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AI capability and organizational performance: Do team learning and creativity play a role?

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ABSTRACT

Drawing on dynamic capability and resource-based theories, we theorize that team learning is a microfoundation through which firms develop artificial intelligence (AI) capabilities, and that team creativity is a value-realizing mechanism through which these capabilities generate service innovations and improve organizational performance. Study 1 examines how team learning contributes to the development of firms' AI capability and subsequent service innovations, using data from 600 managers in service firms in China. Study 2 investigates whether team creativity mediates the effects of AI capability on service innovation and performance, based on data from 276 managers in service firms in China. Across two studies, we found that teams contribute to the development and realization of AI capability. Specifically, team learning facilitates the development of AI capability, and team creativity enables firms to translate this capability into innovation and performance outcomes. Overall, this study advances the understanding of how human–AI collaboration enables firms to convert AI capability into tangible organizational value by integrating a microfoundational perspective with the resource-based logic of value realization.

1. Introduction

Artificial intelligence (AI) has attracted considerable attention from organizational scholars because of its transformative potential across industries [1–3]. AI systems can identify, interpret, and learn from data to achieve strategic goals [4] and are increasingly deployed to enhance innovation and performance. Examples such as Netflix, Spotify, and Lexus illustrate how AI can be used creatively to reshape service offerings and customer experiences [5–7]. Generative AI tools, including ChatGPT and Jasper, further demonstrate AI's potential to support creative processes by producing original content in response to user prompts [8,9].

Despite this potential and growing investment in AI projected to exceed US$26 billion by 2030 [10], many organizations struggle to translate AI adoption into sustained innovation and performance gains. Research increasingly suggests that these shortcomings are not primarily

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technological but social and organizational in nature, arising from difficulties in integrating AI into everyday work processes and decision making [11–13]. In particular, organizations face challenges in developing effective forms of human–AI collaboration [11,14], contributing to the high failure rates of AI initiatives [12,15,16].

These challenges are especially salient because most organizational applications of AI are embedded in team-based settings, in which service innovation, problem solving, and strategic decisions are made collectively rather than individually [14,17]. However, much of the existing literature on human–AI interaction focuses on individual-level outcomes, such as individual creativity, job performance, and technology acceptance. For example, Jia et al. [18] demonstrated that AI-assisted sales generation positively impacts employees' creativity when answering customer questions, which in turn increases sales. While valuable, this focus overlooks the fact that organizational innovation typically emerges from team-level processes, including shared learning, coordination, and collective sensemaking [19,20]. As a result, limited attention has been given to how AI reshapes the social dynamics through which teams learn, generate ideas, and integrate human and machine contributions.

Team learning and team creativity are critical but underexplored mechanisms in AI-enabled organizations. Unlike individual learning or creativity, which depend largely on personal cognition and skills, team learning and creativity are collective phenomena that emerge through interaction, mutual influence, and the alignment of shared mental models [17,19]. These processes are essential for integrating diverse expertise, balancing human judgment and algorithmic input, and transforming AI-generated insights into implementable innovations. In AI-enabled environments, teams must not only learn how to use new technologies but also adapt how they collaborate with nonhuman agents, making team-level capabilities central to the effective development and use of AI.

Building on this logic, we argue that AI capability alone is insufficient to enhance service innovation and organizational performance unless it is complemented by strong team-level learning and creative processes. Although prior studies indicate that human–AI collaboration can improve creativity and innovation outcomes [8,21], it remains unclear how teams enable this collaboration and whether team learning and team creativity strengthen the positive impact of AI capability on innovation and performance. This knowledge gap is particularly important given the increasing reliance on teams—not individuals—to deploy AI strategically within organizations [14,17].

Accordingly, this study investigates the roles of team learning and team creativity in shaping how firms develop and leverage AI capability to improve service innovation and organizational performance. Drawing on dynamic capability theory [22,23] and the resource-based view (RBV) [24,25], we develop and test a team-centred model of human–AI collaboration. In particular, dynamic capability theory and the RBV are complementary rather than competing perspectives in explaining how AI creates value. Dynamic capabilities explain how organizations build and reconfigure AI-related resources through learning and adaptation [22,23], while the RBV explains how those resources are deployed and combined to generate innovation and performance advantages [24,25]. In this study, we integrate these perspectives by theorizing team learning as a microfoundation of AI capability (dynamic capability) and team creativity as the value-realizing mechanism (RBV) through which AI capability is exploited for service innovation and organizational performance.

Using two field studies with senior managers, we examine how team learning is associated with AI capability and how team creativity mediates the relationship between AI capability and organizational outcomes. By theorizing team-level processes and examining managers' assessments of these processes, we advance the understanding of how human–AI collaboration can generate sustained value in service organizations.

