Dancing with AI: A systems perspective on AI-employee collaboration

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Abstract

AI-employee collaboration is an interactive system composed of "AI-human-organization" aimed at efficiently completing tasks. Promoting AI-employee collaboration is crucial for advancing the deep integration of AI with the real economy, as well as for employees' mental health and career development in the digital era. The interactive relationship between AI and employees is intricate and complex; existing research exhibits fragmented characteristics, and there is a lack of holistic understanding of AI-employee collaboration. Therefore, it is necessary to systematically review relevant research on AI-employee collaboration based on clarifying related concepts. Through a systematic review of relevant research, this study clarifies the connotations of AI and AI-employee collaboration, identifies the constituent elements of the AI-employee collaboration system, analyzes the roles and impacts of these elements, and further constructs a research framework from a systematic perspective. Finally, future research prospects are proposed based on the AI-employee collaboration research framework.

Full Text

Dancing with AI: AI-Employee Collaboration from a Systemic Perspective

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Abstract

AI-employee collaboration constitutes an interactive system comprising "AI-human-organization" aimed at efficiently completing tasks. Fostering AI-employee collaboration is crucial for advancing the deep integration of AI with the real economy and for safeguarding employee mental health and career development in the digital era. The interaction between AI and employees is intricate and multifaceted, yet existing research remains fragmented, lacking a holistic understanding of AI-employee collaboration. Therefore, a systematic review of relevant literature is necessary to clarify core concepts and synthesize current knowledge. Through a comprehensive systematic review, this paper clarifies the conceptual boundaries of AI and AI-employee collaboration, identifies the constituent elements of the AI-employee collaboration system, analyzes the interactions among these elements, and constructs an integrated research framework based on a systemic perspective. Finally, future research directions are proposed based on this framework.

Keywords: artificial intelligence; AI-employee collaboration; systemic perspective; research framework; I–P–O

1. Preamble

As a critical driving force for technological leaps, industrial optimization, and overall productivity gains, AI's foundational and pivotal role is becoming increasingly prominent. However, a pressing challenge for AI industry development is how to facilitate the practical implementation of various AI technologies and promote their integration with the real economy. At the micro level, while numerous organizations actively embrace AI, many have encountered failures in their digital transformation journeys amidst the dizzying wave of technological change (Canhoto & Clear, 2020). Many enterprises invest substantial resources in AI yet fail to reap expected returns, sometimes even triggering negative consequences (Fountaine et al., 2019). A Deloitte survey of 152 AI projects found that 47% experienced difficulties in AI-employee collaboration. Similarly, the *China Digital Economy Development Observation Report* revealed that although 64% of executives promoted AI initiatives, only 12% achieved effective collaboration between AI and employees. The root cause lies primarily in the tension between the structural changes brought by AI and employees' cognitive, emotional, and behavioral responses, which prevents the formation of enduring, stable collaborative relationships between AI and employees (Xie et al., 2021). Therefore, uncovering the underlying mechanisms of AI-employee collaboration is essential for helping organizations optimize such collaborations and enhancing AI's organizational effectiveness.

Against this backdrop, research on AI in organizations has flourished. As a foundational technology, AI can be applied in diverse ways, with different application contexts attracting distinct research foci. AI can operate independently (e.g., AI-driven automation systems), serve as a manager (e.g., algorithmic management) performing planning, execution, control, and performance feedback functions (Tong et al., 2021), or act as a colleague or assistant collaborating with employees on tasks (Jia et al., 2023). However, existing literature has not systematically distinguished among these different AI applications when elaborating on the conceptual connotations of AI and AI-employee collaboration, leading to conceptual ambiguity and confusion. Moreover, AI-employee collaboration research exhibits interdisciplinary fragmentation and complexity, characterized by inconsistent research paradigms, unclear theoretical foundations, and poorly articulated mechanisms. Although several review articles have addressed related issues (e.g., Seeber et al., 2020; Tsai et al., 2023), none have systematically synthesized existing research to construct a comprehensive research framework that clarifies the constituent elements and internal mechanisms of AI-employee collaboration, leaving scholars without a holistic grasp of the field's current state and future trajectory.

In light of these gaps, this paper conducted a comprehensive literature search on AI-employee collaboration (search procedures and criteria are shown in). Following Webster and Watson's (2002) recommendations, we coded publication information, theoretical foundations, and core research findings, then organized the content and constructed a research framework using systematic review methods. This paper first elaborates on the concept, connotation, and dimensions of workplace AI and AI-employee collaboration. Second, based on a systemic analysis perspective of AI-employee collaboration, we review the input elements, process variables, and output outcomes of the AI-employee collaboration system, and construct a research framework accordingly. Finally, we propose future research directions based on this framework.

These efforts will deepen our systematic understanding of AI-employee collaboration, advance organizational AI research, and help organizations optimize AI-employee collaboration in practice to enhance AI's organizational effectiveness.

