Opportunity or Threat? A Meta-Analysis of the Impact of Human-AI Collaboration Systems on Employee Job Performance

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Abstract

The rapid development of artificial intelligence has profoundly transformed social structures and production models, and scholars have paid close attention to its impact on employee work effectiveness when applied in organizations. To explore the impact of human-AI collaboration systems on employee work effectiveness and its underlying mechanisms, this study conducted a meta-analysis of 106 independent samples (n = 54,726) from 79 domestic and international literature sources. The findings reveal that human-machine collaboration application, AI autonomy, AI anthropomorphism, and employee KSAs (knowledge, skills, and abilities) have positive effects on employee work effectiveness, manifesting as "opportunities"; whereas AI crisis awareness exerts a negative effect, perceived as a "threat". AI trust and job insecurity mediate the relationship between human-AI collaboration systems and employee work effectiveness, further elucidating the dual pathways of "opportunity" and "threat". Furthermore, employee category, industry attributes, and cultural background exhibit moderating effects. The research conclusions indicate that human-AI collaboration systems possess a double-edged sword effect, capable of enhancing employee work effectiveness through AI trust while also diminishing it through job insecurity, with the positive effects outweighing the negative ones. Grounded in the Conservation of Resources theory framework, this study clarifies the influence mechanisms and boundary conditions of human-AI collaboration systems on employee work effectiveness, providing guidance for organizations to properly understand the impacts of human-AI collaboration systems and effectively leverage AI value.

Full Text

Opportunity or Threat? A Meta-Analysis of the Impact of Human-AI Collaboration Systems on Employee Work Effectiveness

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Abstract
The rapid development of artificial intelligence has profoundly transformed social structures and production models, attracting considerable scholarly attention to its impact on employee work effectiveness in organizational contexts. To investigate the effects and underlying mechanisms of human-AI collaboration systems on employee work effectiveness, this study conducted a meta-analysis of 106 independent samples (n = 54,726) drawn from 79 domestic and international studies. The findings reveal that human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs (knowledge, skills, and abilities) positively influence employee work effectiveness, representing "opportunities," whereas AI crisis consciousness exerts a negative effect, perceived as a "threat." AI trust and job insecurity mediate the relationship between human-AI collaboration systems and employee work effectiveness, further elucidating the dual pathways of "opportunity" and "threat." Moreover, employee category, industry attributes, and cultural background demonstrate moderating effects. The results indicate that human-AI collaboration systems produce a double-edged sword effect: they can enhance employee work effectiveness through AI trust while simultaneously diminishing it via job insecurity, with the positive effects outweighing the negative ones. Grounded in Conservation of Resources Theory, this study clarifies the influence mechanisms and boundary conditions of human-AI collaboration systems on employee work effectiveness, providing guidance for organizations to properly understand the impacts of human-AI collaboration systems and effectively leverage AI value.

Keywords: human-AI collaboration, job insecurity, AI trust, job performance, employee innovation

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Artificial Intelligence (AI), as a key force driving technological advancement, industrial upgrading, and productivity enhancement, is increasingly transforming social structures and production models, and is regarded as an important general-purpose technology for society' s future (Brynjolfsson & Mcafee, 2017). However, rapid technological development has also brought profound impacts and widespread concerns. The introduction of AI may replace traditional positions, alter decision-making processes, and even affect employees' work experiences and outcomes (Felten et al., 2021). This influence exhibits significant duality. From a positive perspective, human-AI collaboration achieves complementary advantages through labor division, liberating employees from low-value tasks and enabling them to focus on developing professional skills and engaging in higher-value creative activities. This collaborative model not only improves work efficiency but also provides employees with greater development space and innovation opportunities (Jia et al., 2024). From a negative perspective, once employees develop negative perceptions of AI—for instance, viewing AI tracking and monitoring at work as privacy violations or believing AI undermines their sense of autonomy—it can adversely affect subsequent work performance (Tong et al., 2021; Savela et al., 2021). In this context, analyzing the impact of human-AI collaboration systems on employee work effectiveness is of great significance.

Work effectiveness is typically regarded as a key indicator of employee output, wherein job performance reflects whether employees' work performance and results meet organizational requirements (Zhou & Wang, 2021; Wu & Song, 2023), while innovation is crucial for helping organizations stand out (Shi & Zhou, 2024). Therefore, the core concern of this study is to comprehensively evaluate the dual impact of human-AI collaboration systems on employee job performance and innovation to reveal its overall effect on employee work effectiveness.

Although scholarly discussion on the impacts of human-AI collaboration systems has been increasing, no consensus has yet emerged. On one hand, some studies argue that human-AI collaboration systems have significant positive effects. For example, AI' s assumption of repetitive, high-risk, or high-precision tasks allows employees to focus on more complex work, thereby enhancing overall performance (Noy & Zhang, 2023). Simultaneously, AI applications provide employees with greater autonomy, stimulate creativity, and promote the completion of innovative tasks (Hauptman et al., 2023). On the other hand, some studies emphasize the negative effects of human-AI collaboration systems, noting that employees may struggle to adapt to rapidly changing technology or fear being replaced by AI, leading to performance declines (Li et al., 2019; Yam et al., 2023). Moreover, in contexts reliant on data and algorithms, employees' over-reliance on AI at the expense of independent thinking may undermine their autonomy and creativity (Verma & Singh, 2022a). As research has deepened, some scholars have proposed that human-AI collaboration systems have dual effects on innovation: AI may serve as a job demand that negatively affects innovative behavior by increasing job insecurity, or as a job resource that positively stimulates innovative behavior by enhancing perceived autonomy (Zhang et al., 2023). Therefore, analyzing the mechanisms of human-AI collaboration from a systematic perspective can deepen research on AI in organizations and provide practical guidance for optimizing human-AI collaboration to enhance AI' s overall effectiveness in organizations.

By reviewing existing literature, we find that the mechanisms through which human-AI collaboration systems affect employee work effectiveness require further refinement in several areas: (1) Is the human-AI collaboration system an "opportunity" or a "threat"? As previously mentioned, human-AI collaboration may have a "double-edged sword" effect. However, limited by the scope and methods of single empirical studies, existing research typically can only analyze limited indicators, and the dimensional division of human-AI collaboration is relatively coarse, failing to comprehensively clarify its multi-dimensional characteristics' "double-edged sword" impacts on employee work effectiveness and their differential intensities. (2) How does the human-AI collaboration system become an "opportunity" or "threat"? Although some studies have explored the specific impact processes of human-AI collaboration on employee work effectiveness, most have focused solely on either positive or negative effects, with limited and fragmented sample inclusion, failing to clearly compare the magnitude of different effects. Thus, the mechanisms underlying the "double-edged sword" effect of human-AI collaboration remain to be further investigated. (3) When does the human-AI collaboration system become an "opportunity" or "threat"? The boundary conditions of human-AI collaboration' s impact require comprehensive discussion. For example, high-tech industries, due to their emphasis on innovation and flexibility, may be more adaptable to the development of human-AI collaboration systems. Additionally, cultural differences, as well as employee gender and age differences, may affect the utility generated by human-AI collaboration systems.

To address the limitations of existing empirical research, this study constructs a theoretical model based on Conservation of Resources Theory (COR). COR theory emphasizes that individuals have a strong tendency to maintain, acquire, and protect resources, and perceptions of resource gain and loss directly affect their attitudes and behaviors (Hobfoll, 2011). In the context of human-AI collaboration, AI can serve as both a "resource gain tool"—for example, by automating processes to free up employees' time and cognitive resources—and a "resource loss threat" —for example, by triggering employees' concerns about job replacement. Based on COR theory, this study innovatively selects job insecurity and AI trust as core mediating variables. First, from the resource acquisition pathway, AI trust reflects employees' subjective evaluation of AI technology' s reliability and value. Employees with high AI trust are more likely to view AI as a resource that expands their capabilities, actively exploring its functions and integrating them into workflows (Glikson & Woolley, 2020; Hauptman et al., 2023). Second, from the resource loss pathway, job insecurity reflects employees' perception of career survival risks. When employees view AI as a job replacement threat, it triggers psychological defense mechanisms, leading to reduced innovation investment and avoidance of technology learning to cope with potential losses (Yam et al., 2023; Sharif et al., 2025). Moreover, from the perspective of theoretical integration value, these two mediating variables form a complementary relationship: AI trust focuses on explaining the positive effects of human-AI collaboration systems, while job insecurity focuses on negative effects, together constituting a complete "double-edged sword" pathway.

