Front. Eng. Manag. 2025, 12(4): 899–915
https://doi.org/10.1007/s42524-025-4210-3

RESEARCH ARTICLE

Ying HAN, Qing YANG, Xingqi ZOU, Pingye TIAN, Yang FENG, Tao YAO

Measuring the impact of human–AI collaboration on knowledge diffusion in new product development projects

Abstract Artificial Intelligence (AI) is playing an increasingly pivotal role in New Product Development (NPD) project management. We propose a comprehensive framework to explore the impact of human–AI collaboration on organizational knowledge diffusion. First, we develop a knowledge diffusion model based on continuous human–AI interactions, and we use the Agent-Based Modeling (ABM) method to simulate the diffusion process within the collaborative team and assess diffusion rates and efficiency based on knowledge levels. Second, we examine the interdependencies among members under different roles of AI, integrating AI cognitive capabilities, human–AI cognitive trust, and task interdependencies, and build a tie strength measurement model from the Social Network Analysis (SNA) perspective. Third, an entropy-based model is introduced to measure AI's cognitive capability, accounting for project complexity and AI-generated solution uncertainty. We also establish a dynamic cognitive trust model that incorporates both the dynamic nature of trust in human–AI interactions and AI's cognitive capability. Task interdependencies are assessed through a multi-dimensional activity network, and visualized by the Dependency Structure Matrix (DSM) method. Finally, an industrial example is provided to demonstrate the proposed model. Results show that organizational knowledge diffusion performs best when AI acts both as a collaborator and a tool. Moreover, this paper provides new insights, including how trust and task interdependencies significantly impact knowledge diffusion in human–AI collaborative organizations.

Keywords human–AI collaboration, knowledge diffusion, trust, Agent-Based Modeling (ABM), product development project

1 Introduction

Artificial Intelligence (AI) is becoming a pivotal force in knowledge-intensive projects by transforming vast data into actionable insights, thereby accelerating knowledge diffusion (Paschen et al., 2020; Seeber et al., 2020; Gama and Magistretti, 2025). Recent organizational practices further highlight AI's value, for example, Symrise utilizes AI to analyze complex customer data and improve decision quality (Arias-Pérez and Huynh, 2023), while large language models such as GPT can expand the scope of problem-solving and facilitated deeper knowledge exchange (Gama and Magistretti, 2025). In such settings, efficient knowledge diffusion is essential not only for enhancing innovation but also for ensuring effective project execution (Chowdhury et al., 2022; Xu et al., 2022).

Despite these advances, most existing studies treat AI as a tool, focusing on its supportive role in the knowledge diffusion process and the transfer or sharing of knowledge based on AI. However, AI can also function as both a collaborator and a supervisor. The knowledge diffusion and collaboration processes between humans and AI, particularly in those various roles, remain underexplored. Moreover, while AI can enhance knowledge sharing, excessive reliance on AI may cause imbalances or misuses, which can, in turn, affect knowledge transfer within the organization and ultimately obstruct project execution (Omrani et al., 2022). These tensions point to an urgent need to understand the knowledge diffusion mechanisms in human–AI collaboration, particularly in

Received Oct. 29, 2024; revised May 16, 2025; accepted May 30, 2025

Ying HAN, Qing YANG (✉), Pingye TIAN, Yang FENG
School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China
E-mail: yangqing@manage.ustb.edu.cn

Xingqi ZOU
Faculty of Management and Economics, Kunming University of Science and Technology, Kunming 650500, China

Tao YAO
Antai College of Economics & Management, Shanghai Jiao Tong University, Shanghai 200030, China

This research was supported by the National Natural Science Foundation of China (Grant Nos. W2441021 and 72271022).

light of AI’s multiple roles.

A central factor that impacts human–AI collaborative knowledge diffusion is cognitive trust. Developers’ cognitive trust in AI is essential for determining the extent of AI’s involvement in projects and its potential to drive innovation (Glikson and Woolley, 2020). Although prior studies have explored cognitive trust and its impact on knowledge diffusion (Capestro et al., 2024), the role of cognitive trust in human–AI collaborative knowledge diffusion remains largely under-examined. Cognitive trust in AI evolves dynamically through continuous human–AI interactions and depends critically on AI’s problem-solving/cognitive capabilities (Glikson and Woolley, 2020). This highlights the need for models that can capture the dynamic nature of cognitive trust and AI’s cognitive capabilities.

Therefore, our research questions are twofold: (1) How to build a knowledge diffusion model to measure knowledge diffusion efficiency within the human–AI collaborative NPD organization? (2) From the cognitive capability and trust’s dynamic nature perspective, how to measure cognitive trust in human–AI collaboration?

In human–AI collaboration, knowledge diffusion occurs through continuous iterative interaction between members, such as developers and the AI platform. Developers input tasks like coding, algorithm optimization, and data analysis, while AI processes the data using its vast knowledge base. This iterative exchange allows AI to learn and improve its problem-solving capabilities, providing feedback to developers in various formats (text, images, or voice) to enhance their expertise (Westphal et al., 2023). This bidirectional interaction facilitates knowledge exchange and promotes diffusion within the NPD organization.

To better understand the knowledge diffusion process, we develop a knowledge diffusion model grounded in human–AI interactions. Since knowledge diffusion emerges from the behavior of individual agents, both developers and AI, we employ an Agent-Based Modeling (ABM) approach to simulate the knowledge diffusion process in human–AI collaboration, and further explore from the Social Network Analysis (SNA) perspective. Central to this process are the interdependencies among members, which shape the pathways and the efficiency of knowledge diffusion. To capture these interdependencies, we create a measurement model integrating both cognitive trust and task interdependencies, while also accounting for AI’s different roles (collaborator, tool, or supervisor). Design Structure Matrix (DSM) is a powerful visualization tool for representing the interdependencies among different elements in complex systems, thus we employ it to visualize and analyze task interdependencies.

Moreover, cognitive trust is rooted in AI’s cognitive capability, and it evolves dynamically through human–AI interactions (Glikson and Woolley, 2020). AI’s cognitive capability demonstrated the capability to reduce task complexity through effective problem-solving. Shannon’s entropy is a standard metric for both uncertainty and complexity, where higher entropy reflects greater unpredictability and complexity (Frankel and Kamenica, 2019; Farquhar et al., 2024). Thus, we develop an entropy-based model to evaluate AI’s cognitive capability by comparing the complexity of a task with the uncertainty of AI-generated solutions. Building on this, we propose a cognitive trust measurement model grounded in AI cognitive capabilities and capture its dynamic nature in interactions.

This paper makes three key contributions: (1) It extends the literature on knowledge diffusion in human–AI collaboration by proposing a knowledge diffusion model that reflects the dynamic knowledge diffusion throughout human–AI interactions; (2) It introduces a comprehensive method to measure knowledge diffusion efficiency, incorporating AI’s organizational roles, cognitive trust, and task interdependencies, which previous approaches ignore; (3) It proposes a more sophisticated model to measure cognitive trust by accounting for the dynamic nature of trust during interactions and AI’s task-specific cognitive capabilities, which have received limited attention in existing research.

2 Literature review

2.1 Knowledge diffusion process

Knowledge diffusion is critical to the success of innovation projects, as it integrates diverse knowledge resources and plays a pivotal role in fostering effective coordination and driving innovation (Chowdhury et al., 2022; Xu et al., 2022). In human–AI collaboration, AI’s data-processing capabilities help identify hidden patterns and generate actionable insights, thereby enhancing organizational innovation potential (Gama and Magistretti, 2025). Hence, understanding how knowledge is transmitted in such collaborative organizations is therefore essential for achieving effective collaboration.

With AI’s rapid development, its role in organizations has become increasingly complex. While much research has explored AI’s influence on knowledge management, these studies primarily focus on AI as a tool for accelerating knowledge transformation (Zhang et al., 2025). Olaisen and Revang (2018) suggested AI aids in managing complex, collective knowledge that is difficult for managers to integrate into business processes. Jarrahi et al. (2023) highlighted AI’s roles in knowledge management activities, including knowledge creation, storage, retrieval, sharing, and application. However, existing studies ignored how AI’s diverse roles (such as tool, collaborator, and supervisor) affect knowledge diffusion in collaborative settings.

Many research has examined multiple factors that influence organizational knowledge diffusion. For instance, Xu et al. (2022) emphasized the role of task interdependence in shaping diffusion pathways, while Todo et al. (2016) and Qiao et al. (2019) explored how tie strength and individual roles impact knowledge spread from the SNA perspective. Other studies highlighted the importance of individual absorptive capacity (Thomas and Gupta, 2022) and cognitive trust (Capestro et al., 2024) in enabling knowledge sharing. Although cognitive trust and task interdependencies have been acknowledged as factors influencing knowledge sharing, prior research typically does so in interpersonal contexts, with limited consideration of their impact on knowledge diffusion. This oversight is especially critical in human–AI collaborative organizations, where developers' cognitive trust in AI and task interdependencies jointly determine how information/knowledge is stored and diffused. Neglecting them may lead to an oversimplified understanding of human–AI collaborative knowledge diffusion.

Hence, we model the knowledge diffusion process in human–AI collaboration by considering the impact of AI's different roles and incorporating developers' cognitive trust in AI and task interdependencies as key factors for assessing knowledge diffusion. This approach enables a deeper understanding of the knowledge diffusion in human–AI collaboration.

2.2 Measurement of human–AI cognitive trust and cognitive capability

Recently, AI has evolved beyond its traditional role as a tool. It now functions as an active participant in team-based activities, particularly in the NPD project (Seeber et al., 2020). AI not only generates new ideas by overcoming the cognitive limitations of humans (Haefner et al., 2021) but also enhances organizational efficiency (Anantrasirichai and Bull, 2022).

Although many research has considered AI's capability to generate ideas and enhance project efficiency, the role of cognitive trust in human–AI collaboration remains underexplored. Cognitive trust, which refers to users' belief in AI's competence and reliability, is critical for fostering effective collaboration (Glikson and Woolley, 2020; Schelble et al., 2024). However, existing research primarily focuses on the static antecedents of trust, such as AI's transparency, reliability, and tangibility (Kyung and Kwon, 2022; Choung et al., 2023). These studies fail to reveal how cognitive trust evolves dynamically through continuous human–AI interactions.

