

When Employees Meet AI: Research on the Construct Measurement, Antecedent Configurations, and Impact Mechanisms of Employee-AI Collaboration

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Abstract

In the era of digital intelligence, employee-AI collaboration has become a significant work model. Against this backdrop, exploring how employees and AI collaborate, why different collaboration modes are adopted, what impacts these modes bring, and how to implement interventions have become crucial research questions. To this end, this study conducts a series of explorations regarding the types, antecedents, and consequences of employee-AI collaboration.

First, based on the dual dimensions of agency and interactivity, employee-AI collaboration modes are categorized into four types: augmenting, symbiotic, assisting, and substituting, with corresponding scales developed. Second, based on socio-technical systems theory, the influencing factors of employee-AI collaboration are identified from four aspects—“employee-AI-task-organization”—and the synergistic effects of these four factors are explored from a configurational research perspective. Finally, based on cognitive-affective system theory, dual mechanisms of cognition and emotion are introduced, and four targeted intervention measures are proposed to reveal the underlying mechanisms through which different employee-AI collaboration modes affect employee job performance and well-being. This study will expand research on employee-AI collaboration and provide an important reference for achieving efficient synergy between employees and AI.

Full Text

Preamble

When Employees Meet AI: Research on the Construct Measurement, Antecedent Configurations, and Impact Mechanisms of Employee-AI Collaboration

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Abstract: In the era of digital intelligence, employee-AI collaboration has emerged as a critical work modality. Against this backdrop, it is essential to investigate how employees and AI collaborate, why different collaboration modes are adopted, what impacts these modes produce, and how to implement effective interventions. To address these issues, this research conducts a series of explorations into the types, antecedents, and consequences of employee-AI collaboration. First, based on the dual dimensions of agency and interactivity, we categorize employee-AI collaboration into four modes: augmenting, symbiotic, assisting, and replacing, and develop a corresponding measurement scale. Second, drawing on Socio-Technical Systems (STS) theory, we identify influencing factors of employee-AI collaboration across four dimensions—employee, AI, task, and organization—and employ a configurational perspective to explore the synergistic effects of these factors. Finally, based on Cognitive-Affective System Theory (CAST), we introduce dual cognitive and affective mechanisms and propose four targeted intervention measures to reveal the underlying mechanisms through which different employee-AI collaboration modes influence job performance and workplace well-being. This study extends the research on employee-AI collaboration and provides a significant reference for achieving efficient synergy between human employees and artificial intelligence.

Keywords: Human-AI collaboration, Artificial Intelligence, Job performance, Workplace well-being

Classification Code: B849: C93

1 问题提出

Artificial Intelligence (AI), as a key force driving technological development, industrial optimization, and the overall leap in productivity, has become increasingly prominent in its strategic role and foundational status. The “Recommendations of the Central Committee of the Communist Party of China on Formulating the Fourteenth Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035” explicitly lists AI as a key industry for the digital economy. Furthermore, the 2025 Government Work Report emphasized “continuously advancing the ‘AI+’ action, better combining digital technology with manufacturing and market advantages, and supporting the widespread application of large-scale models.” Against this backdrop, a large number of organizations are actively embracing AI and implementing various application scenarios (Chowdhury et al., 2023). For instance, Siemens factories have introduced AI to collaborate with engineers in optimizing production processes; China Merchants Bank has introduced AI to work with analysts in identifying and warning against credit risks; and Meituan Waimai has introduced the “Super Brain” system to assist delivery riders in planning

optimal routes. The *2025 AI Index Report* published by Stanford University shows that 78% of organizations have already introduced AI to work alongside employees, making employee-AI collaboration an increasingly important work mode (Wang & Yao, 2022).

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Corresponding Author: Feng Chao, E-mail: chaofeng@nuaa.edu.cn. Employee-AI collaboration refers to the process in which employees and AI cooperate and work together to achieve specific work goals (Yin & Niu, 2024). However, in practice, not all collaborations between employees and AI yield positive results (Jia et al., 2024; Yin et al., 2024). A Deloitte survey of 152 AI projects found that 47% of the projects faced difficulties in employee-AI collaboration. In the manufacturing industry, the blind implementation of fully automated collaborative robots led to “technological strikes” among technicians (He & Yan, 2024). In the healthcare industry, after the introduction of AI-assisted medical diagnosis, some doctors showed a tendency to favor AI judgments, leading to erroneous decision-making (Jussupow et al., 2021). In the creative industry, while text generation tools have lowered the threshold for writing, they have also brought about “skill hollowing” and triggered collective anxiety among writers regarding the “outsourcing of thinking” (Liang et al., 2022; Huang et al., 2025). These issues warn us that multiple distinct collaboration modes may exist between employees and AI. Is AI a tool or a partner? Do employees and AI each perform their own duties, or do they interact closely? Without making these distinctions, it is easy to fall into the trap of a “one-size-fits-all” approach, which significantly compromises the effectiveness of employee-AI collaboration. Therefore, clarifying employee-AI collaboration modes, revealing the causes and effects of different modes, and implementing targeted management interventions are of great significance for promoting efficient employee-AI synergy and enhancing the organizational effectiveness of AI.

In response to this trend, collaboration between employees and AI in organizations has become a major research hotspot. Current research has primarily evolved through three stages: “one-way human reaction to AI,” “behavioral interaction between humans and AI,” and “synergistic coexistence of humans and AI,” with the focus of study gradually shifting from laboratories to field settings (Zhang & He, 2024). Although these studies provide certain insights for the scientific governance of employee-AI collaboration, several theoretical issues remain to be explored.

First, the construct of employee-AI collaboration remains unclear, with inconsistent definitions and a lack of effective measurement tools. Although scholars have attempted to categorize different types of employee-AI collaboration modes, existing classification perspectives are relatively singular and fail to adequately

distinguish between different types of collaboration (Cummings & Bruni, 2010; Makarius et al., 2020). Given that employee-AI collaboration involves two subjects and interactions between them, it is necessary to adopt a dual perspective to comprehensively consider collaboration modes and clarify the characteristics of different types of employee-AI collaboration. Furthermore, the current lack of effective measurement tools for employee-AI collaboration makes empirical research difficult; thus, it is necessary to develop corresponding scales for different types of collaboration. Second, research on the factors influencing employee-AI collaboration tends to explore the “net effect” of individual factors while ignoring the joint effects and interactive relationships of multiple factors. Employee-AI collaboration is a complex decision-making process influenced by various factors. However, existing research tends to investigate the independent influence of single factors (Yin & Niu, 2024), with little holistic and systematic exploration of the joint action of multiple influencing factors. Third, current conclusions regarding the impact of employee-AI collaboration on employee work outcomes are inconsistent, and there is a lack of research into the effects of different collaboration modes, as well as a lack of comprehensive attention to cognitive and emotional processes.

Although some scholars have discussed the “pros and cons” of employee-AI collaboration, the effectiveness of collaboration is not statically positive or negative but is related to the specific type of collaboration (Guo et al., 2025; Li & Chen, 2024). Furthermore, existing research mostly focuses on employees’ cognitive perceptions during the collaboration process, neglecting the important role of emotions (Bankins et al., 2024). Therefore, it is necessary to reveal the differentiated mechanisms through which different types of employee-AI collaboration modes affect work outcomes from both emotional and cognitive perspectives. On this basis, exploring the boundary effects of employee-AI collaboration will provide a more complete and comprehensive theoretical picture for understanding collaboration effectiveness and intervention measures.

In view of the aforementioned practical challenges and theoretical gaps, this study focuses on employee-AI collaboration in the digital intelligence era through the following series of investigations: First, it integrates the perspectives of agency and interactivity to categorize different types of employee-AI collaboration based on dual dimensions and develops targeted measurement tools. Second, it adopts a configurational perspective to explore the interactive effects and joint influence of four factors—“employee-AI-task-organization”—on employee-AI collaboration. Finally, based on Cognitive-Affective System Theory, it explores the mechanisms through which different types of employee-AI collaboration affect work outcomes, while revealing the moderating role of different management interventions. Overall, through three interconnected sub-studies, this research systematically clarifies and defines the types and measurements of employee-AI collaboration and explores its antecedents and consequences. By comprehensively revealing the process of employee-AI collaboration, this study aims to provide scientific and effective theoretical and practical guidance for employees and organizations to actively adapt to and optimize human-machine collabora-

tive work modes and enhance collaborative performance.

2.1 员工-AI 协作的概念内涵

Despite the increasing attention given to human-AI collaboration, previous research has yet to establish a unified standard for its definition. This lack of consensus stems primarily from the fact that most literature focuses on improving artificial intelligence algorithms and models to facilitate better cooperation with humans, rather than explicitly defining the concept of human-AI collaboration itself. Consequently, the field suffers from conceptual overlap and ambiguity. Furthermore, the entities involved in human-AI collaboration are diverse—ranging from humans and general AI systems to humans and conversational agents—and the boundaries between these various subjects remain poorly defined.

Furthermore, human-AI collaboration can be expressed in various forms, such as human-machine cooperation and augmented intelligence. summarizes the definitions of human-AI collaboration provided by previous scholars.

Definitions and Conceptual Framework of Human-AI Collaboration

The evolving landscape of human-machine interaction has led to various conceptualizations of how humans and artificial intelligence work together. These definitions emphasize different aspects of coordination, shared goals, and collective intelligence.

Table 1: Conceptual Definitions of Human-AI Collaboration

Term	Definition	Source
Human-Agent Joint Activity	An extended set of actions performed by a group of coordinated participants, involving at least four fundamental requirements: (1) entering into a “Basic Compact” or agreement to work together; (2) maintaining predictability in their actions; (3) providing mutual directability; and (4) maintaining common ground.	Gary & David (2004)

Term	Definition	Source
Human-Automated Planner Collaboration	A coordinated and synchronized effort between humans and autonomous machines to solve problems based on shared conceptual frameworks.	Cummings & Bruni (2010)
Human-AI Teams	Hybrid entities composed of two or more agents (where at least one is human and one is AI) who are interdependent and perform shared tasks to achieve common, high-value goals.	Nathan et al. (2018)
Human-AI Collaboration	The construction of a synergistic relationship network between humans and AI, where collective intelligence emerges through dynamic interactions between agents.	Kong et al. (2023)
Human-AI Cooperation	A state where humans and AI possess similar functional capabilities for task execution but differ in performance; humans must decide who executes specific tasks to solve problems, while humans retain ultimate responsibility for the outcomes.	Kazuo & Seiji (2020)

Hybrid Intelligence	The combination of human and artificial intelligence to make meaningful decisions and perform appropriate actions, leveraging the strengths of both to achieve superior results.	Dellermann et al. (2019)
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...taking appropriate actions to achieve complex goals that neither humans nor artificial intelligence could accomplish alone, while continuously improving through mutual learning (2019). As shown in , although current conceptual definitions of human-AI collaboration vary, they share common characteristics. The vast majority of research suggests that the fundamental goal of human-AI collaboration is to improve performance, and its essence lies in the allocation of tasks between humans and AI based on specific criteria to ultimately complete a job. Accordingly, this study defines employee-AI collaboration as the process in which employees and AI coordinate and work together to achieve specific organizational or work-related goals.