This study makes several theoretical contributions. First, we advance understanding of how team learning capabilities, both explorative and exploitative, support the development of AI capability, highlighting the critical human foundations of AI integration. Second, we provide empirical evidence of the mediating role of team creativity in the relationship between AI capability and organizational outcomes, offering new insights into team-level creative processes in AI-enabled environments. Third, drawing on the RBV and dynamic capability theory, we develop a theoretically grounded framework that explicates the interplay between AI capability and team dynamics, clarifying how human–AI collaboration can be leveraged to generate innovation and performance outcomes in service firms. Collectively, these contributions advance research at the intersection of AI, teams, and organizational innovation and provide actionable guidance for managers seeking to strengthen organizational adaptability and creativity in the age of AI.

2. Theory and hypotheses development

The concept of dynamic capability stems from the premise that the RBV of the firm is somewhat static and does not fully explain how a firm's resources are developed and integrated into a rapidly changing technological environment [22,23]. The theory contends that the mere possession of resources and capabilities is not sufficient for a firm to generate added value, especially in a fast-paced environment [4]; to survive in a competitive market, the firm needs to nurture dynamic capabilities [23]. While individual learning and creativity refer to the acquisition of knowledge or generation of ideas by a single person, team learning and creativity are collective phenomena that emerge through interaction, coordination, and shared meaning-making among team members [17,19]. From a dynamic capability perspective, team learning constitutes a key microfoundation of AI capability, because repeated cycles of exploration and exploitation enable teams to acquire, adapt, and recombine the human, data, and coordination resources that underpin organizational AI capability.

Team learning involves cycles of reflection and adaptation that allow groups to align mental models and improve collective performance, while team creativity refers to the co-creation of novel and useful ideas through collaboration and mutual influence [20]. Unlike individual creativity, which is often shaped by personal traits or cognitive styles, team creativity depends heavily on group dynamics, communication quality, and diversity of perspectives. In AI-enabled environments, these team-level processes become even more critical as they facilitate the integration of human and machine contributions toward innovation.

A firm's AI capability is its ability to "select, orchestrate, and leverage its AI-specific resources" ([4], p. 3). AI capability draws on both human and AI-specific resources, and it has three main dimensions: (1) tangibles (data, technology, and basic resources); (2) human skills (both technical and business); and (3) intangibles (interdepartmental coordination, organizational change capacity, and risk proclivity) [4,26]. To enhance clarity, we follow Mikalef and Gupta's [4] conceptualisation of AI capability as a multidimensional organizational capability comprising tangible, human, and intangible resources. Tangible resources include the physical and digital infrastructure supporting AI systems, enabling system integration [4]. Human resources refer to employees' technical expertise and their ability to engage with AI systems, including skills in data analytics, model evaluation, and prompt engineering [4]. Intangible resources involve managerial support, a data-driven decision-making culture, and cross-functional collaboration structures [27]. Related research on scaling AI-enabled digital transformation highlights the importance of organizational readiness, standardization, integration, and information-flow management in translating technological initiatives into enterprise-wide value [28]. In practice, organizations with low AI capability may use AI in isolated pilot projects without dedicated staff or leadership support, while those with high AI capability demonstrate strategic integration of AI across business units, have skilled personnel and established AI governance, and continuously invest in adaptive infrastructure. These distinctions

help illustrate how AI capability manifests across firms at different levels of digital maturity. In the context of human–AI collaboration in a firm, human capabilities can be augmented through certain AI applications. In the "augmented intelligence" that this creates, humans and AI work as teammates [5,29]. In another form of human–AI collaboration, some AI systems make use of large datasets to assist managers and employees in designing tasks related to service innovation. They do so by enhancing managers' input information and providing suggestions that would be difficult to develop otherwise [5].

When organizations adopt AI to improve their performance and innovation capabilities, team-related factors can pose significant challenges alongside technological factors. Moreover, team-related factors play pivotal roles in enabling or impeding the organization's AI capability [12,13]. Integrating AI in organizations can also pose daunting challenges for team learning, because this integration requires teams to make active efforts to balance the exploration and exploitation of learning [30,31].

AI capability is also linked to the level of creativity in organizations, which is an important determinant of service innovation and organizational performance [8,32–34]. In particular, through human-augmented intelligence, the technological and nontechnological resources underpinning an organization's AI capability may enhance the conditions that enable team creativity [5]. Yet despite the established importance of creativity for innovation and performance, the role of team creativity in translating organizational AI capabilities into these outcomes remains insufficiently understood. Traditionally defined as "the generation of novel and useful ideas by a team of employees working together" ([17], p.409), team creativity emerges from interactions and mutual influence among team members [20] rather than from isolated individual efforts or human-machine collaboration. Nevertheless, team creativity is likely to be affected when humans collaborate with AI. From the RBV, AI capability becomes valuable only when combined with complementary human resources, such as team creativity, which enables firms to transform algorithmic insights into novel service concepts and operational improvements.