Finally, in terms of data adequacy, both variables appear frequently in human-AI collaboration research, meeting the structural equation modeling requirements for full-model analysis. Therefore, this study selects job insecurity and AI trust as mediating variables for the dual effects of human-AI collaboration systems, exploring the mechanisms through which human-AI collaboration systems affect job performance and employee innovation from the dual pathways of resource gain and loss. Specifically: (1) We examine the main effects of human-AI collaboration systems, systematically analyzing the specific impacts of multi-dimensional characteristics—including human-AI collaboration applications, AI features, and employee characteristics—on job performance and employee innovation. (2) We deepen understanding of the influence mechanisms by employing meta-analytic structural equation modeling to quantify the mediating roles of job insecurity and AI trust and their differences, thereby revealing the specific mechanisms at play. (3) We clarify the boundary conditions of human-AI collaboration systems' impact on employees by constructing a three-dimensional "individual-organization-environment" moderation framework that integrates micro, meso, and macro-level factors. Specifically, we conduct meta-regression analysis with employee gender and age as continuous variables, while performing subgroup analyses with employee category, industry attributes, and cultural background as categorical variables to explore how these factors moderate the relationships between human-AI collaboration system variables and employee work effectiveness.

2.1 Variable Definitions

When examining the relationship between technology and work, traditional perspectives typically view technology as a tool or medium. The tool perspective focuses on how employees use technological tools to enhance performance (Nelson & Irwin, 2014), while the medium perspective emphasizes how technology facilitates team communication (Bechky, 2003). However, these perspectives are largely limited to research on human individuals, neglecting AI' s agency and the dynamic nature of collaborative environments. To address this limitation, Ajoudani et al. (2018) proposed the "human-machine-environment" system, defining human-machine collaboration as "a coupled dynamic system formed through contact among humans, machines, and the environment to accomplish specific tasks." Wang and Yao (2022) noted that the core elements of human-machine collaboration include employee characteristics, robot characteristics, and environmental characteristics. Yin and Niu (2024) reviewed human-AI collaboration from four aspects: AI technology factors, employee individual factors, organizational contextual factors, and task configuration. Building on existing research, this study defines the human-AI collaboration system as an interactive system composed of "human-AI-organization," specifically referring to the comprehensive system in which employees collaborate with AI tools, algorithms, and related technologies to complete tasks within specific organizational contexts

(Yin & Niu, 2024). To explore its impact on employee work effectiveness, this study analyzes three dimensions: organizational context (human-AI collaboration applications), AI characteristics (AI autonomy and AI anthropomorphism), and employee characteristics (KSAs and AI crisis consciousness) (see Figure 1 [Figure 1: see original paper]).

Human-AI collaboration applications refer to systematic practices in which employees continuously interact with AI systems possessing autonomous learning, reasoning, and decision-making capabilities in organizational environments to collaboratively achieve core task objectives (Man Tang et al., 2022; Shi et al., 2024). This concept encompasses both the capability level of AI technology itself and the breadth and depth of AI integration into actual workflows. In empirical research, this variable is operationalized in two common ways: one approach treats it as a categorical variable through experimental manipulation, such as Zhang et al. (2023) using a two-factor design of AI technology application (high/low) and learning goal orientation (high/low) to examine its interactive effects on innovative behavior, or Yin et al. (2024) employing an orthogonal experimental design of AI assistant intelligence level (high/low) and organizational AI readiness (high/low) to investigate the impact of human-AI collaboration on task performance under different contexts. The other approach measures it as a continuous variable, such as Tang et al. (2022) depicting it through behavioral indicators like usage frequency and functional dependence, or Dong et al. (2025) further integrating multiple items including usage frequency, necessity, and interaction density to more comprehensively capture the intensity of human-AI collaboration. This diversified measurement approach provides a flexible operationalization foundation for empirical research and facilitates variable coding and theoretical comparison in subsequent meta-analyses.

AI characteristics mainly include two key variables: AI autonomy, which refers to AI’ s ability to independently execute tasks and make decisions without explicit human intervention; and AI anthropomorphism, which refers to the degree to which AI simulates human characteristics in appearance, voice, and interaction modes (Alabed et al., 2022). These two features significantly influence the naturalness of human-AI interaction and collaboration efficiency. Employee characteristics also include two key variables: KSAs (Knowledge, Skill, Ability), which specifically refer to employees’ experience, familiarity, and sensitivity in using artificial intelligence (Kim et al., 2022); and AI crisis consciousness, which refers to employees’ perception of career risks such as job replacement and skill devaluation that AI technology may cause (Brougham & Haar, 2018). Higher levels of crisis consciousness may negatively affect collaboration attitudes and work behaviors (Yam et al., 2023).

Based on the inductive logic of meta-analysis, this study incorporates two widely researched outcome variables—job performance and employee innovation—to assess the impact of human-AI collaboration on overall employee work effectiveness. To improve predictive validity, following reference materials and related studies, we consolidate conceptually similar variables into broader categories for analysis (Alabed et al., 2022). Specifically, adopting a two-dimensional performance perspective, we combine task performance and contextual performance into the comprehensive variable "job performance" (Su et al., 2017). Additionally, given that both creativity and innovation can drive organizational innovation development, this study operationally defines employee innovation broadly, consolidating related variables such as employee creativity, innovative behavior, innovation outcomes, and innovation performance into the overall variable "employee innovation" (Su et al., 2021), referring to employees' ability to create valuable new products, ideas, or processes within organizations, including idea generation, process implementation, and final outcome realization (Oldham & Cummings, 1996).

2.2 Theoretical Framework

Conservation of Resources (COR) theory provides a systematic perspective for analyzing the complex effects of human-AI collaboration. The theory' s core lies in individuals' acquisition, protection, and maintenance of resources, where "resources" are defined as objective entities (e.g., tools), conditions (e.g., job autonomy), psychological traits (e.g., trust), and energies (e.g., skills) that individuals consider valuable (Hobfoll, 1989). COR theory emphasizes that resource-deficient individuals are more likely to fall into a "loss spiral" (i.e., continuous resource depletion without replenishment), while resource-abundant individuals tend to form a "gain spiral" (i.e., acquiring more resources through accumulation). In human-AI collaboration systems, AI introduction affects employees' resource states through two parallel pathways. Along the resource gain pathway, when AI is perceived as a resource supplement tool, it creates a positive cycle by directly providing resources or improving resource utilization efficiency. For example, AI as a collaborative partner can provide effective support through efficient information processing and predictive capabilities, enhancing employees' confidence and skills. In this case, employees believe AI can enhance their work capabilities and autonomy, which protects their resources, boosts intrinsic motivation, and further strengthens collaborative effectiveness and innovation drive (Huang & Gursoy, 2024). Along the resource loss pathway, when AI is viewed as a resource threat, it triggers resource loss and defensive reactions. Employees may feel their job security is threatened by concerns about AI replacing their positions, leading to job insecurity that may cause further resource loss. When individuals face resource threats, they often adopt conservative and defensive strategies, which may suppress work performance and innovation willingness (Huang & Gursoy, 2024). Therefore, based on COR theory' s dual-pathway logic, this study focuses on the triggering mechanisms of resource gain and loss in human-AI collaboration systems (including human-AI collaboration applications, AI characteristics, and employee characteristics) and explores how they affect employees' job performance and innovative behavior through dynamic resource changes.

2.3 Human-AI Collaboration Systems and Employee Work Effectiveness

Based on COR theory, the human-AI collaboration system, as a multi-level dynamic interactive system, includes elements such as human-AI collaboration applications, AI characteristics, and employee characteristics, which collectively influence employees' job performance and innovative behavior through dual resource gain and loss effects. After organizations systematically deploy and apply AI for collaboration, employees can delegate routine, highly repetitive tasks to AI, thereby saving time and cognitive resources and reallocating them to tasks requiring human judgment, complex reasoning, and interpersonal interaction (He et al., 2024). This effective release and reallocation of resources reduces employees' workload, helps improve task completion efficiency and quality, and thus enhances job performance. Moreover, when employees actively adapt to AI technological changes and view them as opportunities for personal growth and innovation, their motivation for innovative exploration is effectively stimulated, making them more proactive in trying new methods and conceiving new solutions (Yin et al., 2024). Therefore, we propose:

H1a: Human-AI collaboration applications have a positive impact on job performance.
H1b: Human-AI collaboration applications have a positive impact on employee innovation.