2.2 员工-AI 协作的分类与测量

Employee-AI collaboration has been categorized into various modes based on different definitional perspectives. A review of existing literature reveals that research on the classification of employee-AI collaboration primarily focuses on two factors: agency and interaction. In the early stages, scholars categorized collaboration based on the degree of control over task processes and decision-making authority. For instance, [?] established a five-level continuous model for human-automation collaboration, ranging from manual operation and human-led hybrid modes to equal division of labor, automation-led hybrid modes, and full autonomous execution. [?] proposed a dichotomous theoretical framework consisting of augmentation and automation, where augmentation emphasizes human-machine synergy and automation focuses on process substitution. Building upon this, [?] expanded the framework into a ternary application model – “substitute-augment-reveal” –to systematically explain the cross-layer mechanisms of AI-enabled innovation.

The technical evolution model proposed by [?] suggests that customer service intelligence progresses through four stages: mechanical, analytical, intuitive, and empathetic intelligence, with agency and autonomy increasing at each gradient. Domestic scholars have also proposed a binary model of AI as either an “assistant” or a “substitute” [?]. Based on a meta-analysis of existing research, [?] categorized AI into four types according to its agency: assisted intelligence, augmented intelligence, managerial intelligence, and autonomous intelligence.

Another classification approach is based on the frequency and depth of interaction during the employee-AI collaboration process. As intelligent technology evolves, collaboration modes exhibit dynamic evolutionary characteristics. [?] classified human-machine interaction into four collaborative forms: segregated, complementary, reciprocal, and collective. [?] constructed a six-dimensional interaction system based on the breadth of application and depth of intelligence, identifying typical paradigms such as emulating systems (human-like cognition), autonomous systems (independent decision-making), augmenting systems (capability expansion), symbiotic systems (bidirectional learning), automating systems (process substitution), and amplifying systems (predictive assistance).

Research by [?] categorized interaction modes into seven types: AI-first assistance, AI-following assistance, secondary assistance, request-driven AI assistance, AI-guided conversational user engagement, user-guided interaction adjustment, and delegation. From the perspective of cognitive interaction, [?] distinguished between human-machine augmentation and human-machine interference modes, providing a new lens for understanding differences in human-machine collaboration effectiveness.

summarizes the current classifications and measurement methods of employee-AI collaboration modes. Notably, most existing classification research remains in the theoretical stage [?, ?, ?, ?, ?]. The few empirical studies available largely rely on experimental methods [?, ?], and there is a lack of mature scales for measurement, which to some extent hinders the development of empirical research. Although [?] and [?] utilized scales to measure human-machine interaction modes through field research, these scales are often unidimensional or fragmented. There is an urgent need to develop more comprehensive and mature measurement instruments.

Classification and Measurement of Employee-AI Collaboration - **Authors:** [?], [?], [?], [?], [?], [?], [?], [?], [?], [?] - **Key Categories:** Manual operation; Human-led hybrid; Automation-led hybrid; Full autonomous execution; Empathetic intelligence; Human-machine augmentation; Human-machine interference; AI-first assistance; AI-following assistance; Request-driven AI assistance; AI-guided conversational user engagement; User-guided interaction adjustment. - **Research Types/Methods:** Field surveys; Single-item manipulation checks; Field questionnaires. - **Research Gaps:** The perspectives on employee-AI collaboration classification are relatively narrow; the identified types are fragmented and lack an effective integrated framework; there is an urgent need for more comprehensive measurement tools.

2.3 员工-AI 协作的前因研究

Only by clarifying the factors that influence human-AI collaboration can employees, managers, and enterprises achieve effective control and management. Human-AI collaboration involves two primary subjects—human employees and AI—while the collaborative process itself is shaped by task characteristics and

organizational contexts. Consequently, this review focuses on these four dimensions.

1) Employee Factors

Human-AI collaboration depends not only on the characteristics of the AI but is also significantly influenced by the traits of the human employees. Existing research indicates that employees' attitudes toward AI, their Knowledge, Skills, and Abilities (KSAs), and even their Big Five personality traits affect the collaborative process (Yin & Niu, 2024). For instance, Kong et al. (2023) pointed out that high AI awareness can reduce employee acceptance of AI, thereby negatively impacting the human-AI collaborative relationship. Conversely, individuals possessing strong AI literacy and capabilities are better equipped to form complementary advantages with AI (Jia et al., 2024). Interestingly, Tang et al. (2022) found that employees with high levels of conscientiousness and orderliness may actually find it more difficult to benefit from collaborating with AI.

2) AI Characteristics

AI characteristics serve as one of the primary drivers of collaborative systems (Anthony et al., 2023). Current research primarily characterizes AI attributes across three dimensions: physical, mental, and ethical (Glikson & Woolley, 2020). The physical attributes of AI include tangibility and anthropomorphism. Studies have shown that AI with a physical form and a moderate degree of anthropomorphism can enhance employee trust and affinity, leading to superior human-AI collaboration (Glikson & Woolley, 2020; Guha et al., 2023). The mental attributes of AI encompass emotionality and functionality. Research has found that highly emotional AI can bridge the interpersonal gap with humans, thereby facilitating better collaborative interactions (Dutta et al., 2023). While highly functional AI possesses stronger problem-solving capabilities that assist humans in completing work more effectively, it may also trigger job insecurity or even threaten to replace humans during the collaborative process (Seeber et al., 2020; Yam et al., 2023). Furthermore, the ethical attributes of AI, including transparency and reliability, significantly impact human-AI collaboration. Glikson and Woolley (2020) found that low AI transparency can lead to algorithmic bias and diminish human trust in AI, which in turn hinders collaboration. Similarly, when AI reliability is low, its competence is called into question, negatively affecting the collaborative dynamic (Wang et al., 2024).

3) Task Characteristics

Complex tasks necessitate a higher degree of mutual cooperation between employees and AI. The intervention of AI can assist employees by handling many foundational tasks, allowing them to focus more on core responsibilities and enhance their professional capabilities (Jia et al., 2024). Additionally, Glikson

and Woolley (2020) discovered that employees tend to exhibit higher levels of trust when AI is involved in cognitive tasks compared to socio-emotional tasks.

分析性任务的 AI，从而实现更好的优势互补。

- 4) Organizational Context. Wilson and Daugherty (2018) emphasize that collaboration between employees and AI depends on the organization's deep commitment throughout the entire AI application process. In enterprises characterized by high levels of organizational readiness and support, the collaboration between employees and AI tends to be relatively harmonious. Furthermore, organizational climate and culture significantly influence employee acceptance and utilization of AI, which in turn improves employee-AI collaboration and facilitates the achievement of optimal matching patterns (Li Yanping & Tao Nana, 2022).

2.4 员工-AI 协作的后果研究

Early research on the effects of employee-AI collaboration was largely descriptive. In recent years, however, as empirical research (primarily experimental studies) has deepened, researchers have begun to demonstrate the consequences of such collaboration with greater precision and scientific rigor. Current scholarly perspectives on the effectiveness of employee-AI collaboration are divided into three main categories: the positive view, the negative view, and the integrated view. From the perspective of Conservation of Resources (COR) theory, many scholars argue that AI serves as an effective resource that helps employees achieve superior work outcomes. For instance, a field experiment by Jia et al. (2024) found that AI assists in generating sales leads, thereby saving employees' time and energy and achieving the goal of cognitive resource conservation; this is particularly effective for high-skilled employees, enhancing both their creativity and sales volume. Similarly, Han et al. (2024) found that employee-AI collaboration increases support for information seeking and creative exploration, which in turn promotes employee bootlegging innovation. Furthermore, Qiu et al. (2022) demonstrated that AI can act as an external resource that reduces the physical and mental exhaustion of frontline employees and stimulates positive emotions, thereby improving service performance.

The negative view, often grounded in stress theories, suggests that collaborating with AI imposes significant pressure on employees, leading to detrimental outcomes. Based on the Cognitive Appraisal Theory of Stress, Yam et al. (2023) found that collaborating with AI triggers job insecurity, which subsequently leads to burnout and workplace incivility. He et al. (2024) observed that the stress of AI collaboration can induce a sense of relative deprivation among employees, resulting in knowledge-hiding behaviors. Additionally, Role Theory posits that AI collaboration may introduce role ambiguity and role threats. Tang et al. (2022) showed that the autonomous decision-making of AI can negatively impact the performance of highly conscientious employees by reducing

role-breadth self-efficacy and increasing role ambiguity. Cao et al. (2023) further discovered that when employees collaborate with AI, the perceived threat to their professional identity can trigger psychological entitlement, which may lead to unethical behavior.

The integrated view, drawing on the Job Demands-Resources (JD-R) model, posits that AI collaboration can lead to both resource depletion and resource gain. Based on the JD-R model, Jiang et al. (2024) conducted a meta-analysis of the impact of AI applications in the workplace, noting that when AI is perceived as a demanding factor that consumes resources, it leads to negative employee behaviors; conversely, when AI is viewed as a resourceful factor that reduces physical and psychological strain, it stimulates positive behaviors. Gui et al. (2024) utilized the JD-R model to show that an “AI challenge” mindset positively influences innovation performance through approach-oriented human-machine job crafting, while an “AI threat” mindset negatively impacts innovation through avoidance-oriented job crafting, with various AI characteristics moderating these relationships. Zhang et al. (2023) explored the double-edged sword effect of employee-AI collaboration, finding that AI as a job demand can hinder innovation through a depletion path of heightened job insecurity, while AI as a job resource can stimulate innovation through a gain path of enhanced perceived job autonomy. Finally, Han et al. (2025) identified an inverted U-shaped relationship between employee-AI collaboration and innovative behavior, suggesting that only moderate levels of collaboration foster optimal cognitive flexibility and are most conducive to innovation.