Table 1. Search Procedures and Criteria

Step	Description
Databases	(1) Web of Science Core Collection SSCI database; (2) CNKI CSSCI database
Search Terms	TS=(Artificial intelligence OR Human-AI collaboration OR Human-AI interaction OR Human-robot collaboration); Chinese search terms were identical
Screening Process	(1) Limited research scope to business, management, and applied psychology; (2) Due to over 2,000 initial results, screened 38 key journals in management, HRM/OB, applied psychology, and MIS; (3) Reviewed titles and abstracts to exclude duplicates and irrelevant studies; (4) Used "snowballing" to trace citations and identify missing relevant studies

Step	Description
Final Sample	107 relevant articles

Final search date: May 15, 2023

2. The Concept, Connotation, and Dimensions of Workplace AI

As AI becomes widely deployed in workplaces, concepts such as "artificial intelligence," "robots," and "algorithms" proliferate, with AI assuming diverse functions and roles. This section first clarifies the concept, connotation, and dimensions of workplace AI, then elaborates on AI-employee collaboration as the focus of this study.

2.1 The Concept of Workplace AI

AI refers to machines capable of performing cognitive functions typically associated with human thought, such as learning, interaction, and problem-solving (Nilsson, 1971). In psychology and organizational management, AI's functions primarily include: collecting information from external sources (including natural language) or other computer systems; interpreting information, predicting patterns, deriving rules, or forecasting events; generating outputs, answering questions, or providing instructions to other systems; and evaluating the outcomes of its actions to improve its decision-making systems to achieve specific goals (Ferras-Hernandez, 2018). While visions of future technology imagine AI as general intelligence capable of performing all tasks as well as or better than humans, such strong or super AI remains immature due to technological limitations. This study focuses on weak or narrow AI currently widely used in organizations—AI-driven intelligent technologies that simulate fragments of human intelligence, such as facial recognition, speech recognition and comprehension, intelligent recommendation algorithms, and chatbots (Charlwood & Guenole, 2022).

In practice, AI manifests in three forms: robotic AI, virtual AI, and embedded AI (Glikson & Woolley, 2020). Robotic AI refers to physically embodied robots powered by AI technology, with social robots driven by AI (e.g., Pepper) receiving particular attention from organizational researchers. According to the International Federation of Robotics, social robots are physical entities that perform useful tasks for humans or equipment, while industrial robots are automatically controlled, reprogrammable multipurpose manipulators (IFR, 2022). The former is AI-driven, whereas the latter is pre-programmed (Yam et al., 2022). Virtual AI refers to virtual agents powered by AI without physical form, such as ChatGPT, AlphaGo, and Siri. Both robotic and virtual AI are machines, software, or hardware agents manufactured using AI theories and technologies capable of autonomous activity, collectively termed agent AI or intelligent agents (Gong, 2023). Finally, embedded AI lacks visual representation or distinct identity, being integrated into various applications such as search engines and GPS maps. Embedded AI is "invisible" to users, who may be unaware of its existence (Glikson & Woolley, 2020).

2.2 The Connotation of AI-Employee Collaboration

Traditional perspectives on technology-work relationships tend to 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 examines how employees use technology to facilitate team communication (Bechky, 2003). Both perspectives, however, privilege human agency while neglecting AI's agency. To overcome this limitation, Anthony et al. (2023) integrated distributed cognition theory and actor-network theory to propose a systemic analytical perspective on AI-employee collaboration (hereafter "systemic perspective"). This perspective treats AI as an actor equivalent to users and organizations, arguing that AI, users, and organizations jointly drive AI's design, implementation, and use. From this systemic perspective, AI-employee collaboration is an interactive system composed of "AI-human-organization" aimed at efficiently completing tasks (Anthony et al., 2023). Accordingly, this paper adopts the I-P-O paradigm commonly used in systems research (Ilgen et al., 2005) to construct a research framework for AI-employee collaboration from three dimensions: input (comprising AI, employees, and organization as three actors), process (encompassing task configuration in AI-employee collaboration), and output (including impacts on AI, employees, and organization).

In the AI-employee collaboration system, AI refers to software and hardware powered by artificial intelligence technology that can assist or cooperate with humans in performing tasks (Moussawi et al., 2020). This type of AI differs from AI-driven automation systems and AI-driven algorithmic management, typically serving as assistants or colleagues that collaborate with employees to complete tasks. Consequently, studies variously refer to it as AI assistants (Jia et al., 2023), AI colleagues (Savela et al., 2021), or AI team members (Seeber et al., 2019); this paper uses "AI" as the general term. This study covers not only common agent AI such as Amazon's Alexa and Microsoft's Cortana but also software systems driven by embedded AI. Although embedded AI lacks the physical or virtual form of an intelligent agent, it can still collaborate with employees—for example, AI assistants for online customer service that handle simple Q&A, collect customer information, generate customer profiles, and make preliminary assessments of purchase intent (Jia et al., 2023).

3. A Systematic Research Framework for AI-Employee Collaboration

From a systemic perspective, "AI-human-organization" jointly constitutes an interactive system that drives AI's design, implementation, and use around target tasks (Anthony et al., 2023). This means that AI, employees, and organization form the input side of the AI-employee collaboration system, operating independently yet jointly determining final outputs, while task characteristics serve as the process variable that mediates the transformation from input to output. Accordingly, this paper reviews existing literature across three dimensions: AI technical characteristics, employee individual factors, organizational contextual factors, and task configuration.

3.1 AI Technical Characteristics

As machine intelligence grows increasingly powerful, AI and humans are becoming more interpenetrating. From a systemic perspective, AI's agency is recognized as a primary driver of the collaboration system (Anthony et al., 2023). For instance, Seeber et al. (2019) found in interviews with 65 scientists that constructing AI-employee teams should first focus on technical characteristics such as appearance, visibility, and reliability. Yoon and Lee (2019) identified ten technical characteristics essential for successful human-AI interaction, including user-friendliness, accuracy, and reliability. Building on existing literature and drawing on Glikson and Woolley's (2020) dimensions of AI, this paper characterizes AI technical characteristics across three dimensions: physical attributes, mental attributes, and ethical attributes.

