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Chapter: Technological Transformation, Digitalization, and Innovation Dynamics as Drivers of Innovation, Organizational Change, and Process of Improvement

Collaboration Satisfaction in Human–AI Teams: The Dual Roles of Trust and Cognitive Load

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Annotation. With the rapid development of artificial intelligence (AI), organizational collaboration structure and operational logic are being reshaped, and human–AI co-creation is gradually becoming the norm. However, the impact of AI embedding on team collaboration satisfaction remains unclear. To explore how AI embedded in teams affects team collaboration satisfaction, drawing on socio-technical systems theory and information processing theory, utilizing a between-subjects experimental design, 100 participants were recruited via an online platform in April 2025, how AI affects team collaboration satisfaction was investigated through the dual pathways of social and technical subsystems by manipulating team composition (human–human teams *vs*. human–AI teams). Results indicate that the introduction of AI significantly weakens human members' team trust while effectively reducing their cognitive load. The opposite effects of these two pathways lead to a canceling indirect effect, which makes the overall impact of AI on collaboration satisfaction neutral. Further analysis reveals that team project experience significantly moderates the above mechanisms. Specifically, experienced members rely more on interpersonal cooperation and are more sensitive to AI's emotionless collaboration style, thereby reducing trust. However, they perceive less value in AI's assistance because they have internalized efficient cognitive strategies. The conclusions of this study deepen the present understanding of the human–AI collaborative mechanism in AI technology embedding, reveal the interaction between structural technological change and individual experience, and provide theoretical support for the design and management of future intelligent collaboration systems.

Keywords: artificial intelligence, human–AI team collaboration, collaboration satisfaction, socio-technical systems theory, information processing theory.

JEL classification: O15, D23.

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Introduction

With the in-depth evolution of information technology, the new generation of intelligent technologies, centered on artificial intelligence (AI) and intelligent collaborative systems, is accelerating their penetration into various industries. These technologies are now being widely applied in high-frequency decision-making scenarios such as healthcare, education, transportation, manufacturing, and retail, thereby continuously reshaping the operational logic and structural foundations of organizations (Konya-Baumbach *et al.*, 2023). AI technology is rapidly evolving from a tool for partial task substitution to an embedded structural agent. This technology is not only involved in data analysis and task execution but also begins to play a quasi-subject role in resource allocation, process collaboration, and even management decision making (Jia *et al.*, 2024; Seeber *et al.*, 2020). This transformation has triggered a significant reconfiguration of organizational socio-technical systems, thereby forcing organizations to redesign their human resource structures, collaborative boundaries, and role systems (Larson, DeChurch, 2020). An increasing number of organizations are also exploring the construction of human–machine collaborative teams, which enable AI and human members to form a dynamic division of labor based on goal coupling and to achieve functional collaboration through information sharing and decision complementarity (Dennis *et al.*, 2023; Zhang *et al.*, 2023). In this context, AI is gradually breaking free from the boundaries of traditional passive tools and is being incorporated into the team collaboration system as a member. This technology is expected to undertake multiple roles, such as task inputter, suggestion provider, and process coordinator (Erengin *et al.*, 2025), thus leading to systematic adjustments in organizational boundaries, responsibilities, and interpersonal interaction mechanisms (Robertson *et al.*, 2025).

In recent years, research at the intersection of AI and organizational behavior has grown rapidly, with the academic community gradually shifting from a tool-based perspective to explore the deep impact of AI as a team member on collaborative processes. Previous studies have examined how human behavior is influenced by AI functioning as a suggestion system or an execution assistant from the perspectives of human–machine trust, willingness to cooperate, and information adoption (Erengin *et al.*, 2025; Hyun Baek, Kim, 2023; Zhang *et al.*, 2023). However, most of these studies regard AI as an external input source or auxiliary system and do not pay much attention to the deep organizational behavior mechanisms (e.g., role reshaping, reconstruction of interaction patterns, and disturbance of emotional mechanisms) brought about by the formal incorporation of AI into the team composition and its role as a structural collaborator. Specifically, in team task collaboration, the non-human characteristics of AI, such as its lack of self-awareness and social emotional responses, may cause significant gaps in human members' sense of belonging, trust stability, and interaction smoothness.

Furthermore, in highly complex and collaborative tasks, AI may not only weaken the social connections and interaction tacitness among members but may also bring discomfort to human members due to its lack of interaction rhythm and relationship maintenance strategies, thereby leading to communication withdrawal and subtle yet critical psychological reactions, such as identity threat, collaborative alienation, or substitution anxiety (Przegalinska *et al.*, 2025; Wu *et al.*, 2025). Previous research on these issues remains mostly descriptive and lacks a systematic theoretical model to explain how AI, as a structural agent embedded in a team, jointly affects team members' subjective experiences and collaboration evaluations through trust and cognitive mechanisms. Therefore, against the backdrop of AI gradually shifting from a peripheral technology to being deeply embedded in organizational structures, clarifying how such technology reshapes the logic of team composition and interferes with human members' cooperative experiences and subjective evaluations has become a key theoretical issue for understanding the coupling quality of socio-technical systems in the intelligent era. This transformation also poses higher demands on how organizations coordinate human–machine role boundaries and ensure team members' collaborative experiences.

Despite the unprecedented speed at which AI is being embedded into the core processes of organizations, the academic community has yet to reach a systematic consensus on its effects on team collaboration. Previous research has pointed out from multiple dimensions that the introduction of AI can, under certain conditions, expand individuals' cognitive boundaries and promote their divergent thinking, problem restructuring abilities, and task execution efficiency (Grilli, Pedota, 2024; Koivisto, Grassini, 2023). This technology can also optimize individuals' subjective engagement experiences by reducing task load and process complexity (Urban *et al.*, 2024). These findings suggest that AI has significant cognitive synergy value and can increase human members' satisfaction with team collaboration outcomes (Jia *et al.*, 2024). However, other studies show that AI's non-human attributes and lack of emotional interaction capabilities may weaken the emotional connections, trust tacitness, and willingness to collaborate among team members, which, in turn, can affect human members' sense of security and motivation to participate in the team (Alshahrani, Queiroz, 2025; Georganta, Ulfert, 2024). In teams with intensive interactions and complex tasks, AI's inability to provide relationship maintenance and emotional feedback may lead to structural barriers, such as communication withdrawal, collaboration imbalance, and even role misalignment (Sheridan, 2019).

Although the above studies have revealed the potential impacts of AI on cognitive experiences and social interactions, some structural deficiencies remain in the literature. First, previous research has largely focused on the unidirectional effects of AI embedding and lacks a systematic theoretical perspective that can integrate both positive and negative effects. Second, despite being included in some research frameworks, satisfaction is mostly presented as a task-related emotional reaction and is seldom regarded as a core mechanism variable for measuring the collaborative quality of human–machine teams. Finally, previous studies lack a clear mechanism and a well-structured theoretical model that can reveal how AI, as a structural agent embedded in a team, affects the psychological construction process of individual satisfaction through the dynamic coupling of social and technical factors.