AI' s own characteristics can influence employee work effectiveness by affecting resource accumulation. First, AI autonomy enables it to independently complete complex tasks and make real-time decisions. On one hand, it significantly reduces employees' cognitive load by enhancing system usability and adaptability, helping them preserve limited psychological resources (Glikson & Woolley, 2020; He et al., 2024). On the other hand, it releases employees' time and energy resources by replacing routine operations, providing necessary conditions for improving job performance and employee innovation (Dell' Acqua et al., 2023). Second, AI anthropomorphism provides socio-emotional support through human-like interaction interfaces (e.g., smiling, gaze, and voice interaction), thereby improving emotional connections between AI and employees and enhancing trust in and willingness to collaborate with the technology. This positive emotional resource helps alleviate psychological barriers in human-AI collaboration and promotes job performance (Papadopoulos et al., 2016). Simultaneously, AI anthropomorphic design can also enhance employee satisfaction with technology through emotional interaction, motivating them to more actively explore new tools and respond to innovation challenges, thereby fostering innovative behavior (Alabed et al., 2022). Therefore, we propose:

H2a: AI autonomy has a positive impact on job performance.
H2b: AI autonomy has a positive impact on employee innovation.
H2c: AI anthropomorphism has a positive impact on job performance.
H2d: AI anthropomorphism has a positive impact on employee innovation.

Employees' individual skills and cognitive characteristics can influence work effectiveness through both resource gain and resource loss pathways. Along the resource gain pathway, employee KSAs, as core human capital resources, enable them to utilize AI technology more efficiently, promoting a virtuous cycle of resources in human-AI collaboration while improving work efficiency (Kim et al., 2022). Meanwhile, employees with higher AI skills can better integrate professional knowledge with AI technology, forming a "skill-resource" synergy effect that, under conditions of resource abundance, actively promotes innovative behavior and generates unique outcomes (Yin et al., 2024). Along the resource loss pathway, employees' concerns about AI substitution can easily trigger job insecurity and psychological resource depletion. To avoid further resource loss, individuals may adopt conservative strategies, reducing work engagement or even exhibiting negative behaviors, thereby negatively affecting job performance (Brougham & Haar, 2018). Additionally, this crisis consciousness consumes psychological resources needed for innovation, reducing employees' use of AI technology, especially in high-risk and challenging innovation activities (Ding, 2021; Verma & Singh, 2022b). This resource threat not only suppresses employees' innovation willingness but may also reduce their enthusiasm for exploring new ideas. Based on this, we propose:

H3a: Employee KSAs have a positive impact on job performance.
H3b: Employee KSAs have a positive impact on employee innovation.
H3c: Employee AI crisis consciousness has a negative impact on job performance.
H3d: Employee AI crisis consciousness has a negative impact on employee innovation.

2.4 The Process Mechanism of the Dual Effects of Human-AI Collaboration Systems—The Mediating Roles of Job Insecurity and AI Trust

First, from a practical background perspective, the rapid iteration of AI technology and organizational changes have intensified employees' job insecurity (Wu et al., 2024), while the development of human-AI collaboration highly depends on employees' trust in AI (McGrath et al., 2025). These two variables provide important empirical foundations for explaining the dual effects of human-AI collaboration systems on job performance and employee innovation from both negative and positive directions. Second, from a theoretical perspective, both job insecurity and AI trust are closely related to individuals' resource states. Specifically, job insecurity reflects employees' perceived threat of resource loss, which may stem from risks such as skill devaluation and job replacement brought by AI technology (Gull et al., 2023). AI trust, in contrast, represents resource gains obtained through technology adoption, which helps enhance the effectiveness of human-AI collaboration (Glikson & Woolley, 2020). Finally, from the perspective of explanatory power, job insecurity and AI trust respectively reveal the dual impacts of human-AI collaboration systems on job performance and employee innovation from resource loss and resource gain perspectives. Job insecurity suppresses employee performance and innovation by triggering anxiety and reducing work engagement (Frey & Osboren, 2017), while AI trust enhances collaborative effectiveness by increasing technology acceptance and promoting knowledge sharing (Glikson & Woolley, 2020). Together, they constitute key psychological mediating mechanisms in human-AI collaboration systems.

Therefore, it is important to sequentially elaborate on the specific pathways through which human-AI collaboration applications, AI characteristics, and employee characteristics influence outcomes via job insecurity and AI trust.

2.4.1 The Mediating Role of Job Insecurity

Job insecurity refers to employees' perceived threat to their job survival and skill value due to AI technology application (Shoss, 2017). According to COR theory, when individuals perceive potential resource loss, it triggers defense mechanisms and conservative strategies to avoid further losses, thereby broadly affecting work behaviors and outcomes. Research shows that while AI introduction and systematic human-AI collaboration improve efficiency, they also redefine the boundaries of traditional positions, intensifying employees' concerns about being replaced (Wu et al., 2024). Specifically, job insecurity generates anxiety, distraction, and psychological pressure, reducing work engagement and task focus, thereby negatively affecting job performance (Sverke et al., 2002). It also suppresses employees' risk-taking spirit and creative thinking, making them inclined to adopt conservative work strategies and avoid trying novel methods or ideas, thus hindering innovative behavior (Jiang & Lavaysse, 2018). This insecurity triggered by human-AI collaboration applications leads employees to reduce work engagement and innovation attempts, thereby diminishing job performance and innovation capacity. Therefore, we propose:

H4a: Job insecurity mediates the relationship between human-AI collaboration applications and job performance.
H4b: Job insecurity mediates the relationship between human-AI collaboration applications and employee innovation.

As AI autonomy continues to improve, its ability to execute routine tasks is increasingly enhanced, leading employees to compare their own capabilities with AI and evaluate the possibility and consequences of being replaced. If employees believe AI poses a threat to their employment, their negative emotions increase significantly, exacerbating job insecurity (Shoss, 2017). Under conditions of resource threat, employees tend to adopt conservative strategies and reduce resource investment in high-risk tasks (such as innovation activities). This protective behavior leads to decreased work motivation and may suppress employees' innovation capacity and performance (Hobfoll, 1989). AI anthropomorphism may intensify employees' threat perception of artificial intelligence through its realistic appearance and emotional expression capabilities. When AI behaves too similarly to humans, employees may perceive it as a direct competitor rather than a simple support tool. This may trigger employees' concerns about job replacement, further intensifying job insecurity and negatively affecting their psychological states and work behaviors (Papadopoulos et al., 2016). Therefore, we propose:

H5a: Job insecurity mediates the relationship between AI autonomy and job performance.
H5b: Job insecurity mediates the relationship between AI autonomy and employee innovation.
H5c: Job insecurity mediates the relationship between AI anthropomorphism and job performance.
H5d: Job insecurity mediates the relationship between AI anthropomorphism and employee innovation.

On one hand, employee KSAs can effectively alleviate insecurity by enhancing their technology adaptation and transformation capabilities. Employees proficient in AI typically have greater confidence in career development and are more likely to view AI as an empowering tool rather than a replacement threat. Their rich skill reserves help maintain existing position stability and provide a foundation for exploring new career opportunities, thereby significantly reducing job insecurity (Huang & Yu, 2023). On the other hand, employees' AI crisis consciousness directly strengthens their insecurity. Employees highly sensitive to AI substitution are more likely to fall into resource loss expectations, triggering conservative and defensive behaviors (Brougham & Haar, 2018). These employees, due to continuously perceived career threats, often actively avoid participating in risky innovation activities, ultimately suppressing their job performance and innovation (Shoss, 2017). Therefore, we propose:

H6a: Job insecurity mediates the relationship between employee KSAs and job performance.
H6b: Job insecurity mediates the relationship between employee KSAs and employee innovation.
H6c: Job insecurity mediates the relationship between employee AI crisis consciousness and job performance.
H6d: Job insecurity mediates the relationship between employee AI crisis consciousness and employee innovation.