3.1.1 Physical Attributes AI's physical attributes are characterized primarily through tangibility and anthropomorphism. Tangibility refers to AI's virtual or physical form (Glikson & Woolley, 2020), while anthropomorphism denotes the degree to which AI's appearance, voice, expressions, gender, and other physical traits resemble humans (Alabed et al., 2022). Research on AI tangibility and anthropomorphism is relatively mature, yielding consistent conclusions. Studies show that physically embodied AI (e.g., robotic AI) garners greater trust and favorability than virtual AI (Glikson & Woolley, 2020; Alabed et al., 2022). Compared to industrial agents lacking human-like appearance, individuals more readily develop emotional identification with highly anthropomorphized agents, demonstrating higher tolerance for their failures and evaluating their social and functional value more positively (Yam et al., 2021; Belanche et al., 2021; Zhang & Wang, 2021). Features such as female gender, natural-sounding interactive voice, human-like age, and nicknames convey warmth, subtlety, and nuanced human scales that reduce the artificiality of AI and increase user acceptance (Borau et al., 2021; Guha et al., 2023).

While moderate human-likeness in agents can trigger empathy and enhance human-AI interaction, excessive anthropomorphism can produce the "uncanny valley" effect, causing psychological discomfort (Glikson & Woolley, 2020; Stein et al., 2020). The uncanny valley effect describes how positive emotions increase as an agent's appearance and behavior become more human-like, but beyond a certain peak, further similarity triggers feelings of eeriness (Mori, 2012). In summary, optimizing AI-employee collaboration requires industrial design that endows AI with moderate human-like features—appearance, expressions, voice, gender—to enhance employee trust, favorability, acceptance, and usage intention.

3.1.2 Mental Attributes Individuals typically perceive other entities' mental capacity from emotional and functional perspectives (Gray et al., 2007). Accordingly, AI's mental attributes are characterized through affectivity and functionality. Affectivity refers to AI's capacity for communication, emotional perception, and emotional support. With technological advances, AI with empathic intelligence and multi-sensory interaction can accurately recognize, understand, respond to, and even influence human emotions (Lv et al., 2022; Huang & Rust, 2018). Research demonstrates emotional contagion between AI and users (Chuah & Yu, 2021; Han et al., 2022), with highly affective AI transmitting positive emotions, reducing psychological distance, fostering intimate and stable relationships (Lee et al., 2022; Song et al., 2022), and enhancing user satisfaction (Gelbrich et al., 2020; Lee et al., 2022). Dutta et al. (2022) found that AI-employee communication creates a trusting atmosphere that enhances employee work engagement. Interestingly, low-affectivity AI, while unable to provide emotional support, can enhance employee adaptability precisely because of its non-human characteristics. For example, introducing low-affectivity AI into work teams strengthens employees' identification with human identity, reduces exclusion of out-groups (e.g., different races, religions, immigrants, sexual orientations), and mitigates intergroup bias and tension (Jackson et al., 2019). In human-AI interaction, because low-affectivity AI lacks empathy, morality, and social judgment capabilities (Giroux et al., 2022; Lanz et al., 2023), humans do not experience embarrassment, shame, or other negative emotions when interacting with it (Pitardi et al., 2022; Holthöwer & van Doorn, 2023). Consequently, when AI serves as an evaluator, employees' natural resistance and aversion are reduced due to the perception of AI as non-human (Desideri et al., 2019).

Functionality refers to AI's capacity for rational thinking, planning, and action (Yam et al., 2021). Highly functional AI assistants exhibit strong problem diagnosis and resolution capabilities, rapid response times, and high usability (Yoon & Lee, 2019), enhancing user identification and adoption intention (Belanche et al., 2020; Pantano & Scarpi, 2022). Guha et al. (2023) found that AI with diverse task execution capabilities and agility—indicators of high intelligence—elicits positive user evaluations. Glikson and Woolley (2020) noted that while employee trust in AI strengthens through interaction, AI's intelligence level moderates this process, with high-functioning AI typically developing high trust more rapidly. However, high-functioning AI also negatively impacts employees. When collaborating with AI, employees engage in social comparison, and high-functioning AI can damage self-esteem, trigger job insecurity, and provoke frustration, anger, and even workplace incivility and counterproductive behaviors (Seeber et al., 2019; Spatola & Normand, 2020; Wang et al., 2019; Yam et al., 2023). Low-functioning AI, prone to technical failures or deviations from programmed rules, directly and indirectly causes user dissatisfaction (Filieri et al., 2022). For instance, as intelligent autonomous service systems proliferate in service industries, frequent technical failures lead to service failures and customer complaints (Lü et al., 2021). When service employees collaborate with such systems, they face more angry and disappointed customers, intensifying emotional labor and psychological resource depletion, and fostering resistance to the system (Groth et al., 2019; Johnson et al., 2020).

These analyses reveal that AI's affective and functional impacts are neither singular nor linear but highly contextual. From a systemic perspective, AI design and implementation must fully consider user and organizational characteristics.