In this study, we propose a theoretical model of how team learning and creativity can enhance AI capability for improving service innovation and organizational performance. To inform this model, we draw on dynamic capability theory [23] and RBV theory [35]. Our model posits that team learning affects organizational AI capability, which in turn affects team creativity. In addition, the model postulates that team creativity enhances the impact of AI capability on service innovation and organizational performance. Together, these relationships form an integrated dynamic resource framework in which team learning builds AI capability (dynamic capability logic) and team creativity exploits that capability through complementary human resources to generate service innovation and organizational performance (RBV logic). Fig. 1 depicts our overall proposed theoretical model, which was empirically tested through Study 1 and Study 2, and the following sections present the hypotheses proposed in this research.

2.1. Role of team learning

In the context of learning, the concepts of exploration and exploitation were introduced in the early 1990s [36]. Since then, they have emerged as the dominant factors underpinning team learning, technological innovation, strategic management, and new product development [37]. Exploitative learning is about refining existing capabilities, while explorative learning is about challenging existing ideas [36–38]. Exploitative learning occurs along established routines (e.g., through refining, choosing, producing, improving efficiency, implementing, and executing), while explorative learning occurs along entirely uncharted trajectories and involves searching, discovering, experimenting, and innovating [37]. Because the antecedents of organizational innovation are sometimes investigated in isolation, their synergistic effects are likely to be overlooked. Thus, it is imperative to explore how AI use and knowledge-based dynamic capabilities (i.e., knowledge generation capability, knowledge acquisition capability, and market-sensing

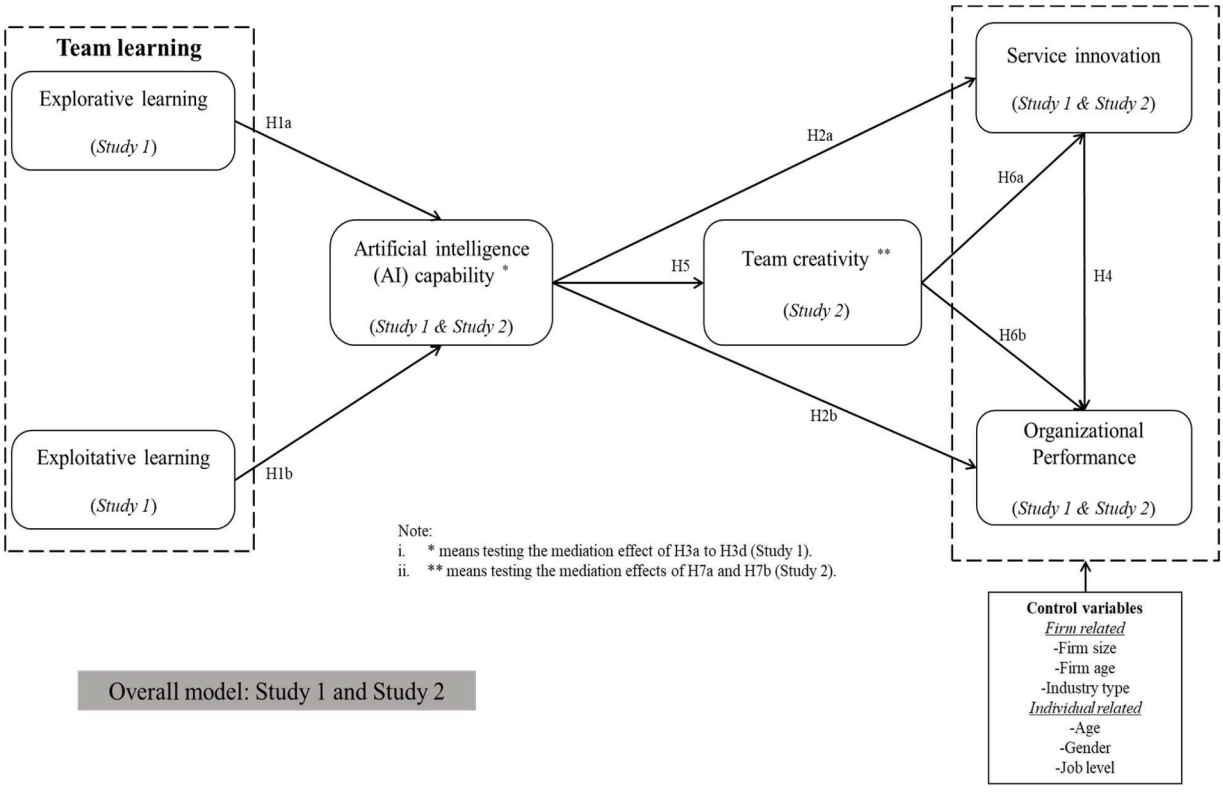


Fig. 1. Overall proposed theoretical model for both Study 1 and Study 2.

capability) jointly facilitate explorative and exploitative innovation [39]. In this context, the recent noteworthy study by Shao et al. [40] revealed how the interactive features of enterprise collaboration platforms enhance employees' ambidextrous innovation behavior through the mediation of perceived job autonomy and perceived job feedback.