2.4.2 The Mediating Role of AI Trust

AI trust represents employees' positive beliefs about AI technology's capabilities, integrity, and benevolence. As a key psychological pathway for resource gain, it can significantly promote technology acceptance and collaborative behavior (Glikson & Woolley, 2020). In human-AI collaboration systems, AI trust enhances employees' psychological safety and sense of control, prompting them to more actively invest cognitive and emotional resources into work tasks, thereby improving job performance (Diab & Demiris, 2025). Simultaneously, AI trust provides employees with psychological safety assurance for trying new methods and innovative thinking, effectively reducing perceived risk of innovation failure and thus promoting innovative behavior (Hengstler et al., 2016). Human-AI collaboration applications help accumulate positive human-AI interaction experiences by providing continuous and reliable technical support, making employees more likely to recognize AI' s collaborative value (McGrath et al., 2025). This sense of trust not only enhances employees' confidence in task execution but also motivates them to more actively engage in innovation exploration, thereby positively affecting job performance and innovation. Therefore, we propose:

H7a: AI trust mediates the relationship between human-AI collaboration applications and job performance.
H7b: AI trust mediates the relationship between human-AI collaboration applications and employee innovation.

AI autonomy strengthens shared awareness and collaborative intention between employees and AI by enhancing task execution accuracy and independence, making employees more trusting of AI' s capabilities and functions (Bhaskara et al., 2020). This competence-based trust not only provides employees with key psychological resources to help them cope with challenges in technological change but also enhances their work motivation and effectiveness by reducing workload and increasing support. AI anthropomorphism promotes emotional connections between employees and AI through highly simulated appearance, emotional expression, and natural interaction, significantly reducing uncertainty in human-AI collaboration (Munnukka et al., 2022). This emotional trust helps employees adapt to collaborative environments more quickly, reduces cognitive pressure from uncertainty, thereby enhancing collaborative 默契 (rapport) and promoting innovation exploration, ultimately improving job performance and innovation outcomes. Therefore, we propose:

H8a: AI trust mediates the relationship between AI autonomy and job performance.
H8b: AI trust mediates the relationship between AI autonomy and employee innovation.
H8c: AI trust mediates the relationship between AI anthropomorphism and job performance.
H8d: AI trust mediates the relationship between AI anthropomorphism and employee innovation.

Employee KSAs strengthen trust in AI by enhancing their understanding and sense of control over the technology. Employees with high KSAs better understand AI' s operational logic and limitations, thereby establishing rational trust based on cognition (Huang & Yu, 2023). This trust enhances their confidence in using AI to handle complex tasks and engage in innovative work, thereby contributing to improved job performance and innovation levels. In contrast, employees' AI crisis consciousness generates negative emotions such as fear and anxiety (Yu et al., 2018; Xie et al., 2021). When employees perceive resource threats and lack the ability to cope with new technology, they often exhibit lower levels of AI trust. As a key psychological resource, AI trust not only enhances employees' sense of autonomy and control, promotes human-AI collaboration, and improves job performance, but also helps employees better understand and adapt to human-AI collaboration in organizational environments, reducing uncertainty cognition and thereby motivating innovative behavior (Tams et al., 2018). Therefore, we propose:

H9a: AI trust mediates the relationship between employee KSAs and job performance.
H9b: AI trust mediates the relationship between employee KSAs and employee innovation.
H9c: AI trust mediates the relationship between employee AI crisis consciousness and job performance.
H9d: AI trust mediates the relationship between employee AI crisis consciousness and employee innovation.

2.4.3 Comparing the Mediating Roles of AI Trust and Job Insecurity

According to COR theory, individuals' perceptions of resource gain and resource loss are asymmetrical (Hobfoll, 1989). In human-AI collaboration systems, AI trust not only represents positive beliefs about capabilities and benevolence but also implies fundamental expectations for continuous resource expansion and technological empowerment, whose influence may transcend short-term fluctuations and demonstrate more profound and stable effects. Empirical research shows that employees' trust in AI can significantly promote technology adoption, collaboration satisfaction, and innovation willingness (Tams et al., 2018). These effects stem from the psychological safety and cognitive openness brought by trust, which help build long-term, positive human-AI collaboration relationships. In contrast, while job insecurity may trigger immediate defensive behaviors and resource protection reactions, its effects often diminish as individuals adapt, receive organizational support, or experience situational changes, showing strong context-dependency and short-term characteristics (Shoss, 2017). In other words, in the process of human-AI collaboration systems affecting work effectiveness, AI trust, as a gain-oriented psychological resource, may have stronger and more stable mediating effects than the loss-oriented job insecurity. Therefore, we propose:

H10a: In the impact of human-AI collaboration systems on job performance, the mediating effect of AI trust is stronger than that of job insecurity.
H10b: In the impact of human-AI collaboration systems on employee innovation, the mediating effect of AI trust is stronger than that of job insecurity.

2.5 Moderating Effects of Potential Factors

When examining the moderating effects of employee gender, age, type, industry attributes, and cultural background, due to data limitations, we cannot analyze the differential effects of some moderating variables across all dimensions. Following the approach of Duan et al. (2025) and Su et al. (2024), this study treats "human-AI collaboration system"as an integrated construct encompassing three core dimensions—human-AI collaboration applications, AI characteristics, and employee characteristics—to more systematically grasp the wholeness and mechanisms of human-AI collaboration at the theoretical level.

2.5.1 The Moderating Effect of Gender

From the COR theory perspective, gender' s influence on resource perception and transformation is more related to contextual factors shaped by social culture. Research shows that in technology collaboration, traditional gender division concepts may create implicit gender tendencies in organizational resource allocation, giving certain groups more opportunities for deep interaction with AI (Venkatesh & Morris, 2000; Good et al., 2022). These groups are often male employees in real-world scenarios, who typically receive more AI technology training resources and opportunities to participate in high-autonomy tasks due to societal gendered perceptions of technology workers (Russo et al., 2025). Continuous technology practice accumulates rich adaptation experience, making them more likely to develop AI trust. This trust encourages them to deeply integrate AI technology into workflows, efficiently transforming technological resources into psychological effectiveness by optimizing task execution methods. As their own KSAs continuously strengthen, they ultimately achieve improvements in job performance and breakthroughs in innovation capacity. In human-AI collaboration scenarios, this group can quickly adapt to technological changes, viewing AI as an important tool for gaining resource advantages, effectively alleviating job insecurity through resource accumulation, and further consolidating work effectiveness. Moreover, research indicates that in human-AI collaboration positions in mechanical R&D, the proportion of male employees is significantly higher than that of females, and their technology acceptance is higher, making them more inclined to participate in challenging work that stimulates their motivation and creativity (He et al., 2024). In contrast, due to long-standing gender stereotypes in technology fields, female employees often face numerous restrictions in resource acquisition. They frequently need to expend extra effort at work, not only to complete their job duties but also to address implicit societal questioning of their technical abilities (Ahn et al., 2022). This dual pressure causes them to consume more psychological resources to cope with external evaluations and self-identity challenges during AI collaboration. Especially in contexts where AI triggers career crisis consciousness, concerns about technological substitution and lack of social identity can easily cause psychological resource depletion, thereby weakening their work effectiveness. Therefore, we propose:

H11a: Gender moderates the relationship between human-AI collaboration systems and job performance. The higher the proportion of male employees, the stronger the impact of human-AI collaboration systems on job performance.
H11b: Gender moderates the relationship between human-AI collaboration systems and employee innovation. The higher the proportion of male employees,

the stronger the impact of human-AI collaboration systems on employee innovation.