3.1.3 Ethical Attributes AI's ethical attributes are characterized primarily through transparency and reliability. China's Ministry of Science and Technology explicitly states in the *New Generation Artificial Intelligence Ethics Guidelines* that AI development should "enhance transparency and reliability" throughout design, implementation, and application. AI entrepreneurs and scientists including Elon Musk have called for pausing large-scale AI development until ethical risks and governance mechanisms are clarified, and Italy banned ChatGPT due to privacy violations. These developments underscore the critical importance of AI transparency and reliability.

Transparency refers to the visibility of a technology's underlying operational rules and internal logic to users (Glikson & Woolley, 2020). Since AI design is not "perfect" and failures inevitably occur in practice, high transparency helps governments and enterprises clarify and trace rights, responsibilities, and obligations among machines, designers, and other stakeholders, establishing definable regulatory standards. Transparency also enables employees to understand AI decisions and recommendations, allowing humans to "teach back" to AI through supervised learning to enhance its intelligence (Seeber et al., 2019). Additionally, transparency relates to safety and privacy concerns. Many AI systems require data input—including names, family relationships, work and home locations, and other private information—to develop personalized response patterns (Moussawi et al., 2020). When closed AI systems threaten employee safety and privacy, employees face legal and ethical issues, experience anxiety, reduce trust, and consequently diminish their willingness to use AI (Pillai & Sivathanu, 2020). While some argue that AI is a "black box" and complete transparency is unrealistic, complex methods can help employees understand its internal mechanisms (Charlwood & Guenole, 2022). For example, evaluation metrics such as SHAP values (Sundararajan & Najmi, 2020) have been developed to enhance model interpretability. In summary, optimizing AI-employee collaboration requires enhancing AI transparency and interpretability through both technical and institutional design, enabling employees to understand AI functions and outputs without specialized knowledge of internal structures.

Reliability refers to the accuracy, consistency, and stability of AI's functional and behavioral performance, as well as its practical deployability (Glikson & Woolley, 2020). According to *Research Progress and Trends in Intelligent Software Reliability*, AI reliability encompasses data reliability, model reliability, and platform reliability. As commercial AI systems grow more complex, involving substantial data resources, trade secrets, and employee privacy, workplace AI reliability becomes paramount. Will employees accept, use, and trust an AI that frequently makes mistakes and behaves erratically? The answer is clearly no. Moreover, society's tolerance for AI errors is far lower than for human errors. Esterwood and Robert (2023) found that in AI-employee collaboration, once AI makes three errors, employee trust becomes irreparable through any strategy. Robinette et al. (2017) discovered that in high-risk situations, participants lose trust in low-reliability AI. Some studies show that declines in AI behavioral consistency and stability affect trust more than declines in accuracy (Desai et al., 2013). Wang et al. (2022) found that employees' assessments of AI capabilities depend on AI reliability; when reliability is low, employees perceive AI as incompetent. Therefore, optimizing AI-employee collaboration requires prioritizing AI reliability testing, evaluation, and improvement to provide employees with stable, secure, and reliable AI systems.

3.2 Employee Individual Factors

From a systemic perspective, while AI is treated as a rational actor, human agency cannot be erased. The system is rooted in human-computer interaction and ultimately requires human participation; indeed, humans remain dominant in "weak AI" applications (Anthony et al., 2023). Consequently, AI-employee collaboration is influenced by employee characteristics (Chi et al., 2020). Based on a review of existing literature, this paper discusses employee individual factors across four dimensions: attitudes, KSAs, personality, and demographic characteristics.

3.2.1 Attitudes When employees embrace AI with innovative willingness and positive attitudes, they form better collaborative relationships with AI, strengthening their own identity and well-being while enhancing AI's organizational effectiveness (Savela et al., 2021; Zhao et al., 2021). Scholars have proposed the concept of STARA (smart technology, artificial intelligence, robotics, algorithms) awareness or AI awareness—employees' perceptions of how intelligent technologies affect career prospects (Brougham & Haar, 2017; Kong et al., 2021). High STARA awareness implies lower technology acceptance and more pessimistic career estimates, reducing AI acceptance and negatively impacting collaboration and employees themselves (Li et al., 2019). For example, Brougham and Haar (2017) found that STARA awareness weakens organizational commitment and career satisfaction, increasing turnover intentions and cynicism and depression.

Lingmont and Alexiou (2020) found that STARA awareness causes employee insecurity, while Kong et al. (2021) demonstrated that AI awareness leads to job burnout. Recent research has revealed the "bright side" of STARA and AI awareness. Studies of hospitality employees found that STARA and AI awareness can stimulate internal motivation and work engagement, enhancing employee productivity and creativity (Ding, 2021; Liang et al., 2022).

3.2.2 KSAs The introduction of workplace AI creates new demands for employee knowledge, skills, and abilities (KSAs). Only by continuously learning and updating KSAs can employees adapt to and master AI technology. Existing research focuses on two aspects: first, AI-related KSAs such as AI usage experience, AI familiarity, AI sensitivity, and AI literacy (Parker & Grote, 2022; Kim et al., 2022). Jaiswala et al. (2021) identified five essential skills for the digital intelligence era: data analysis, digital tool usage, complex cognition, decision-making, and continuous learning. Wilson and Daugherty (2018) noted that in collaborating with AI, employees need skills to train AI for specific tasks, explain AI's work, and ensure AI safety and reliability. Second, research examines general individual capabilities and qualities such as work ability, career construction capability, and communication skills (Wang et al., 2019; Basu et al., 2022; Guha et al., 2023). Jia et al. (2023) found that only employees with high work skills benefit from AI collaboration and enhance creativity. Huang and Rust (2018) argued that as AI technology penetrates human work domains, emotion—an ability that intelligent technology cannot effectively imitate—becomes key to human-AI complementarity. Therefore, managers should shift recruitment focus from analytical to interpersonal skills, while employees and educators should cultivate emotional intelligence and interpersonal abilities to learn how to collaborate with AI (Huang et al., 2019).