This study aims to systematically reveal the formation mechanism of human–machine collaboration satisfaction in the context of AI embedding, thus highlighting how structural technological changes affect human cooperative experiences. Specifically, based on the integrated framework of socio-technical systems (STS) theory and information processing theory (IPT), this study constructs a dual-path mediation model to explore how the introduction of AI as a team member affects human members' satisfaction with team collaboration by disrupting the trust mechanism in the social subsystem and simultaneously altering the cognitive load state in the technical subsystem. Furthermore, considering the individual differences when facing AI systems, this study introduces team project experience as a moderating variable to examine how such experience affects the perceived strength and direction of the trust and cognitive paths under AI embedding, thereby revealing the potential tension evolution mechanism and optimization opportunities in the AI–human collaborative system. Based on this theoretical framework, this study proposes the following research questions: (1) does the embedding of AI affect the collaboration satisfaction of human members in the team? (2) Do trust and cognitive load mediate the relationship between AI embedding and satisfaction? (3) Does team project experience moderate the impact of AI on trust and cognitive load, thereby changing its indirect effect on satisfaction? By answering these questions, this study not only helps clarify the psychological mechanisms and cognitive tensions within the STS after the embedding of technological agents but also provides theoretical support and design inspiration for future organizations in building high-quality human–machine collaborative systems.

The contributions of this study are threefold. First, in the rapidly evolving context of human–machine collaboration, this study addresses the gaps in organizational behavior research regarding the lack of a mechanistic explanation for how the AI embedded in teams affects the cooperative experience of human members. Second, based on STS theory and IPT, this study constructs an integrated dual-path mediation model that incorporates trust and cognitive load to reveal how AI, as a structural agent, simultaneously disrupts social relationships and technical processes to affect the key perceptual indicator of collaboration satisfaction, thereby enriching the systematic theoretical explanation of AI's impact mechanisms. Finally, by introducing team project experience as a key moderating variable, this study captures the sensitivity, strategic behavior, and adaptability differences exhibited by human members in response to technological substitution or collaboration due to the heterogeneity of team cooperation experience, thus expanding the explanatory scope of individual characteristics in AI deployment research.

The rest of this study is structured as follows. Section 2 presents the theoretical analysis and research hypotheses, constructs the research model based on STS theory and IPT, and proposes that team composition affects collaboration satisfaction through the dual paths of trust and cognitive load, with team cooperation experience playing a moderating role. Section 3 introduces the research methods, research design, sample selection, experimental materials, and data analysis process, verifies the hypotheses, and presents the empirical results. Section 4 summarizes the main findings and presents the theoretical and practical implications of the study. Section 5 provides the conclusions and managerial implications in the context of short video marketing in the tourism industry, points out the limitations of the study, and offers directions for future research.

1. Theoretical Analysis and Hypothesis Development

1.1 Team Composition and Collaboration Satisfaction from the Perspective of Socio-Technical Systems Theory

STS theory views organizations as complex entities where technical and social subsystems are interwoven and dynamically coupled. The effectiveness of an organization relies on the structural alignment and procedural collaboration between these two subsystems (Appelbaum, 1997). The technical subsystem is responsible for task execution and information processing, while the social subsystem maintains role division, interaction mechanisms, and cooperation norms, thus forming an essential contextual foundation for organizational operations (Pasmore *et al.*, 2019; Walker *et al.*, 2008). When a fundamental change in the technical architecture takes place, the failure to achieve synchronous evolution in the social structure can create tension between technological upgrades and structural imbalance, thereby interfering with team members' perceptions and evaluations of organizational performance (Govers, van Amelsvoort, 2023).

With the increasing integration of AI systems into the core of organizational operations, team composition is undergoing a paradigm shift from human–human to human–machine collaboration. AI is transforming from a traditional task tool to a structural agent and currently assumes multiple roles, such as data processor, decision advisor, and collaboration facilitator within teams (Queiroz *et al.*, 2024; Sharma *et al.*, 2023). This transformation requires team members to complete their tasks in a diversified collaboration context that involves intelligent agents, leading to a reconceptualization of team boundaries, role attributes, and cooperation expectations (Atchley *et al.*, 2024). Although the introduction of AI enhances task automation and cognitive efficiency, this technology also poses new challenges to human members' participation methods, interaction patterns, and psychological adaptation (Vaccaro *et al.*, 2024). This process of technical–social restructuring makes team composition a structural variable that affects human members' subjective collaborative experiences (Alshahrani, Queiroz, 2025).

From the perspective of STS, changes in team composition have a profound impact on human members' collaboration satisfaction. On the one hand, the introduction of AI members may bring improvements in process efficiency and cognitive resource expansion and enhance the smoothness and systematic nature of task execution, thereby increasing satisfaction perception (Queiroz *et al.*, 2024). On the other hand, AI members' lack of social responsiveness and emotional interaction mechanisms may disrupt the original interaction logic and role order of the team, which can cause human members to experience uncertainty and adaptation pressure in identity confirmation, relationship building, and collaborative integration (Lu *et al.*, 2024; Daly *et al.*, 2025). Therefore, from the perspective of STS theory, changes in team composition are not merely formal alterations but also serve as key mechanisms in the co-evolution of STS. These changes directly affect members' overall evaluation of the current collaboration model and determine whether human–machine integration can achieve true system synergy.

1.2 Impact of Team Composition on Trust and Cognitive Load

Within the framework of STS theory, organizations are understood as composite systems constituted by the synergy of technical and social subsystems, with their effective operation relying on the high-quality coupling between these subsystems (Appelbaum, 1997; Govers, van Amelsvoort, 2023). According to this theory, teams are not only the most basic execution units but also the key interface for the dynamic alignment of social and technical elements. The composition pattern of a team determines the boundary demarcation and energy flow between the social interaction and technical configuration structures, thereby profoundly affecting task execution mechanisms and psychological experience outcomes (Schmutz *et al.*, 2024).

As AI transitions from a tool-based attribute to a structural agent, its embedding is no longer a linear addition of technological enhancement but now constitutes a systemic perturbation (Robertson *et al.*, 2025) that challenges the existing social subsystem architecture. Specifically, AI lacks key characteristics, such as emotional resonance, value coordination, and responsiveness to social norms, which may prevent such technology from fitting into the trust logic constructed by human members based on role perception, intention judgment, and emotional belonging (Ulfert *et al.*, 2024). Unlike human members, AI lacks predictable social motives, cannot commit to repairing mistakes, and cannot accumulate credibility through social interaction, thereby reducing individual psychological safety (Bach *et al.*, 2024). In highly interactive tasks, trust is derived not only from result reliability but also from the situational appropriateness of process interaction. AI's context independence and behavioral rigidity can easily cause disconnections, misinterpretations, or indifference in cooperation, thereby systematically suppressing the generation of team trust (Lu *et al.*, 2025). Findings from the literature corroborate this theoretical deduction. For example, Zhang *et al.* (2023) found in their experimental study that human members tend to regard AI as a functional tool rather than a collaborator who can share risks, thereby hindering the effective development of a trust mechanism. Therefore, teams with AI embedding have a highly fragile trust foundation and face huge challenges in establishing collaborative security. Based on these arguments, the following hypothesis is proposed.