From an ambidexterity perspective, effective teams do not rely on exploration or exploitation in isolation but dynamically balance both. In AI-enabled contexts, exploration allows teams to experiment with new data sources, algorithms, and use cases, while exploitation enables them to refine, standardize, and scale successful AI applications. Thus, the ability to balance these learning modes is central to developing a robust and adaptive AI capability. According to the theory of organizational learning, both exploitative learning and explorative learning, separately and combined, are essential for organizational innovation [36]. Although these two types of learning relate to fundamentally distinct innovation strategies, which encompass different objectives and structures [37,41], they are viewed as complementary rather than mutually exclusive [42]. Numerous studies have examined the impact of exploitative and explorative learning on innovation and new product development in firms [37,43,44]. However, few have analyzed the impact on a firm's AI capability with a view to improving innovation performance.

The classification of learning as exploitative or explorative is also useful for assessing a firm's strategic choices about what resources it needs to develop its AI capability in innovation processes [45]. By engaging in explorative learning activities, a firm can take advantage of technological and market information that extends far beyond its own experience [43]. By pursuing exploitative learning activities, a team can expand its ability to use new technological and market information suited to developing the team's business and technical skills while also obtaining the data and technological knowledge required for developing AI capability. Moreover, explorative learning adds novel elements to a team's repertoire, enhancing the likelihood of finding useful new combinations of problem-solving solutions suited to developing a firm's AI capability [37]. Therefore, we envisage that explorative learning will have a significant positive impact on a firm's AI capability. These learning processes are embedded in broader sociotechnical conditions. In AI-enabled teams, such factors as trust in algorithmic outputs, perceived autonomy in decision-making, and psychological safety shape whether team members are willing to experiment with AI, critically evaluate its recommendations and incorporate them into collective learning processes.

By engaging in exploitative learning activities, firms can tap into the limited but well-defined technological and market solution spaces that relate to their previous experiences to attain efficiency and implement new solutions [37]. In addition, focusing on current and known expertise (e.g., by drawing on more reliable information in AI processes), a firm may be able to reduce the likelihood of problem-solving errors and the risks associated with venturing into the unknown [46]. Exploitative learning provides more opportunities to find new combinations of existing knowledge, from which new problem-solving insights may emerge [37,43]. Through these insights, a team may be able to enhance the firm's AI capability by improving the team's skills, its use of data and technology, and its interdepartmental coordination. Consistent with our empirical design, references to explorative and exploitative learning in the hypotheses should be interpreted as manager-assessed team learning behavior. We propose the following hypothesis:

H1. Explorative learning (H1a) and exploitative learning (H1b) have a significant positive effect on AI capability.

2.2. Influence of AI capability on service innovation and organizational performance

Service innovation is critical for maintaining a competitive advantage in today's turbulent market environment [47,48]. Recent research has examined the connections between AI capability and service innovation (e.g., [49,50]) and found that AI can facilitate service innovation by enabling a firm to evaluate consumer needs and preferences, provide tailored services, and automate service delivery processes. Recent research has also highlighted the relationship between AI capability and innovation outcomes, including product innovation intensity in B2B markets under varying conditions of market turbulence [49–51]. Thus, it is worth investigating whether service organizations with better AI capability are more likely to develop and deliver new or improved services that better meet their customers' needs.

Along with examining the impact of AI capability on service innovation, we analyze its impact on organizational performance. In the field of management, organizational performance refers to an organization's accomplishment of its goals and objectives [52]. It is a multidimensional concept that encompasses financial performance, operational efficiency, customer satisfaction, and employee productivity, among others [52]. Various methods can be used to evaluate organizational performance, including financial measures (e.g., revenue growth, profitability), nonfinancial measures (e.g., customer satisfaction, employee engagement), and balanced scorecards, which incorporate both measures [53].

To effectively manage their organizational performance, firms need to focus on continuous improvement and be willing to adapt to changing circumstances [54]. This requires performance management systems that enable firms to monitor and evaluate their performance, identify areas for improvement, and address any performance gaps. Such systems need to be aligned with organizational goals and strategies, involve all stakeholders in the assessment, and provide regular feedback and communication [55].

AI has the potential to transform how organizations operate by improving efficiency and productivity, particularly decision-making processes related to data analysis and customer service [5,56]. This potential has increased interest in the relationship between AI capability and organizational performance [57]. The literature on the subject explains that organizations with higher levels of AI capability tend to demonstrate better performance in terms of operational efficiency, customer satisfaction, and overall performance [4,58]. AI capability is a key driver of improvement in service innovation and organizational performance, because it enables organizations to leverage data analytics and automation to improve their decision-making and achieve better business outcomes. Thus, we hypothesize:

H2. AI capability has a significant positive effect on service innovation (H2a) and organizational performance (H2b).