3.2.3 Personality Employees' diverse personality traits affect AI-employee interactions (Wang & Yao, 2022; Kim et al., 2022; Parker & Grote, 2022). For example, Oksanen et al. (2020) found that employees high in openness to experience more readily accept AI applications. Tang et al. (2022a) also examined the Big Five personality traits, finding that due to complementarity between AI and employees, AI helps employees low in conscientiousness enhance role breadth self-efficacy and reduce role ambiguity, thereby improving performance, while highly conscientious and orderly employees benefit less from AI collaboration. Tang et al. (2022b) revealed the role of core self-evaluation, showing that over-reliance on AI damages employee self-esteem and threatens performance, but employees with high core self-evaluation maintain motivation and mitigate these negative effects.

3.2.4 Demographic Characteristics Demographic characteristics such as age, gender, social class, and education level also influence AI-employee interactions. Regarding age, Dutta et al. (2022) found that older employees, who inevitably experience cognitive decline, have lower familiarity and mastery of new technology and benefit less from AI collaboration. Younger employees, conversely, are tech-savvy, more willing to use emerging tools, and gain more from AI collaboration (Guha et al., 2023). Similarly, individuals from lower social classes and education levels exhibit lower familiarity, mastery, and learning speed regarding new technology (Oksanen et al., 2020; Zhang & Wang, 2021; Wang & Yao, 2022), making adaptation to AI collaboration difficult.

3.3 Organizational Contextual Factors

From a systemic perspective, AI-employee interaction is embedded in sociotechnical systems, with the evolution and development of AI-employee collaboration influenced by broad organizational stakeholders (Anthony et al., 2023). Wilson and Daugherty (2018) noted that achieving AI-employee collaboration requires deep organizational involvement throughout the AI application lifecycle. Accordingly, organizational contextual factors play a crucial role. Based on literature review, this paper discusses three aspects: organizational readiness, organizational support, and organizational climate and culture.

3.3.1 Organizational Readiness Organizational readiness refers to the degree and availability of organizational resources required to adopt a technology (Hossain et al., 2016). Applied to AI, it reflects the degree and availability of resources needed for AI adoption (Prikshat et al., 2021). Organizational readiness includes technological maturity, financial preparedness, availability of technical experts, and top management support (Hossain et al., 2016). In organizations with high readiness, AI technologies are more mature, sufficient funds are available for AI acquisition and maintenance, adequate technical professionals support AI implementation, and top managers express support with adequate financial and human resources (Prikshat et al., 2021). In such contexts, employees can more rapidly assess, prepare for, and integrate AI systems, exhibit stronger psychological adaptation to AI, and are more motivated to act on AI-provided information, while organizations are better positioned to leverage AI for new product and service development (Makarius et al., 2020).

3.3.2 Organizational Support Organizational support first requires managers to be familiar with and understand AI, maintain inclusive and accepting attitudes toward AI technology, and champion intelligent transformation (Basu et al., 2022). Conversely, if managers distrust AI's organizational benefits or experience anxiety about AI, providing support becomes impossible (Susenoa et al., 2021). Specifically, managers must express commitment and support for AI introduction to build employee confidence (Prikshat et al., 2022; Li & Tao, 2022; Wang & Yao, 2022) and proactively provide education and training in digital skills and knowledge (Li et al., 2019; Vrontis et al., 2021). Additionally, because technology often benefits employers more than employees due to power imbalances, organizations should implement internal policies to ensure safe, healthy, and meaningful work design, particularly regarding technology, precarious work, and surveillance (Parker & Grote, 2022). Organizations must also establish and improve safety guarantees and ethical norms for technology application (Kim, 2022) and clarify stakeholder responsibilities and obligations through relevant regulations (Seeber et al., 2019).

3.3.3 Organizational Climate and Culture According to the Unified Theory of Acceptance and Use of Technology, social pressure influencing whether individuals adopt a new technology is a key factor (Venkatesh et al., 2003). Employees often observe peers' opinions and enhance belongingness by aligning with group norms, especially when lacking sufficient information for rational decision-making. Therefore, AI acceptance and usage are influenced by social norms and role models (Gursoy et al., 2019; Li & Tao, 2022; Basu et al., 2022). Furthermore, an organizational climate that is inclusive, supportive, and encouraging of AI use facilitates collaboration. Research shows that inclusive organizational climate (Pei et al., 2021), innovation-encouraging culture (Malik et al., 2020), failure-tolerant and progress-supportive culture (Webber et al., 2019), and competitive psychological climate (Li et al., 2019) promote AI acceptance and usage, thereby improving AI-employee collaboration.