H1: Teams with AI teammates have significantly lower levels of trust compared with teams composed solely of human members.

Compared with the constrained trust mechanism in the social subsystem, the embedding of AI in the technical subsystem may bring potential cognitive synergy benefits. According to STS theory, cognitive load is an important indicator of the alignment efficiency between the technical subsystem and the task environment, thus reflecting the resource pressure and information processing difficulty perceived by members when completing complex tasks (Jorge *et al.*, 2024; Zhang *et al.*, 2023). As task complexity and information volume surge, the pressure on individuals to integrate information and make judgments increases day by day, and the existence of effective information processing resources in the system becomes a key variable affecting the level of cognitive load (Xie *et al.*, 2023).

In the interdisciplinary, information-coupled tasks set in this study, team members need to make integrated judgments and collaborative decisions on complex information within a limited timeframe, thus entailing high cognitive demands. In this context, the structural advantages of AI members begin to emerge. Specifically, AI demonstrates far greater stability and efficiency than humans in data processing, pattern recognition, and solution recommendation (Roesler *et al.*, 2024) and can undertake high-intensity information integration and computational work in tasks, thereby reducing the cognitive burden of human members in the initial analysis and strategy formation process (Felin, Holweg, 2024). In addition, AI has the characteristics of continuity, immediacy, and low emotional interference when performing tasks, and its automated support for repetitive processes and detailed tasks can effectively free up human members' attention resources, thereby allowing them to focus more on creative judgment and complex trade-offs (Heigl, 2025). This cognitive offloading effect is essentially a structural compensation of the technical subsystem to the social subsystem, which helps enhance the system's task performance capability and the human members' execution comfort (Risko, Gilbert, 2016).

The embedding of AI can significantly alleviate the social cognitive load brought about by team collaboration, that is, the additional psychological pressure caused by coordination, communication, and role collaboration (Felin, Holweg, 2024). Unlike human members, AI has clear action logic and immediate feedback, which can reduce the psychological resistance caused by uncertainty (Alshahrani, Queiroz, 2025). Therefore, even if AI cannot effectively participate in social interaction, such technology can still reduce the burden imposed upon the team in the technical dimension as a stable information execution unit, thereby enhancing human members' subjective experience of task fluency and control. Based on these arguments, the following hypothesis is proposed.

H2: Members' subjective cognitive load is significantly lower in teams with AI teammates than in teams composed solely of human members.

1.3 Dual-Path Mediation Mechanism of Team Trust and Cognitive Load

Since the formal embedding of AI into team composition, the impact of this technology has long surpassed the scope of task substitution or efficiency enhancement, thus profoundly reshaping the psychological processing mechanisms of human members regarding team collaboration and affecting their subjective satisfaction with collaborative outcomes (Alshahrani, Queiroz, 2025). As an important psychological variable measuring individuals' evaluations of the team interaction process and outcomes, collaboration satisfaction not only reflects members' acceptance of the current collaborative structure but also indicates the operational quality of the intrinsic coupling relationship within the socio-technical system (Govers, van Amelsvoort, 2023). From the perspective of STS theory, this satisfaction results from the joint action of the social and technical subsystems (Appelbaum, 1997). Therefore, the impact of AI teammates on satisfaction should not be merely regarded as the result of technological intervention but should also be systematically understood from their dual-path effects on trust building and cognitive load.

On the one hand, from the perspective of the social subsystem, team trust is the core guarantee for collaborative efficiency and psychological security. Trust not only includes members' cognitive judgments about one another's capabilities and stability but also involves emotional trust based on the consistency of motives and emotional connection (Dennis *et al.*, 2023; Erengin *et al.*, 2025; Georganta, Ulfert, 2024). However, as a non-personal entity, AI lacks the intention expression, emotional response, and value contract required for social interaction, thus introducing challenges in inspiring human members' trust and belonging based on social intuition (Bach *et al.*, 2024). In team tasks that require high-frequency interaction and close cooperation, AI's social absence may lead to human members' negative perception of the overall trust atmosphere of the team, thereby inhibiting their positive evaluation of the collaborative process and outcomes (Jorge *et al.*, 2024).

On the other hand, from the perspective of the technical subsystem, the introduction of AI may have a positive impact on satisfaction through the path of reducing cognitive load. According to cognitive load theory, in complex tasks or multitasking environments, human working memory is easily overloaded, which affects information integration and decision-making fluency (Felin, Holweg, 2024; John, 2011). With its information integration, automatic recommendation, and pattern recognition functions, AI can undertake high-load information processing tasks, thereby alleviating human members' attention bottlenecks and enhancing their sense of task control and collaborative fluency (Dennis *et al.*, 2023). This type of cognitive support not only optimizes the execution process but also strengthens individuals' satisfaction with the team collaboration experience (Alshahrani, Queiroz, 2025; Przegalinska *et al.*, 2025). In sum, the impact of AI on collaboration satisfaction is neither linear nor consistent but is jointly acted upon by two mediating paths in opposite directions, namely, trust weakening and cognitive enhancement. This dual-path mechanism reveals the psychological tension caused by technological embedding in human–machine teams, thus emphasizing the synergy and conflict between social trust and cognitive resources in the construction of satisfaction. Based on these arguments, the following hypotheses are proposed.

H3: Team trust and cognitive load mediate the impact of AI teammates on collaboration satisfaction.

H3a: AI teammates reduce collaboration satisfaction by lowering team trust.

H3b: AI teammates enhance collaboration satisfaction by reducing cognitive load.

1.4 Moderating Role of Team Collaboration Project Experience

In the context of intelligent technologies gradually being embedded into organizational structures and AI participating in collaboration as a team member, individual differences among team members have become one of the key factors determining the effectiveness of human–machine collaboration mechanisms. Specifically, team members' collaboration project experience, as a highly internalized representation of information processing strategies, social interaction rules, and role division logic from previous collaborations, will profoundly influence the adaptation paths of trust and cognitive mechanisms brought about by AI (Wang *et al.*, 2023). Therefore, this study introduces IPT in combination with STS theory to explore how collaboration experience acts as a key moderating variable in the impact of AI embedding on team trust and cognitive load.

IPT suggests that when facing complex tasks and uncertain situations, individuals' behavioral responses depend on their existing cognitive structures, experiential schemas, and processing strategies (Gurbin, 2015). Members with richer project experience have more mature internal models of collaboration processes, role relationships, and information judgment pathways, which enable them to easily form coherent processing procedures and role expectations in tasks, thereby reducing their dependence on external technical systems (Gordon, Woods, 2021). By contrast, those members with less experience are more likely to perceive the complexity of tasks and are more sensitive to structural feedback and process guidance, thus being more open to the embedding of AI (Mayer, 2012).