Furthermore, we posit that AI capability mediates the relationships between explorative and exploitative learning and the two organizational outcomes: service innovation and organizational performance. Previous research suggests that organizational learning has a positive effect on performance as well as innovation [59]. Innovation occurs when employees share their knowledge with their organization and when this shared knowledge generates new and common insights. Meanwhile, organizational learning enables the development, acquisition, transformation, and exploitation of new knowledge suited to enhancing organizational innovation [60,61]. The literature explains that innovation, including service innovation, requires the transformation and exploitation of existing knowledge (e.g., [59,62]). However, a firm's AI capability may further strengthen the impact of explorative and exploitative learning on service innovation and performance, because developing AI capability requires that organizations develop resources (i.e., tangible, intangible, and human skills). The presence of these resources can strengthen organizational learning, contributing to the development of new services that offer value to end users [4]. Indeed, prior studies have found that AI enables organizations to enhance their creativity and service innovation by strengthening their explorative and exploitative learning [5,29]. Thus, we hypothesize:

H3. AI capability mediates the effects of explorative learning on

service innovation (H3a) and organizational performance (H3b) and mediates the effects of exploitative learning on service innovation (H3c) and organizational performance (H3d).

In addition to the relationships hypothesized above, our model proposes that service innovation enhances organizational performance. Indeed, prior research has identified the ways in which service innovation has a positive impact on organizational success [63–65]. Wu and Wu [66] found that service innovation increases customer satisfaction and loyalty, enhances brand reputation, and improves financial performance, all of which improve organizational performance. Similarly, service innovation reduces operational costs while increasing sales revenues or the profitability of the firm [43,67]. We therefore hypothesize:

H4. Service innovation has a significant positive effect on organizational performance.

2.3. Role of team creativity

Along with proposing that AI capability has a direct influence on organizational performance and service innovation, we propose that it has an indirect impact on these outcomes through its influence on team creativity. That is, we anticipate that AI capability will have a direct impact on team creativity, which in turn will affect organizational performance and service innovation. Creativity is a critical element in this context (e.g., [68,69]). The efficient integration of AI within an organization can be directly linked to its team-level creativity [5,70]. In sociotechnical AI environments, team creativity is also conditioned by whether teams feel empowered to challenge AI outputs, exercise discretion, and use algorithmic insights as inputs rather than constraints. We conceptualize AI capability as a generative infrastructure that expands teams' creative affordances. By providing real-time analytics, pattern recognition, content generation, and rapid experimentation capabilities, AI systems enlarge the problem space that teams can explore and reduce the cognitive and coordination costs of idea generation. These technological affordances enable teams to engage in more divergent thinking, test more alternatives, and recombine knowledge in novel ways, thereby enhancing team creativity. Although creative teams may be more inclined to experiment with new technologies, our theorization and model focus on AI capability as a preexisting organizational infrastructure that conditions how teams work rather than as a behavioral outcome of creativity. Consistent with our empirical design, references to team creativity in the hypotheses should be interpreted as manager-assessed team creativity. We hypothesize:

H5. AI capability has a significant positive effect on team creativity.

Prior research has explained that the capacity of organizations to use AI efficiently often depends on team creativity [5]. Subsequently, organizations with highly creative teams may be better positioned to enhance innovation and performance [4]. Thus, we postulate that when organizations have invested in developing their AI capability, they need team creativity to generate service innovation in their business operations. We hypothesize:

H6. Team creativity has a significant positive effect on service innovation (H6a) and organizational performance (H6b).

In addition to asserting that AI capability directly influences service innovation and organizational performance, we hypothesize that these relationships are strengthened in the presence of strong team creativity. Team creativity tends to be enhanced by the presence of firms' AI capability; in other words, the resources required for the effective use of AI ([5,71]). In addition, AI can boost team creativity in many ways; for example, through machine learning, AI can use algorithms to make predictions, extract features, make estimates, and optimize results [72]. It can make split-second decisions and handle large amounts of unstructured data [72]. These features enable teams to obtain more in-depth insights and spend more time on creative activities. Consequently, they can be more successful in developing innovative services and improving performance [5,73,74]. Therefore, we hypothesize:

H7. Team creativity mediates the effects of AI capability on service innovation (H7a) and organizational performance (H7b).

3. Overview of the studies

We conducted two complementary studies to investigate the development and impact of AI capability. **Study 1** (testing H1–H4) examined how firms' explorative and exploitative learning contribute to AI capability, which subsequently enhances service innovation and organizational performance (Fig. 2). **Study 2** (testing H2, H4, and H5–H7) extended this model by introducing team creativity as a key mediating mechanism. This allowed us to explore the indirect effects of AI capability on service innovation and organizational performance through creative team processes (Fig. 3), offering a more dynamic explanation grounded in RBV theory, an aspect not captured in Study 1. We used two independent samples to examine complementary aspects of the proposed framework. However, each study relied on a single managerial informant per firm. This two-study design enabled a progressive model-building strategy in which Study 2 builds on and extends the findings of Study 1, avoiding the pitfalls of testing an overly complex model within a single study. Overall, the sequential structure of our research enhances theoretical precision, nomological validity, and clarity. Given the single-informant design, both studies distinguish between the theoretical constructs of team learning and team creativity and their empirical operationalisation as manager-assessed team processes.