总结上述研究发现，现有研究大多将员工-AI 协作认为是一个整体构念，缺乏对不同协

research on the impact of collaboration types. In recent years, some scholars have also attempted to explore the outcomes of employee-AI collaboration through classification frameworks. For instance, Li Xiaoman and Chen Li (2024) investigated the differential impacts of human-machine augmenting interaction and human-machine impeding interaction on employee job innovation, mediated by the perceived sense of technological substitution. Furthermore, Guo et al. (2025) conducted a field survey of 400 doctors across 200 hospitals in China to further examine these dynamics.

分析了不同类型 AI 的使用对医生工作表现的影响。遗憾的是，这类研究目前还十分匮乏，

There is an urgent need to enrich the existing body of research in this field. [Figure 1: see original paper] provides a systematic organization of the current literature regarding employee-AI collaboration.

[Figure 1: see original paper] Summary framework of existing literature on employee-AI collaboration.

2.5 研究述评与启示

By reviewing the current state of research on human-AI collaboration, this study identifies several critical gaps that remain to be addressed:

1. The Need for Typological Classification and Scale Development

Clear conceptual definitions and accurate measurement scales are the cornerstones of research on human-AI collaboration. Although scholars have previously classified collaboration types based on either role agency or the degree of interaction, these single-dimension approaches are relatively fragmented and incomplete. Consequently, it is necessary to develop a typology of human-AI collaboration based on the dual dimensions of agency and interaction. Furthermore, current research is predominantly theoretical or experimental, lacking mature measurement tools for this construct, which significantly hinders the progress of empirical studies. While some scholars have attempted to develop scales in the past two years, these efforts either treat human-AI collaboration as a monolithic construct \cite{Kong_{{et}}_{{al}}_{{2023}}} or classify and measure it based on a single characteristic, lacking systematic rigor. Therefore, it is essential to develop corresponding measurement tools for each type of human-AI collaboration to provide an empirical foundation for exploring their respective antecedents and outcomes.

2. Advancing the Driving Paths of Different Collaboration Types

Although some studies suggest that employees, AI, tasks, and organizations collectively constitute the inputs of a human-AI collaboration system, most of this research treats collaboration as a holistic construct. This oversight ignores the differentiated drivers of various collaboration modes. Current research also tends to focus on the “net effect” of single factors, neglecting the joint effects of multiple factors and the interactive relationships between them. In reality, human-AI collaboration is a complex process; no single factor can lead to a specific collaboration type in isolation. Instead, the combination and matching of various elements result in different levels and modes of collaboration. Unfortunately, there is a lack of systematic evidence explaining which configurations of elements lead to specific types and levels of human-AI collaboration. It is therefore necessary to simultaneously incorporate the fourfold factors of “Employee-AI-Task-Organization” and utilize Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to reveal the configurations that lead to diverse collaboration modes.

3. In-depth Research on the Impact of Collaboration Types on Work Outcomes

Current research on the impact of human-AI collaboration has yielded inconsistent conclusions. The underlying mechanism for these discrepancies may be related to the specific type of human-AI collaboration involved. Although scholars have noted the diversity of collaboration modes

\cite{Raisch_{{Krakowski}}{2021}}, existing research has not paid sufficient attention to how each mode affects work outcomes or why these effects occur. Furthermore, impact studies currently focus on objective work outcomes while neglecting employees' subjective experiences. Regarding the underlying mechanisms, research has focused heavily on cognitive processes, with insufficient attention paid to emotional mechanisms, thereby failing to fully reveal the internal logic of human-AI collaboration. Finally, when exploring these impacts, most studies focus on the role of the employee \cite{Bankins{{et}}{al}}{2024} while ignoring the role of organizational management interventions. Based on this, it is necessary to consider the impact of different collaboration modes on both objective and subjective work outcomes through dual cognitive and emotional mechanisms, while identifying targeted organizational measures for effective management.

(Summary of existing literature gaps: Antecedents including Employee factors (Attitude, KSAs, AI Literacy, Big Five), AI characteristics (Physical and Mental attributes), and Organizational context; Theoretical perspectives such as Role Theory, Stress Theory, and Conservation of Resources; and Outcomes ranging from positive views like Job Crafting to negative views like Work Withdrawal).

3 研究构想

Research Framework

This study focuses on constructing a theoretical model of employee-AI collaboration in the digital intelligence era. First, we aim to clarify the specific types of employee-AI collaboration and develop corresponding measurement scales. Second, we will investigate the diverse drivers of employee-AI collaboration and the synergistic effects between these various factors. Finally, we will explore the underlying mechanisms through which employee-AI collaboration influences employee job performance and workplace well-being. The overall research framework is illustrated in [Figure 2: see original paper].

[Figure 2: see original paper] Overall Research Framework

To address the scientific questions proposed above, this study will employ a multi-methodological approach. We will integrate comprehensive literature reviews, focus group interviews, eye-tracking technology, and electroencephalography (EEG) to ensure a robust analysis of the collaborative dynamics between humans and artificial intelligence.

实验、问卷调查、二手数据、行为日志等多种研究方法。具体而言，研究一采用质性研究

Combined with quantitative research, this study develops a measurement scale for human-AI collaboration by deriving specific items through literature analysis, the Delphi method, in-depth interviews, and questionnaire surveys. Study 2

utilizes an online questionnaire survey and employs Fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify the configurational effects of “Employee-AI-Task-Organization” on human-AI collaboration. Study 3, through...

实验室眼动追踪和脑电实验，结合实地调查问卷、二手数据和行为日志，探究不同类型员

Impact of Human-AI Collaboration

The effectiveness and impact of Human-AI collaboration have been extensively studied. summarizes the sample selection criteria, data acquisition methods, and primary analytical approaches employed across various studies.

Summary of Data Acquisition and Analysis Methods Across Studies

Sample Selection Criteria	Primary Acquisition Method	Primary Data Collected	Primary Analytical Method
During the scale development stage, no specific industry boundaries were defined; participants were recruited from diverse industries.	Scale Development and Validation	Quantitative survey responses regarding perceptions of AI interaction.	Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA).

As shown in the table, research in this field often begins with broad sample selection to ensure the generalizability of measurement tools. By recruiting participants from a wide range of professional backgrounds, researchers can develop robust scales that capture the multifaceted nature of Human-AI interaction. These methodological frameworks typically rely on rigorous statistical validation to ensure that the data collected accurately reflects the underlying dynamics of collaboration between human workers and artificial intelligence systems.

背景、具有丰

Research on the Construct Measurement, Antecedent Configurations, and Impact Mechanisms of Employee-AI Collaboration

This research project systematically investigates the dynamics of employee-AI collaboration through three interconnected studies. It aims to answer funda-

mental questions regarding the types of collaboration, their measurement, their underlying causes, and their subsequent impact on work outcomes and interventions.

Study 1: Classification and Measurement of Employee-AI Collaboration

The first phase focuses on defining and quantifying the nature of collaboration between humans and artificial intelligence. By integrating literature analysis, the Delphi method, and in-depth interviews, this study identifies four distinct modes of collaboration based on the degree of interaction and the distribution of decision-making sovereignty:

- **Symbiotic Type:** Characterized by high interaction and shared agency.
- **Replacement Type:** Characterized by low interaction where AI takes over primary tasks.
- **Augmentation Type:** High interaction where AI enhances human capabilities.
- **Assistance Type:** Low interaction where AI serves a supportive, secondary role.

The validation stage involves large-scale questionnaire distribution across various industries via the JianShu platform. Methodologically, this phase employs coding and factor analysis to develop and validate a robust scale for measuring employee-AI collaboration.

Study 2: Configuration Effects of Factors Influencing Employee-AI Collaboration

This study explores the complex causal recipes that lead to different collaboration modes. Using Fuzzy-set Qualitative Comparative Analysis (fsQCA), the research examines how various characteristics combine to influence the collaborative relationship. The analyzed factors include:

- **Employee Characteristics:** AI literacy and AI awareness.
- **AI Characteristics:** Technical proficiency and reliability.
- **Task Characteristics:** Complexity and task type.
- **Organizational Characteristics:** Available resources and organizational culture.

By analyzing these multi-level data points, the study identifies the specific configurations of employee, AI, task, and organizational features that drive the adoption of different collaboration types.

Study 3: Mechanisms and Interventions of Employee-AI Collaboration on Work Outcomes

The final study investigates how different collaboration modes affect work performance and employee well-being through cognitive and emotional processes.

Cognitive and Emotional Pathways: - **Cognitive Processes:** Ranging from cognitive expansion (positive) to cognitive loading (negative). - **Emotional Processes:** Including both positive and negative affective states.

Methodology: This phase utilizes a multi-method approach, including: - **Multimodal Data Analysis:** OLS regression and Analysis of Variance (ANOVA). - **Experimental Data:** Eye-tracking and EEG metrics (e.g., fixation time ratio, pupil diameter change rate, saccade path entropy, and θ , γ , and α wave asymmetry). - **Text Analysis:** Qualitative insights from employee feedback.

Management Interventions and Outcomes: The research concludes by proposing targeted management interventions to optimize collaboration, such as: - **Nurturing AI Agency and Employee Agency:** Balancing control and autonomy. - **Functional Expansion Planning:** Dynamically assessing contributions. - **Transition Guidance and Support:** Facilitating the shift toward more effective collaboration modes.

The ultimate goal is to enhance **Work Performance** and **Work Well-being** by understanding the nuanced mechanisms through which AI integration transforms the modern workplace.

结果的作用机

Research Methodology

The research methodology for this study is structured into two primary components: controlled laboratory experiments and comprehensive field research.

Laboratory Experiments

The laboratory phase of the study utilizes a high-level academic environment, recruiting participants from university settings. These experiments leverage advanced neurophysiological and behavioral tracking technologies, specifically integrating laboratory-based eye-tracking and electroencephalogram (EEG) measurements. These tools allow for the precise collection of cognitive and attentional data, providing a granular understanding of participant responses under controlled conditions.

