot.	.957	5.4270	1.61508	.935	5.5556	1.65334
UED2		I found this chatbot full of meaning and purpose.	.895	5.5838	1.50869	.826	5.7391	1.48113
UED3		I felt excited when using this chatbot.	.966	5.4865	1.50917	.939	5.6377	1.55767
	Vigor		**Cronbach @ = .872**			**Cronbach @ = .889**		
UEV1		I felt very resilient, mentally, as far as this chatbot is concerned.	.865	5.4243	1.49469	.842	5.7343	1.45547
UEV2		It was easy to perform well on this chatbot.	.905	5.4351	1.40744	.886	5.6715	1.44084
Paradox Mindset Klein et al. (2024)			**Cronbach @ = .893**			**Cronbach @ = .917**		
Definition: Paradox mindset is the degree to which individuals embrace and feel invigorated by tensions provides insight into how employees manage and respond to these tensions (Klein et al., 2024)			Removed			Removed		
PM1		I am comfortable dealing with conflicting demands at the same time.	.847	5.5081	1.58112	.819	5.7198	1.53241
PM2		Accepting contradictions is essential for my success.	.865	5.6486	1.55855	.844	5.8213	1.47534
PM3		Tensions between ideas energize me.	.843	5.4811	1.60146	.813	5.7246	1.49320
PM4		I enjoy it when I manage to pursue contradictory goals.	.644	5.6216	1.43799	Removed		
PM5		I often experience myself as simultaneously embracing conflicting demands.	Removed			Removed		
PM6		I am comfortable working on tasks that contradict each other.	Removed			Removed		

(*continued on next page*)

Table 1 (*continued*)

Construct	Sub-construct	Item measurements	Factor Loading	Mean	Std. Deviation	Factor Loading	Mean	Std. Deviation
PM7		I feel uplifted when I realize that two opposites can be true.	Removed			Removed		
PM8		I feel energized when I manage to address contradictory issues.	Removed			Removed		
Technological Frame Spieth et al. (2021)			**Cronbach @ = .958**			**Cronbach @ = .962**		
Definition: A Technological Frame consists of the assumptions, expectations, and knowledge that an individual uses to comprehend the application and implications of a technology within a specific context (Spieth et al., 2021)			Removed			Removed		
	Personal Attitude		Removed			Removed		
TFP1		My attitude towards digital technologies is positive.	.832	5.5189	1.60822	.899	5.7295	1.60831
TFP2		I have high expectations of digital technologies.	.832	5.5135	1.54467	.889	5.7198	1.53241
TFP3		Digital technologies are an important part of my life.	.837	5.4541	1.58389	.893	5.7246	1.54119
TFP4		I regularly try to obtain information about digital technologies.	Removed			Removed		
			Removed			Removed		
	Application Value		**Cronbach @ = .960**			**Cronbach @ = .930**		
TFAV1		Digital technologies could facilitate the coordination of my work tasks.	.935	5.3946	1.42793	.917	5.6280	1.20750
TFAV2		Digital technologies make my work more flexible.	.916	5.1838	1.57513	.877	5.4928	1.35414
TFAV3		Digital technologies reduce the possibility of making mistakes in my work.	.930	5.3216	1.53260	.895	5.5749	1.26297
TFAV4		Digital technologies increase the effectiveness of my work steps.	.939	5.2919	1.56041	.888	5.5507	1.22913
	Organizational Influence		**Cronbach @ = .972**			**Cronbach @ = .957**		
TFOI1		My colleagues remind me to use digital technologies in my job.	.816	5.5622	1.65038	Removed		
TFOI2		My colleagues regularly recommend digital technologies to me.	.839	5.5622	1.61385	.873	5.9034	1.35472
TFOI3		My colleagues demand that I use digital technologies for my job.	.853	5.4973	1.64498	.898	5.8792	1.42444
TFOI4		My colleagues help me use digital technologies for my job.	.866	5.5378	1.65112	.899	5.9227	1.40865
	Industry Influence		**Cronbach @ = .956**			**Cronbach @ = .941**		
TFII1		Our competitors demand the use of digital technologies.	.891	5.5595	1.60216			
TFII2		Our competitors successfully use digital technologies.	.882	5.4865	1.63003	.883	5.6957	1.53886
TFII3		Our customers demand the use of digital technologies.	.872	5.4459	1.65886	.897	5.6329	1.53297
TFII4		Our suppliers demand the use of digital technologies.	.851	5.5757	1.50912	.918	5.7101	1.41868
	Supervisor Influence		**Cronbach @ = .845**			**Cronbach @ = .884**		

(*continued on next page*)

Table 1 (*continued*)