4. Study 1: exploring the effects of team learning

Study 1 used survey data collected from managers. The aim of Study 1 was to analyze the impact of team learning activities (explorative and exploitative) on firms' AI capability and explore how this capability subsequently affects firms' service innovation and organizational performance.

4.1. Participants and procedures

We collected data from managers of firms in China, a global leader in AI applications. In July 2017, China's State Council published its *New Generation Artificial Intelligence Development Plan*, which set out the country's intention to become *the* world leader in AI by 2030. Unlocking the full potential of AI opportunities typically requires significant investment from Chinese firms. This investment requires a multifaceted approach, encompassing the development of extensive data resources and technological infrastructure to support AI systems, the cultivation of an organizational mindset conducive to AI development, the adoption of new business models, and responsiveness to environmental pressures. Therefore, the data that we collected for Study 1 (and Study 2) were focused on how Chinese firms can obtain the most value from implementing AI, to examine how firms can harness AI's potential, particularly in service innovation, to boost organizational performance.

The survey used for Study 1 contained two sections. The first section included questions focused on demographic information and basic business details, such as gender, education, and firm size. The second section included questions closely related to the variables we proposed in our conceptual model. For these, we used a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). For all factors integrated into our proposed model, we adopted measurement items from the existing literature (see Appendix B for Study 1). We used five items to measure both *explorative learning* and *exploitative learning* [75]. In this study, explorative and exploitative learning are operationalised through managers' assessments of team learning behaviors. Therefore, empirical references to team learning should be interpreted as

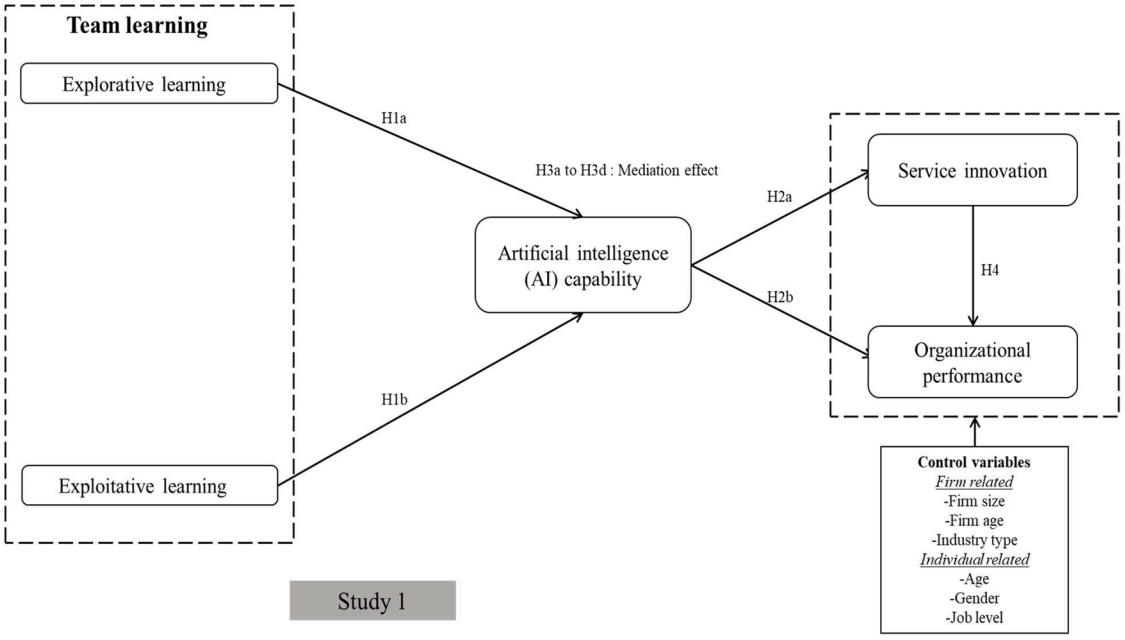


Fig. 2. Structural model tested in Study 1.