Field Research

The field research component focuses specifically on the intelligent manufacturing sector. This phase employs a multi-method approach to ensure data triangulation and ecological validity. Data collection strategies include: - **Field Surveys:** Distributing structured questionnaires to industry professionals and stakeholders to capture real-world perspectives. - **Secondary Data Analysis:** Utilizing existing industrial datasets and historical records to identify broader trends and patterns. - **On-site Investigations:** Conducting direct observations and interviews within manufacturing facilities to contextualize the

laboratory findings within the practical realities of the intelligent manufacturing industry.

3.1.1 员工-AI 协作的类型划分

Existing research predominantly categorizes the role of Artificial Intelligence (AI) into dichotomies such as tools versus partners or replacers versus assistants. However, these classification methods focus solely on AI's agency and autonomy, neglecting the collaborative attributes inherent in the relationship between employees and AI. Recently, scholars have proposed classifying employee-AI collaboration modes based on the degree of interaction (Gomez et al., 2025). To more comprehensively capture the characteristics of employee-AI collaboration, this study builds upon previous research by integrating agency and interaction depth to categorize collaboration types. We propose that employee-AI collaboration comprises two core dimensions: employee-AI agency (employee-centric agency vs.

AI-centric agency) and employee-AI interaction degree (low vs. high). Dimension 1: Employee-AI Agency (Employee-centric vs. AI-centric). In employee-AI collaboration, the configuration of agency aims to characterize the distribution of the ability to initiate actions, make judgments, bear responsibility, and exert influence between the employee and the AI within a specific task workflow. Currently, there are two representative theoretical perspectives regarding AI roles: Structuration Theory (Giddens, 1984) and Actor-Network Theory (Leonardi, 2011). These theories differ significantly in the priority and subordinate relationship between human agency and technology agency. Structuration theory and its derivatives suggest that while both technology and human agency influence behavior, human agency remains in a leadership position, with technology serving an auxiliary and complementary role (Orlikowski, 2000). However, with the advancement of AI technology—particularly the emergence of AI Agents—AI has evolved from a mere auxiliary tool into an actor capable of proactively making decisions and taking actions to achieve specific goals (Yin, 2024).

Actor-Network Theory (ANT) recognizes the agency and performativity of technology, as well as the semantic equivalence between technology and humans, treating technology as an equal actor (Shen & Li, 2021). Given this, the present study adopts “agency” (divided into “employee-centric agency” and “AI-centric agency”) as the first dimension of the employee-AI collaboration model. In employee-centric collaboration, AI is primarily triggered by employee instructions and lacks autonomous decision-making capabilities; in AI-centric collaboration, AI can proactively take action to achieve specific objectives. It should be emphasized that many past studies have used terms such as “dominance,” “subjectivity,” and “autonomy” to describe the relationship. However, “dominance” focuses on the static structure of power relations and possesses a strong control attribute that easily leads to binary opposition (Cummings & Bruni, 2010). “Subjectivity” refers to the internal state of conscious experience, touching upon fundamental philosophical and ethical issues such as whether

AI should be granted legal/moral status and the dissolution of work meaning (Ding, 2025). “Autonomy” describes the degree of AI self-determination and independent operation but ignores the role attributes of the employee (Jiang et al., 2024). Only “agency” accurately depicts the generative process of the relationship between employees and AI within an actor network, providing a theoretical foundation for understanding their collaboration modes (Latour, 2005; Leonardi, 2011). Furthermore, agency is a multidimensional, dynamic, and context-dependent concept. The employee-centric and AI-centric agency configurations defined in this study represent two extreme and typical models intended to help identify and describe fundamental characteristics within complex phenomena.

In fact, agency exists on a continuum ranging from “fully employee-centric” to “fully AI-centric.” In actual work settings, there are numerous hybrid states where employees and AI influence each other, and dynamic shifts between employee and AI agency are common.

Dimension 2: Employee-AI Interaction Degree (Low vs. High). Employee-AI interaction degree refers to the frequency of interaction and the depth of information exchange between the employee and the AI (Makarius et al., 2020). Preliminary interviews conducted for this study revealed significant differences in the frequency and depth of current employee-AI collaboration modes. For instance, in the R&D of a certain brand of rice cooker, one interviewee stated: “To understand user feedback, I only need to input comments from e-commerce platforms in bulk, and the AI automatically generates an analysis report; it doesn’t require much from me.” Conversely, another respondent noted: “To develop a new type of rice cooker, I use AI through continuous reinforcement learning to simulate heating curves for different ingredients, thereby optimizing the taste of the rice.” Consequently, this study adopts employee-AI interaction degree (low vs.

high) as the second dimension of the employee-AI collaboration model. A low interaction degree implies low frequency and shallow content, sometimes resulting in situations where the employee and AI act independently with a lack of effective coordination (Sowa et al., 2021). A high interaction degree indicates close interaction and deep exchange. Thus, employee-AI interaction is a continuum ranging from “low interaction (one-off commands)” to “high interaction (real-time deep interaction).”

In summary, this study proposes a 2×2 conceptual model to classify different types of employee-AI collaboration modes. As shown in , these are named: Augmentation employee-AI collaboration, Symbiosis employee-AI collaboration, Assistance employee-AI collaboration, and Substitution employee-AI collaboration.

It should be specifically noted that this study does not view employee-AI collaboration as an aggregate construct composed of multiple sub-dimensions; rather, each category is a distinct construct. Below, we provide clear definitions and

typical examples for each mode, compare them with related constructs, and ultimately form an integrated framework for employee-AI collaboration.

Conceptual Model of Employee-AI Collaboration (Columns: Employee-centric Agency | AI-centric Agency) (Row 1: Augmentation employee-AI collaboration) Definition: A collaboration mode where the employee serves as the core actor of the task and AI acts as an intelligent partner. Through high-frequency bidirectional interaction, knowledge transfer, cognitive expansion, and decision support, the AI continuously enhances the employee's professional capabilities. Typical Examples:

AI-assisted clinical decision-making; recommendation strategies for marketing analysis tools. Related Constructs: Augmentation mode (Raisch & Krakowski, 2020); Human-machine augmented interaction (Li & Chen, 2024). (Row 2: Assistance employee-AI collaboration) Definition: A collaboration mode where the employee is the core actor and AI serves as a passive tool. Through low-frequency unidirectional interaction, the AI responds to specific, clear instructions without participating in the employee's cognitive decision-making or capability evolution process. Typical Examples:

Collaborating with text proofreading tools; collaborating with customer service chatbots. Related Constructs: Auxiliary tools (Shneiderman et al., 2017); Assisted intelligence (Jiang et al., 2024); AI assistance (Wang et al., 2022). (Row 3: Symbiosis employee-AI collaboration) Definition: A collaboration mode where the employee and AI form a tightly coupled joint cognitive system. They are interdependent and complementary, jointly optimizing tasks and decisions. Typical Examples:

Real-time cooperation between surgeons and the Da Vinci surgical robot; iterative creation between designers and AI. Related Constructs: Deep human-machine integration (Wang et al., 2023; Weng et al., 2025); Human-machine coexistence (Jia et al., 2024); Hybrid intelligence (Dellermann et al., 2019). (Row 4: Substitution employee-AI collaboration) Definition: A collaboration mode where AI independently completes tasks originally performed by employees through autonomous perception, decision-making, and execution. The employee retains only minimal supervisory or system control rights, with extremely low interaction frequency. Typical Examples:

Employee-AI collaboration in automated warehousing systems; employee-AI collaboration in autonomous driving systems. Related Constructs: Automation mode (Raisch & Krakowski, 2020); AI substitution (Wang et al., 2022); Autonomous intelligence (Jiang et al., 2024). Augmentation employee-AI collaboration. Located in the upper-left corner of the framework, this quadrant involves the employee as the core actor interacting frequently and deeply with AI. We define it as a mode where the employee is the core actor and AI acts as an intelligent partner, enhancing professional capabilities through high-frequency bidirectional interaction. Representative scenarios include AI-assisted clinical decisions and marketing tool strategies. Similar constructs include the aug-

mentation mode (Raisch & Krakowski, 2020) and human-machine augmented interaction (Li & Chen, 2024).

Symbiosis employee-AI collaboration. Located in the upper-right corner, this quadrant features high AI agency and high-frequency interaction. We define it as a mode where the employee and AI form a tightly coupled joint cognitive system, characterized by real-time feedback, dynamic adaptation, and systemic inseparability. Representative scenarios include surgeons working with Da Vinci robots and iterative design processes. Similar constructs include deep human-machine integration (Wang et al., 2023) and hybrid intelligence (Dellermann et al., 2019). Notably, the primary difference between symbiosis and augmentation lies in agency: in symbiosis, AI possesses high agency and acts as an integral part of the unit, whereas augmentation maintains the human as the core actor.

Assistance employee-AI collaboration. Located in the lower-left corner, the employee is the core actor and AI serves primarily as an auxiliary tool with low interaction frequency. We define it as a mode where AI, as a passive tool, responds to specific instructions through low-frequency unidirectional interaction without involving cognitive evolution. Representative scenarios include text proofreading and basic chatbots. Similar constructs include auxiliary tools (Shneiderman et al., 2017). The key difference between assistance and augmentation is whether employee capability is enhanced: assistance only reduces physical or time consumption while maintaining existing skill levels, whereas augmentation enhances capabilities through technological compensation or extension.

Substitution employee-AI collaboration. Located in the lower-right corner, this quadrant features high AI agency and autonomy with low interaction frequency. We define it as a mode where AI independently completes tasks through autonomous perception and execution, leaving the employee with only minimal supervisory rights. Representative scenarios include automated warehousing and autonomous driving. Similar constructs include the automation mode (Raisch & Krakowski, 2020) and AI substitution (Wang et al., 2022).

It should be emphasized that the four types of employee-AI collaboration proposed in this study are summarized as the most prevalent and mainstream types based on current research; this does not preclude the existence of other types. Future research could further categorize collaboration from the perspectives of delegation (Fügener et al., 2022) or sequence (Gomez et al., 2025). Furthermore, these four modes represent “ideal types” —analytical tools constructed by extracting key features (agency and interaction) rather than rigid classifications of reality. In practice, any specific collaboration can be positioned as a point within the two-dimensional coordinate system of , rather than strictly falling into a single quadrant. The four modes correspond to four typical regions within a continuous spectrum, with smooth transitions between them. Consequently, they are meaningful theoretical constructs describing typical regions on a continuum rather than mutually exclusive categories. This necessitates the use of continuous scales to measure these four modes, thereby accurately charac-

terizing the collaborative state, which underscores the necessity and importance of the scale developed in this study.