Construct	Sub-construct	Item measurements	Factor Loading	Mean	Std. Deviation	Factor Loading	Mean	Std. Deviation
TFSI1		My supervisor is willing to integrate digital technologies into the firm.	Removed			Removed		
TFSI2		My supervisor requests that I use digital technology.	.746	5.5243	1.34978	Removed		
TFSI3		My supervisor regularly speaks about digital technologies.	.911	5.5703	1.41868	.919	5.6232	1.38404
TFSI4		My supervisor is an expert in the handling of digital technologies.	.920	5.5432	1.45744	.930	5.5797	1.40808
AI Empathy Meier et al. (2024)			**Cronbach @ = .947**			**Cronbach @ = .926**		
Definition: AI Empathy involves encoding human cognitive and affective empathy into computational models for designing and implementing AI agents (Liu-Thompkins et al., 2022)			Removed			Removed		
AE1		Gen AI in the hotel would understand my specific needs.	Removed	5.4946	1.41660	Removed		
AE2		Gen AI in the hotel would usefully give me individual attention.	.887	5.4757	1.45788	.864	5.5700	1.37370
AE3		Gen AI in the hotel would be available whenever it is convenient for me.	.872	5.4865	1.40309	.895	5.4928	1.32881
AE4		If I would require help, Gen AI in the hotel would do its best to help me.	.881	5.4432	1.42501	.868	5.5507	1.25260
AE5			.873	5.4649	1.34753			

SL = standardized loading

Table 2
Sample descriptive characteristics (Study 1/Study 2)

	Frequency	Per cent		Frequency	Per cent
Gender			**Age**		
Male	193/104	52.2/50.2	under 25	1/1	.3/7.7
Female	177/103	47.8/103	25–34	32/16	8.6/7.7
Education			35–44	137/78	37.0/37.7
High school	24/11	6.5/5.3	45–54	131/74	/35.7
Postgraduate and above	199/111	53.8/53.6	55–64	62/35	16.8/16.9
Undergraduate	147/85	39.7/41.1	65 and over	7/3	1.9/104

Table 3a
Validity, reliability, and correlation matrix

	CR	AVE	MSV	Paradox Mindset	Employee–AI Collaboration	AI -Mastery Goal	Absorption	Dedication	Vigor
Paradox Mindset	0.901	0.703	0.111	**0.838**					
Employee–AI Collaboration	0.928	0.764	0.130	0.324	**0.874**				
AI–Mastery Goal	0.921	0.799	0.132	0.157	0.240	**0.894**			
Absorption	0.896	0.744	0.150	0.111	0.180	0.117	**0.863**		
Dedication	0.960	0.888	0.040	0.157	0.200	0.174	0.099	**0.943**	
Vigor	0.899	0.820	0.111	0.333	0.006	0.043	−0.027	0.017	**0.906**

Table 3b
Validity, reliability, and correlation matrix

	CR	AVE	MSV	Vigor	Employee – AI Collaboration	AI -Mastery Goal	Absorption	Dedication	Paradox Mindset
Vigor	0.887	0.798	0.268	**0.893**					
Employee–AI Collaboration	0.896	0.744	0.144	0.122	**0.863**				
AI -Mastery Goal	0.942	0.844	0.166	0.303	0.262	**0.919**			
Absorption	0.913	0.777	0.154	0.265	0.379	0.393	**0.882**		
Dedication	0.946	0.854	0.135	0.221	0.208	0.272	0.323	**0.924**	
Paradox Mindset	0.913	0.778	0.268	0.518	0.320	0.408	0.327	0.368	**0.882**

Table 4
Model estimations

	Study 1				Study 2	
Variables	Main Effects Model	Parallel Mediation Model	Full Model			
Direct Effects						
Employee–AI Collaboration→AI Mastery Goal	.277 (3.15), $p = .00$	.20 (3.15), $p = .00$	.20 (3.15), $p = .00$		.40 (4.464), $p = .00$	
Employee–AI Collaboration→Paradox Mindset	.285 (5.21), $p = .00$	.28 (5.21), $p = .00$	.30 (5.66), $p = .00$		.43 (4.88), $p = .00$	
Employee–AI Collaboration→User Engagement	.089 (2.38), $p = .01$	.07 (.52), $p = .59$	.05 (1.33), $p = .18$		.09 (1.41), $p = .15$	
AI Mastery Goal→User Engagement	.082 (2.59), $p = .00$	.14 (1.17), $p = .24$	.06, (1.93). $p = .05$		.18 (3.77), $p = .00$	
Paradox Mindset→User Engagement	.17 (4.67), $p = .00$	.40 (2.87), $p = .00$	.13 (3.37), $p = .00$		.27 (5.17), $p = .00$	
Indirect Effects						
Employee–AI Collaboration→AI Mastery Goal→User Engagement		.01 $p < .05$ [−.0283,.0849]	.03 [−.3060.2247]		.09 [−.0068.2173]	
Employee–AI Collaboration →Paradox Mindset→User Engagement		.06 $p > .05$ [.0052,.1466]	.08 [.1325.3656]		.08 [.0490.3672]	
Interaction			Low	High	Low	High

(*continued on next page*)

Table 4 (*continued*)