2.5.2 The Moderating Effect of Age

From the COR theory perspective, age' s influence on resource perception and transformation is essentially the result of the interaction between individual lifecycle characteristics and organizational contexts. When facing resource threats or gains brought by AI technology, individuals adopt differentiated resource acquisition and allocation strategies based on their age-stage resource reserve characteristics, thereby affecting the effectiveness output of human-AI collaboration systems (Hobfoll, 2011). In human-AI collaboration systems, different age groups show significant differences in resource transformation pathways. Older employees, leveraging long-accumulated domain knowledge and practical experience, tend to view AI technology as a complementary tool to compensate for physical and reaction speed disadvantages. Their rule-following awareness and stable work style formed through career development make them more likely to integrate AI into existing workflows as deterministic technical support for auxiliary decision-making. This cognitive pattern may strengthen their psychological resource reserves—for example, by verifying professional judgments through AI collaboration, thereby enhancing AI trust and professional competence (He et al., 2024). Research shows that older employees' stable trust in AI technology can significantly reduce job insecurity, thereby improving task execution continuity and accuracy (Huang & Yu, 2023). Based on COR theory' s resource preservation logic, older employees' trust in AI may continuously enhance job performance stability by reducing resource loss risks. In contrast, younger employee groups, relying on the technological sensitivity and open, inclusive cognitive traits of digital natives, view AI technology as a breakthrough tool for stimulating innovation potential (Dutta et al., 2023). Driven by AI autonomy and anthropomorphism, younger employees are more likely to break through constraints of traditional work paradigms, rapidly absorbing new technological knowledge to transform AI resources into psychological resources such as creative thinking and self-efficacy. Moreover, younger employees have stronger willingness to use emerging technology tools, are more willing to explore new technologies and accept new work methods, and are more likely to significantly enhance innovation output by actively expanding resource boundaries. Therefore, we propose:

H12a: Age moderates the relationship between human-AI collaboration systems and job performance. The older the age, the stronger the impact of human-AI collaboration systems on job performance.
H12b: Age moderates the relationship between human-AI collaboration systems and employee innovation. The younger the age, the stronger the impact of human-AI collaboration systems on employee innovation.

2.5.3 The Moderating Effect of Employee Category

Based on employees' knowledge categories, this study divides organizational employees in the samples into non-knowledge workers and knowledge workers. Non-knowledge workers mainly include employees with lower education levels, such as frontline staff in hotels, retail, and other service industries, as well as those engaged in repetitive physical labor. Knowledge workers refer to employees engaged in knowledge processing and information management, such as staff in high-tech, medical and pharmaceutical, internet industries, and government and public institutions. Due to differences in work nature and resource reserves, these two types of employees show significant differences in performance and benefits in human-AI collaboration systems. Knowledge workers, with higher education levels and profound knowledge reserves, view AI as an empowerment tool for knowledge deepening and innovation breakthroughs. After AI' s data analysis and complex task management functions are embedded in their workflows, employees optimize knowledge allocation and stimulate creative thinking by integrating technological resources (Wang & Xie, 2023; Dong et al., 2025). This collaboration model strengthens employees' trust in AI, believing that AI can extend professional capabilities, thereby more actively exploring AI applications in innovation scenarios. Based on COR theory' s resource gain logic, knowledge workers continuously accumulate knowledge capital through human-AI collaboration, deepening AI trust and forming a positive cycle of innovation capacity enhancement. In contrast, non-knowledge workers, limited by knowledge resources and physical constraints, are more inclined to view AI technology as a guarantee tool for repetitive task substitution and efficiency improvement (Chowdhury et al., 2022). AI automation processes and intelligent assistance tools can effectively compensate for their resource shortcomings in standardized operations, significantly improving task execution efficiency by reducing work intensity and operational errors. This collaboration model directly reduces employees'workload, allowing them to reallocate released psychological and physical resources back into work to improve job performance (Ma et al., 2024). Based on COR theory' s resource preservation logic, non-knowledge workers can effectively avoid resource loss risks through human-AI collaboration, achieving steady improvements in job performance. Therefore, we propose:

H13a: Employee category moderates the relationship between human-AI collaboration systems and job performance. Compared with knowledge workers, the impact of human-AI collaboration systems on job performance is stronger among non-knowledge workers.

H13b: Employee category moderates the relationship between human-AI collaboration systems and employee innovation. Compared with non-knowledge workers, the impact of human-AI collaboration systems on employee innovation is stronger among knowledge workers.

2.5.4 The Moderating Effect of Industry Attributes

From the COR theory perspective, industry attributes significantly influence resource acquisition, allocation, and utilization in human-AI collaboration systems. This study divides sample enterprises into three categories based on industry attributes: high-tech industry, manufacturing, and service industry, emphasizing differences in production, service, and value creation across industries. The high-tech industry, with knowledge-intensive activities at its core, has production processes highly dependent on complex knowledge innovation and iteration (Frey & Osborne, 2017). Employees in this industry can use AI to handle repetitive tasks and optimize complex data management, releasing psychological and time resources to focus on creative thinking and high-value activities. This resource reconfiguration significantly reduces resource dissipation rates and enhances employees' innovation capacity and work efficiency through concentrated resources. Moreover, employees in high-tech industries typically possess higher levels of knowledge reserves and technological adaptability, enabling them to demonstrate stronger AI trust in dynamic resource transformation, thereby further enhancing collaborative effectiveness output (Frey & Osborne, 2017). In contrast, manufacturing, dominated by standardized production, focuses on labor costs and efficiency as core concerns. AI is mostly applied to production process automation. Although it can reduce operational errors and improve efficiency, employees find it difficult to achieve large-scale knowledge innovation through human-AI collaboration due to the fixed nature of production processes. The service industry's value creation process highly depends on employee quality and customer feedback, which may cause employees to focus more on AI' s impact on interpersonal interaction when facing AI technology. Over-reliance on AI may weaken service humanization and lead to customer satisfaction decline. This industry characteristic can easily trigger employees' concerns about service quality loss of control, causing them to experience more pressure and anxiety in human-AI collaboration, thereby reducing job performance and suppressing innovation motivation. Therefore, we propose:

H14a: Industry attributes moderate the relationship between human-AI collaboration systems and job performance. Compared with manufacturing and service industries, the impact of human-AI collaboration systems on job performance is stronger in high-tech industries.
H14b: Industry attributes moderate the relationship between human-AI collaboration systems and employee innovation. Compared with manufacturing and service industries, the impact of human-AI collaboration systems on employee innovation is stronger in high-tech industries.

2.5.5 The Moderating Effect of Cultural Background

According to COR theory, cultural background, as a macro-level institutional resource, profoundly influences employees' resource perception, acquisition strategies, and transformation efficiency in AI collaboration. Different cultural value systems shape individuals' cognitive frameworks and behavioral norms, causing employees to exhibit differentiated resource dynamic patterns in human-AI collaboration. In Western cultures, individualism and low power distance tend to emphasize individual value and autonomy, so employees are more likely to view AI as a resource gain tool. This cultural environment encourages employees to actively explore autonomous AI applications—for example, using data analysis tools to optimize personal workflows—thereby releasing time and cognitive resources for innovation activities (Darwish & Huber, 2013). Simultaneously, employees view AI as a career development opportunity, believing in its empowering effect on personal capabilities to help improve individual efficiency and innovation capacity. In contrast, Eastern cultures' collectivism and high power distance emphasize team collaboration and hierarchical relationships. In this cultural context, employees usually rely more on managers' or organizational guidance for AI applications, tending to view AI as a tool for enhancing team effectiveness rather than a simple means of personal resource gain. In this scenario, employees may worry that over-reliance on AI will lead to skill devaluation or weakened interpersonal collaboration relationships, directly increasing job insecurity. Due to concerns about resource loss, employees in Eastern cultures often exhibit more conservative attitudes and show less autonomy and innovation drive. Therefore, cultural background moderates the relationship between human-AI collaboration systems and job performance/employee innovation by influencing employees' perception of AI resource gain or loss. Thus, we propose:

H15a: Cultural background moderates the relationship between human-AI collaboration systems and job performance. Compared with Eastern culture, the impact of human-AI collaboration systems on job performance is stronger in Western cultural contexts.
H15b: Cultural background moderates the relationship between human-AI collaboration systems and employee innovation. Compared with Eastern culture, the impact of human-AI collaboration systems on employee innovation is stronger in Western cultural contexts.

3 Research Methodology

This study follows Lipsey and Wilson' s (2001) meta-analysis procedures, which mainly include the following steps:

3.1 Literature Search and Screening

This study conducted a systematic search of relevant literature on human-AI collaboration. Based on the search strategies of scholars such as Vaccaro et al. (2024), Yin and Niu (2024), and Jiang et al. (2024), we selected core keywords and subject terms. In Chinese databases (CNKI, VIP, Wanfang, etc.), we precisely searched keywords such as "human-machine collaboration," "human-machine interaction," "human-machine relationship," and "human-machine coordination," combined with a search strategy of "artificial intelligence and employee" for subject retrieval. In English databases (Google Scholar, EBSCO, Web of Science, etc.), we used keywords such as "human-AI/robot/machine collaboration," "human-AI/robot/machine interaction," "human-AI/robot/machine relationship," and "human-AI/robot/machine cooperation," combined with the core combination of "AI/artificial intelligence and employee/worker" for exact matching retrieval. To ensure research breadth and depth, we also searched representative scholars in the human-AI collaboration field for their relevant published literature on this topic. Additionally, following Su et al.' s (2024) approach, we systematically searched conference papers, dissertations, and working papers from important domestic and international academic conferences in organizational and management fields. This study selected 2014 as the starting year for retrieval, as research after this year has focused more on the impact of human-AI collaboration on employee performance and innovation, providing a more relevant literature foundation for this study. The retrieval time range was from January 2014 to December 2024, yielding a total of 4,035 relevant documents, including 1,365 Chinese documents and 2,670 English documents.