3.1.2 针对四类员工-AI 协作模式的量表开发

Currently, the most commonly used scales in human-AI collaboration research include the Human-AI Trust Scale, Collaborative Self-Efficacy Scale, Acceptance Scale, Automation Adaptation Scale, and scales for algorithm appreciation and algorithm aversion. However, these existing scales either focus on human attitudes toward AI—such as trust, appreciation, or aversion \cite{罗映宇等, 2023}—or concentrate on collaboration levels and outcomes, such as the Collaborative Self-Efficacy and Automation Adaptation scales. There is a notable lack of instruments addressing the employee-AI relationship specifically \cite{张志学等, 2024}. Furthermore, current research on employee-AI collaboration relies predominantly on experimental designs, leaving the development of psychometric scales relatively lagging.

A review of the literature reveals two primary types of measurement tools for employee-AI collaboration. The first is a unidimensional five-item scale developed by Kong et al. (2023), which treats employee-AI collaboration as a holistic concept; a representative item is “AI participates in my work decision-making process.” However, this scale overlooks the existence of different types of employee-AI collaboration, and its unidimensional items fail to fully capture the specific processes of collaboration. In essence, it measures the degree of AI embedding rather than the collaborative process itself. The second type includes the human-machine augmented interaction and human-machine blocking interaction scales developed by Li and Chen (2024)—based on the four-stage human-computer interaction model widely used in engineering—as well as the AI automation and AI augmentation scales adapted by Guo et al. (2025) from Raisch and Krakowski (2021). Nevertheless, the scale by Li and Chen (2024) emphasizes the cognitive dimension while neglecting the prevalence of structured tasks. Similarly, the scale by Guo et al. (2025) focuses primarily on the agency of the AI’s role while ignoring the intensity of employee-AI interaction. Crucially, neither approach accounts for the existence of assistive and symbiotic collaboration modes.

Given the limitations of existing research in scale development, this study asserts the necessity of clarifying the connotation of employee-AI collaboration and developing a more scientific and rigorous scale tailored to the four identified modes of employee-AI collaboration. This will provide a foundation for subsequent empirical research. This study intends to follow standardized scale development procedures [?, ?]. First, evaluation items for employee-AI collaboration will be collected from multiple channels—including literature analysis, in-depth interviews, and semi-open-ended questionnaires—to form an initial item pool. Next, an expert panel will discuss, categorize, and revise these generated items. The initial scale will then be converted into an electronic questionnaire for a pre-test conducted within enterprises that utilize employee-AI collaboration models, fol-

lowed by scale refinement through exploratory factor analysis (EFA). Finally, a large-scale survey will be administered to develop the formal employee-AI collaboration scale through confirmatory factor analysis (CFA), reliability analysis, convergent and discriminant validity analysis, and criterion-related validity testing.

presents sample items for the four types of employee-AI collaboration modes; specific items are subject to further adjustment in subsequent research.

Employee-AI Collaboration Modes and Sample Items Employee-AI Collaboration Mode: Augmented Employee-AI Collaboration

1. 我与 AI 共同制定任务解决方案，而非单方面执行它的建议

Symbiotic Employee-AI Collaboration

1. Introduction

In the era of rapid technological advancement, the relationship between human labor and artificial intelligence (AI) has evolved beyond simple tool usage into a complex, symbiotic partnership. The concept of the “symbiotic employee” refers to a new paradigm of work where human cognitive abilities and AI’s computational power are deeply integrated, creating a collaborative synergy that exceeds the capabilities of either entity alone. This shift necessitates a fundamental re-evaluation of organizational structures, job design, and the required skill sets for the modern workforce.

2. The Mechanism of Human-AI Symbiosis

The core of symbiotic collaboration lies in the complementary nature of human and machine intelligence. While AI excels at processing vast datasets, identifying patterns, and executing repetitive tasks with high precision, humans provide critical thinking, emotional intelligence, ethical judgment, and creative problem-solving.

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the interaction is not unidirectional. It involves a continuous feedback loop where the AI assists the employee in decision-making, and the employee, in turn, provides the contextual nuance and oversight necessary to refine the AI’s outputs. This relationship can be modeled mathematically to understand the optimization of task allocation. For instance, if we denote the total productivity as P , human contribution as H , and AI contribution as A , the symbiotic effect can be represented as:

$$P = f(H, A) + \sigma(H, A)$$

where $\sigma(H, A)$ represents the synergistic gain derived from the interaction between the two entities, rather than a mere summation of individual efforts.

3. Key Dimensions of Collaboration

3.1 Augmentation vs. Automation Unlike traditional automation, which seeks to replace human labor, symbiotic collaboration focuses on augmentation. AI acts as a “cognitive prosthetic,” enhancing the employee’s ability to handle complexity. For example, in medical diagnostics, an AI might analyze thousands of radiological images to flag anomalies, while the physician makes the final diagnosis based on the patient’s clinical history and holistic health status.

3.2 Dynamic Task Allocation Effective symbiosis requires dynamic task allocation based on the evolving strengths of both the employee and the AI. Using machine learning algorithms, systems can now predict which parts of a workflow are best suited for human intervention. Let \mathcal{T} be the set of tasks in a project. The allocation function $\mathcal{A} : \mathcal{T} \rightarrow \mathcal{H} \cup \mathcal{AI}$

2. 我将 AI 视为一个功能更强大的工具，类似于计算器或搜索引擎，而非一

Collaborative Paradigms in Human-AI Interaction

In the evolving landscape of human-AI interaction, two distinct collaborative frameworks have emerged: the “Augmentative Employee-AI Collaboration” and the “Substitutive Employee-AI Collaboration.” These paradigms define how artificial intelligence integrates into professional workflows and impacts the roles of human workers.

Augmentative Employee-AI Collaboration

The augmentative model positions AI as a collaborative partner or a “co-pilot” designed to enhance human capabilities. In this framework, the AI functions as a supportive tool that handles repetitive, data-intensive, or highly technical sub-tasks, thereby freeing the human employee to focus on high-level strategy, creative problem-solving, and nuanced decision-making.

Key characteristics of this model include: - **Synergy:** The strengths of human intuition and emotional intelligence are combined with the AI’s computational power and speed. - **Human-in-the-Loop:** The human remains the primary agent of accountability and final decision-making. - **Skill Evolution:** Rather than replacing the worker, the technology necessitates upskilling, allowing the employee to manage more complex systems and achieve higher productivity.

Substitutive Employee-AI Collaboration

In contrast, the substitutive model views AI as a replacement for specific roles or functions previously performed by human employees. This paradigm often occurs in environments where tasks are highly standardized, predictable, and rule-based. While it is frequently discussed in the context of automation and labor displacement, it also represents a shift toward autonomous systems that can operate with minimal human intervention.

Key characteristics of this model include: - **Task Autonomy:** The AI system takes full ownership of the workflow from input to output. - **Efficiency Gains:** Organizations may prioritize this model to reduce human error, lower operational costs, and achieve 24/7 productivity. - **Role Redefinition:** This model often leads to a structural reorganization of the workforce, where human roles shift from “doing” to “monitoring” or “maintaining” the AI infrastructure.

Understanding the tension between these two models is critical for organizations as they navigate the ethical, economic, and operational implications of integrating machine learning and deep learning technologies into the modern workplace.

3.2 研究 2: 员工-AI 协作影响因素的组态效应研究

After clarifying the types, connotations, and measurements of employee-AI collaboration modes (Study 1), Study 2 focuses on the antecedents of these different modes. Specifically, it addresses the question: why do different collaboration modes emerge even when employees are interacting with the same AI technologies?

Although existing research suggests that the interaction system composed of “Employee-AI-Task-Organization” influences collaborative behavior between humans and AI (Yin & Niu, 2024), two primary limitations remain. First, prior studies often treat employee-AI collaboration as a monolithic variable, thereby overlooking the differentiated driving paths behind distinct collaboration modes. Second, when exploring the factors influencing employee-AI collaboration, researchers have primarily focused on the “net effect” of individual factors. This approach ignores the joint effects of multiple elements and fails to reveal the complex interactions between them.

To address these gaps, Study 2 adopts Socio-Technical Systems (STS) theory and employs configurational thinking to integrate elements from four dimensions: employee, AI, task, and organization. By doing so, this study investigates how various combinations of these elements lead to different types and levels of employee-AI collaboration modes.

3.2.1 影响因素识别和独立影响论述

Employee-AI collaboration is influenced by various factors. Grounded in Socio-technical Systems Theory, Study 2 selects elements from four dimensions—Employee, AI, Task, and Organization—to explore the factors influencing different types of employee-AI collaboration. Socio-technical Systems Theory posits that a system is composed of two interrelated subsystems: the social system and the technical system. The social system focuses on human attributes, interpersonal relationships, and the organizational environment, while the technical system involves operational processes, technical methods, and infrastructure [?, ?]. Based on this theory, the employee-AI collaborative work model requires attention to

the connection and joint optimization between the organization' s social system (i.e., employee, task, and organizational characteristics) and its technical system (i.e., AI characteristics). The following sections introduce the selection of specific variables and discuss the independent influence of each element in detail.

- 1) **Employee Characteristics:** Employee AI literacy and employee AI awareness are selected as two key indicators to measure employee-level drivers. First, employee AI literacy refers to the comprehensive ability of employees to effectively use, understand, and manage AI in work scenarios. Employees with high AI literacy can better collaborate with AI, achieving effective empowerment and complementary advantages [?, ?]. Second, employee AI awareness refers to the perception that AI may replace their jobs in the future; this is oriented toward attitudes and motivations rather than specific abilities. High AI awareness implies lower tolerance for technology and a more pessimistic assessment of career prospects. This negatively impacts the collaborative relationship between employees and AI, affecting employees' willingness to interact closely with AI and leading to differentiated collaboration modes.
- 2) **AI Characteristics:** AI technical level and AI reliability are selected as two key indicators to measure AI-level drivers. First, AI technical level refers to the capability level and performance characteristics demonstrated by AI in specific fields or tasks, reflecting its efficiency, complexity, and innovativeness in problem-solving [?, ?]. A high AI technical level can better empower employees or even replace them, whereas a low AI technical level can only serve as a simple auxiliary tool, and employees may even be reluctant to work with it [?, ?]. Second, AI reliability refers to the accuracy, consistency, and stability of AI functions and behaviors, as well as its reliability in practical implementation [?, ?], encompassing data, model, and platform reliability. Low-reliability AI fails to gain employee trust [?, ?], which in turn affects the frequency and depth of employee collaboration with it.
- 3) **Task Characteristics:** Task complexity and task type are selected as two key indicators to measure task-level drivers. First, task complexity directly affects the difficulty of task completion and the resources required. In employee-AI collaboration scenarios, it determines the division of roles and the frequency of interaction, thereby influencing the choice of collaboration mode. For low-complexity tasks, AI generally plays an auxiliary role with the employee leading the process; for high-complexity tasks, mutual cooperation between the employee and AI is often required [?, ?]. Second, task types can be categorized into cognitive-analytical and emotional-social [?, ?]. Cognitive-analytical tasks require high capabilities in processing complex information and data analysis, consuming significant cognitive resources. Emotional-social tasks require high emotional intelligence, communication skills, interpersonal skills, and organizational

coordination, consuming significant emotional resources [?, ?].