3.4 Task Configuration

System components and their functions serve to execute specific tasks, with AI, employees, and organization operating around work tasks and influencing outputs through task execution (Anthony et al., 2023). The process component describes how system inputs transform into outcomes (Ilgen et al., 2005), including goal specification and mutual coordination (Marks et al., 2001). Thus, task configuration is the process variable in AI-employee collaboration systems. Task configuration comprises two dimensions: "what to do" (task objectives) and "how to do it" (interaction modes). Task objectives characterize the nature of collaborative tasks, while interaction modes depict role positioning, task allocation, and resource distribution between AI and employees (Seeber et al., 2019; Kim, 2022). Optimizing AI-employee collaboration requires aligning interaction modes with task objectives, as only high technology-task matching maximizes collaborative effectiveness (Lee, 2018; Zhao et al., 2020; Wang et al., 2020).

3.4.1 Interaction Modes Makarius et al. (2020) developed eight interaction modes based on AI's application scope and its novelty and intelligence levels: simulation (e.g., super AI), autonomy (e.g., autonomous vehicles), augmentation (e.g., surgical robots), symbiosis (e.g., deep learning), automation (e.g., assembly line robots), and amplification (e.g., predictive AI). Other research has constructed interaction mode matrices based on the identities (human or AI) of interacting parties. For example, Robinson et al. (2020) built a matrix of four interaction modes based on whether employees and customers are human or AI: intra-human relationships, interspecies AI employee-human customer relationships, interspecies AI customer-human employee relationships, and intra-AI relationships. Existing research has focused heavily on automation and augmentation (Raisch & Krakowski, 2020).

Automation implies machine takeover of human tasks, with the advantage that employees can delegate tasks to AI with minimal or no involvement, achieving more comprehensive, rational, and efficient processing by removing humans from the system (Davenport & Kirby, 2016). However, this creates numerous negative effects: dependence on automation causes employee deskilling and manager disintermediation, threatening long-term development and value realization, and potentially causing severe unemployment and social inequality (Raisch & Krakowski, 2020). Augmentation, conversely, involves sustained, close interaction between humans and AI, using uniquely human capabilities (e.g., emotion, intuition) to complement AI (Wilson & Daugherty, 2018). Augmentation aims to enhance employee capabilities, improve organizational structure, and strengthen communication, enabling employees to deepen and broaden their work through AI use (Hunter, 2019). However, augmentation requires continuous human involvement and experimentation, is subject to human emotions and subjective factors, and yields non-replicable technological outcomes. Pure augmentation also means human biases persist, making results difficult to stabilize, ensure reliability, and sustain (Amershi et al., 2014).

3.4.2 Task Objectives Although AI can significantly enhance employee productivity, organizations must consider appropriate task objectives when introducing AI; otherwise, counterproductive outcomes may result. Existing research distinguishes between cognitive-analytical tasks and socio-emotional tasks based on differences in emotional-social versus cognitive-analytical components (Wirtz et al., 2018; Lee, 2018; Glikson & Woolley, 2020). Socio-emotional tasks demand high emotional intelligence, affective communication, interpersonal skills, and organizational coordination, consuming substantial emotional resources. Cognitive-analytical tasks require complex information processing and data analysis capabilities, consuming substantial cognitive resources (Huang et al., 2018; Huang & Rust, 2018; Wirtz et al., 2018). According to Glikson and Woolley (2020), employees trust AI more for cognitive-analytical tasks than socio-emotional tasks. Similarly, Lee (2018) found greater employee trust in AI for analytical and computational tasks than for manual tasks.

For socio-emotional tasks—such as service work with complex emotional and social attributes—AI can only simulate surface-level emotional display at a high level, while employees' deep acting, innovative thinking, and socially complex genuine emotions remain difficult for AI to imitate or replace (Wirtz et al., 2018). In service failure situations or emotionally charged service work (e.g., medical testing, funeral services, wedding planning), frontline service employees must express respect, appreciation, or specific emotions toward disappointed, insulted, or offended customers—needs that AI struggles to meet empathetically (Rafaeli et al., 2017; Delcourt et al., 2017). AI is typically perceived as having false, artificial emotional expression, and despite potential efficiency gains, actual service effectiveness is unsatisfactory (Robinson et al., 2020). Some relationally-motivated customers value social elements in service, preferring to experience employees' emotional expression and using nonverbal cues to reduce ambiguity, increase comfort, and build trust (Lim et al., 2017). However, AI's lack of rich emotional cues makes it difficult to satisfy such customers (Robinson et al., 2020). Therefore, in socio-emotional tasks, AI should not completely replace employees; instead, organizations should leverage employees' strengths in emotional communication and interpersonal skills.

In cognitive-analytical tasks, however, machine-dominated collaboration modes are appropriate. This means mechanical, analytical tasks that consume substantial physical and cognitive resources are primarily completed by AI, while employees serve as assistants or supervisors maintaining AI system operation and safety (Wilson & Daugherty, 2018). This division of labor not only enables more rational and efficient task processing (Davenport & Kirby, 2016) but also liberates humans from repetitive, rule-based, mechanical, and cognitively demanding work, granting employees greater autonomy to engage in new roles related to judgment, creativity, and value creation. For example, widespread application of intelligent manufacturing technology has transformed workers from repetitive assembly tasks to on-site anomaly diagnosis and analysis, significantly enhancing their sense of work meaning. Conversely, excessive human involvement in cognitive-analytical tasks introduces subjective factors that prevent fully rational outcomes and productivity leaps (Huang et al., 2012; Raisch & Krakowski, 2020), while employees trapped in repetitive, mechanical tasks cannot unleash their creativity and new value.