After completing the literature search, we screened documents according to the following criteria: (1) Studies must simultaneously address both "human-AI collaboration" and "job performance" or "employee innovation" themes; (2) Documents must be empirical studies, excluding reviews, case studies, and pure theoretical analyses; (3) Documents must report sample sizes and include correlation coefficients, or provide t-values, F-values, chi-square statistics, or other calculable data; (4) Documents must be independent studies based on different samples to avoid duplicate publication. After screening and elimination, this study identified a total of 79 Chinese and English documents (21 Chinese, 58 English), including 106 independent empirical studies with 54,726 samples and 172 effect sizes.

For mediation effect testing, correlation coefficients between other variables were also required. Following Li et al.' s (2023) approach, we obtained correlation coefficients for job insecurity with job performance, job insecurity with employee innovation, job insecurity with trust, and job performance with employee innovation from studies by Sverke et al. (2002), Lim et al. (2024), Cheng and Chan (2008), and Ng (2017). For variables without available correlation coefficients, we supplemented by collecting 24 additional documents and conducting meta-analysis to obtain correlation coefficients. The literature search and screening process is shown in Figure 2 [Figure 2: see original paper].

3.2 Data Coding and Processing

This study developed a coding manual and had two scholars conduct independent coding. We extracted study descriptors (e.g., author, title, journal) and effect size statistics (e.g., correlation coefficients, reliability coefficients, sample sizes) from the 79 screened documents. Although most empirical studies included only one independent sample, some documents contained multiple independent samples requiring separate coding. The study also coded five potential moderating variables in detail: employee gender, age, employee category, industry attributes, and cultural background. In the initial coding review, the consistency rate reached 86.74%. Inconsistencies were mainly due to coding errors and differences in understanding coding content, which were resolved through discussion and verification, resulting in a complete coding table.

4 Results

4.1 Publication Bias Test

To ensure result robustness, this study adopted Fail-Safe N test, Egger' s regression coefficient test, and Begg rank correlation test to further assess publication bias. As shown in Table 1 , Fail-Safe N values were all greater than 5K + 10; Begg rank correlation test results also did not reach significance levels ($p > 0.05$), indicating no serious publication bias in this study. Egger' s test results showed that there might be some publication bias between AI crisis consciousness and employee performance ($p = 0.044$). We further adopted p-curve analysis to examine the impact of publication bias on meta-analysis results for AI crisis consciousness and employee innovation. The test results are shown in Figure 3 [Figure 3: see original paper]. The data showed a right-skewed distribution, with all 10 significant samples having evidential value ($p < 0.025$), supporting the existence of true effects, and significant results were mostly concentrated in low p-value intervals. Therefore, this study does not have serious publication bias issues.

4.2 Homogeneity Test and Main Effect Analysis

Homogeneity tests typically use Q statistics and I^2 indicators to assess sample homogeneity levels. When $Q > k\text{-}1$, $I^2 > 0.75$, and p-values are significant, samples exhibit significant heterogeneity, and a random effects model (R) is adopted; otherwise, a fixed effects model (F) is used. Results shown in Table 2 indicate that Q values for all variables were significant ($P < 0.05$), showing obvious heterogeneity among variables. Additionally, I^2 values for all variables were above 75%, indicating significant heterogeneity among variables, thus a random effects model was adopted. Meanwhile, main effect analysis showed that point estimates were all significant, indicating that human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs have positive impacts on job performance, while AI crisis consciousness has a negative impact on job performance. Human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs have positive impacts on employee innovation, while AI crisis consciousness has a negative impact on employee innovation. Therefore, hypotheses H1a-H3d are supported.

4.3 Mediation Effect Test

Mediation effect testing was conducted using meta-analysis with a structural equation model approach to examine the potential mediating effects of employee job insecurity and AI trust on the relationships between various indicator variables under human-AI collaboration systems and job performance/employee innovation. This mainly included two stages. Stage one used multivariate meta-analysis to obtain a joint correlation matrix (see Table 3). Stage two used Mplus 8.0 to input the joint correlation matrix into a structural equation model to test the mediation model. Based on the mediation analysis results, we used R 4.3.2 software to conduct Monte Carlo confidence interval tests for indirect effects.

As shown in Figure 4 [Figure 4: see original paper], job insecurity is negatively and significantly correlated with job performance (β = -0.05, p < 0.001) and employee innovation (β = -0.23, p < 0.001); AI trust is positively and significantly correlated with job performance (β = 0.44, p < 0.001) and employee innovation (β = 0.38, p < 0.001). Human-AI collaboration applications (β = 0.18, p < 0.001), AI autonomy (β = 0.29, p < 0.001), AI anthropomorphism (β = 0.31, p < 0.001), and employee AI crisis consciousness (β = 0.26, p < 0.001) significantly positively affect job insecurity, while employee KSAs significantly negatively affect job insecurity (β = -0.31, p < 0.001). Human-AI collaboration applications (β = 0.38, p < 0.001), AI autonomy (β = 0.56, p < 0.001), AI anthropomorphism (β = 0.42, p < 0.001), and employee KSAs (β = 0.48, p < 0.001) significantly positively affect AI trust, while employee AI crisis consciousness significantly negatively affects AI trust (β = -0.46, p < 0.001).

Results shown in Table 4 indicate that in studying the impact mechanisms of human-AI collaboration systems on employee work effectiveness, mediation effect analysis reveals that human-AI collaboration applications, AI autonomy, AI anthropomorphism, employee KSAs, and AI crisis consciousness have indirect effects on job performance through job insecurity of -0.01, -0.01, -0.01, 0.01, and -0.01 respectively, and indirect effects on employee innovation of -0.04, -0.07, -0.07, 0.07, and -0.06 respectively. Job insecurity plays a partial mediating role, thus supporting H4a-H6d. Human-AI collaboration applications, AI autonomy, AI anthropomorphism, employee KSAs, and AI crisis consciousness have indirect effects on job performance through AI trust of 0.15, 0.21, 0.16, 0.18, and -0.18 respectively, and indirect effects on employee innovation of 0.17, 0.25, 0.18, 0.21, and -0.20 respectively. AI trust plays a partial mediating role, thus supporting H7a-H9d. These results indicate that various indicator variables in human-AI collaboration systems can produce both negative and positive dual effects by influencing employee job insecurity and AI trust through two different pathways.

Finally, following Wen et al.' s (2022) method for comparing mediation effects, when the effect values of two mediation pathways are opposite, the absolute difference between mediation effects should be used for comparison. Results show that compared with job insecurity, human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs more positively affect job performance through AI trust, with differences in mediation effects between AI trust and job insecurity of 0.14 (p < 0.001, 95% CI [0.13, 0.15]), 0.20 (p < 0.001, 95% CI [0.19, 0.21]), 0.15 (p < 0.001, 95% CI [0.14, 0.16]), and 0.17 (p < 0.001, 95% CI [0.16, 0.18]) respectively. They also more positively affect employee innovation through AI trust, with differences of 0.13 ($p < 0.001$, 95% CI [0.12, 0.13]), 0.18 ($p < 0.001$, 95% CI [0.17, 0.19]), 0.11 ($p < 0.001$, 95% CI [0.10, 0.12]), and 0.14 ($p < 0.001$, 95% CI [0.13, 0.14]) respectively. Additionally, compared with job insecurity, AI crisis consciousness more negatively affects job performance and employee innovation through AI trust, with differences of -0.16 ($p < 0.001$, 95% CI [-0.15, -0.17]) and -0.14 ($p < 0.001$, 95% CI [-0.13, -0.15]) respectively. In summary, H10a and H10b are supported.