According to the summary by [?, ?], employees tend to trust AI more when performing cognitive-analytical tasks compared to emotional-social tasks, making deep collaboration with AI more likely in the former case.

- 4) **Organizational Characteristics:** Organizational resources and organizational culture are selected as two key indicators to measure organizational-level drivers.

First, organizational resources refer to the tangible and intangible assets owned or controlled by an organization that can create value. For instance, when an organization has sufficient financial, personnel, and technical preparation for AI intervention, employees can better cooperate with AI without worrying about failing to adapt or being replaced. Second, organizational culture refers to the shared values, beliefs, and behavioral norms of organizational members, such as the organization's tolerance, support, and encouragement of AI. A high degree of AI inclusiveness promotes employee acceptance and trust in AI, helping to improve employee-AI collaboration and foster closer, symbiotic collaborative relationships.

3.2.2 员工-AI 协作的组态效应

Study 2 aims to explore the complex interactions that may exist among various influencing factors, revealing the configurational patterns of different types of human-AI collaboration modes. Specifically, it encompasses the following two aspects.

First, the elements of “Employee-AI-Task-Organization” cannot function in isolation to influence human-AI collaboration; rather, these elements are closely intertwined and interact to jointly determine the type and level of collaboration. Research by Xie et al. (2021) indicates that for the same employee, the collaboration mode and level will vary when collaborating with different machines or facing different tasks. Similarly, when collaborating with the same machine, the collaboration modes of different employees will also differ. Jia et al. (2024) found that while working alongside AI, the technology is more likely to empower high-skilled employees, whereas for low-skilled employees, it may pose a risk of substitution. This suggests that human-AI collaboration is driven by the complex interaction of various factors. Second, the driving paths for different types of human-AI collaboration modes (Augmenting, Symbiotic, Assisting, and Substituting) vary; furthermore, even for the same type of collaboration mode, multiple causal paths may exist. When AI technical proficiency and reliability are high, employees with high AI literacy are likely to stimulate augmenting or even symbiotic collaboration modes. Conversely, if employees have low AI literacy or high AI awareness, it is more likely to lead to assisting or even substituting modes. Additionally, even within the assisting mode, the cause may be a lack of employee AI literacy (i.e., the employee cannot use it), mediocre AI technical capabilities (i.e., the AI cannot perform complex tasks), or the sim-

plicity of the task itself, which precludes the need for complex interaction (i.e., task complexity-driven).

It is evident that although all fall under the umbrella of human-AI collaboration, the causal paths and driving mechanisms of their influencing factors differ. In summary, human-AI collaboration is a complex process; no single factor can in isolation lead to a specific collaboration mode. Instead, the combination and matching of various elements lead to the selection of different levels and types of human-AI collaboration. Unfortunately, there is currently a lack of systematic empirical evidence explaining which combinations of elements are effective for specific human-AI collaboration modes.

Given the lack of such prior knowledge, this study is essentially exploratory. Following the common practice for configurational research as described by Du and Jia (2017), Study 2 does not propose a priori hypotheses but instead adopts an inductive approach to generate propositions based on the research results. To guide this exploratory research, Study 2 proposes the following research framework, as shown in [Figure 3: see original paper].

Regarding the research design, Study 2 conducted a large-scale questionnaire survey via the Credamo platform. The participants were limited to corporate employees who had experience collaborating with AI within the past month, aiming to reveal the configurational paths of human-AI collaboration modes. The online format and the lack of industry restrictions help to cover a wide range of samples, highlighting the differences between various employee, AI, task, and organizational characteristics, thereby allowing for a more comprehensive analysis of the impact of these four dimensions on collaboration modes. Furthermore, how do the various driving factors interact? What is the explanatory logic behind these driving paths? What interaction mechanisms do they reflect? To answer these questions, this study employs Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to explore the joint effects of multi-level driving factors and reveal the potential interactive relationships between different factors (Du & Jia, 2017).

Figure 3: Configurational Research Framework for Human-AI Collaboration

3.3 研究 3: 员工-AI 协作影响员工工作结果的作用机制与干预措施研究

While previous research has explored the outcomes of human-AI collaboration for employees, the findings remain contradictory. This study posits that the mechanisms underlying the advantages and disadvantages of human-AI collaboration may be related to the specific type of collaboration involved. To address this issue, Study 3 will investigate the impact of different types of human-AI collaboration modes on employee outcomes, as well as corresponding intervention measures. The research model is illustrated in [Figure 4: see original paper].

[Figure 4: see original paper] Research model of the impact of human-AI collaboration on employee outcomes. Specifically, Study 3 selects job performance

and job well-being as the primary employee outcomes. When exploring the consequences of human-AI collaboration, previous studies have mostly been limited to objective outcomes, such as task performance and innovation performance, often neglecting the subjective experiences of employees. Therefore, Study 3 integrates both objective and subjective dimensions by selecting job performance and job well-being. Job performance refers to the efficiency and effectiveness with which work is completed; it is the foundation of corporate survival and development, and serves as a critical basis for management decisions such as promotions and compensation. Job well-being is the psychological feeling that an individual's work goals and potential are fully realized. It represents the ultimate goal of human productive activity and is a vital indicator for measuring the quality of work-life [?, ?].

Furthermore, based on Cognitive-Affective System Theory (CAPS), Study 3 reveals the mechanisms through which different types of human-AI collaboration modes differentially impact employee outcomes from both cognitive and affective perspectives. CAPS posits that an individual's behavioral response to a situation is jointly influenced by cognitive-affective processing units [?, ?]. Accordingly, Study 3 selects cognitive expansion and cognitive loafing to reflect the cognitive processes of employees during human-AI collaboration, and selects positive and negative affect to reflect their emotional processes.

Finally, Cognitive-Affective System Theory suggests that the environment exerts a moderating effect on the “cool” cognitive processing system and the “hot” affective processing system [?, ?]. Organizational management interventions constitute the most direct context for human-AI collaboration and significantly influence its effectiveness. Consequently, Study 3 proposes four targeted intervention measures for the four distinct collaboration modes. Specifically, for the *Augmenting* collaboration mode, “decision-making sovereignty cultivation” is introduced to ensure the core status of the employee. For the *Symbiotic* mode, “dynamic contribution assessment” is introduced to clarify individual contributions and ensure fairness. For the *Assistive* mode, a “functional expansion plan” is introduced to break the limitations of instrumental thinking. For the *Substitutive* mode, “transformation guidance and support” is introduced to alleviate the pressure of replacement and achieve employee skill upgrading. The following sections discuss the research model in detail.

3.3.1 Augmenting Human-AI Collaboration and Employee Outcomes

In the augmenting human-AI collaboration mode, AI serves as an “external cognitive scaffold,” taking over heavy and low-level cognitive tasks such as information gathering, preliminary classification, and pattern recognition. This releases employee cognitive resources from the role of “information mover,” directly reducing cognitive load and preventing decision fatigue and cognitive exhaustion caused by information overload. Simultaneously, by virtue of its powerful data analysis capabilities, AI can provide insights from perspectives difficult for humans to perceive, stimulating curiosity and reflection. This en-

courages employees to explore diverse possibilities, shifting cognitive activity from passive task processing to active problem-solving, effectively countering cognitive boredom arising from monotonous work [?, ?]. On this basis, employees are able to invest their valuable cognitive resources continuously and focus on complex work that requires human-specific traits. Here, AI acts as a “capability enhancer,” providing personalized decision support, data analysis, and auxiliary judgment, thereby expanding the employee’s cognitive boundaries and knowledge acquisition while facilitating deep thinking and bold creativity [?, ?]. This represents not only the mitigation of cognitive loafing but also a holistic leap in individual cognitive capacity. Therefore, this study argues that augmenting human-AI collaboration will reduce cognitive loafing and enhance cognitive expansion. Weakened cognitive loafing and enhanced cognitive expansion will help improve employees’ capacity for proactive learning and innovation, thereby increasing job performance [?, ?].

Additionally, the augmenting human-AI collaboration mode can provide timely and personalized feedback and support, making employees feel valued and supported. This, in turn, generates positive affect—such as pride, a sense of achievement, and job satisfaction—thereby enhancing employee job well-being [?, ?]. Based on this, the study proposes the following:

Proposition 1: Augmenting human-AI collaboration improves job performance by reducing cognitive loafing and enhancing cognitive expansion; it improves job well-being by stimulating positive affect in employees.

3.3.2 共生型员工-AI 协作与员工工作结果

In a symbiotic employee-AI collaboration model, employees and AI establish a complementary relationship. Employees leverage uniquely human creativity and emotional judgment, while AI provides support through big data analytics and process automation; the integration of these two forces generates a synergistic effect. This model not only enhances employees’ ability to solve complex problems by structurally reshaping job content and cognitive demands—thereby strengthening the sense of work meaningfulness and engagement while mitigating cognitive loafing—but also promotes cognitive expansion through the complementarity of human and machine capabilities. Consequently, this leads to a balanced cognitive state that facilitates improved work efficiency (Glikson & Woolley, 2020).

Furthermore, symbiotic employee-AI collaboration emphasizes mutual benefit between humans and AI, allowing employees to experience a sense of “partnership” during the collaborative process. This emotional connection helps alleviate the uncertainty and anxiety brought about by technology, enhancing an emotional sense of belonging and security. This stability enables employees to maintain more consistent emotional states when facing complex tasks, thereby exerting a positive impact on employee well-being. Based on this, the present study proposes the following proposition:

Proposition 2: Symbiotic employee-AI collaboration improves employee job performance by reducing cognitive loafing and enhancing cognitive expansion; it also enhances employee well-being by stimulating positive emotions.