From the perspective of the social subsystem, project experience strengthens human members' reliance on interpersonal interaction, collaborative tacitness, and emotional connection and reinforces their social judgment criteria for trustworthy others (Duan *et al.*, 2024). When AI is introduced into the team, this less socially intelligent agent, which lacks non-verbal feedback, situational understanding, and trust generation mechanisms, often fails to meet the social expectations that experienced members hold for their fellow team members and is thus more likely to be excluded from the trust framework (Zhang *et al.*, 2023). Therefore, the higher the collaboration experience, the more significant the impact of AI on the overall trust atmosphere of the team.

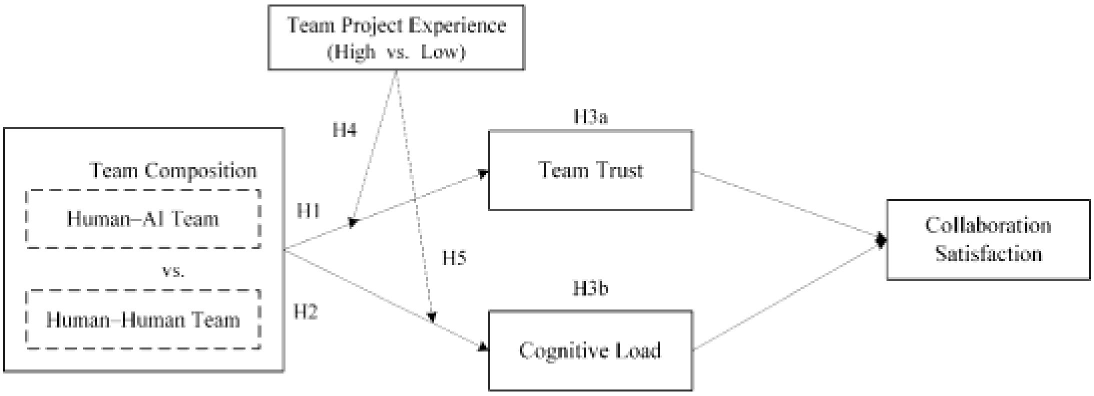
From the technical subsystem perspective, those members with more experience have a higher level of automated processing ability, stronger cognitive resource allocation, and clearer processing pathways. The process coordination and task suggestion functions provided by AI may seem redundant and even disrupt the existing rhythm and thinking patterns for such members (Alshahrani, Queiroz, 2025; Dennis *et al.*, 2023; Felin, Holweg, 2024). By contrast, those members with less experience and whose cognitive structures are not yet fully formed are more likely to regard AI's computational power and recommendation mechanisms as important processing compensations, thereby perceiving a reduction in cognitive load (Alshahrani, Queiroz, 2025). Therefore, the level of collaboration experience constitutes a key perceptual threshold for the impact of AI on the trust–cognitive path in the team.

Based on the above analysis, team project experience can be regarded as a systemic cognitive resource that affects how individuals understand and evaluate the behavioral attributes of AI, thereby moderating the intensity of AI's intervention in the team's social and technical mechanisms. Specifically, members with rich experience rely more on interpersonal trust and interactive collaboration and are more likely to encounter trust barriers when facing the impersonal characteristics of AI, thereby strengthening the negative effect of AI on team trust. At the same time, members with high experience already have mature task strategies and cognitive structures and perceive lower value in the assistance provided by AI, thereby weakening the effect of AI in reducing cognitive load. Based on these arguments, the following hypotheses are proposed.

H4: The higher the team project experience, the more pronounced the weakening effect of AI teammates on team trust.

H5: The higher the team project experience, the less noticeable the alleviating effect of AI teammates on cognitive load.

Based on the above hypotheses, the research model is constructed as shown *in Figure 1*.



Source: created by the authors.

Figure 1. **Research Model**

This model takes team composition (human–AI team vs. human–human team) as the independent variable and collaboration satisfaction as the dependent variable, and introduces team trust and cognitive load as dual-path mediating mechanisms while simultaneously considering the moderating effect of team project experience in the front part of the path. To test the effect structure and mechanism of action of this theoretical model, this study adopts a between-group experimental design to simulate human–machine and human–human collaboration situations and adopts questionnaire measurements of key variables to systematically evaluate the impact of AI teammates on human members' collaborative experience.

2. Methodology

2.1 Research Design and Sample

This study employs single-factor between-subjects experimental design with team composition type (human–machine team vs. human-only team) as the manipulated variable to examine the impact mechanism of AI member embedding on human members' collaboration satisfaction. The experiment includes two condition groups. The control group consists of three human members, while the experimental group comprises two human members and one AI agent working together to complete the same task. To ensure internal validity, all participants were randomly assigned to the two experimental groups after measuring their team project experience, thereby ensuring comparability between groups.

To investigate the moderating role of team project experience in the trust and cognitive load paths, project experience was collected as a measured moderator through a questionnaire survey during the sample screening stage. The participants were required to have at least one real team project experience (such as workplace collaboration or cross-departmental cooperation) and were divided into high- and low-experience groups based on their team project experience scores. The research team set the screening criteria and grouped the initial 165 participants according to the top and bottom 30% of experience scores, ultimately retaining 100 participants (50 participants in each group) to ensure a significant difference between the high- and low-experience groups (M_high = 6.12, M_low = 3.08, t = 9.23, $p < 0.001$).

All participants were recruited through Credamo (https://www.credamo.com/), a leading online research platform in China, in April 2025. A total of 40 experimental teams were formed, comprising 20 three-person human-only teams (60 participants) and 20 two-person human–machine teams (40 participants).

In the final sample, 59% were female, with an age distribution of 21–25 years (34%), 26–30 years (35%), and 31–35 years (31%). The sample size met the minimum effect size standard recommended by the G*Power calculation (F-test, f = 0.25, α = 0.03, power = 0.76, groups = 2), thereby providing a sufficient statistical basis for the subsequent hypothesis testing.

2.2 Pre-experiment Testing

A script-driven AI agent was employed to standardize its role positioning and behavioral rhythm within the team. The frequency and content of the AI's speech were strictly controlled, requiring clear semantics, moderate length, and a rational and restrained language style. The AI was deliberately designed to avoid emotional expressions, social hints, or dominant wording to maintain its characteristic as a limited-intelligence, low-sociality agent.

In terms of script content generation, the DeepSeek large language model was used to build an initial corpus and to develop semantic generation rules based on task themes and language norms. All candidate sentences were manually screened and modified by the researchers to exclude expressions involving human responses, process guidance, or emotional projection. Only task-focused, logically clear, and stylistically neutral statements were retained to construct the AI's participatory role in the team.