A key underexplored driver of cognitive trust is AI's cognitive capability, which refers to its capability to process complex information and reduce uncertainty by providing effective solutions (Boyacı et al., 2024). Existing research tends to treat cognitive capability as an assumed or background factor rather than operationalizing it as a measurable construct. Moreover, prior trust measurement models do not capture how cognitive trust evolves with AI cognitive capabilities and human–AI interactions (Farquhar et al., 2024).

To address these gaps, we construct a dynamic model of cognitive trust evolution, and introduce an entropy-based approach to quantify AI's cognitive capability. Overall, our paper responds to the need for a dynamic, capability-based perspective on trust in human–AI collaboration. By linking AI's cognitive performance to the development of cognitive trust over time, we contribute a novel framework for understanding how cognitive trust develops within the collaboration process.

3 Modeling knowledge diffusion in human–AI collaboration

3.1 Knowledge diffusion process in human–AI collaboration

Knowledge diffusion is critical for effective collaboration and innovation (Chowdhury et al., 2022). In human–AI collaboration, the AI platform serves as both a knowledge source and an active participant in the knowledge diffusion process. Developers input tasks such as coding, algorithm optimization, and data analysis, to which AI responds by processing the data with its extensive knowledge base. This iterative interaction allows AI to continuously learn and refine its problem-solving capabilities while providing feedback to developers in various formats (text, images, or voice) to help them enhance their expertise (Westphal et al., 2023). As a result, knowledge gradually diffuses within the organization, improving both individual and organizational knowledge levels. To further explore this dynamic, this paper presents a knowledge diffusion model based on human–AI interactions (see Fig. 1), illustrating the knowledge process within the collaborative team.

Usually, both developers and the AI platform possess

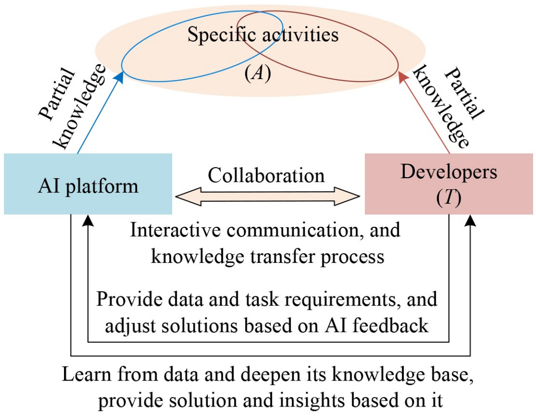


Fig. 1 Knowledge diffusion model based on human–AI interactions.

only partial knowledge regarding specific activities. Thus, they must collaborate to accomplish particular tasks through continual interactions. During this interactive communication process, AI adapts to task requirements, continuously enhancing its knowledge base, while developers learn from AI feedback and refine their solutions. This mutual knowledge transfer fosters a collaborative and dynamic knowledge ecosystem. Furthermore, since AI is a new technology, effective collaboration also requires developers to possess relevant skills, which encourages experience sharing related to AI, creating a foundation for knowledge diffusion within teams.

3.2 Measuring the ratio of knowledge diffusion between members

In the human–AI collaboration, organizational members collectively form a network, their continuous interactions facilitate knowledge diffusion. From the SNA perspective, the Tie Strength (TS) between members is generated by the dependency between members, and reflects the degree of interaction and communication, serving as the foundation for knowledge diffusion (Todo et al., 2016, Zou et al., 2023). More frequent interactions among members lead to more efficient knowledge transfer (Jarrahi et al., 2023; Sassine and Rahmandad, 2024). Meanwhile, knowledge diffusion is influenced by the knowledge distance between individuals. A larger knowledge distance (knowledge potential difference) between two organizational members (such as AI, developers) typically increases the potential for knowledge sharing, as such interactions can yield greater knowledge benefits.

However, the effectiveness of knowledge diffusion is not only dependent on the knowledge distance but also on the absorptive capacity of developers (team). Generally, when AI provides operational guidance directly related to tasks that do not require further analysis (explicit knowledge such as rules and standards), the higher the developers' knowledge level, the stronger their learning and absorptive capacity (Beaulieu et al., 2017). Additionally, the AI platform can also offer decision support to developers by analyzing task data (such as strategy and suggestion). During this process, the developers' absorptive capacity is also affected by their roles within the organization. Particularly, those developers who serve as bridging nodes in the network can connect different sources of information and teams, enhancing the flow of information and thereby improving the effectiveness of decision support, which further facilitates effective knowledge transfer. This can be quantified using the betweenness centrality index, which measures the extent to which node j lies on the shortest path between other nodes in the network.

Therefore, the knowledge diffusing ratio $ks_t(i,j)$ from developer i to j at time t is driven by three factors: tie strength from i to j, the knowledge distance between them, and the developer j's absorptive capacity. Based on this, we propose a measurement model for knowledge diffusing ratio as follows:

$$ks_t(i,j) = TS(i,j) \times ka_t(j) \times \frac{\Delta k_t(i,j)}{\max|k_t(i) - k_t(j)|}, \tag{1}$$

$$ka_t(j) = \frac{k_t(j)}{\max k_t(j)} \times \left(1 + \alpha \times \sum\nolimits_{s\neq t\neq j} \frac{\sigma_{st}(j)}{\sigma_{st}}\right), \tag{2}$$

where $TS(i,j)$ represents the tie strength from developer i to j, $ka_t(j)$ represents j's knowledge absorptive capacity, $\Delta k_t(i,j)$ and $\max|k_t(i) - k_t(j)|$ represent the knowledge distance between i and j and the maximum knowledge distance among all nodes in the human–AI collaborative organization at time t, respectively. Additionally, $k_t(j)$ and $\max k_t(j)$ indicate the knowledge level of developer j and the highest knowledge level of all developers in the organization at time t, respectively. The adjustment coefficient α takes a value of 1 when AI provides decision support to developers, and 0 otherwise. σ_{st} and $\sigma_{st}(j)$ denote the number of shortest paths between developers (e.g., s and t) in the organization and the number of shortest paths through node j, respectively.

3.3 Agent-based modeling for human–AI collaborative knowledge diffusion

To further understand knowledge diffusion in human–AI collaboration, we use ABM as a tool to simulate and analyze the knowledge diffusion process. ABM can reflect agent behavior by effectively capturing autonomous agent/individual interactions (Zhang et al., 2020; Sankar et al., 2020). Existing literature summarized four essential elements of ABM: Agent, Interrelationship, Network, and Decision-making rule (knowledge diffusion rule) (Kiesling et al., 2012; Park and Puranam, 2024). Hence, we build the knowledge diffusion model in human–AI collaboration from the above four aspects.

3.3.1 Agent

In our setup, human–AI collaborative team members in ABM are referred to as agents (i.e., developer and AI), and j is used to denote a specific agent. Each agent behaves autonomously, meaning that its knowledge-sharing and absorption actions are influenced by its unique properties, such as its knowledge base. Therefore, we use initial knowledge level $k_0(j)$, and AI's knowledge absorptive capacity $ka_t(j)$ to define each agent. The knowledge level is the number of technical abilities the agent has (Pan et al., 2022), which depends on the experience accumulated by the developer/AI in the previous product development process. From the organizational perspective, the initial knowledge level of the organization is the sum of individuals' initial organizational knowledge level, which can be calculated as:

$$K_0(t) = \sum_{j \in M} |k_0(j)|. \tag{3}$$

3.3.2 Interrelationship

3.3.2.1 AI roles in human–AI collaboration

In human–AI collaboration, the role of AI platform defines collaboration patterns and knowledge diffusion mechanisms within the team. Considering AI's task involvement and functionality, here, we categorize AI roles into Collaborator, Tool, and Supervisor (Seeber et al., 2020; Jarrahi, 2018).

i) Collaborator: AI actively engages in task execution (e.g., Autodesk Dreamcatcher), exhibiting reasoning and analyzing capabilities (Seeber et al., 2020). It collaborates with developers and refines its cognition through ongoing interaction. This also fosters bidirectional knowledge diffusion, where developers acquire insights and methodologies from AI and AI adapts by learning human decision logic and domain expertise.

ii) Tool: AI autonomously handles repetitive, well-defined activities (e.g., IBM Watson Analytics), supporting developers with its extensive knowledge base and advanced data processing and analysis capabilities for informed decision-making (Jarrahi, 2018). Through continuous interactions, developers refine their decisions using AI solutions, while AI adjusts its models and outputs based on human feedback, fostering bidirectional knowledge diffusion.

iii) Supervisor: AI primarily monitors processes/workflows and provides real-time alerts for illegal or risky operations, but does not execute specific tasks (e.g., Codacy). Here, knowledge diffusion occurs only among developers.

3.3.2.2 Analyzing dependency strength between members

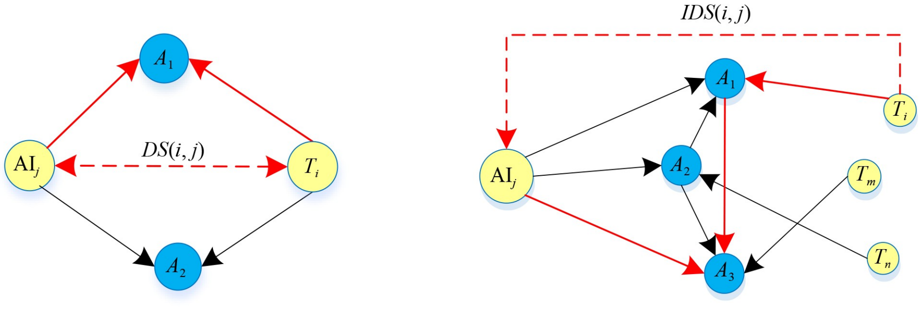
Knowledge diffusion is built on the dependencies among members (e.g., the AI platform and developers). Fig. 2 shows these interdependencies, which can be categorized as either direct or indirect. Specifically, direct dependencies arise when members collaborate on shared tasks. Indirect dependencies, on the other hand, may arise from the complex dependencies between activities or from the communication/coordination that occurs through members' shared reliance on the AI platform during the collaboration process (Yang et al., 2022).