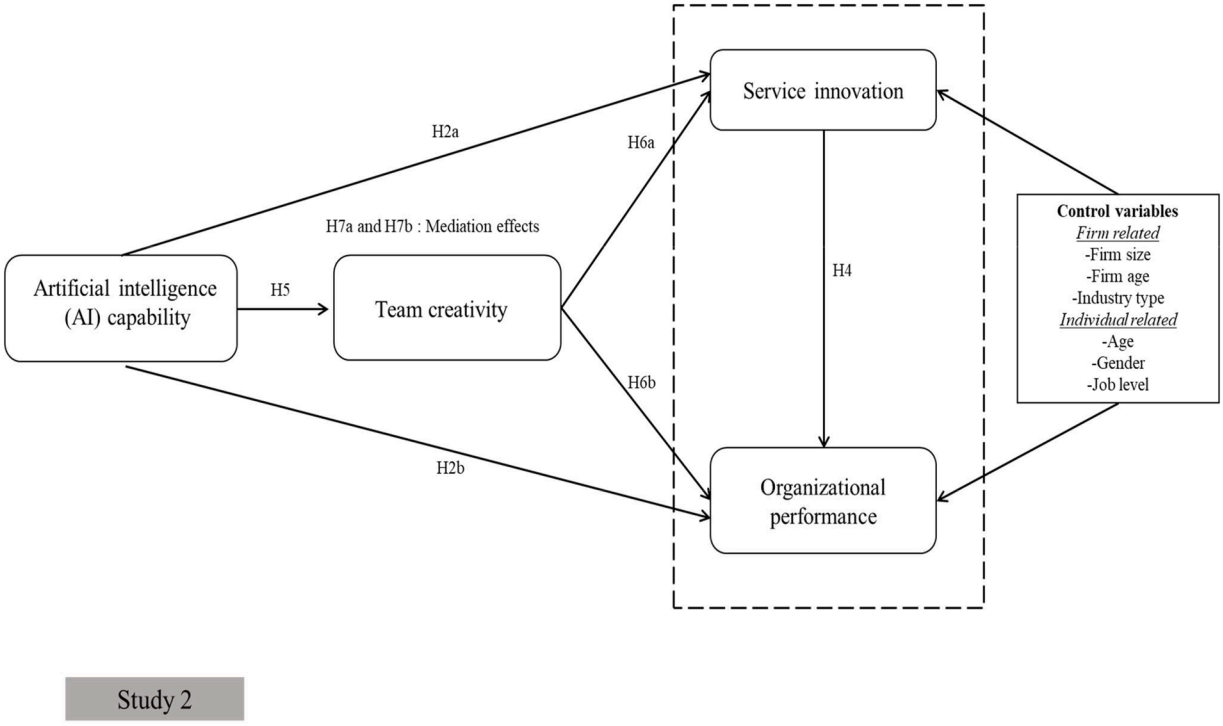


Fig. 3. Structural model tested in Study 2.

manager-assessed team learning rather than as aggregated team member responses. This approach is consistent with key informant research, in which knowledgeable organizational respondents are used to report on phenomena they are well positioned to observe [76,77]. Managers were appropriate informants because they held roles that enabled them to observe learning activities, AI use, coordination, and performance within their organizational units. *AI capability*, a formative factor, includes human skills (technical and business), tangibles (data, technology, and basic resources), and intangibles (interdepartmental coordination, organizational change capacity, and risk proclivity) [4]. For *service innovation*, we included eight measurement items [78]. Finally, we measured *organizational performance* using five items adopted from Mikalef and Gupta [4]. To give our respondents enough time to consider their options before answering, we allowed a minimum of 5 seconds to answer each question, allocating longer minimum times to the more complex questions. We translated the survey into Chinese using the standard translation and back-translation procedure [79].

To minimize the likelihood of errors in the survey and establish content validity, we pretested the questionnaire with a panel of experts comprising managers with experience in using AI in their business

operations. On the basis of their feedback, we refined some of the items for greater clarity; for instance, we revised the wording in some sections and added new questions to the "basic resources," "technology," "human skills," and "business skills" sections. We then invited 57 managers with AI experience to take part in a pilot study to assess the questionnaire and identify any remaining issues before the main study. Following the pilot, we made some further refinements for clarity.

4.2. Data collection and analysis

We recruited respondents through Wen-Juan-Xing, a large online survey platform in China, with more than 6 million registered users that has collected more than 25.9 billion survey responses as of 2025. Using two sampling criteria, we identified those on the platform who (1) were employed by a firm using AI and offering services and (2) held a managerial position. We distributed the survey to the identified respondents at random. To establish an accurate representative sample, we collected data from one manager per firm. This approach enabled us to gain insight into decision-making processes at the managerial level while minimizing potential biases arising from surveying multiple participants from the same firm [80]. A member of our team, along with a dedicated client manager from Wen-Juan-Xing, monitored the data collection and inspected the data to ensure that only one manager from each firm completed the survey.

Study 1 examined the relationships between team learning (i.e., explorative and exploitative learning), AI capability, service innovation, and organizational performance. Because these constructs are well established, firm-level, and commonly assessed through executive surveys, the study relied on a relatively concise questionnaire. This design facilitated the inclusion of a larger and more diverse sample of firms, thereby enhancing the generalizability of the findings. Our final sample comprised questionnaires completed by managers of 600 firms, with one respondent per firm (see Appendix A on Study 1). Most firms had between 101 and 500 employees (51.83%) and had been in business for more than 15 years (31.33%). The majority of respondents were mid-level managers (75%). In terms of demographics, most respondents were female (54.67%), held a master's degree (67.50%), and were between 26 and 35 years old (49.33%).

All respondents indicated that their firms offered services that could be classified as AI-smart services, and that they interacted directly with AI-enabled platforms in their organizations. Nearly one-half of the respondents reported interacting with these platforms multiple times per week (49.17%), with analytics the most common application of AI (59.67%). Most sampled firms operated in the financial services sector (65.17%) and provided both B2B and B2C services (69.83%).