3.4.3 Matching Interaction Modes and Task Objectives The above analysis shows that AI-employee interaction modes exhibit "double-edged sword" effects, and different task objectives should be matched with different interaction modes. Therefore, in socio-emotional tasks, employee-dominated augmentation is appropriate, emphasizing and leveraging employees' emotional communication and intuitive judgment capabilities. In cognitive-analytical tasks, AI-dominated automation is suitable, enhancing efficiency while liberating employee individuality and value. For example, Jia et al. (2023) designed a work system where AI handles procedural and repetitive sales tasks (e.g., making calls, collecting basic customer information), after which human agents conduct deeper communication to close sales once customers show purchase intent. Field experiments demonstrated that this design significantly enhances human agents' creativity. Similarly, Jarrahi (2018) analyzed task configuration in decision-making processes, noting that given humans' advantages in intuition and AI's advantages in analysis, humans should determine data collection and processing directions for highly complex problems while AI performs high-speed, large-scale data processing. For uncertain problems lacking sufficient information, human intuition should prevail; for ambiguous problems requiring negotiation and balancing multiple interests, humans should lead while AI assists with diverse information interpretation (Jarrahi, 2018).

Moreover, as work content becomes richer and more complex, employees are increasingly required to complete tasks with both socio-emotional and cognitive-analytical components. In such cases, the optimal task configuration should build a virtuous cycle between automation and augmentation, forming a symbiotic relationship where human and machine intelligence complement and drive each other (Raisch & Krakowski, 2020). For example, IBM's AI perfumer assistant matches fragrance formulas with big data on sales regions and customers to generate perfumes targeting customer preferences, after which perfumers create product stories that trigger human emotions and memories based on AI-generated formulas. This symbiotic relationship not only maximizes competitive advantage (Makarius et al., 2020) but also enhances employees' competence and work vigor (Zhu et al., 2021). In summary, optimizing AI-employee collaboration requires matching interaction modes with task objectives, but as work becomes more complex, dynamic matching should be established, creating a symbiotic relationship of mutual complementarity and reinforcement.

3.5 The Systematic Research Framework for AI-Employee Collaboration

From a systemic perspective, the AI-employee collaboration system exerts broad impacts on all actors (Anthony et al., 2023), and the mutual influence and shaping relationships among actors are central research concerns (Xie et al., 2023). Accordingly, at the output end of the AI-employee collaboration system, this paper synthesizes impacts on and changes in the three actors—employees, AI, and organization—and integrates the system's inputs, process, and outputs to construct a systematic research framework, shown in [Figure 1: see original paper].

[Figure 1: see original paper] The Systematic Research Framework for AI-Employee Collaboration

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4. Research Summary and Future Directions

This review clarifies the conceptual boundaries of workplace AI and AI-employee collaboration, promoting unified academic discourse and laying a foundation for future research. Building on Anthony et al.'s (2023) systemic perspective and using the I-P-O paradigm, we construct a research framework that concretizes the abstract systemic perspective with explicit descriptions of constituent elements and internal mechanisms. Through systematic synthesis of empirical studies, we provide additional empirical support for the systemic perspective. Overall, this paper enriches the literature on systemic perspectives of AI-employee collaboration and represents an important application of this perspective. It also deepens understanding of AI-employee collaboration and provides a theoretical framework to guide future research. Nevertheless, both workplace AI research and the systemic perspective on AI-employee collaboration remain in their infancy. Based on our framework and identified research gaps, we propose the following future research directions.

4.1 Strengthen Research on AI Ethics in Collaboration Systems

Although many studies emphasize the importance of addressing ethical issues in AI-employee collaboration, most remain theoretical, lacking sufficient empirical evidence. Future research should emphasize experimental designs to overcome challenges such as limited sample access and high variability in AI applications. Furthermore, the development of AI-generated content (AIGC) (e.g., ChatGPT, NovelAI) has sparked new ethical discussions about bias, discrimination, misinformation, and legal/copyright issues that have not received adequate attention in organizational management research (Paul et al., 2023). Future studies should explore the potential negative impacts of emerging ethical issues on employees and organizations. For instance, because AIGC content derives from deep imitation and fabrication of existing knowledge, employees' long-term dependence on AIGC assistance may weaken their moral judgment, leading to unethical workplace behaviors that threaten organizational safety climate and internal trust. From a systemic perspective, discrimination and bias in AI algorithms can shape employee cognition in reverse (Anthony et al., 2023), causing cognitive biases and irrational behaviors that negatively impact performance, social responsibility, and organizational legitimacy.

4.2 Explore Organizational Consequences in Collaboration Systems

Empirical research on organizational consequences of AI-employee collaboration remains scarce. Future research should strengthen investigations of organizational outcomes. For example, from an employee-organization dyadic perspective, strategic core theory posits that core members occupying central workflow positions exert the strongest influence on group social exchange processes, meaning individual attitudes and behaviors can shape the entire organization (Grijalva et al., 2023). Thus, individual employees' AI usage behaviors may bottom-up shape organizational AI usage culture and climate. Moreover, organizations introduce AI fundamentally to enhance performance and gain competitive advantage. Distinguishing AI-driven performance from broader performance metrics and objectively measuring performance improvements from AI-employee collaboration represent key challenges for future organizational consequence research. For instance, sociotechnical capital—the productivity derived from combining social capital with digital technology—is valuable, inimitable, and organization-specific, capable of building sustainable competitive advantage (Makarius et al., 2020). Sociotechnical capital may thus serve as one indicator for exploring AI-employee collaboration effectiveness at the organizational level.