3.3.3 辅助型员工-AI 协作与员工工作结果

In the supportive employee-AI collaboration mode, employee cognitive slack exhibits a U-shaped relationship. Specifically, at low to moderate levels of collaboration, AI serves as a cognitive offloading tool that takes over repetitive and procedural tasks. This allows employees to reallocate their cognitive resources toward core responsibilities that require human judgment. Such job reshaping improves the alignment between task challenges and employee skill levels, thereby enhancing intrinsic motivation and the experience of flow. In other words, employee-AI collaboration effectively inhibits cognitive slack—often triggered by task boredom or resource depletion—by optimizing cognitive resource allocation and elevating the perceived meaning of work (Kitic & Kitapci, 2023).

When the degree of collaboration crosses a specific threshold into the critical zone of moderate collaboration, AI's comprehensive takeover of routine tasks causes employees to lose vital opportunities to hone professional intuition, develop adaptive judgment, and accumulate tacit knowledge through exposure to subtle task variations during repetitive practice. At this stage, the employee's metacognitive activity quietly diminishes, marking the inflection point of the U-shaped relationship and the onset of instrumental dependence. Upon entering deep collaboration, excessive reliance on the tool triggers systemic cognitive regression. On one hand, employees develop an instrumental mindset inertia (Miller, 2019), which reduces their willingness to engage in proactive thinking. On the other hand, the long-term lack of active application and practice of higher-order cognitive skills—such as critical thinking and complex judgment—leads to the degradation of these abilities due to “disuse,” resulting in a continuous blunting of metacognition (Wu et al., 2025). Ultimately, this dependence on AI tools and the erosion of metacognitive capacity cause the level of cognitive slack to rise again. Therefore, the impact of the supportive employee-AI collaboration mode on cognitive slack follows a U-shaped pattern, initially decreasing and subsequently increasing. Cognitive slack, in turn, affects employee work engagement, ultimately leading to a decline in job performance. It should be noted that in this mode, AI serves as a supportive tool to alleviate burdens rather than an instrument to expand the boundaries of employee capabilities; thus, there is no significant relationship between this mode and employee cognitive expansion.

Furthermore, in the supportive employee-AI collaboration mode, the interaction between AI and the employee is primarily functional and instrumental. Because no emotional bond is established, this collaboration mode does not exert a significant influence on the employee's emotional processes. Based on this, the present study proposes the following proposition:

Proposition 3: Supportive employee-AI collaboration has a U-shaped effect on

employee job performance through cognitive slack, while it has no significant relationship with the employee's emotional processes or workplace well-being.

3.3.4 替代型员工-AI 协作与员工工作结果

In the replacement-based employee-AI collaboration model, AI takes over work tasks either partially or entirely. This shift reduces the active participation of employees in their daily routines, leading to insufficient cognitive engagement and, consequently, the emergence of cognitive slack (Parasuraman & Manzey, 2010).

Simultaneously, employees may feel that their personal value is being marginalized. They are deprived of the cognitive stimulation and growth opportunities originally provided by their work tasks, which ultimately undermines overall job performance.

Furthermore, when AI partially replaces an employee's role, the individual is likely to experience a sense of loss of control, anxiety, and an identity crisis. These factors trigger a range of negative emotions, such as insecurity, frustration, and even resistance (Tang et al., 2021). Over time, these negative affects diminish the employee's enthusiasm and engagement, leading to a significant reduction in workplace well-being. Based on these observations, this study proposes the following proposition:

Proposition 4: Replacement-based employee-AI collaboration reduces job performance by triggering cognitive slack and diminishes workplace well-being by inducing negative affect.

3.3.5 四种员工-AI 协作模式与员工工作结果的比较

It is important to note that while both augmentative and symbiotic collaboration can improve job performance and enhance well-being by reducing cognitive slack, fostering cognitive expansion, and stimulating positive emotions, augmentative collaboration still emphasizes employee agency. In this mode, AI serves an enhancing role, resulting in a "unidirectional" improvement effect. In contrast, the symbiotic collaboration model emphasizes bidirectional interaction and co-evolution, thereby exerting more sustained and profound positive effects on both job performance and well-being. Based on this, the present study proposes the following proposition:

Proposition 5a: Compared to augmentative human-AI collaboration, symbiotic human-AI collaboration is more effective at reducing cognitive slack and stimulating cognitive expansion and positive emotions; it therefore has a more significant positive impact on employee job performance and well-being.

Furthermore, although both supportive and substitutive human-AI collaboration involve cognitive slack, employees in the supportive collaboration mode typically retain the right to active participation and autonomous decision-making,

which stimulates the cognitive process to a certain extent. Conversely, the substitutive collaboration mode often leads employees to perceive role marginalization and a loss of control, making it more likely to trigger cognitive slack and negative emotions such as anxiety and insecurity. This, in turn, exerts a more significant negative impact on job performance and well-being. Based on this, the present study proposes the following proposition:

Proposition 5b: Compared to supportive human-AI collaboration, substitutive human-AI collaboration is more likely to trigger cognitive slack and negative emotions; it therefore has a more significant negative impact on employee job performance and well-being.

3.3.6 不同管理干预措施的匹配调节作用

(1) The Moderating Role of Decision Sovereignty Cultivation in Augmented Employee-AI Collaboration

In the context of augmented employee-AI collaboration, a critical issue is how to clarify the agency and even the subjectivity of employees within the collaborative hierarchy. Decision sovereignty cultivation measures play a vital role in this process.

Decision sovereignty cultivation refers to a dynamic developmental process in human-machine collaboration scenarios. Through institutional design, capacity building, and technical adaptation, it systematically enhances employees' autonomy, controllability, and sense of responsibility during decision-making, ensuring they retain core decision-making power even with AI assistance [?, ?]. Its essence lies in balancing technological empowerment with human subjectivity through organizational intervention. Under the augmented employee-AI collaboration mode, such cultivation helps maintain employees' independent judgment and strengthens their ability to critically interpret AI suggestions, thereby further alleviating cognitive loafing and reinforcing cognitive expansion. Furthermore, high decision autonomy ensures that employees establish appropriate trust in AI [?, ?], reduces anxiety triggered by technical uncertainty, and strengthens positive emotional experiences. Weakened cognitive loafing, combined with enhanced cognitive expansion and positive emotional experiences, will further improve job performance and well-being. Based on this, this study proposes the following proposition:

Proposition 6a: Decision sovereignty cultivation positively moderates the mediating roles of cognitive loafing, cognitive expansion, and positive affect in the relationship between augmented employee-AI collaboration and both job performance and employee well-being. Specifically, when the level of decision sovereignty cultivation is high, the positive impact of augmented employee-AI collaboration—achieved by alleviating cognitive loafing and enhancing cognitive expansion to improve performance, and by stimulating positive affect to enhance well-being—will be strengthened.

(2) The Moderating Role of Dynamic Contribution Evaluation in Symbiotic Employee-AI Collaboration

The symbiotic employee-AI collaboration mode emphasizes equal co-creation between humans and machines, where employees and AI form a bidirectional feedback mechanism in goal setting, task execution, and output optimization [?, ?]. The core of this collaboration mode is value co-creation; therefore, clarifying contributions and ensuring fairness are essential. Dynamic contribution evaluation measures play a significant role in this process.

Dynamic contribution evaluation is a value quantification mechanism based on human-machine collaboration scenarios. It continuously assesses the knowledge creation, innovative value, and relational benefits generated by employees and AI in collaborative tasks through real-time tracking, multi-dimensional analysis, and iterative feedback [?, ?]. Real-time feedback mechanisms help employees adjust their knowledge integration strategies in a timely manner during AI collaboration, deepening the practical value of cognitive restructuring. Transparent contribution allocation enhances perceptions of fairness and strengthens emotional identification, thereby further improving job performance and well-being. Based on this, this study proposes the following proposition:

Proposition 6b: Dynamic contribution evaluation positively moderates the mediating roles of cognitive loafing, cognitive expansion, and positive affect in the relationship between symbiotic employee-AI collaboration and both job performance and employee well-being. Specifically, when the level of dynamic contribution evaluation is high, the positive impact of symbiotic employee-AI collaboration—achieved by alleviating cognitive loafing and enhancing cognitive expansion to improve performance, and by stimulating positive affect to enhance well-being—will be strengthened.

(3) The Moderating Role of Functional Expansion Programs in Assisted Employee-AI Collaboration

In the assisted employee-AI collaboration mode, the employee serves as the core decision-maker while AI acts as a replaceable tool; its primary value lies in improving the efficiency of standardized tasks. In this mode, employees are prone to developing technological dependence; thus, it is necessary to break the inertia of “tool-oriented thinking” by upgrading their skills.

Functional expansion programs are systematic interventions designed by organizations to enhance the collaborative efficacy between employees and AI tools. These programs aim to facilitate the transition of employees from basic functional operations to high-level functions and innovative applications of AI tools through tool-usage training, functional exploration incentives, and cross-scenario application support [?, ?]. By mastering advanced AI functions (such as predictive analytics), employees achieve cognitive upgrading, shifting from simple dependence to strategic utilization. Consequently, the negative effects of

cognitive dependence and loafing are weakened, as is their negative impact on job performance. Based on this, this study proposes the following proposition:

Proposition 6c: Functional expansion programs negatively moderate the mediating role of cognitive loafing in the relationship between assisted employee-AI collaboration and job performance. The more extensive the functional expansion measures, the more they alleviate the U-shaped relationship between assisted employee-AI collaboration and cognitive loafing.

(4) The Moderating Role of Transition Guidance Support in Substitutive Employee-AI Collaboration

The substitutive employee-AI collaboration mode is characterized by AI completely replacing an employee's original position, requiring the employee to redefine their role through professional transition (e.g., a production line worker transitioning to a robot maintenance technician). The core conflict in this mode lies in the dynamic tension between the pressure of technological substitution and the need for employee capability transformation.