Prior to the formal experiment, a small-scale pre-test was organized in which 30 online users with real team project experience were invited to evaluate the AI script. The evaluation dimensions included task contribution, semantic credibility, language style rationality, and sociality perception, which were rated on a 7-point rating scale (1 = Strongly Disagree, 7 = Strongly Agree). A set of scripts that scored in the middle range on both intelligence and sociality dimensions was eventually selected for the formal experiment to ensure that the AI's behavior realistically elicits trust judgments and cognitive feedback from human members within a controllable scope.

2.3 Experimental Procedure and Data Collection

The experiment was organized and conducted at the team level using an online timed synchronous method. The experimental task was completed through a web-based platform independently developed by the research team, ensuring that all groups operated and interacted within a unified system environment. The experiment officially began in April 2025. The participants were assigned to specific experimental sessions through prior reservation and logged into the platform at the designated time.

Before the experiment, the system presented all participants with a unified introduction to the experimental background, team composition, and task objectives. These participants were informed that they would collaborate with two other team members to complete a rescue resource prioritization task in an earthquake-stricken area, to reach a consensus on the ranking of 15 rescue supplies within 20 minutes. For those participants in the human–machine collaboration group, the system explicitly indicated the following before the task began: "Your team includes one AI member." This AI member was identified in the team interface with the nickname AI-Bot and a blue icon as its avatar, which greatly differed from the gray avatars and Chinese nicknames used by the other human members, thereby facilitating structural identity recognition.

After the task officially began, all members browsed the information of the 15 resources in the left window and engaged in free text communication in the right discussion area. The AI agent's speech was automatically displayed according to the preset script, with an average frequency of one message every two to three minutes, totaling seven messages. All AI messages were unidirectional expressions of viewpoints that provide rational and neutral suggestions around the ranking task without responding to others' messages or participating in negotiation, summarization, or integration processes. The control group, which comprised three human members, completed the task independently without AI embedding.

When the task time ended or when the team submitted the ranking result, the system automatically redirected to the post-test phase. The post-test questionnaire included measurements of core variables, such as collaboration satisfaction, team trust, cognitive load, and team project experience, as well as a retrospective evaluation of the task experience. To minimize order effects and measurement interference, the order of presentation of the scales was randomized by the system. All process data were automatically recorded and anonymized for encrypted storage by the platform, thereby ensuring data security and participant privacy.

The entire experimental process, from platform login, information import, and task collaboration to post-test completion, lasted for approximately 35 minutes. The experimental platform set unified logical rules in terms of time management, prompt mechanisms, and discussion permissions, thereby ensuring the consistency of conditions and enhancing the comparability and internal validity of the experiment from a technical perspective.

2.4 Variable Measurement

The measurement indicators were adapted from validated scales in the literature to ensure their applicability to the present research context, as shown in *Table 1*. All measurements were conducted using a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).

Table 1. Variables and Items

Variables	Measurement Items	Source
Team Trust (TT)	1. I believe that the members of our team can collaborate effectively to achieve the task goals. 2. I trust the overall performance of the team. 3. I believe that all members of the team will support one another to ensure the successful completion of the task. 4. I believe that our team members will demonstrate a high sense of responsibility during the collaboration process.	(Ulfert *et al.*, 2024)
Cognitive Load (CL)	1. During the team collaboration process, I feel that the amount of information and tasks that need to be coordinated exceeds my processing capacity. 2. When working with team members, I often need to deal with a large number of opinions and suggestions at the same time, which I find somewhat challenging. 3. In the process of team cooperation, I feel that it takes a lot of effort to understand the viewpoints and task requirements of other members. 4. In team collaboration, I often feel that my cognitive resources are heavily consumed, making it difficult to maintain efficient communication and coordination.	(Paas, 1992)
Collaboration Satisfaction (CS)	1. I am satisfied with the collaboration process with the AI team member. 2. I think collaborating with the AI team member went more smoothly than I expected. 3. Collaborating with the AI team member has been satisfying. 4. Overall, I am satisfied with the AI's performance in team tasks.	(Przegalinska *et al.*, 2025)

Source: authors' own results.

Table 2. Descriptive Statistical Analysis

Team Composition	Number of People	Age	Women (%)	AI Usage Experience (Years)	Team Project Experience (Number of Times)
Human–AI Team	40	28.98 (SD 0.47)	53.47 (SD 0.32)	0.94 (SD 0.24)	2.57 (SD 1.55)
Human–Human Team	60	31 (SD 0.81)	48.65 (SD 0.15)	0.97 (SD 0.18)	3.01 (SD 1.67)

Source: authors' own results.

This study also collected common demographic information, including gender, age, education level, AI usage experience, and team project experience (specific question: "How many team projects have you participated in over the past year?"), to conduct a descriptive analysis of the sample and to control for potential confounding factors. The descriptive statistical analysis of the experiment is shown in *Table 2*.

3. Results Analysis

3.1 Reliability and Validity Tests and Correlation Analysis

Given that all variables were collected within the same period, a Harman single-factor test was conducted to assess the potential threat of common method bias (CMB). Results show a maximum variance of 32.15%, which did not exceed the critical value. Therefore, CMB is not a significant issue in this study. The loadings for each item were all above 0.50 (Hulland, 1999), indicating a strong correlation between each item and its corresponding construct. Cronbach's alpha and composite reliability (CR) both exceeded the recommended threshold of 0.70, and the average variance extracted (AVE) was greater than 0.50, indicating the good reliability and convergent validity of the constructs (*Table 3*).

Table 3. Reliability and Validity Analysis

Variables/Items	Loadings	Alpha	CR	AVE
Team Trust (TT)		0.757	0.817	0.685
TT1	0.739			
TT2	0.716			
TT3	0.702			
TT4	0.725			
Cognitive Load (CL)		0.875	0.832	0.726
CL1	0.782			
CL2	0.797			
CL3	0.801			
CL4	0.847			
Collaboration Satisfaction (CS)		0.816	0.807	0.795
CS1	0.819			
CS2	0.786			
CS3	0.791			
CS4	0.745			

Source: authors' own results.