Variables	Study 1				Study 2	
	Main Effects Model	Parallel Mediation Model	Full Model			
Employee–AI Collaboration × AI empathy → User Engagement		−.00 (−.02), $p = .98$	0.62 (2.22), $p = 0.02$	−0.03 (−0.35), $p = 0.72$	−0.03 (−0.32), $p = 0.7461$	0.06 (0.29), $p = 0.7739$
AI Mastery Goal × AI empathy → User Engagement		−.01 (−.76), $p = .44$	0.62 (2.22), $p = 0.02$	−0.03 (−0.35), $p = 0.72$	−0.03 (−0.61), $p = 0.5424$	0.18 (2.01), $p = 0.0459$
Paradox Mindset × AI empathy → User Engagement		−.04 (−1.95), $p = .05$	−0.04 (−0.23), $p = 0.81$	0.06 (1.53), $p = 0.12$	−0.08 (−1.68), $p = 0.0938$	0.20 (4.34), $p = 0.0000$
AI Mastery Goal × AI empathy × Technological Frame → User Engagement			−0.01 [−0.0567, 0.0706]	0.01 [0.0006, 0.0348]	0.03 (0.36), $p = 0.7169$	0.16 (1.15), $p = 0.2515$
Employee–AI Collaboration × AI empathy × Technological Frame → User Engagement			0.03 [−0.0276, 0.1034]	0.09 [0.0265, 0.1594]	−0.05 (−0.75), $p = 0.4522$	0.17 (2.59), $p = 0.0103$
AI Mastery Goal × AI empathy × Technological Frame → User Engagement			−0.01[−0.0567, 0.0706]	0.01 [0.0006, 0.0348]	0.07 (1.59), $p = 0.1143$	0.09 (1.85), $p = 0.0663$
Paradox Mindset × AI empathy × Technological Frame → User Engagement			0.08 [−0.1325, 0.3656]	0.03 [0.0084, 0.0710]	−0.00 (−0.07), $p = 0.9408$	0.21 (1.18), $p = 0.2404$
Gender	−.22, $p = .11$	.05, $p = .55$	−.22, $p = .12$		.12 (1.01), $p = 0.3115$	
Age	−.03, $p = .61$	−.03, $p = .51$	−.02, $p = .75$		−.07 (−1.03), $p = .3045$	
Education	.13, $p = .27$	−.02, $p = .75$	.15, $p = .22$		−.10 (−0.98), $p = .3279$	
F-statistic	7.97, $p = .00$	8.70, $p = .00$	8.48, $p = .01$		10.48, $p = 0.00$	
R^2	.11	.19	.09		.5	
	Model 6	Model 89	Model 19		Model 19	

Notes: Main effects multiple regression analysis SPSS; parallel mediation Hayes Process Model 4;full PROCESS Model 19. Sample size is 370; t-values are denoted in parentheses; Where Hayes PROCESS does not report the p-values, confidence intervals at 95 % are indicated in square brackets; 5000 samples were used for bootstrapping; We conducted two-sided tests for significance.∼ * For simplicity of presentation, indirect effects in the full model are reported as the moderated indirect effects, i.e., at the 84th percentile values of the moderators.

Table 5
Future research questions

Limitation	Suggested Future Research
Market Context: Study conducted in a developed market where AI adoption is high.	- Conduct research in less developed or emerging markets to compare findings and assess if similar results hold. - Explore cultural and regulatory differences that may impact AI adoption and employee–AI collaboration in emerging markets. - Investigate the readiness of firms in emerging markets for AI integration and how this affects employee behavior.
Industry Focus: The study is limited to the healthcare setting.	- Investigate employee–AI collaboration in other business domains (e.g., retail, education, finance) to assess if findings apply across industries. - Examine whether different industry structures (e.g., highly regulated vs. less regulated sectors) influence the outcomes of AI–employee collaboration.
Generalizability of Qualitative Findings: Conducted entirely in a healthcare setting.	- Include qualitative research in diverse sectors to explore variations in AI–employee collaboration dynamics across contexts. - Compare how the nature of employee–AI collaboration may differ in high-stress environments (e.g., healthcare) versus more customer-oriented sectors (e.g., retail). - Investigate how employees' responses such as engagement to AI differ based on sector-specific factors.
Data Collection Method: Potential gaps in interview data due to limited scope and specific healthcare context.	- Use triangulation methods, such as combining interviews with focus groups or observational data, to enrich qualitative findings. - Implement a broader range of qualitative techniques (e.g., ethnography) to capture the complexities of employee–AI interactions in various settings.
Study Design: The cross-sectional nature of the study limits the understanding of long-term effects.	- Implement longitudinal studies to capture how AI–employee collaboration evolves over time, especially its impact on AI mastery goal and paradox mindset development. - Study how employees' attitudes and skills in AI mastery develop through training and repeated AI interactions over a longer period. - Investigate the long-term effects of AI adoption on user engagement, the paradox mindset, and AI mastery goal.
Training impact on findings: Limited exploration of how training programs develop AI mastery goal and the paradox mindset.	- Investigate the effectiveness of training programs in enhancing both AI mastery goal and the paradox mindset over time through longitudinal research. - Explore different training methodologies (e.g., simulation-based training, hands-on AI projects) and their impact on employee confidence and adaptability to AI.

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