Situation 1: Direct dependencies among members fall into two categories. First, when they collaborate on the same activity (i.e., AI serves as a collaborator), stronger dependencies emerge with clearer AI cognition and greater developer effort, as increased interaction reinforces their direct dependencies (see Fig. 2(a)). Second, when AI acts as a collaborator or tool, the developer's cognitive trust in AI further reinforces this direct dependency. Moreover, since AI does not directly engage in activities when acting as a supervisor, the direct dependencies exist solely among developers.

Hence, the direct dependency strength between members can be calculated as follows:

$$DS(i,j) = \begin{cases} \sum\limits_{I \in N} (\alpha \times Aa(A_I) \times He(i, A_I) + \beta \times TR_I(i,j)), & \text{if one of } i \text{ and } j \text{ is AI}, \\ \sum\limits_{I \in N} He(j, A_I) \times He(i, A_I), & \text{else}, \end{cases} \tag{4}$$

where N is the number of activities in the project. The adjustment coefficient $\alpha = 1$ when AI acts as a collaborator, and 0 otherwise, and $\beta = 1$ when AI acts as a collaborator or tool, and 0 otherwise. $TR_I(i,j)$ represents



(a) (b)

Fig. 2 Example of dependencies among human–AI collaborative organization members. (a) Direct dependency relationship; (b) Indirect dependency relationship.

the cognitive trust between i and j in activity A_I, $Aa(A_I)$ represents AI's cognition of A_I, $He(i,A_I)$ represents the proportion of effort contributed by developer i to A_I, we use a number from 0 to 1, with higher values indicating more effort. These three items will be further discussed in the next section.

For example, Fig. 2 shows that developer i collaborates with AI platform j to complete A_1 and A_2, with effort proportion levels of 0.3 and 0.8, and build cognitive trust of 0.45 and 0.5. Here, AI is in the role of collaborator, AI's cognition of A_I and A_2 is 0.7 and 0.4, then $DS(i,j) = 1\times[(0.45+0.7\times0.3)+(0.5+0.4\times0.8)] = 1.48$.

Situation 2: Task interdependencies drive continuous interactions among members, thereby fostering their indirect dependencies. Specifically, when AI serves as a collaborator or tool, both cognitive trust and task interdependencies contribute to the formation of indirect dependencies between members (see Fig. 2(b)). Given that task dependencies are directional, the relationships among members also reflect this directional pattern. Instead, when AI acts as a supervisor, the indirect dependencies also exist solely among developers.

Hence, the indirect dependency strength between members can be calculated as follows:

$$IDS(i,j) = \begin{cases} \lambda \times \sum\limits_{I,J\in N} He(i,A_I)\times ADS(A_I,A_J)\times A_a(A_I), \text{ if one of } i \text{ and } j \text{ is AI}, \\ \gamma \times TR(i,j)\times TR(i,j) + \sum\limits_{I,J\in N} He(i,A_I)\times ADS(A_I,A_J)\times He(j,A_J), \text{ else}, \end{cases} \tag{5}$$

where $ADS(A_I,A_J)$ represents the dependency strength between activity A_I and A_J, which will be discussed in the next section. Both adjustment coefficient λ and γ equal to 1 when AI acts as a collaborator or tool, and 0 otherwise.

Continue the example in Fig. 2, developer a and AI platform j complete A_1 and A_3 respectively, and j acts as a collaborator, i's effort proportion levels in A_1 is 0.3, and AI's cognition of A_3 is 0.5, the dependency between A_1 and A_3 is 0.9. Then, we calculate the indirect dependency strength $IDS(i,j) = 0.3\times0.5\times0.9 = 0.135$.

Therefore, the integrated dependency strength can be calculated as follows:

$$TDS(i,j) = DS(i,j) + IDS(i,j). \tag{6}$$

3.3.2.3 Measuring tie strength between members from the network perspective

Further, from the SNA perspective, the Tie Strength (TS) among organizational members (e.g., AI and developer) is calculated from the dependency relationship among them. TS is generated by the dependency between members (Yang et al., 2022), with stronger dependency relationships resulting in greater TS. Hence, the Tie Strength (TS) between members can be expressed as the ratio of the integrated dependency strength between a and j to the sum of the integrated dependency strength between i and all associated nodes in the network.

$$TS(i,j) = \frac{TDS(i,j)}{\sum\limits_{q=1}^{M} TDS(i,q)} \text{ for } i \neq j, \tag{7}$$

where M is the number of human–AI collaborative organization members.

3.3.3 Network

The fundamental of knowledge-based collaboration is a knowledge collaboration team, composed of members from diverse organizational and knowledge backgrounds (Song et al., 2013). Here, we construct a knowledge diffusion network consists of organizational members as nodes (i.e., developers T_i, T_m, T_n, and the AI platform), with the tie between them forming the edges, shaping the knowledge diffusion network structure within the team. (Fig. 3).

As depicted in Fig. 3, each node is an agent, and each directed edge illustrates the potential direction of knowledge diffusion between two agents. For example, the AI platform can acquire new knowledge from the text provided by developer T_n. Meanwhile, developer T_m can absorb new knowledge from the outputs (such as text and images) generated by the AI platform. Moreover, during the collaborative problem-solving process, the AI platform and developer T_j may engage in mutual learning, actively sharing and diffusing knowledge between them. This continuous interaction fosters an evolving network of

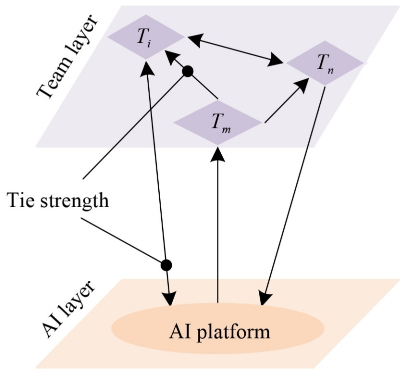


Fig. 3 Knowledge diffusion network within the team.

knowledge diffusion within the team.

3.3.4 Knowledge diffusion rule

The knowledge diffusion rule dictates when and how knowledge can be diffused between agents in human–AI collaboration. In our model, these rules are based on several factors: the knowledge distance between agents, the tie strength between them, and their knowledge absorptive capacities (Todo et al., 2016; Thomas and Gupta, 2022). During each interaction, agents assess whether sharing knowledge based on the difference between their knowledge level and that of the other agent. The larger the knowledge distance and the stronger the tie strength is, the easier it is for the agent to initiate knowledge sharing. Agents with higher absorptive capacity can absorb more knowledge from other members, making them more effective knowledge receivers in the diffusion process.

However, apart from these internal factors, external uncertainty (such as market uncertainty, technological change, etc.) also plays a key role in diffusion (Qiao et al., 2019). When the agent's absorptive capacities are insufficient to counter external uncertainties, knowledge diffusion may be hindered. Therefore, based on these considerations, we develop knowledge diffusion rules (Fig. 4), which provide detailed rules for analyzing knowledge diffusion in human–AI collaboration.

Fig. 4 illustrates the knowledge diffusion rules in human–AI collaboration. In our model, the knowledge diffusion rule is, when there is a tie from i to j, denoted as $TS(i, j)$, and agent i has the knowledge that j does not have, that is, there is a knowledge distance $\Delta k_t(i, j)$, agent i can diffuse knowledge to j. Meanwhile, since external uncertainty $u_t(j)$ also impacts knowledge diffusion, we model it as a random number between 0 and 1. Then, after receiving knowledge, agent j will determine whether to incorporate the new knowledge and update its knowledge level $k_t(j)$ based on the uncertainty. In other words, when $u_t(j)$ is less than j's knowledge absorptive capacity, j can successfully overcome the external uncertainty, incorporate the new knowledge effectively, and update its knowledge level.

As agents exchange knowledge, the organizational knowledge level increases. However, this growth does not continue indefinitely. Therefore, we assume the knowledge diffusion model will converge when the growth rate of the organizational knowledge level $\Delta KG_t(t)$ from time $t-1$ to t is less than 0.0001, indicating that the knowledge diffusion process in human–AI collaboration has reached a steady-state. Hence, we develop the knowledge growth rate model of human–AI collaborative organization as follows:

$$\Delta KG_t(t) = \frac{K_t(t)}{K_{t-1}(t)} - 1, \tag{8}$$

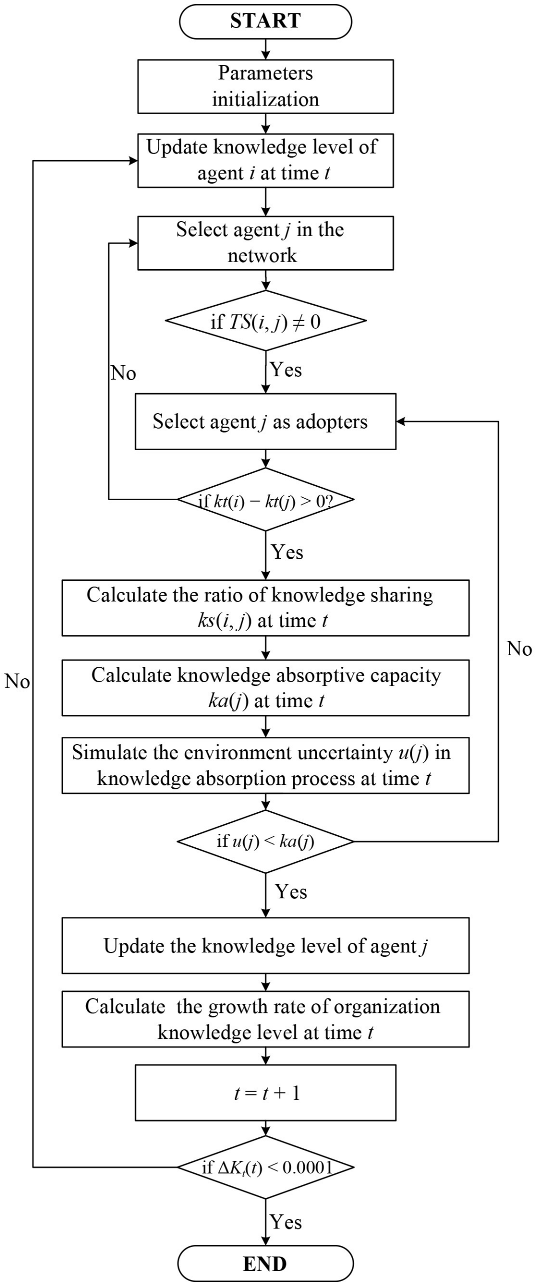


Fig. 4 Knowledge diffusion rules in human–AI collaboration.

where $K_t(t)$ represents the organizational knowledge level in time t.