4.4 Moderation Effect Test

This study examined the moderating effects of two statistical characteristic variables—employee gender and age—on the relationships between variables under human-AI collaboration systems and employee work effectiveness. Meta-regression analysis was conducted with the proportion of male employees and average age as predictor variables. Moderation effect analysis results shown in Table 5 indicate that employee gender does not significantly moderate the relationships between relevant variables under human-AI collaboration systems and job performance/employee innovation ($p > 0.05$, 95% CI includes 0). Similarly, employee age does not significantly moderate these relationships ($p > 0.05$, 95% CI includes 0). Therefore, H11a, H11b, H12a, and H12b are not supported.

Due to data limitations preventing comparative analysis across all dimensional variables under human-AI collaboration systems, this study followed Duan et al. (2025) and Su et al. (2024) to test the moderating effects of human-AI collaboration systems on job performance and employee innovation. As shown in Table 6 , this study selected three contextual variables from micro, meso, and macro perspectives (employee category, industry attributes, and cultural background) to test their moderating effects on the relationships between human-AI collaboration systems and job performance/employee innovation. Results are as follows: (1) At the micro-level, employee category significantly moderates the relationship between human-AI collaboration systems and job performance ($Q = 7.42$, $p < 0.05$), with $|rkw| = |0.21| < |rnkw| = |0.44|$ (where rkw and rnkw refer to correlation coefficients between human-AI collaboration systems and job performance among knowledge and non-knowledge workers respectively), indicating that human-AI collaboration systems have a stronger positive impact on job performance among non-knowledge workers than among knowledge workers. Employee category also significantly moderates the relationship between human-AI collaboration systems and employee innovation ($Q = 8.746$, $p < 0.05$), with $|rkw| = |0.47| > |rnkw| = |0.24|$, indicating that human-AI collaboration systems have a stronger positive impact on innovative behavior among knowledge workers than among non-knowledge workers. Therefore, H13a and H13b are supported. (2) At the meso-level, industry attributes significantly moderate the relationships between human-AI collaboration systems and both job performance and employee innovation. For job performance ($Q = 9.50$, $p < 0.05$) and employee innovation ($Q = 6.67$, $p < 0.05$), $|rhw| = |0.57| > |rsw| = |0.38| > |rmw| = |0.27|$, and $|rhi| = |0.50| > |rsi| = |0.34| > |rmi| = |0.27|$ (where rhw, rmw, and rsw refer to correlation coefficients between human-AI collaboration systems and job performance in high-tech, manufacturing, and service industries respectively; rhi, rmi, and rsi refer to correlation coefficients between human-AI collaboration systems and employee innovation in these industries), indicating that human-AI collaboration systems have stronger impacts on both job performance and employee innovation in high-tech industries than in manufacturing and service industries. Therefore, H14a and H14b are supported. (3) At the macro-level, cultural background significantly moderates the relationship between human-AI collaboration systems and job performance ($Q = 7.032$, $p < 0.05$), with $|rww| = |0.51| > |rew| = |0.26|$ (where rww and rew refer to correlation coefficients between human-AI collaboration systems and job performance under Western and Eastern cultural influences respectively), indicating that human-AI collaboration systems have a stronger impact on job performance in Western cultures than in Eastern cultures. However, cultural background does not significantly moderate the relationship between human-AI collaboration systems and employee innovation ($p > 0.05$). Therefore, H15a is supported, while H15b is not supported.

5 Conclusions and Discussion

This study tested the impact of human-AI collaboration systems on employee work effectiveness through meta-analysis of 106 independent samples from 79 domestic and international studies. Results indicate that human-AI collaboration systems have a "double-edged sword" effect. Specifically, human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs positively influence employee work effectiveness, likely because human-AI collaboration applications enable employees to fully utilize AI tools to unleash potential, thereby improving job performance and innovation capacity (Soomro & Pitafi, 2024). AI autonomy not only reduces human error but also improves work quality and efficiency, while releasing employee time for high-value activities and capability enhancement by sharing repetitive tasks (He et al., 2024). AI anthropomorphism enhances employee work experience through natural interaction methods, promoting problem-solving abilities and creative thinking (Zhang et al., 2025a). Additionally, employees with AI KSAs can more effectively apply AI technology to improve job performance and innovation capacity due to their technical skills and understanding of AI (Chen et al., 2024a; AL-Khatib, 2024). However, this study also found that AI crisis consciousness has a significant negative impact on employee work effectiveness. Employees may develop resistance and distrust due to concerns about AI threatening their job security, thereby reducing work enthusiasm and suppressing work efficiency and innovation performance (Zang et al., 2024; Dong et al., 2025).

Regarding specific mechanisms, this study found that employee work effectiveness in human-AI collaboration systems is significantly influenced by the dual-pathway mediating effects of job insecurity and AI trust. In the complex ecology of human-AI collaboration, job insecurity mostly stems from employees' stress reactions to the unknown of career boundary reshaping during the initial stage of technology introduction, which impacts work effectiveness in the short term (Wu et al., 2024; Zang et al., 2024). However, as employees gradually adapt to technological development and recognize AI' s potential value, their trust in AI gradually strengthens, thereby compensating for and surpassing the negative impact of insecurity. AI trust not only helps employees use AI tools more proactively but also enhances their sense of control over work tasks and trust in the organization, thereby promoting work effectiveness improvement (Zhou et al., 2024; Shahzad et al., 2025). Comparative analysis reveals that the mediating effect of AI trust is stronger than that of job insecurity. Related research indicates that job insecurity experienced by employees can reduce their performance, but this negative effect is often stage-specific, representing an initial reaction to new technology impact. As time passes and understanding of AI deepens, if trust can be established, positive effects will gradually emerge and become dominant (Khan et al., 2025), which explains why the mediating effect of trust is significantly stronger than that of job insecurity.

Furthermore, the study found that employee gender and age do not significantly moderate work effectiveness under human-AI collaboration systems, reflecting the joint effects of gender equality and technology popularization. In recent years, with continuous advancement of gender equality, contemporary women have gradually equaled men in technology application and adaptation capabilities, weakening traditional gender stereotypes. Women' s acceptance and learning ability for new technologies in the workplace have approached or reached men' s levels (Huyer & Nuñez, 2022). Moreover, human-AI collaboration systems provide more standardized and structured workflows, which may further reduce the impact of gender differences on technology adaptation processes. The non-significant moderating effect of age on work effectiveness may be related to the gradual narrowing of generational differences. With the popularization of information technology education and the promotion of lifelong learning concepts in aging societies, the gap in technology adaptability among employees of different age groups has significantly decreased (Ranta & Ylinen, 2023). Additionally, compared with knowledge workers, human-AI collaboration systems have a more significant effect on improving job performance among non-knowledge workers. This may be because non-knowledge workers' work content is usually dominated by repetitive, standardized tasks, and AI technology introduction can significantly reduce their workload and improve efficiency. Meanwhile, AI technical support as an external resource can provide real-time feedback and support, helping non-knowledge workers adapt to work requirements faster, compensating for their skill and experience deficiencies, and enabling them to benefit more from AI system support (Kim et al., 2022). In contrast, human-AI collaboration systems have a more significant effect on improving innovation capacity among knowledge workers than non-knowledge workers. This may be because knowledge workers' jobs usually have higher complexity and creativity, and AI can provide data analysis, pattern recognition, and predictive support to stimulate their creativity (Dong et al., 2025). Moreover, knowledge workers' high skill levels and technology acceptance enable them to better transform AI technology into innovation outcomes.

Regarding macro factors such as industry and culture, compared with manufacturing and service industries, high-tech industries show more significant moderating effects on the relationship between human-AI collaboration systems and employee work effectiveness. This may be because high-tech enterprises typically possess advanced technical infrastructure, higher R&D investment, and flexible organizational structures that effectively support employees' innovation needs and challenges. High-tech industry work environments are usually full of uncertainty and complexity, which helps stimulate employee creativity and proactivity. Meanwhile, these industry enterprises generally encourage innovation in organizational culture and structure, enabling employees to fully utilize human-AI collaboration technology to improve work effectiveness (Wan et al., 2023). Cultural background only moderates the relationship between human-AI collaboration systems and job performance, but not the relationship with employee innovation. The reason may be that both Eastern and Western cultures typically standardize the application and resource allocation of human-AI collaboration, which reduces the moderating effect of cultural background on innovation (Tenakwah et al., 2022). Moreover, job performance evaluation is usually more objective and quantifiable, making the influence of cultural background easier to manifest through these standards, while innovation evaluation involves more subjective and complex factors, making the influence of cultural background more indirect. Finally, globalization and cultural exchange between East and West have significantly improved Eastern cultures' technology acceptance, gradually weakening the impact of cultural differences on the relationship between human-AI collaboration and employee innovation.