Table 4. Results of Correlation Analysis

Variables	1	2	3	4	5	6	7	8
1 Team Trust	1							
2 Cognitive Load	–0.43**	1						
3 Collaboration Satisfaction	0.55***	–0.38**	1					
4 Team Project Experience	–0.21**	0.19**	–0.17	1				
5 Gender	0.10	-0.05	0.08	-0.03	1			
6 Age	-0.12	0.11	0.07	0.15*	-0.02	1		
7 Education Level	0.15*	-0.08	0.04	0.09	0.04	0.30**	1	
8 AI Usage Experience	0.18*	0.13*	0.10	0.26*	0.05	0.25**	0.28**	1

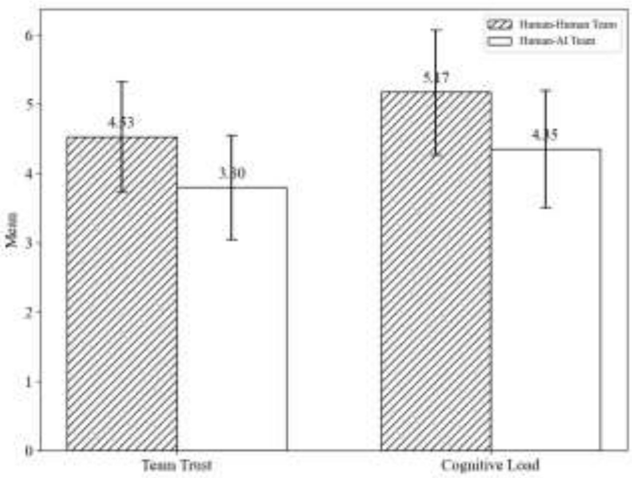
Notes: *** indicates p < 0.001, ** indicates p < 0.01, * indicates p < 0.05.

Source: authors' own results.

Discriminant validity was confirmed by ensuring that the correlations among all constructs were below 0.85, and the square root of the AVE for each construct exceeded its highest correlation with any other construct. Additionally, the heterotrait–monotrait ratio (HTMT) was within the acceptable range below 0.90. These results indicate that the measurement tool has good reliability and validity and meets the requirements for subsequent analyses. To further explore the relationships among the variables, a correlation analysis was conducted, and the results are presented in *Table 4*.

3.2 Hypothesis Testing

Results of one-way analysis of variance reveal that team composition significantly affected team trust and cognitive load among team members. As shown in *Figure 1*, the human–machine team scored significantly lower in team trust than the human–human team ($M_{\textit{human-AI team}}$ = 3.80, SD = 0.75 vs. $M_{\textit{human-human team}}$ = 4.53, SD = 0.80), with a significant difference between groups ($F(1, 98) = 8.50$, $p < 0.01$), thereby supporting H1. In terms of cognitive load, the human–machine team also scored significantly lower than the human–human team ($M_{\textit{human-AI team}}$ = 4.35, SD = 0.85 vs. $M_{\textit{human-human team}}$ = 5.17, SD = 0.90), $F(1, 98) = 6.20$, $p < 0.05$, validating H2. *Figure 1* intuitively displays the mean differences and standard deviation ranges of these two teams in key psychological variables, and the results further support the dual mechanism of AI embedding in trust and cognitive states.



Source: own calculations.

Figure 1. **Mean Comparison of Team Trust and Cognitive Load under Different Team Compositions**

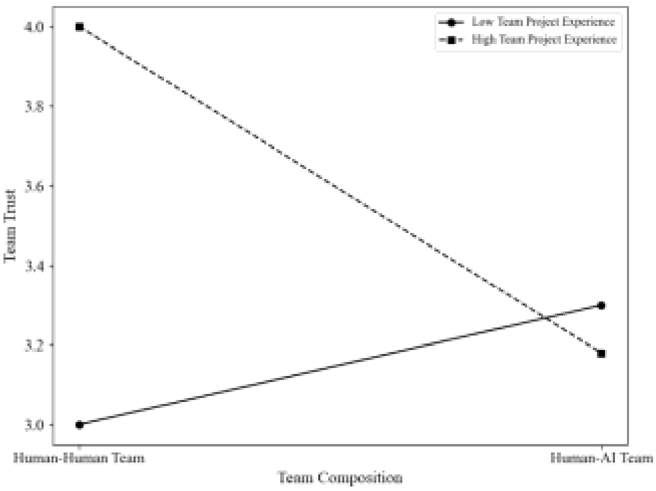
To examine whether team project experience (high vs. low) moderates the impact of team composition (human–human team vs. human–AI team) on team trust and cognitive load, a regression analysis was conducted using SPSS 25.0. In this analysis, team project experience was treated as a moderator to check whether such a variable altered the effect of team composition (1 = human–AI team, 0 = human–human team) on team trust and cognitive load. The regression results are presented in *Table 5*.

Table 5. Moderation Effect Analysis

Variables	*Team Trust*	*Team Trust*	*Cognitive Load*	*Cognitive Load*
Control Variable				
Gender	0.034	0.028	-0.116	-0.107
Age	-0.105	-0.101	0.145	0.132
Education Level	0.502**	0.427***	-0.354*	-0.343**
AI Usage Experience	0.316***	0.304***	0.298*	0.256*
Independent Variable				
Team Composition		-0.038**		-0.146*
Moderator				
Team Project Experience		0.741*		-0.555*
Team Composition × Team Project Experience		-0.162*		0.101***
R^2	0.112	0.332	0.109	0.340
ΔR^2	0.101	0.321	0.095	0.328
F	2.99	7.70	2.91	7.98

Notes: *** indicates p < 0.001, ** indicates p < 0.01, * indicates p < 0.05.

Source: own calculations.

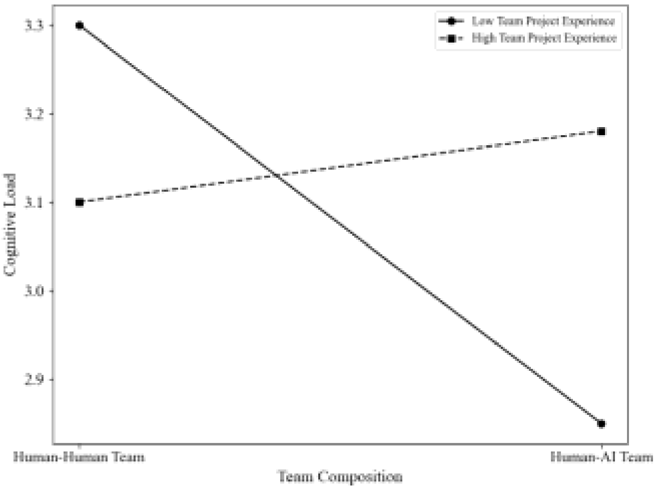


Source: own calculations.

Figure 2. **Moderating Effect of Team Project Experience on the Path of Team Trust**

The results of the regression analysis indicate that team project experience significantly moderated the impact of team composition on team trust (β = -0.162, *p* = 0.041), thereby suggesting that as team project experience increases, the negative impact of team composition on team trust is further exacerbated. Specifically, under high team project experience levels, AI teammates significantly undermined the trust of human members, while under low team project experience levels, such a negative effect was more mitigated *(Figure 2*). This finding supports H4. The possible reason is that human members with more team project experience usually have a more human-reliant collaboration mode, and the non-human nature and lack of emotional interaction of AI teammates hinder these high-experience human members from building trust, thereby leading to a further decline in trust.