Furthermore, we measure the knowledge diffusion efficiency by calculating the knowledge gain ratio, which reflects the proportion of actual knowledge increase relative to the initial knowledge level. Based on this, we developed a human–AI collaborative organization knowledge diffusion efficiency measurement model as follows:

$$EKG_t(t) = \frac{K_t(t) - K_0(t)}{K_0(t)}. \tag{9}$$

Based on the previous modeling analysis of the knowledge diffusion process in human–AI collaboration, we will further quantify the key influencing factors (such as cognitive trust, and interdependency relationship among activities) of this process in the next section.

4 Analyzing key factors in human–AI collaborative knowledge diffusion

4.1 Measuring human–AI trust in human–AI collaboration

In human–AI collaboration, developers' cognitive trust in AI is primarily shaped by its capability to process information, learn, and generate solutions to meet project/task needs (Glikson and Woolley, 2020). In other words, cognitive trust is built on the AI's demonstrated competence in solving project/task problems. Thus, measuring AI's cognitive capability is the key to quantifying human–AI cognitive trust.

4.1.1 Measuring human–AI cognitive capability

In human–AI collaboration, AI's cognitive capability is largely demonstrated by its capability to reduce project complexity through solutions offered to developers. The reduction in uncertainty is closely related to the amount of information it processes, which determines its cognitive performance (Boyacı et al., 2024). However, due to its limited knowledge base, AI typically addresses only a subset of challenges, leaving residual uncertainty. Thus, AI's cognitive capability can be measured by the reduction in uncertainty for a specific project.

Shannon's entropy is a standard metric for both uncertainty and complexity, where higher entropy reflects greater unpredictability and complexity (Frankel and Kamenica, 2019). Hence, this paper proposes a novel approach to measuring AI's cognitive capability by evaluating project complexity and the uncertainty in AI's solutions, both quantified through entropy.

4.1.1.1 Project complexity measurement model based on entropy

Since projects/tasks consist of numerous components that interact in intricate ways, each requiring specific domain knowledge for completion (Zou and Yang, 2019). Hence, project complexity is captured by the domain knowledge required to manage the internal intricacies of a single project. The more extensive the domain knowledge required, the greater the project complexity. Certain domain knowledge may require minimal effort but determines the successful delivery of the project, thus, it is essential to account for the importance of each domain knowledge, which can be assessed by experts. Accordingly, the probability related to domain knowledge $p(k)$ can be calculated as follows:

$$p(k)=\frac{\alpha_k\cdot w_k}{\sum_{j=1}^{K}\alpha_j\cdot w_k}, \tag{10}$$

where α_k represents the importance weight of domain knowledge k, $\alpha_k\in[0,1]$, w_k indicates the workload associated with domain knowledge k, typically calculated by working hours recorded in project logs, and K represents the total number of domain knowledge required for the project.

Then, according to Eq. (10), we build the project complexity measurement model based on entropy, denoted as $H(p)$, as follows:

$$H(p)=-\sum_{k=1}^{K}p(k)\log(p(k)). \tag{11}$$

4.1.1.2 AI solution uncertainty measurement model based on entropy

AI aims to deliver what it perceives as the optimal solution for each project. However, due to its limited knowledge, it often addresses only a subset of challenges, resulting in residual uncertainty. This uncertainty typically arises from gaps in domain knowledge, insufficient training data, or limitations in model capabilities (Yadkori et al., 2024). Hence, we use AI solution uncertainty to describe this phenomenon and assess the proportion of domain knowledge effectively addressed by the AI solution in the project context.

$$p(a)=1-\frac{|k_a\cap k_p|}{|k_p|}, \tag{12}$$

where k_a and k_p represent AI's knowledge and the project's required knowledge, respectively. The required domain knowledge can be captured by the key parameters of the solution's output, which reflect the knowledge utilized during the project.

Then, we build the following model to measure AI solution uncertainty $H_a(p)$:

$$H_a(p)=-p(a)\log[p(a)]. \tag{13}$$

In summary, AI's cognitive capability is largely defined by its capability to reduce complexity. This can be measured by comparing "project complexity $H(p)$" and "AI solution uncertainty $H_a(p)$," which corresponds to the mutual information between prior and posterior distributions in information theory. As mutual information is always positive, cognitive capability inherently reduces uncertainty due to the concavity of entropy (Boyacı et al., 2024). Therefore, we calculate AI's cognitive capability $A_a(p)$ for a specific project as follows:

$$A_a(p)=\frac{H(p)-H_a(p)}{\max(H(p),H_a(p))-\min(H(p),H_a(p))}. \tag{14}$$

4.1.2 Measuring human–AI cognitive trust

In human–AI collaboration, cognitive trust between developers and AI is closely related to the AI's demonstrated cognitive capabilities, which are determined by the knowledge it possesses (Akula et al., 2022). Additionally, developers' trust in AI is dynamic, shaped by their collaborative/interactive time. Generally, trust grows with time, but as developers become more familiar with AI, the rate of growth slows (Ng and Zhang, 2025). Hence, we build a dynamic human–AI cognitive trust measurement model that integrates knowledge intersection and AI cognitive capabilities while also considering its dynamic nature (Fig. 5).

Fig. 5 shows that for a specific task T, the knowledge required to complete task T, and the knowledge possessed by developer i and AI j are respectively represented as $k(T)$, $k(i)$, and $k(j)$. The AI platform has its cognitive capability $A_a(p)$. When AI acts as a collaborator, AI can work alongside developers to complete different parts of a project (shaded area ②), while as a tool, it provides decision-making support to developers (shaded area ①). In the above contexts, the knowledge of AI and developers forms overlapping and complementary relationships in certain aspects, thereby fostering cognitive trust. Moreover, when AI functions as a supervisor, developers' cognitive trust in AI is constant, here, we set it as 1. Hence, we build a cognitive trust measurement model from the following aspects.

1) When AI functions as a collaborator (shaded area 1 of Fig. 5), AI assists developers in solving the part of work that they cannot solve by themself. In this scenario, the larger the proportion of shaded area 1, the stronger AI's capability to assist in unknown domains, and the higher the human–AI cognitive trust (Haefner et al., 2021).

2) When AI functions as a tool (shaded area 2 of Fig. 5), it offers decision support to developers. Thereby fostering human–AI cognitive trust. The larger the proportion of area 2, the higher the human–AI cognitive trust (Haefner et al., 2021).

Therefore, the human–AI cognitive trust between developer i and AI j in task T can be calculated as follows:

$$TR_T(i,j)=\begin{cases}1, & \text{if AI serves as a supervisor,}\\ A_a(p)\times\left[\dfrac{|k(j)\cap k(i)\cap k(T)|}{|k(i)\cap k(T)|}+\dfrac{\left|k(j)\cap\overline{k(i)}\right|}{\overline{k(i)}}\right]\times(1+\Delta(t)), & \text{else,}\end{cases} \tag{15}$$

where $k(T)$ is the knowledge required for solving task T, $k(i)$ and $k(j)$ represent the possessed knowledge by developer i and AI platform j respectively. $\overline{k(i)}$ represents the set of knowledge that developer i cannot solve while performing task T. $k(j)\cap\overline{k(i)}$ indicates that AI can assist the developer in solving the part of task T that it cannot solve (shaded area ① in Fig. 5). $\Delta(t)$ is the increment of trust, which varies with interaction time/numbers. According to the learning curve, we assume that $\Delta(t)=-\mathrm{e}^{-t}$, whereas t is the interaction time.

4.2 Analyzing interdependency relationship among activities

As mentioned before, complex dependencies among activities lead to the dependencies between members (i.e., AI and developers), forming the foundation for understanding knowledge diffusion within the human–AI collaborative organization. Existing studies classify interdependencies among activities into three dimensions: technical, process, and resource (Zou and Yang, 2019),

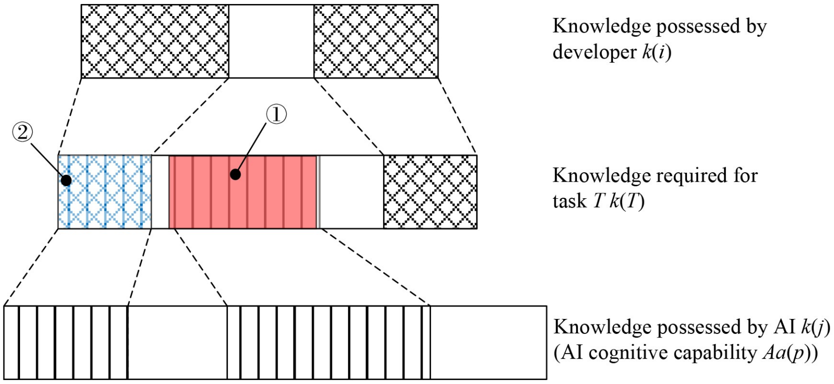


Fig. 5 Human-AI cognitive trust measurement model.

whereas technical dependencies drive the exchange of technological insights, process dependencies influence task workflows, and resource dependencies foster coordination on shared information. These dependencies facilitate communication and coordination among members, ultimately fostering knowledge diffusion within the team.