5.1 Theoretical Contributions

The theoretical contributions of this study include: (1) Systematically exploring the impacts and differences of human-AI collaboration systems on employee work effectiveness. Existing research mostly focuses on the positive impacts of human-AI collaboration, emphasizing AI tools' performance enhancement effects (Shi & Zhou, 2024; Vaccaro et al., 2024), but pays less attention to the potential double-edged sword effects of human-AI collaboration systems. This study clearly identifies the positive effects of human-AI collaboration applications, AI autonomy, AI anthropomorphism, and employee KSAs on job performance and innovation, which theoretically echoes He et al.' s (2024) model from technology empowerment to capability release. Simultaneously, the study reveals the negative effects of AI crisis consciousness on these outcomes, supplementing relevant research on employee psychological aspects in human-AI collaboration contexts. (2) Based on COR theory, it reveals the dynamic balance of dual-pathway mediation. This study finds that human-AI collaboration systems can not only enhance employees' AI trust to improve job performance and stimulate innovation but may also increase job insecurity to reduce job performance and innovation, with the overall positive impact through AI trust being greater than the negative impact through job insecurity. Although AI use may trigger insecurity in the short term (Wu et al., 2024), the establishment of long-term trust can significantly offset negative effects (Zhou et al., 2024). This result expands the application of COR theory in human-AI collaboration scenarios, revealing the compensation mechanism of "resource acquisition" (trust enhancement) over "resource loss" (security reduction), providing a new perspective for explaining the dynamic process of technology acceptance. (3) From micro, meso, and macro levels, it clarifies moderating effects from individual-organization-environment three-dimensional perspectives. At the micro individual level, it breaks traditional assumptions that gender and age determine technology adaptation, finding that gender equality advancement (Huyer & Nuñez, 2022) and lifelong learning popularization (Poquet & De Laat, 2021) weaken generational differences and narrow gaps between gender and age groups in technology adaptation. Meanwhile, the study finds that knowledge and non-knowledge workers have different paths to work effectiveness improvement in human-AI collaboration. Non-knowledge workers can significantly improve work efficiency through AI substitution of standardized tasks (Kim et al., 2022), while knowledge workers can stimulate creative thinking through AI assistance in creative tasks (Dong et al., 2025). At the meso organizational level, it confirms that high-tech industries, due to complete technical infrastructure and active innovation culture (Wan et al., 2023), can better unleash human-AI collaboration effectiveness, supplementing the moderating mechanism of industry characteristics on technology application. At the macro environmental level, cultural background only moderates performance but not innovation, indicating that cultural background's moderation on performance is explicit and context-dependent, while its influence on innovation is implicit and value-oriented, providing a key analytical dimension for understanding cross-cultural adaptation of human-AI collaboration.

5.2 Practical Implications

The practical implications of this study include: (1) Managers need to recognize the "double-edged sword" effect of human-AI collaboration systems. On one hand, promote collaborative AI culture, uphold the "AI empowerment" concept, strengthen employees' trust in AI through training (e.g., establishing real-time feedback mechanisms, sharing success cases), and enhance employees' control capabilities when using AI. On the other hand, establish psychological safety buffer mechanisms, alleviate employees' crisis consciousness through intervention strategies such as career development planning and skill reshaping programs, position AI as a capability expansion partner rather than a replacement, ensure employees' dominance in work control and decision-making rights, and reduce negative emotion generation. (2) Design differentiated AI support solutions. Managers should not treat all employees as a single category but should design different AI system application schemes based on employee category differences. For example, for non-knowledge workers, focus on repetitive task automation, provide standardized AI tools to improve efficiency, and compensate for skill gaps through real-time technical support; for knowledge workers, emphasize AI' s innovation assistance functions, design open collaborative interfaces based on their high technology acceptance, and promote human-AI co-creation. Through rational allocation of employee resources, form complementary teams, promote knowledge flow and sharing, and thereby achieve dual improvement in job performance and innovation capacity. (3) Leverage human-AI collaboration advantages according to industry characteristics and cultural backgrounds. Governments should introduce policies supporting AI technology application across industries, such as tax incentives and technology subsidies. Enterprises should increase AI R&D investment to quickly respond to technology iterations, relying on complete technical infrastructure and active innovation culture to drive cutting-edge technology research and application, thereby unleashing human-AI collaboration effectiveness.

5.3 Research Limitations and Future Directions

This study has some inevitable limitations that need improvement in future research: (1) This study' s literature collection was limited to Chinese and English documents, not covering studies in other languages, which may cause literature selection bias. Although this study included relevant results from public preprints and applied consistent quality screening processes as for published literature, for unpublished non-preprint documents, due to cross-database retrieval technical barriers, permission restrictions, and publication bias risks, they were not included in the analysis. Future research could explore cooperation with academic institutions to obtain internal reports or use AI translation tools to expand multi-language literature analysis, but attention must be paid to quality verification and sample representativeness issues for non-public documents. (2) From a systematic perspective, this study divides the "human-AI-organization" interactive system into human-AI collaboration applications, AI characteristics (autonomy and anthropomorphism), and employee characteristics (KSAs and AI crisis consciousness), but fails to comprehensively cover all possible influencing variables, such as perceived usefulness and perceived ease of use in technology acceptance models, which may significantly affect AI collaboration system effectiveness. Future research could further explore the effects of other machine and employee characteristics (e.g., AI transparency, employee personality), organizational contextual factors (e.g., organizational AI readiness), and task types (e.g., interaction modes and task objectives). (3) Although meta-analysis can synthesize multiple research results, it is difficult to fully reveal complex relationships between variables. To better understand these effects and their interactions, future research should consider combining meta-analysis with other statistical methods. Moreover, this study mainly focused on the impacts of human-AI collaboration systems on job performance and employee innovation, without considering other outcome variables, such as how human-AI collaboration affects interpersonal collaboration and interaction within organizations (Chen & Lü, 2019). Given that technological progress is typically an important driver of organizational interpersonal relationship evolution (Chen et al., 2022), and the aggregation and emergence of human capital resources that generate performance and innovation greatly depend on effective collaboration and skill complementarity among members based on interpersonal networks (Huang et al., 2025), future research could pay more attention to the substitution and competition between "human-AI relationships" and "interpersonal relationships" brought by human-AI collaboration systems and how they affect organizational performance and innovation—this would be a very important and interesting topic. (4) This study explored variable relationships based on cross-sectional data, without fully considering dynamic changes under the background of rapid AI technology iteration. As employees accumulate AI use experience and organizational transparency mechanisms improve, the mediation pathways of job insecurity and AI trust may exhibit dynamic evolution characteristics. Future research could adopt longitudinal tracking or multi-time-point research designs to construct dynamic models revealing the changing patterns of human-AI collaboration mechanisms at different stages. (5) This study only considered the moderating effects of employee gender, age, employee type, industry attributes, and cultural background, without involving factors such as AI type, person-job fit, and task workload. For example, AI system types (e.g., chatbots, large language models) may produce differential impacts on the effects of human-AI collaboration systems on job performance and employee innovation. Future research should further test the effects of these potential moderating variables through meta-analysis to provide more comprehensive understanding. Moreover, in studies included in the meta-analysis, respondents' gender and age are often non-randomly selected, which affects the rigor of moderation effects; therefore, the moderation effects in this study need to be interpreted with caution. (6) This study focused on moderation effects in main effects without deeply exploring moderated mediation effects. The main reasons are: first, existing literature on moderated mediation mechanisms of human-AI collaboration systems is relatively scarce, lacking mature theoretical frameworks as analytical foundations; second, limited by meta-analysis data structure and statistical methods, it is difficult to effectively test moderated mediation models directly. Future research could combine empirical studies and use structural equation modeling methods to deeply analyze complex interaction mechanisms among variables.

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(* indicates literature included in the meta-analysis)

Note: Figure translations are in progress. See original paper for figures.