In terms of cognitive load, team project experience also played a significant moderating role (β = 0.101, p = 0.001). As team project experience increased, the role of AI teammates in alleviating cognitive load weakened. Specifically, when team project experience was low, AI teammates helped reduce human members' cognitive load; however, when team project experience was high, this alleviating effect became insignificant (*Figure 3*). This result supports H5. The possible reason is that experienced human members are more inclined to rely on their own experiences and skills to deal with task complexity, thereby reducing the role of AI teammates in reducing cognitive load.



Source: own calculations.

Figure 3. **Moderating Effect of Team Project Experience on the Path of Cognitive Load**

Table 6. Mediation Effect Results

Path	Coefficient	SE	Lower Limit of 95% Confidence Interval	Upper Limit of 95% Confidence Interval	*p*
Team Composition → Team Trust	-0.102	0.045	-0.239	-0.061	0.035
Team Composition → Cognitive Load	-0.158	0.050	-0.218	-0.022	0.021
Team Trust → Collaboration Satisfaction	0.213	0.095	0.243	0.617	0.012
Cognitive Load → Collaboration Satisfaction	-0.172	0.102	-0.546	-0.154	<0.001
Team Composition → Collaboration Satisfaction (Direct Effect)	-0.032	0.040	-0.110	0.045	0.425
Team Composition → Team Trust → Collaboration Satisfaction	-0.065	0.09	-0.27	-0.54	<.001
Team Composition → Cognitive Load → Collaboration Satisfaction	0.042	0.018	0.008	0.077	0.020

Source: own calculations.

This study used the PROCESS model in SPSS (Model 4, with 5000 bootstrap samples) to examine whether the effect of team composition (human–human team vs. human–machine team) on collaboration satisfaction was mediated by team trust and cognitive load. *Table 6* presents the results of the mediation effect analysis of team composition on collaboration satisfaction. Overall, the analysis results support H3, indicating that team trust and cognitive load play an important mediating role in the impact of team composition on collaboration satisfaction. Specifically, team composition indirectly reduces collaboration satisfaction by lowering team trust, thus significantly supporting H3a (p < 0.001). At the same time, team composition indirectly enhances collaboration satisfaction by reducing cognitive load, significantly supporting H3b (p = 0.020). However, the direct effect of team composition on collaboration satisfaction was not significant (p = 0.425), indicating that the mediating effect plays a dominant role in this relationship.

4. Discussion

First, team composition (human–human team vs. human–AI team) significantly affects collaboration satisfaction through the dual mediating mechanism of team trust and cognitive load. From the perspective of STS theory, this result suggests that the introduction of a technical system not only changes task allocation and cognitive load but also reshapes the social interaction patterns among team members (Dennis *et al.*, 2023; Erengin *et al.*, 2025). AI teammates demonstrate strong computational and processing capabilities when performing repetitive and high-cognitive-load tasks, which helps reduce human members' psychological stress. This finding is consistent with IPT, which emphasizes that technology can expand individuals' information processing bandwidth (Felin, Holweg, 2024). However, the limitations of AI teammates in the social interaction dimension, that is, their lack of emotional expression and interpersonal signaling feedback, pose challenges for human members to regard these AI team members as social others, thereby hindering the formation of affective trust (Daly *et al.*, 2025; Duan *et al.*, 2024; Jorge *et al.*, 2024). This phenomenon also supports the social agency hypothesis in recent human–machine collaboration research, which states that when a technical system fails to provide sufficient social presence, the users' trust and acceptance of such a system will be significantly reduced (Grilli, Pedota, 2024; Koivisto, Grassini, 2023). Building on this argument, this study further shows that the utility of AI teammates in a team not only depends on their information processing capabilities but is also constrained by their limitations in social embeddedness. This finding expands the present understanding of the dual path of technology–society in STS theory and emphasizes the core role of affective trust in regulating the effectiveness of AI technology.

Second, team project experience plays a key role in moderating the mechanisms of AI teammates. As team project experience increases, the negative impact of AI teammates on team trust is enhanced, while their role in alleviating cognitive load is weakened. This phenomenon can be explained by the tension between technical and social routines in STS theory, that is, experienced human members have developed social routines based on human collaboration and have higher expectations for the social interaction capabilities of their AI teammates. When these expectations are not met, a stronger sense of distrust arises (Go, Sundar, 2019). Moreover, experienced human members rely on their well-honed skills and strategies for information processing, thus reducing the perceived value of AI support (Wang *et al.*, 2023), which aligns with the individual processing advantage proposed by IPT. In other words, when human members possess a high level of knowledge structure, the marginal effect of technological intervention diminishes (Gordon, Woods, 2021). Building on this argument, this study further reveals that team project experience not only affects human–AI collaboration outcomes as a contextual variable but also changes the weight balance of the technical system in the social and cognitive dimensions. This result provides a new perspective on the contextual boundary conditions for IPT and STS theory. By contrast, low-experience human members lack mature collaboration patterns and cognitive strategies, making the task support role of AI teammates more prominent in this context, which is consistent with recent findings showing that AI is more suitable for providing decision support to novice teams (Dennis *et al.*, 2023).

Finally, this study reveals the dual nature of AI teammates in teams—their cognitive strengths and social limitations-which reflect the core tension of technology–society fit theory. Technical systems can optimize information processing and task efficiency, but if they fail to meet team members' emotional needs in the relational dimension, these systems may suppress overall effectiveness (Dennis *et al.*, 2023; Grilli, Pedota, 2024). While AI teammates alleviate cognitive load, their lack of social presence leads to trust deficits, and this cognitive–emotional tension becomes a key mechanism affecting collaboration satisfaction (Jorge *et al.*, 2024). By revealing this tension, this study expands the current understanding of the social role of AI in human–machine collaboration. AI systems should therefore optimize both technical functions and social interaction dimensions in their future designs to achieve the co-evolution of technical and social systems. Recent studies on affective AI point out that enhancing the social interaction capabilities of AI (e.g., tone of voice, facial expressions, and active listening) can effectively alleviate users' distrust, thereby further validating the theoretical significance of the affective trust mediation mechanism proposed in this study (Ulfert *et al.*, 2024; Zogaj *et al.*, 2023).

Conclusions and Implications

Conclusions

This study aims to explore the impact of team composition (human–human teams vs. human–machine teams) on collaboration satisfaction and to reveal the mediating role of team trust and cognitive load in this process. Through a systematic empirical analysis, this study draws the following conclusions:

(1) Team composition significantly affects collaboration satisfaction. The introduction of AI teammates has an important impact on collaboration satisfaction by influencing human members' trust perceptions and cognitive load. Specifically, AI teammates negatively impact collaboration satisfaction by reducing team trust, but positively impact such satisfaction by alleviating cognitive load. This result indicates that the introduction of AI teammates not only reduces the cognitive burden of human members but may also suppress collaboration satisfaction due to a lack of trust.

(2) Team trust and cognitive load play a significant mediating role in the relationship between team composition and collaboration satisfaction. The analysis shows that AI teammates indirectly affect collaboration satisfaction to varying degrees by influencing human members' trust and cognitive load. This finding validates the theoretical framework of mediating effects and further confirms the core role of trust and cognitive load in team collaboration.