To capture and analyze multi-dimensional dependencies among activities, we use the framework illustrated in Fig. 6. Specifically, we first establish a single-dimensional network for each dimension, as shown in Figs. 6(a)–6(c). Each network captures the distinct dependency structure within its respective dimension. Then, by overlaying these single-dimensional networks, we obtain a multi-dimensional network (Fig. 6(d)), which reflects integrated dependencies across all dimensions. Here, we assume that all dimensions carry equal weight in influencing activity outcomes and dependencies.

In Figs. 6(a)–6(d), the direction of edges indicates the orientation of dependencies, while the weights indicate their strength. For example, in Fig. 6(b), within the technological dimension, each node's attribute value signifies the technology required for activity completion. If A_i relies on technology provided by A_j, this indicates a technical dependency between them, represented by a directed edge from A_j to A_i, their dependency strength in this dimension is assigned as 1.

$$ADS_d(i,j)=\begin{cases}1, & \text{if there is a dependency relationship between } A_i \text{ and } A_j,\\ 0, & \text{else.}\end{cases} \tag{16}$$

Finally, DSM is a powerful visualization tool for representing the interdependencies among different elements in complex systems. To effectively illustrate the multi-dimensional dependencies strength between activities, we utilize the Process DSM, as depicted in Fig. 6(e). DSM is an $N \times N$ matrix, where the diagonal line represents elements (activities) and non-diagonal markers represent dependencies between corresponding elements (Yang et al., 2022). For example, row 2 and column 3 of the Process DSM indicates an integrated dependency (e.g., the process and resource dependency) from A_2 to A_3, the higher the value, the stronger the dependencies. Hence, the integrated dependencies between A_i and A_j can be calculated as:

$$ADS(i,j)=\sum_{d\in D} ADS_d(i,j), \tag{17}$$

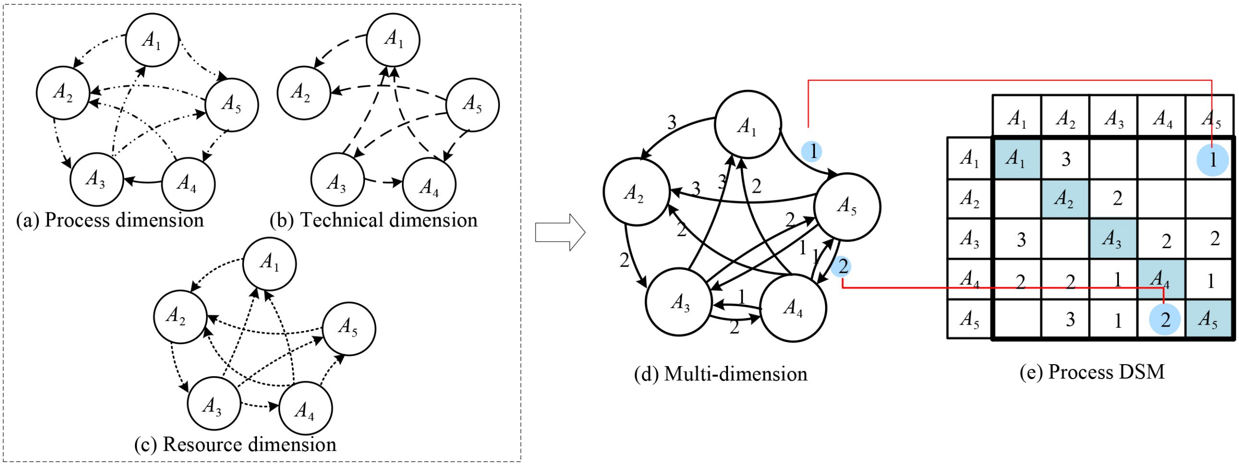
where D represents dependency dimensions, here, $D=\{\text{process}, \text{technocial}, \text{resource}\}$.

5 Illustrative application

5.1 Background and data

To validate the proposed model, we utilized data from an Integrated Development Platform (IDP) project in an IT software company, where all members operated on a Collaborative Work Platform (CWP), a unified in-house AI platform. To obtain the project data, we interviewed the product managers, project managers, and engineers, and combined them with the enterprise case database to sort out various activities in the IDP project. Meanwhile, by analyzing the interaction logs between the developers and AI, as well as the log records of AI's participation in projects, we found that, in our context, AI primarily functions as a collaborator or a tool.

The IDP project involved a total of 15 activities and 13 developers. Each activity is performed by different



(a) Process dimension
(b) Technical dimension
(c) Resource dimension
(d) Multi-dimension

	A_1	A_2	A_3	A_4	A_5
A_1	A_1	3			1
A_2		A_2	2		
A_3	3		A_3	2	2
A_4	2	2	1	A_4	1
A_5		3	1	2	A_5

(e) Process DSM

Fig. 6 Framework of analyzing multi-dimensional dependencies among activities.

developers and AI. The knowledge required for each activity involving AI and developers and their knowledge set are shown in Table 1. Here, we assume the significance of domain knowledge of each activity is equal. The knowledge possessed by AI is {d,e,f,g,i,j,k,l,m,n,p,q,r,t,x,y,z,aa,bb,mL,ff}.

5.2 Analyzing knowledge diffusion in the IDP project

We calculate the dynamic human–AI cognitive trust by using Eqs. (10)–(15) as shown in Fig. 7(a). According to the interview, the interdependency relationships among activities are determined using Eqs. (16)–(17) and clearly illustrated in Fig. 7(b). These serve as inputs to our proposed model. We calculate the tie strength among members using Eqs. (4)–(7), and subsequently measure the ratio of knowledge diffusion with the proposed model.

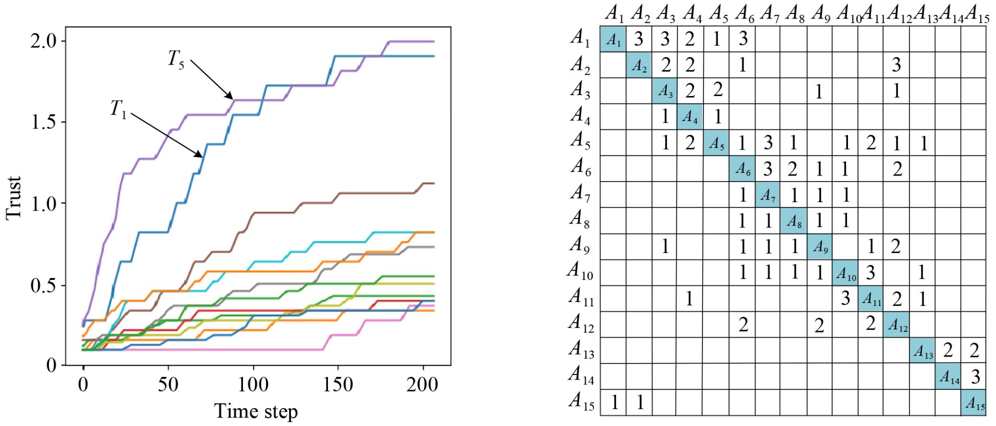
Then, following the knowledge diffusion rule in Fig. 4, we simulate the knowledge diffusion process in human–AI collaboration using Python 3.10, and analyze the knowledge level, knowledge growth rate, and knowledge diffusion efficiency from the organizational perspective. Figs. 8(a)–8(c) show the results.

As shown in Figs. 8(a)–8(c), the growth of organizational knowledge follows a “fast-then-slow” pattern. This trend reflects rapid diffusion in the early stages, driven by the novelty of knowledge and significant knowledge gaps, as members assimilate new knowledge, its marginal growth rate gradually declines over time, supporting existing research on knowledge diffusion.

Meanwhile, we analyze the results of organizational

Table 1 IDP project-related data

No.	Activity	Required knowledge for activity	Developer and its knowledge
A_1	Opportunity identification	{a,b,c,d,x,y,dd}	Product manager T_1{a} Requirements engineer T_2{b,c,e}
A_2	Requirement analysis	{d,x,y,e,f,ee}	Requirements engineer T_2{b,c,e}
A_3	Concept development	{d,e,f,x,p,y}	Architecture manager T_3{d,e,g,h,f,i}
A_4	Feasibility assessment	{g,h,i,l,n,p}	Architecture manager T_3{d,e,g,h,f,i}
A_5	Detailed design	{i,j,o,s}	System engineer T_4{i,j,o}
A_6	Front-end coding	{m,n,s,t}	Front-end development engineer T_5{m,n}
A_7	Middleware platform coding	{p,s,t,q,l}	Middleware platform development engineer T_6{p,s,q}
A_8	Back-end coding	{t,l,p,s}	Back-end development engineer T_7{l,p}
A_9	Algorithm optimization	{o,p,q,r,y,z}	Algorithm manager T_8{p,q,r,y}
A_{10}	Component pre-production testing	{u,v,g,m,s}	Test engineer T_9{u,v,g,k}
A_{11}	Integration testing	{d,v,k}	Test engineer T_9{u,v,g,k}
A_{12}	User experience design	{m,n,aa,bb}	User experience designer T_{10}{m,aa,bb}
A_{13}	Quality assurance testing	{r,s,t,v,mL}	Quality assurance engineer T_{11}{t,v,k,l,p,q}
A_{14}	Deployment planning	{d,e,x,k}	Delivery manager T_{12}{d,e,f}
A_{15}	Post-deployment support	{x,y,z,ff}	DevOps engineer T_{13}{o,r,z,ff}



(a)

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}
A_1	A_1	3	3	2	1	3									
A_2		A_2	2	2		1						3			
A_3			A_3	2	2				1			1			
A_4			1	A_4	1										
A_5			1	2	A_5	1	3	1		1	2	1	1		
A_6						A_6	3	2	1	1		2			
A_7						1	A_7	1	1	1					
A_8						1	1	A_8	1	1					
A_9			1			1	1	1	A_9		1	2			
A_{10}						1	1	1	1	A_{10}	3		1		
A_{11}				1						3	A_{11}	2	1		
A_{12}						2			2		2	A_{12}			
A_{13}													A_{13}	2	2
A_{14}														A_{14}	3
A_{15}	1	1													A_{15}

(b)

Fig. 7 Process DSM and developers’ dynamic cognitive trust levels: (a) Developers’ dynamic cognitive trust levels; (b) Process DSM.

knowledge diffusion under different roles of AI. In Figs. 8(a)–8(c), when AI serves both as a collaborator and a tool (see black line), the organizational knowledge level is 351, with a diffusion efficiency of 4.25, despite requiring 233 steps for diffusion. This knowledge diffusion results are significantly higher than when AI functions solely as a collaborator (see red line), which have the organizational knowledge level of 303 and diffusion efficiency of 3.3. Here, the time to reach steady-state is 181 steps. When AI acts only as a tool (see blue line), the knowledge level is lowest at 270, and diffusion efficiency is at 3.1, with a longer time to reach steady-state, approximately 240 steps. Above findings suggest that AI's role as a collaborator fosters deeper engagement, more frequent interaction, and enhance knowledge sharing, which accelerates knowledge diffusion. Conversely, when AI is a tool, limited interaction reduces knowledge transfer and extends the time required to reach steady-state.