4.3 Expand Individual Characteristics in Collaboration Systems

For employees, individual characteristics are relatively malleable and controllable factors, and expanding research on these characteristics can help employees proactively adapt to collaboration systems. First, AI's machine learning process requires human data labeling and training guidance, which not only facilitates smoother output but also contributes to AI functional realization and performance improvement (Raisch & Krakowski, 2020). Therefore, employees may hold more important positions in AI-employee collaboration systems than previously recognized. For example, AIGC can only generate answers based on known knowledge bases and clear problem descriptions, making the ability to ask imaginative and valuable questions a critical skill in the AI era for unleashing AI's potential. Highly professional prompt engineers have become a hot recruitment target. Future research could identify additional individual characteristics relevant to AI-employee interaction, such as AI dialogue ability, develop measurement scales, and empirically test their impacts. Second, technology globalization faces significant regional differences, with identical AI systems exhibiting vastly different design patterns and application effects across cultural contexts. Yet existing research has neglected the role of cultural values in AI-employee collaboration, limiting the applicability and generalizability of findings. Future research should examine how individual cultural values influence AI-employee collaboration systems.

4.4 Strengthen Research on Task Configuration in Collaboration Systems

The systemic perspective on AI-employee collaboration emphasizes contextual features, with collaboration design maximizing AI effectiveness only when combined with task environments (Anthony et al., 2023). However, research on task configuration remains largely theoretical, with few empirical studies (Lee et al., 2018; Jia et al., 2013). We call for future research using contextual experiments or field experiments to test task configuration effects. Furthermore, while this paper focused on cognitive-analytical versus socio-emotional tasks and automation versus augmentation modes, future research should provide more nuanced characterizations of task configuration. For task objectives, tasks could be further subdivided into mechanical, analytical, intuitive, and empathic tasks (Huang & Rust, 2018). For interaction modes, spatial and process perspectives could yield four modes: independent, sequential, synchronous, and supportive (El Zaatari et al., 2019), offering stronger operability for research design (Jia et al., 2023).

4.5 Refine and Extend the AI-Employee Collaboration Framework

This paper uses the I-P-O paradigm to construct a research framework that concretizes systemic theory. To advance systemic theory development, the framework requires further refinement and extension. Marks et al. (2001) expanded process dimensions beyond goal specification and coordination to include task analysis, strategy formulation, monitoring, and conflict management. Ilgen et al. (2005) extended I-P-O to I-M-O-I, proposing feedback loops where outputs reciprocally influence inputs and processes. Future research could expand process variables and add feedback loops to reveal deeper internal mechanisms. For process variables, future studies could examine AI-related regulatory mechanisms, failure tolerance mechanisms, and "rejection" coordination mechanisms.

For feedback loops, although highly anthropomorphized AI can enhance emotional identification, when they exhibit hostile behaviors, high emotional identification amplifies negative experiences (Yam et al., 2022; Sullivan et al., 2022), ultimately affecting employee attitudes—suggesting a possible feedback loop of AI (input) → employee perception (output) → employee attitude (input). Finally, Anthony et al. (2023) noted that AI-employee collaboration systems include broader stakeholders such as governments, regulators, developers, designers, and engineers, whose policies and behavioral preferences profoundly affect the system (Parker & Grote, 2020). Unfortunately, empirical research on these stakeholders remains scarce, and we call for future studies to address this gap.

References

Gong, Q. (2023). On the moral examination of weak artificial intelligence agents. *Philosophical Research*, (3), 37–45.

Li, Y., & Tao, N. (2022). A multi-level dynamic influence model of employee AI technology adoption: A literature review. *Human Resource Development of China*, 39(1), 35–56.

Lü, X., Yang, Y., Xu, S., & Liu, X. (2021). Complementing intelligence with emotion: A study on the remedial effect of AI empathic responses. *Tourism Tribune*, 36(8), 86–100.

Pei, J., Liu, S., Zhong, C., & Chen, Y. (2021). Can AI algorithmic decision-making improve employees' perceived procedural justice?. *Foreign Economics & Management*, 43(11), 41–55.

Wang, C., Zhou, W., & Zhao, S. (2019). Large-scale robot application and job insecurity: A study based on the moderation of employee vocational ability. *Business Management Journal*, 41(4), 111–126.

Wang, Z., & Yao, M. (2022). A review of research on the impact of human-machine collaboration in the workplace on employees. *Foreign Economics & Management*, 44(9),

Xie, X., Zuo, Y., & Hu, Q. (2021). Human resource management in the digital era: Based on a human-technology interaction perspective. *Management World*, (1), 200–216.

Zhang, Y., & Wang, Y. (2022). Research on the influence mechanism of service robot anthropomorphism on consumer usage intention: The moderating role of social class. *Foreign Economics & Management*, 44(3), 3–18.

Zhao, Y., Zhao, S., & Luan, J. (2020). Artificial intelligence-based human resource management: Theoretical models and research prospects. *Nanjing Journal of Social Sciences*, 2, 36–43.

Zhu, X., Wang, S., & He, Q. (2021). Research on the influence of job skill requirements on employee work vigor from the perspective of AI embedding. *Foreign Economics & Management*, 43(11), 15–25.

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