Transition guidance support refers to systematic support measures provided by organizations to facilitate employees' adaptation to the transformation of human-machine collaboration modes. Its core function is to help employees complete the transition from traditional work modes to AI-augmented work modes through cognitive restructuring, emotional counseling, and behavioral empowerment [?, ?]. Measures such as skill training, psychological counseling, and resource support change employees' cognitive frameworks and emotional responses to substitutive collaboration by reducing transition uncertainty. Transparent transition paths (e.g., clear skill migration roadmaps) and psychological counseling (e.g., framing AI substitution not as a threat but as a career upgrade opportunity) weaken threat perceptions and reduce defensive cognitive and negative emotional reactions, thereby mitigating the negative impact on job performance and well-being. Based on this, this study proposes the following proposition:

Proposition 6d: Transition guidance support negatively moderates the mediating roles of cognitive loafing and negative affect in the relationship between substitutive employee-AI collaboration and both job performance and well-being. When the level of transition guidance support is high, the negative impact of substitutive employee-AI collaboration—which typically reduces performance by triggering cognitive loafing and decreases well-being by triggering negative affect—will be attenuated.

To test the above hypotheses, this study first employs laboratory experiments to collect eye-tracking and EEG data to establish causal relationships and ensure internal validity. Subsequently, field research (utilizing questionnaires, secondary data, and behavioral logs) is conducted to capture the cognitive and emotional processes of employee-AI collaboration in real-world work settings and their impact on work outcomes, while simultaneously verifying the effectiveness of

various management interventions to ensure external validity. Specifically, the laboratory experiment uses university students as subjects, requiring them to collaborate with an intelligent machine on an “Intelligent Marketing Assistant” platform to write marketing copy for a campus milk tea shop; four distinct employee-AI collaboration scenarios are constructed by controlling the platform. All participants wear Tobii Pro Fusion-250 eye trackers and portable wireless EEG systems to capture eye-movement and brainwave information to determine cognitive and emotional states, with work outcomes assessed based on the quality of the final copy. For the field research, smart manufacturing enterprises are selected as the research subjects. These enterprises possess complete business processes and cutting-edge technology applications, clearly demonstrating the full spectrum of collaboration modes—from substitution to symbiosis—across the “R&D-Production-Supply Chain-Sales-Service” chain. Examples include: AI customer service replacing employees to handle standardized service tickets (substitutive collaboration); R&D teams using AI for data analysis and document processing (assisted collaboration); supply chain experts collaborating with AI systems for dynamic scheduling, demand forecasting, and risk early warning (augmented collaboration); and “carbon-based employees” forming collaborative networks with “silicon-based employees” to reshape business processes and organizational structures (symbiotic collaboration). Thus, smart manufacturing enterprises fully encompass all types of employee-AI collaboration modes, providing an ideal setting for this study to explore the impacts of employee-AI collaboration.

4.1 理论贡献

With the rapid advancement of artificial intelligence (AI), the question of how employees collaborate with AI has become a critical issue, positioning human-AI collaboration as a frontier and a focal point of academic interest. Grounded in the significant organizational practice of human-AI collaboration, this study aims to address how employees and AI collaborate in the digital intelligence era. Specifically, it explores the existing modes of collaboration, the reasons for the emergence of different collaboration types, the impacts of these various modes, and the implementation of effective management interventions. By constructing an integrated “Type-Antecedent-Consequence” research model, this study extends and enriches research on human-machine collaboration. It aims to help employees and organizations better understand and utilize AI to achieve efficient synergy, thereby enhancing employee work efficiency and organizational productivity. The theoretical contributions of this research are primarily reflected in the following three aspects:

First, this study constructs a classification model for human-AI collaboration, reveals the conceptual connotations of different collaboration modes, and develops corresponding scales, thereby laying a foundation for subsequent empirical research. Establishing a scientifically sound classification model is fundamental to theoretical research on human-AI collaboration. Although scholars have

attempted to categorize various modes of human-AI collaboration, existing classifications—whether based on the perspective of agency or interactivity—remain relatively one-sided and incomplete, lacking a systematic integration framework (Raisch & Krakowski, 2021; Sowa et al., 2021). Furthermore, the current lack of effective measurement tools for human-AI collaboration has hindered empirical progress, necessitating the development of scales tailored to different collaboration types. To address this, this study integrates agency and interactivity to construct a 2×2 conceptual model of human-AI collaboration across dual dimensions. This model categorizes collaboration into four types: augmenting, symbiotic, assisting, and substituting. By clarifying the connotations and differences among these four modes, the study provides an essential theoretical basis for a comprehensive and accurate understanding of human-AI collaboration. Additionally, the development of these scales offers a valid methodology for measuring human-AI collaboration, facilitating future empirical investigations.

Second, this study explores the formation mechanisms of different human-AI collaboration modes and utilizes configuration research to reveal the causes behind the diverse types and levels of collaboration. This deepens the understanding of the drivers of various collaboration modes and significantly enriches the research on the antecedents of human-AI collaboration. Human-AI collaboration is a complex process; no single factor can lead to a specific collaboration type in isolation. Although some studies have discussed the antecedents of human-AI collaboration, they often fail to distinguish between the differentiated drivers of various collaboration modes. Moreover, most existing research tends to focus on the “net effect” of single factors, with few systematic explorations of how multiple factors interact. Consequently, current literature struggles to explain the multiple concurrent factors and complex causal mechanisms influencing collaboration types. To fill this gap, this study draws on Socio-Technical Systems (STS) theory to identify four dimensions of influencing factors: employee characteristics (AI literacy and AI awareness), AI characteristics (AI technical level and AI reliability), task characteristics (task complexity and task type), and organizational characteristics (organizational resources and organizational culture). By employing fuzzy-set Qualitative Comparative Analysis (fsQCA), this study investigates the synergistic effects of these four dimensions and reveals the configurational paths that lead to different human-AI collaboration modes, thereby expanding the explanatory scope of antecedents from a holistic perspective.

Third, this study investigates the differentiated cognitive-affective mechanisms through which different types of human-AI collaboration influence work outcomes, opening the “black box” of these effects while identifying targeted intervention strategies. This provides a new explanation and solution for the current phenomenon of contradictory positive and negative effects in human-AI collaboration. Existing research often yields inconsistent conclusions, the roots of which may lie in two areas: first, a tendency to treat human-AI collaboration as a monolithic construct without distinguishing between the effects of different collaboration modes (Kong et al., 2023; Tang et al., 2022); and second, a focus on cognitive mechanisms that neglects the role of affect (Bankins et al.,

2024), leading to an incomplete understanding of the underlying processes. To address these limitations, this study applies Cognitive-Affective System Theory to propose that cognitive processes (cognitive expansion and cognitive loafing) and affective processes (positive and negative affect) jointly explain the mechanisms linking different collaboration modes (augmenting, symbiotic, assisting, and substituting) to work outcomes (job performance and work well-being). This approach provides a comprehensive revelation of the internal mechanisms of human-AI collaboration. Furthermore, while current research predominantly focuses on the role of the employee (Bankins et al., 2024; Jia et al., 2024), it often overlooks the role of the organization, particularly regarding intervention and guidance. Consequently, this study introduces specific management interventions—namely, decision sovereignty cultivation, dynamic contribution assessment, functional expansion programs, and transformation guidance support—to manage the four collaboration modes. This theoretically extends research on the boundary effects of human-AI collaboration and provides a more complete theoretical picture for understanding collaboration outcomes and interventions.

4.2 实践启示

This study offers three significant practical implications for organizational management. First, at the employee level, this research helps individuals understand the characteristics of various collaboration modes, enabling them to match and optimize these modes to enhance their core competitiveness and adaptability to future changes. With the rapid advancement of artificial intelligence, the question of how employees collaborate with AI has become critical. Categorizing types of human-AI collaboration allows employees to recognize their own strengths and weaknesses within these partnerships, facilitating targeted skill training, professional development, and adjustments to their work methods. Furthermore, by identifying the four-dimensional factors of “employee-AI-task-organization” and exploring their joint effects, this study reveals differentiated configurational paths and outcomes across different collaboration types. This helps identify the specific modes and contexts in which employees are more likely to achieve positive work experiences and psychological satisfaction, thereby improving work outcomes and achieving efficient synergy between humans and AI in the digital intelligence era.

Second, at the managerial level, this study assists managers in clarifying the pros and cons of human-AI collaboration, enabling them to arrange AI implementation plans rationally and formulate personalized management strategies. While AI brings convenience, it also triggers employee distrust and resistance; it is the responsibility of managers to help employees adapt to coexisting and collaborating efficiently with AI. By clarifying different types of human-AI collaboration modes and systematically analyzing their antecedents and consequences, this research helps managers accurately grasp the diverse manifestations of human-AI interaction. This allows them to evaluate the effectiveness of different collaboration modes, identify problems and optimization points, and implement targeted

interventions to achieve high-efficiency synergy.

Third, at the organizational level, this study helps organizations optimize resource allocation and improve overall performance. By providing corresponding management interventions for the differentiated effects of various human-AI collaboration modes—such as decision-making sovereignty cultivation, dynamic contribution assessment, functional expansion plans, and transformation guidance support—this research clarifies the resource requirements of different collaboration modes. This enables organizations to provide targeted support and interventions, improving resource utilization efficiency through precise investment and ensuring that every link within the organization can smoothly adapt to the new transformations brought by AI.

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When employee meets AI: Research on employee-AI collaboration's construct measurement, antecedent configuration and influence mechanism CHEN Hui, FENG Chao (1 Ginling College, Nanjing Normal University, Nanjing 210097, China) (2 College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China) Abstract: In the Digital-intelligence era, employee-AI collaboration has become an important work pattern. Against this backdrop, it has significance to explore how employee collaborates with AI, why different collaboration patterns emerge, what the impacts of distinct collaboration patterns are, and how to intervene in them. To address these questions, this study conducts a series of explorations focusing on the typologies, antecedents, and consequences of employee-AI collaboration. Firstly, based on the dual dimensions of agency and interaction, the employee-AI collaboration is divided into four typologies: Augmentation, Symbiosis, As-

sistance, and Substitution, while developing corresponding measurement scales. Secondly, grounded in sociotechnical systems theory, this study identifies influencing factors across four dimensions (employee, AI, task, and organization) and investigates their synergistic effects through a configurational approach. Finally, based on the cognitive-affective processing system theory, this study introduces cognitive-affective dual mechanisms, and explores the moderating role of four management interventions to reveal how different types of employee-AI collaboration shape employee performance and well-being. This study theoretically expands the frameworks for employee-AI collaboration research, and practically it provides critical insights for achieving high efficiency of employee-AI collaboration in organizations.

Keywords: Human-AI collaboration, AI, job performance, job well-being

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

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