More specifically, as observed in the highlighted area in Fig. 8(c), although the knowledge growth rate generally declines over time, in the early stages of diffusion, AI's role as a tool (see blue line) results in a higher knowledge growth rate compared to its role as a collaborator (see red line). This indicates that, during the initial stages of diffusion, AI's role as a tool promotes faster knowledge accumulation, as it handles more repetitive tasks, allowing for quicker knowledge transfer. Further observation supports that when AI functions as both a collaborator and a tool (see black line), organizational knowledge growth initially increases significantly before gradually declining. The results suggest that during the early phase, project managers should focus on leveraging AI as a tool for decision support to accelerate knowledge accumulation. In later stages, particularly when AI serves as a collaborator, the focus should shift to fostering an environment that encourages collaborative knowledge sharing.

Next, we analyze the knowledge level, knowledge growth rate, and knowledge diffusion efficiency from the individual perspective, Fig. 9 shows the results.

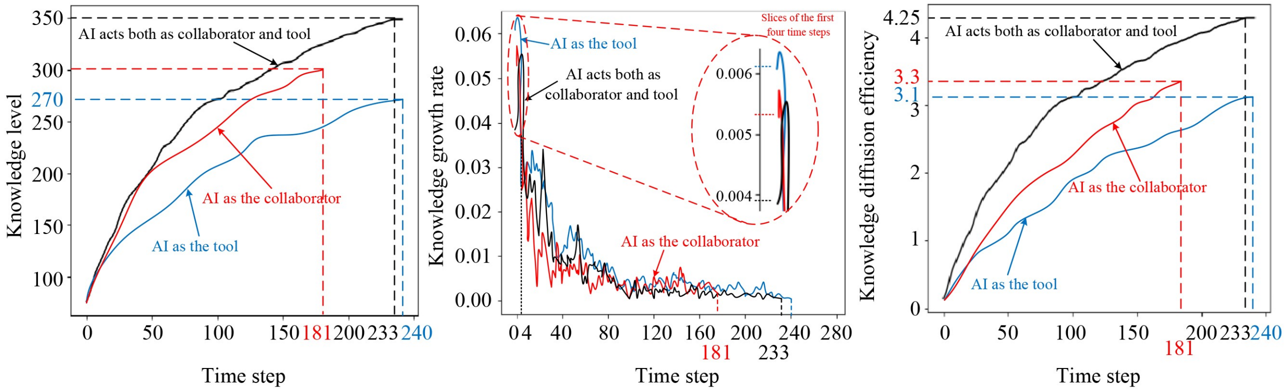
As shown in Fig. 9, the time to reach a steady-state in the knowledge diffusion process varies across members due to differences in their knowledge absorption capacities (Fig. 9(a)). In a human–AI collaborative organization, AI can derive knowledge from data (Jarrahi et al., 2023), which results in a higher initial knowledge level (red line in Fig. 9(a)) but slower growth rate (red line in Fig. 9(b)) compared with other developers.

During the diffusion process, developers exhibit a higher knowledge growth rate and diffusion efficiency, particularly for developers T_1 and T_5 (blue and purple lines in Figs. 9(b)–9(c)), they acquire more knowledge through collaboration with AI. One possible reason is the AI platform serves as the primary knowledge provider in this project, enabling developers to benefit from its insights. Thus, to enhance knowledge diffusion efficiency within the team, project managers should focus on improving knowledge transfer mechanisms within the collaborative team.

Moreover, we also analyze the knowledge diffusion process under AI supervision to further evaluate the impact of AI's direct participation on knowledge diffusion within the team.

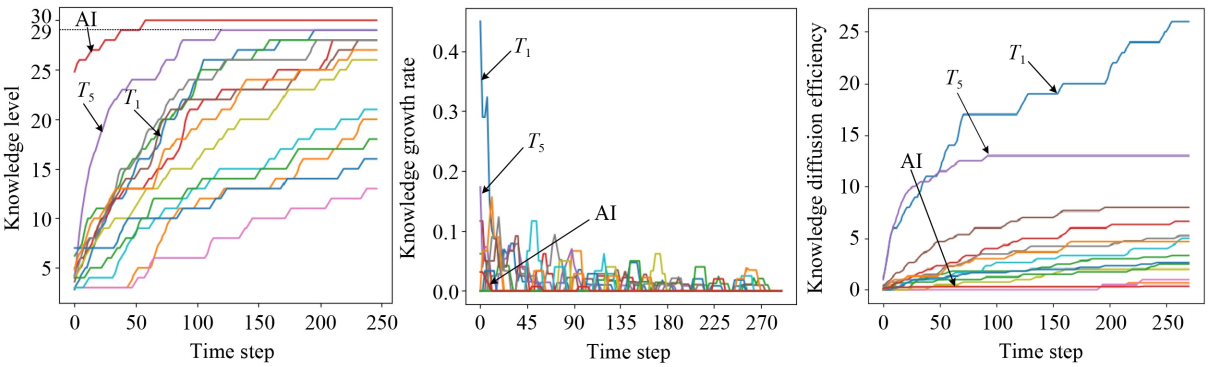
As shown in Fig. 10(a), when AI serves only as a supervisor, task completion depends solely on human collaboration. In this context, organizational knowledge diffusion stabilizes after 206 steps, with a lower knowledge level and knowledge diffusion efficiency than when AI acts as a collaborator or tool (194 vs. 351, 3.0 vs. 4.25). This provides strong evidence that AI's direct engagement can enhance organizational knowledge diffusion.

Meanwhile, from an individual perspective, Fig. 10(c) shows a similar pattern. However, under AI supervision, T_1 and T_5 achieve significantly lower knowledge levels than results in Fig. 9(a) (21 vs. 29, 14 vs. 29), further indicating that AI's active participation enhances organizational knowledge diffusion and fosters individual knowledge acquisition.



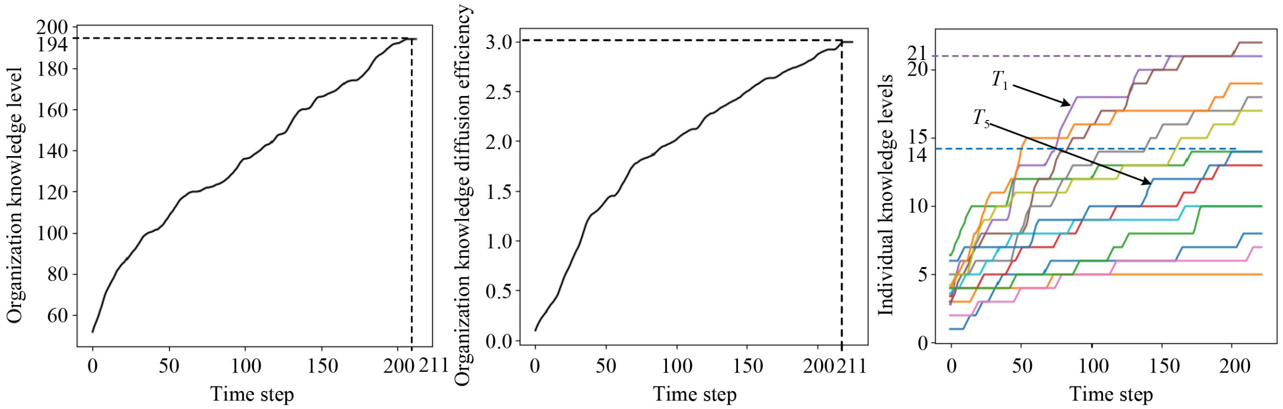
(a) (b) (c)

Fig. 8 Dynamics organizational knowledge diffusion: (a) Knowledge level, (b) Knowledge growth rate, and (c) Knowledge diffusion efficiency.



(a) (b) (c)

Fig. 9 Dynamic knowledge diffusion from the individual/developer perspective: (a) Knowledge level, (b) Knowledge growth rate, and (c) Knowledge diffusion efficiency.



(a) (b) (c)

Fig. 10 Dynamic knowledge diffusion within the collaborative team under AI supervision: (a) Organizational knowledge level, (b) Organizational knowledge diffusion efficiency, and (c) Individual knowledge levels.

5.3 Sensitivity analysis

In human–AI collaboration, knowledge diffusion is significantly influenced by two key factors: the tie strength between members and their absorptive capacities. These factors are further influenced by each member's initial knowledge level, human–AI cognitive trust, and interdependence among activities. Previous research has proved the impact of initial knowledge level on knowledge diffusion. Hence, we focus on two aspects: how human–AI cognitive trust and interdependence among activities affect knowledge diffusion.

We take organizational knowledge level and knowledge diffusion efficiency as indicators, to analyze the impact of human–AI cognitive trust and interdependence among activities on knowledge diffusion. Figure 11 shows the results.

It can be observed that human–AI cognitive trust and interdependence among activities significantly impact knowledge diffusion, but the trends are different.