(4) Team project experience significantly moderates the impact of AI teammates. As team project experience increases, the negative impact of AI teammates on trust is exacerbated, while their role in alleviating cognitive load is weakened. This finding indicates that human members with more project experience have lower trust in AI teammates and less need for AI to reduce their cognitive load, thereby affecting the role of AI teammates in the team.

This study also proposes a novel theoretical framework that combines trust theory and cognitive load theory to systematically explore the complex role of AI teammates in team collaboration. Through an in-depth analysis of team trust and cognitive load, this study not only validates existing theories but also provides theoretical support for the design and optimization of future AI collaboration systems.

Managerial Implications

From an organizational perspective, the above results indicate that AI teammates significantly affect collaboration satisfaction by negatively affecting team trust and positively alleviating cognitive load. Therefore, organizations must prioritize trust-building when deploying AI systems. In practical management, organizations should develop transparent communication strategies, provide regular training, and clearly explain the functions and decision-making mechanisms of AI systems to help human members understand and accept AI technology. These solutions will help enhance the team's trust in AI and consequently optimize team collaboration efficiency and satisfaction. Establishing trust serves as the foundation for the effective integration of AI into teams, and only with trust can AI systems maximize their role in improving work efficiency and team collaboration.

From the perspective of AI deployment, although AI can effectively reduce the cognitive load of human members, lower trust levels may diminish this positive effect. Therefore, managers should pay attention to the cognitive load management of the team when designing and deploying AI systems. Specifically, when handling repetitive and low-value tasks, AI should take on more responsibilities to relieve the cognitive pressure on human members, allowing them to focus on more creative and strategic tasks. In practice, AI systems should be able to adjust flexibly and dynamically optimize their functions based on feedback from human members to offer continuous and effective support for teamwork and to improve overall collaboration efficiency.

This study also shows that team project experience significantly moderates the impact of AI teammates. For experienced human members, AI design should focus more on decision support rather than interfering with their work processes because more experienced human members often rely on their intuition and experience when making decisions and have less need for AI involvement. By contrast, AI can be more embedded for less experienced human members to reduce their cognitive load, improve their decision-making efficiency, and enhance their work capabilities. Therefore, when deploying AI, organizations should customize the design while taking the differences in the experiences of their human members into account to ensure that AI intervention can be adjusted according to the needs of these members, thereby maximizing the collaborative benefits of AI in the team.

Limitations and Future Directions

First, although this study verified the dual mediating role of trust and cognitive load in the relationship between team composition and collaboration satisfaction, the cross-cultural applicability of this mechanism has not been validated. Human members' adaptability to AI may vary significantly across cultural contexts, and these cultural differences may affect the formation of team trust and the perception of cognitive load. Therefore, future research should further examine the role of cultural differences in AI teammate collaboration and explore how human members in different cultural contexts react differently to AI teammates in terms of trust and collaboration satisfaction. This examination will provide a solid theoretical basis for the theoretical construction and practical optimization of cross-cultural AI collaboration models.

Second, this study mainly focused on the moderating effect of team project experience on AI teammates, but this moderating effect may vary across different team characteristics. In addition to team experience, the personality traits of human members, task types, and team collaboration history may also play a key role in the interaction between AI and human members. Future research can explore the impact of other team characteristics on the moderating effect of AI teammates, especially how to enhance the applicability and effectiveness of AI systems in different teams through personalized design.

Finally, the research sample mainly focused on a specific field. Although the results provide a theoretical basis for understanding the role of AI teammates in team collaboration, their generalizability needs to be further verified in other industries and task contexts. Future research can expand the sample scope to cover different fields, industries, and task complexities, thereby validating the broad applicability of the results of this study and providing more comprehensive empirical support for the design and implementation of AI collaboration systems.

In sum, this study provides a new perspective and theoretical framework for understanding the role mechanism of AI teammates in human–machine collaboration, promotes the application of trust and cognitive load theories in AI collaboration, and offers theoretical support for the design and optimization of future AI collaboration systems. With the widespread application of AI technology, future research should pay more attention to cross-cultural differences, personalized needs, and task adaptability to improve the integration of AI into teams.

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BENDRADARBIAVIMO PASITENKINIMAS ŽMOGAUS IR DIRBTINIO INTELEKTO KOMANDOSE: DVIGUBAS PASITIKĖJIMO IR KOGNITYVINIO KRŪVIO VAIDMUO

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Santrauka. Sparčiai tobulėjant dirbtiniam intelektui (DI), keičiasi organizacinė bendradarbiavimo struktūra ir veiklos logika, o žmogaus ir DI bendras kūrimas pamažu tampa norma. Tačiau DI integravimo poveikis komandos bendradarbiavimo pasitenkinimui lieka neaiškus. Siekta ištirti, kaip DI integravimas į komandas veikia komandos bendradarbiavimo pasitenkinimą. Remtasi sociotechninių sistemų teorija ir informacijos apdorojimo teorija. Pasitelktas tarpdisciplininis eksperimentinis dizainas. 2025 m. balandžio mėn. per e. platformą buvo suburta 100 dalyvių. Buvo tiriama, kaip DI veikia komandos bendradarbiavimo pasitenkinimą manipuliuojant komandos sudėtimi (žmogaus ir žmogaus komandos vs. žmogaus ir DI komandos), naudojant dvigubus socialinių ir techninių posistemių kelius. Rezultatai atskleidė, kad DI įdiegimas reikšmingai susilpnina žmonių pasitikėjimą komanda, nors ir veiksmingai sumažina jų kognityvinį krūvį. Priešingas šių dviejų kelių poveikis lemia panaikinantį netiesioginį poveikį, todėl bendras DI poveikis bendradarbiavimo pasitenkinimui yra neutralus. Tolesnė analizė atskleidė, kad komandinio projekto patirtis reikšmingai sumažina minėtus mechanizmus. Patyrę nariai labiau pasikliauja tarpasmeniniu bendradarbiavimu ir yra jautresni DI bejausmiam bendradarbiavimo stiliui, taip sumažindami pasitikėjimą. Tačiau jie suteikia mažiau vertės DI pagalbai, nes yra internalizavę efektyvias kognityvines strategijas. Šio tyrimo išvados praturtina dabartinį žmogaus ir DI bendradarbiavimo mechanizmo supratimą diegiant DI technologijas, atskleidžia struktūrinių technologinių pokyčių ir individualios patirties sąveiką, taip pat siūlo teorinį pagrindą būsimų intelektualių bendradarbiavimo sistemų projektavimui ir valdymui.

Reikšminiai žodžiai: dirbtinis intelektas; žmogaus ir DI komandos bendradarbiavimas; bendradarbiavimo pasitenkinimas; sociotechninių sistemų teorija; informacijos apdorojimo teorija.