1) As human–AI cognitive trust increases, the rate of knowledge growth gradually declines (Fig. 11(a)), and the knowledge diffusion efficiency shows an inverted U-shaped trend as cognitive trust increases. This may be because human–AI cognitive trust fosters more open knowledge sharing, while excessive cognitive trust leads to the abuse and misuse of AI (Capestro et al., 2024; Omrani et al., 2022), thus hindering knowledge diffusion.

Therefore, moderate human–AI cognitive trust can accelerate knowledge sharing. Project managers can promote knowledge diffusion by building an organization with a moderate cognitive trust level.

2) The interdependency relationship among activities significantly impacts knowledge diffusion, displaying a U-shaped trend (Fig. 11(b)). When dependencies are low, activities remain relatively independent, and the knowledge diffusion between members is limited. At this stage, organizations require time to adapt to the new collaboration environment, leading to lower knowledge diffusion efficiency. However, as dependencies increase, the organization gradually adapts to the collaborative environment, thus, both the knowledge diffusion efficiency and the knowledge level improve.

Hence, project managers should harness the potential

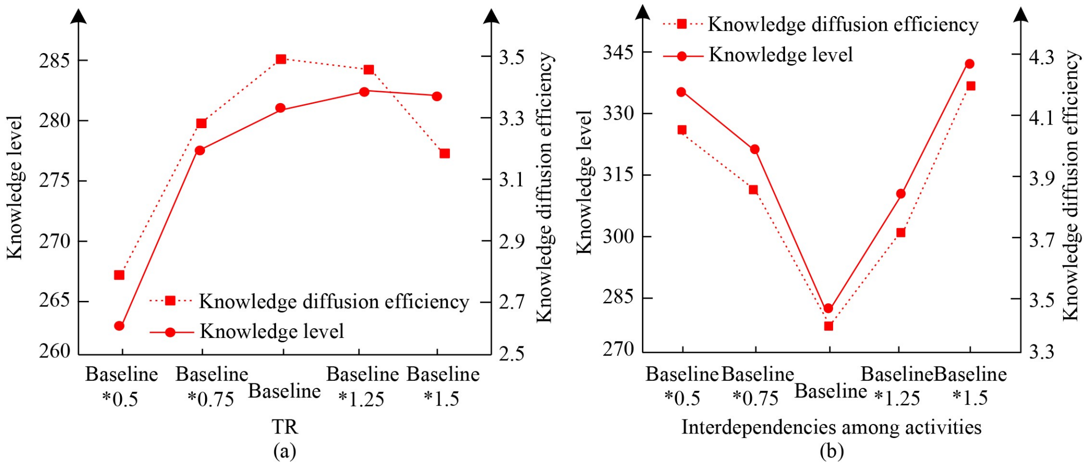


Fig. 11 Sensitivity analysis results.

of human–AI collaboration to address activities and projects with complex interdependence, promoting effective communication and collaboration within the team, enhancing knowledge-sharing efficiency and ultimately achieving rapid knowledge diffusion and efficient project completion.

5.4 Comparison tests and parallel experiment

Comparing our proposed model with existing methods is essential. As shown in Table 2, the SIR model is a widely used approach for modeling knowledge diffusion and serves as a fundamental baseline for comparison. In our simulations, we ran 200 iterations and recorded the knowledge diffusion process of the organization at each step.

The experimental results in Table 2 indicate that our proposed model outperforms the SIR model across several key metrics. Specifically, our model exhibits higher means in knowledge level and growth rate (358.72 vs. 349.63, 4.35 vs. 4.08), with lower variance in organizational knowledge levels, knowledge diffusion efficiency, and diffusion time (7.48 vs. 15.12, 0.02 vs. 0.05, 3.20 vs. 4.01), suggesting a more stable diffusion process. Furthermore, our model captures individual-level knowledge dynamics (denoted by √ in Table 2), whereas the SIR model cannot (denoted by × in Table 2). Therefore, our model offers advantages in two key aspects: organizational knowledge diffusion and individual knowledge evolution, making it a more comprehensive approach for modeling knowledge diffusion.

Next, we conduct a robustness analysis of our model. Specifically, while keeping all other parameters constant, we examine the impacts of iteration count and individual knowledge absorption capacity on organizational knowledge diffusion (Fig. 12).

As observed across different conditions, the trends remain consistent, demonstrating the robustness of our model in simulating organizational knowledge diffusion. This stability further supports its applicability in real-world settings, where variables often fluctuate.

Moreover, to validate our model's credibility with empirical evidence, we interviewed three additional participants from the same company, whose roles match those in the case (i.e., developer, product manager, and test engineer). We designed six interview questions that correspond to the key mechanisms of our model. Table 3 shows interview questions and feedback.

More specifically, their feedbacks align with our key findings: (i) AI can acts as multiple roles, influencing knowledge sharing, (ii) AI's involvement fosters communication and knowledge exchange, (iii) task interdependence leads to increased interaction and coordination, and (iv) cognitive trust in AI increases over time. These results effectively demonstrate that our model captures

Table 2 Experimental results

	Our proposed method	SIR model
Means of organizational knowledge levels	358.72	349.63
Means of organizational knowledge diffusion efficiency	4.35	4.08
Variance of organizational knowledge diffusion efficiency	0.02	0.05
Variance of organizational knowledge diffusion time	3.20	4.01
Individual knowledge levels	√	×
Individual knowledge grow rate	√	×
Individual knowledge diffusion efficiency	√	×

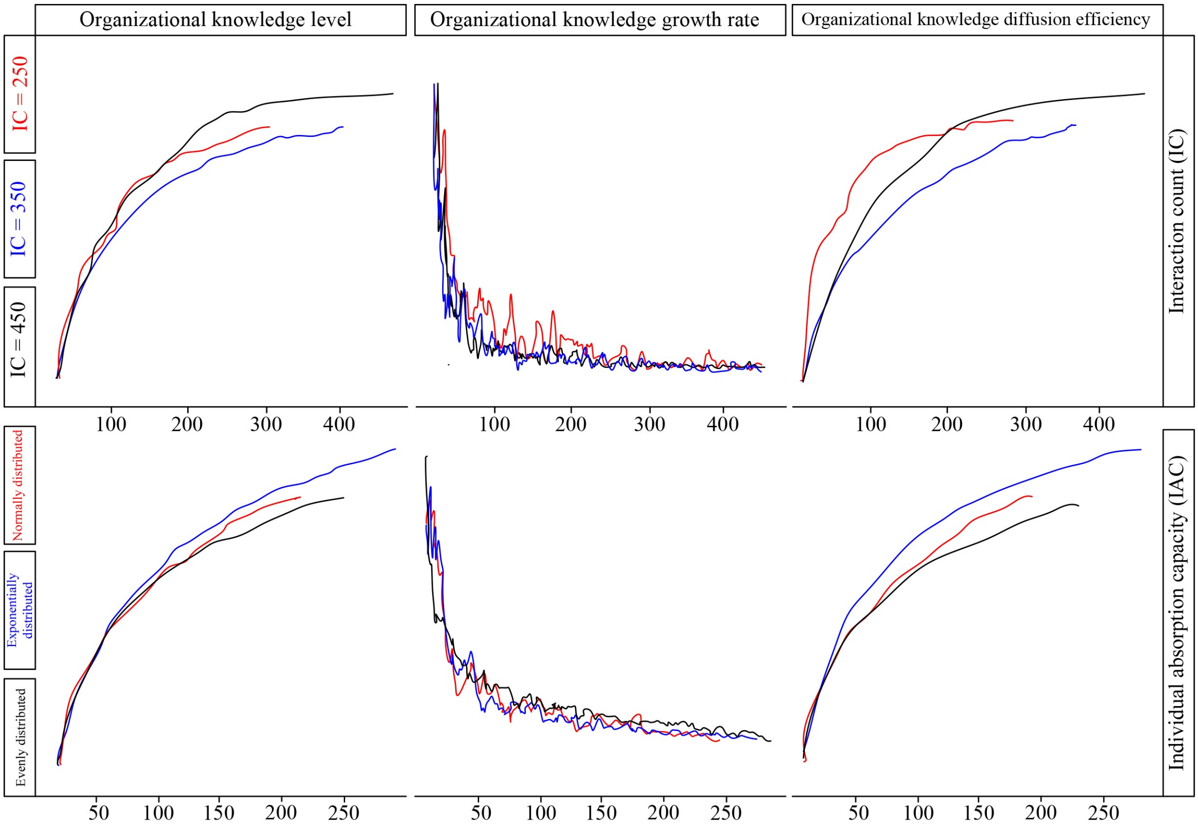


Fig. 12 Robustness verification results of organizational knowledge diffusion.

Table 3 Interview questions and feedback

Questions	Developer A	Product manager B	Test engineer C
Q1: Does AI take on multiple roles (e.g., tool, collaborator, supervisor) in your work?	"…Mostly a tool, but sometimes a collaborator in tasks like debugging…"	"…Acts as a collaborator and occasionally a supervisor in risk analysis..."	"…Mainly a tool for test case generation and error checking…"
Q2: Has AI facilitated knowledge sharing or communication in your team?	"…AI may promote idea exchange and team discussions during complex tasks..."	"…AI often helps align team focus by providing data-driven insights…"	"…Compared to before, people talk more about what AI suggests. That naturally spreads knowledge faster…"
Q3: Do you feel AI has contributed to team-level knowledge accumulation and diffusion?	"…Yes, it encourages more open sharing compared to before…"	"…We share what AI outputs, so everyone can see issues and solutions from different parts of the project…"	"…AI helps us systematically accumulate knowledge that we used to lose or overlook…"
Q4: Do interdependent tasks promote communication and knowledge sharing in your team?	"…Task interdependence pushes us to communicate more and update our understanding, especially when relying on AI-generated results…"	"…We communicate more on interdependent tasks, and AI becomes a shared platform that improves communication...."	"…Yes, interdependent tasks force us to coordinate more, we discuss how to interpret and apply its output together..."
Q5: Has AI involvement helped enhance your learning capability and knowledge acquisition within teams?	"…Solving difficult problems with AI improved my confidence and knowledge level..."	"…Grown to rely on AI for insights and decision support, and adapt to learning from AI..."	"…AI helps to acquire knowledge during work, and helps me understand complex issues better..."
Q6: Has your trust in AI increased over time? At what level of trust are you more likely to rely on AI's knowledge and recommendations?	"…Trust grows as AI proves reliable, but I avoid overreliance and combine AI insights with my own judgment…"	"…Yes, my trust in AI has increased through repeated interactions, but I remain cautious and verify its advice to avoid errors…"	"…My trust improved through repeated use, I would share knowledge more openly when trust is higher…"

key knowledge diffusion patterns in human–AI collaboration, providing empirical validation for its practical reliability.

6 Conclusions and future trends

This paper focuses on knowledge diffusion in human–AI collaboration and presents an innovative approach to quantitatively analyze this process. It addresses two key issues: (1) How to build a knowledge diffusion model to measure knowledge diffusion efficiency within the human–AI collaborative NPD organization? (2) From the cognitive capability and trust's dynamic nature perspective, how to measure cognitive trust in human–AI collaboration? To answer these questions, we propose a simulation framework based on ABM and develop a dynamic cognitive trust model that integrates AI's cognitive capabilities and interaction time.

This paper makes several key contributions. Theoretically, (1) it introduces a dynamic knowledge diffusion model that reflects the diffusion process across human–AI interactions, deepening our understanding of how knowledge is diffused within human–AI collaborative teams. (2) By incorporating key factors such as AI's role, cognitive trust, and task interdependencies, this paper offers a more comprehensive approach to measuring knowledge diffusion efficiency. (3) It develops a dynamic cognitive trust model that incorporates AI's task-specific cognitive capabilities and reflects the dynamic nature of trust during collaboration. Practically, our findings suggest that AI's active participation, especially when functioning both as a tool and collaborator, significantly improves knowledge diffusion efficiency. Specifically, project managers should treat AI as a tool to support knowledge accumulation in the early stages, and as a collaborator to promote mutual knowledge sharing in later stages. Moreover, maintaining a moderate cognitive trust level facilitates knowledge exchange. In managing complex interdependent tasks and projects, human–AI collaboration can enhance internal communication and cooperation, ultimately supporting project success.

Despite its contributions, this paper has several limitations. First, while focusing on cognitive trust, it does not account for emotional trust, which may also significantly influence knowledge diffusion. Future studies could examine how both types of trust evolve and interact across various project lifecycles. Second, although the model is validated in the software development project, knowledge diffusion mechanisms may differ across industries/domains. For example, in highly specialized domains such as aerospace, the demand for AI explainability could affect or even alter collaboration patterns. Future research should explore how these characteristics (such as project scale, and specialization) affect knowledge diffusion. Third, this paper does not differentiate between tacit and explicit knowledge. Given the rapid advancement in AI is accelerating the knowledge transformation, future work should investigate the transformation mechanisms and whether different types of knowledge follow distinct diffusion pathways. Finally, integrating additional variables (such as culture, hierarchy, or power distance) could further enrich the model and broaden its practical applicability.

Competing Interests The authors declare that they have no competing interests.

References

Akula A R, Wang K, Liu C, Saba-Sadiya S, Lu H, Todorovic S, Chai J, Zhu S C (2022). CX-ToM: Counterfactual explanations with theory-of-mind for enhancing human trust in image recognition models. iScience, 25(1): 103581

Anantrasirichai N, Bull D (2022). Artificial intelligence in the creative industries: A review. Artificial Intelligence Review, 55(1): 589–656

Arias-Pérez J, Huynh T (2023). Flipping the odds of AI-driven open innovation: The effectiveness of partner trustworthiness in counteracting interorganizational knowledge hiding. Industrial Marketing Management, 111: 30–40

Beaulieu T, Dupin-Bryant P, Olsen D (2017). Dynamic SQL knowledge as a mechanism for increasing individual absorptive capacity. International Journal of Management & Information Systems, 21(2): 27–40

Boyacı T, Canyakmaz C, de Véricourt F (2024). Human and machine: The impact of machine input on decision making under cognitive limitations. Management Science, 70(2): 1258–1275

Capestro M, Rizzo C, Kliestik T, Peluso A M, Pino G (2024). Enabling digital technologies adoption in industrial districts: The key role of trust and knowledge sharing. Technological Forecasting and Social Change, 198: 123003

Choung H, David P, Ross A (2023). Trust in AI and its role in the acceptance of AI technologies. International Journal of Human-Computer Interaction, 39(9): 1727–1739

Chowdhury S, Budhwar P, Dey P K, Joel-Edgar S, Abadie A (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. Journal of Business Research, 144: 31–49

Evans M M, Frissen I, Choo C W (2019). The strength of trust over ties: Investigating the relationships between trustworthiness and tie-strength in effective knowledge sharing. Electronic Journal of Knowledge Management, 17(1): 19–33

Farquhar S, Kossen J, Kuhn L, Gal Y (2024). Detecting hallucinations in large language models using semantic entropy. Nature, 630(8017): 625–630

Frankel A, Kamenica E (2019). Quantifying information and uncertainty. American Economic Review, 109(10): 3650–3680

Gama F, Magistretti S (2025). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. Journal of Product Innovation Management, 42(1): 76–111

Glikson E, Woolley A W (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2): 627–660

Haefner N, Wincent J, Parida V, Gassmann O (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. Technological Forecasting and Social Change, 162: 120392

Jarrahi M H (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4): 577–586

Jarrahi M H, Askay D, Eshraghi A, Smith P (2023). Artificial intelligence and knowledge management: A partnership between human and AI. Business Horizons, 66(1): 87–99

Kiesling E, Günther M, Stummer C, Wakolbinger L M (2012). Agent-based simulation of innovation diffusion: a review. Central European Journal of Operations Research, 20(2): 183–230

Kyung N, Kwon H E (2022). Rationally trust, but emotionally? The roles of cognitive and affective trust in laypeople's acceptance of AI for preventive care operations. Production and Operations Management: poms.13785

Ng S W T, Zhang R (2025). Trust in AI chatbots: A systematic review. Telematics and Informatics, 97: 102240

Olaisen J, Revang O (2018). Exploring the performance of tacit knowledge: How to make ordinary people deliver extraordinary results in teams. International Journal of Information Management, 43: 295–304

Omrani N, Rivieccio G, Fiore U, Schiavone F, Agreda S G (2022). To trust or not to trust? An assessment of trust in AI-based systems: Concerns, ethics and contexts. Technological Forecasting and Social Change, 181: 121763

Pan M, Chandrasekaran A, Hill J, Rungtusanatham M (2022). Multidisciplinary R&D project success in small firms: The role of multi-project status and project management experience. Production and Operations Management, 31(7): 2806–2821

Park S, Puranam P (2024). Vicarious learning without knowledge differentials. Management Science, 70(5): 2999–3019

Paschen J, Wilson M, Ferreira J J (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3): 403–414

Qiao T, Shan W, Zhang M, Liu C (2019). How to facilitate knowledge diffusion in complex networks: The roles of network structure, knowledge role distribution and selection rule. International Journal of Information Management, 47: 152–167

Sankar C P, Thumba D A, Ramamohan T R, Chandra S S V, Satheesh Kumar K (2020). Agent-based multi-edge network simulation model for knowledge diffusion through board interlocks. Expert Systems with Applications, 141: 112962

Sassine J G, Rahmandad H (2024). How does network structure impact socially reinforced diffusion? Organization Science, 35(1): 52–70

Schelble B G, Lopez J, Textor C, Zhang R, McNeese N J, Pak R, Freeman G (2024). Towards ethical AI: Empirically investigating dimensions of AI ethics, trust repair, and performance in human–AI teaming. Human Factors, 66(4): 1037–1055

Seeber I, Bittner E, Briggs R O, De Vreede T, De Vreede G J, Elkins A, Maier R, Merz A B, Oeste-Reiß S, Randrup N, Schwabe G, Söllner M (2020). Machines as teammates: A research agenda on AI in team collaboration. Information & Management, 57(2): 103174

Song W, Ming X, Xu Z (2013). Risk evaluation of customer integration in new product development under uncertainty. Computers & Industrial Engineering, 65(3): 402–412

Thomas A, Gupta V (2022). Tacit knowledge in organizations: bibliometrics and a framework-based systematic review of antecedents, outcomes, theories, methods and future directions. Journal of Knowledge Management, 26(4): 1014–1041

Todo Y, Matous P, Inoue H (2016). The strength of long ties and the weakness of strong ties: Knowledge diffusion through supply chain networks. Research Policy, 45(9): 1890–1906

Westphal M, Vössing M, Satzger G, Yom-Tov G B, Rafaeli A (2023). Decision control and explanations in human–AI collaboration: Improving user perceptions and compliance. Computers in Human Behavior, 144: 107714

Xu L, Ding R, Wang L (2022). How to facilitate knowledge diffusion in collaborative innovation projects by adjusting network density and project roles. Scientometrics, 127(3): 1353–1379

Yadkori Y A, Kuzborskij I, György A, Szepesvári C (2024). To Believe or Not to Believe Your LLM. arXiv preprint arXiv:2406.02543

Yang Q, Yang N, Browning T R, Jiang B, Yao T (2022). Clustering product development project organization from the perspective of social network analysis. IEEE Transactions on Engineering Management, 69(6): 2482–2496

Zhang J, Adomavicius G, Gupta A, Ketter W (2020). Consumption and performance: Understanding longitudinal dynamics of recommender systems via an agent-based simulation framework. Information Systems Research, 31(1): 76–101

Zhang W, Zhang W, Daim T, Yalçın H (2025). AI challenges conventional knowledge management: light the way for reframing SECI model and Ba theory. Journal of Knowledge Management, 29(5): 1618–1654

Zou X Q, Yang Q (2019). R & D project portfolio selection based on domination and diffusion relationship in the project network. Chinese Journal of Management Science, 27: 198–209

Zou X Q, Yang Q, Wang Q R (2023). Analyzing the knowledge diffusion among multiple projects and its impact on the program. Operations Research and Management Science, 32(2): 261–270