Common method variance (CMV) in our data was considered likely, because all our measures relied on self-reported data from the same measurement instrument, using a survey approach. Therefore, we followed preemptive steps to reduce this likelihood. First, we ensured the complete anonymity of our respondents by using pseudonymous codes [81]. Second, to avoid desired response behaviors, we asked our respondents to express their genuine opinions and informed them that there were no right or wrong answers and that there would be no adverse consequences. Third, to prevent item-context–induced mood states and other biases related to the context of the questions, we randomized the sequence of the items for each respondent. Finally, we ensured that none of the items were ambiguous or complex (e.g., items containing double-barreled statements, words with multiple meanings, technical jargon, or colloquialisms), ensured that there were no item priming effects, and varied the scale wording [82].

We used partial least squares structural equation modeling (PLS-SEM) to analyze the measurement model and the structural model. In the management field, the PLS-SEM method is recognized as a quasi-technique useful for evaluating complex relationships among different latent variables (e.g., higher-order constructs, mediation, and moderation) while simultaneously maximizing the explained variance [83,84]. In prediction-oriented or exploratory studies such as ours, the PLS-SEM method outperforms other methods [84,85].

4.3. Results

4.3.1. Measurement model

Given the use of cross-sectional data, we undertook a series of complementary assessments to evaluate the potential influence of CMV. First, Harman's single-factor test indicated that the largest factor accounted for 20.66% of the total variance, well below the commonly cited 40% threshold [81]. Second, following recent recommendations, we examined full collinearity variance inflation factors (VIFs), all of which fell below the conservative cutoff of 3.3 [84] (see Appendix B and Appendix D(i)). Building on the preceding assessments, we further examined CMV using the marker variable technique [86]. Prior to the inclusion of the latent method factor, the R^2 values were 0.459 for AI capability, 0.428 for service innovation, and 0.446 for organizational performance (see Table 2 for Study 1). After incorporating the latent method factor, the R^2 values changed only marginally ($\Delta R^2 < 0.10$), to 0.508, 0.429, and 0.449, respectively. This trivial variation indicates that controlling for potential method variance does not materially affect the explanatory power of the endogenous constructs. Taken together, these results suggest that CMV is unlikely to pose a serious threat to the validity of the findings of Study 1.

In the measurement model stage (see Table 1), the loadings of most items exceeded the minimum threshold of 0.50 [84] (see Appendix B on Study 1 for full details). Importantly, for all the variables in Study 1, the average variance extracted (AVE) exceeded 0.50 and the composite reliability (CR) exceeded 0.70 [84]. These results provide robust evidence of the convergent validity and internal consistency of our constructs. To assess discriminant validity, we used the heterotrait-monotrait (HTMT) ratio of correlations [84]. As shown in Appendix C(i), the HTMT ratios were below the maximum of 0.85 for all our variables in Study 1, which indicates discriminant validity.

Finally, we assessed AI capability as a third-order construct specified as formative-formative-formative using the procedure outlined by Becker et al. [83]. In the first step, the VIF values fell below the maximum of 3.33 (see Appendix D(i) on Study 1), indicating that all the items and dimensions were distinct. The results of the subsequent statistical test show that all but two items—by means of Technology 3 and RP2—in the first-order constructs of AI capability were statistically significant ($p < 0.05$). The statistical significance of the second-order constructs enabled us to establish the statistical significance of the third-order construct (AI capability), which also showed statistical significance in all second-order constructs or dimensions (i.e., tangible, human, and intangible AI capability). Hence, the third-order AI capability construct is also confirmed and established (see Appendix D(i) on Study 1).

To corroborate this result, we developed and assessed a global item (AI capability: *Overall, the company is well equipped with AI capability.*).

Table 1
Summary of the results of the measurement model for both Study 1 and Study 2.

Assessment criteria for the measurement model		Study 1	Study 2
Reflective	Loading (> 0.5)	✓	✓
	Average variance extracted (> 0.5)	✓	✓
	Composite reliability (> 0.7)	✓	✓
	Discriminant validity using the HTMT criterion (< 0.85)	✓	✓
Formative	Convergent validity using redundancy analysis (> 0.70)	✓	✓
	Variance inflation factor (< 3.33)	✓	✓
	Significance and relevance of formative dimensions to form AI capability (p <0.05)	✓	✓

Note: ✓ means that the result of our measurement model for both study 1 and study 2 meets the satisfactory value suggested by Hair et al. [84]

The redundancy analysis yielded a path coefficient value of 0.891, above the minimum of 0.70 [84], indicating convergent validity for AI capability.

4.3.2. Structural model

To assess the structural model, we first examined the proposed relationships posited in our research model. In doing so, we found that both explorative learning ($\beta = 0.453$, $p < 0.01$) and exploitative learning ($\beta = 0.362$, $p < 0.01$) exert a significant influence on AI capability (see Table 2); therefore, H1a and H1b are supported. Overall, these relationships explain 45.9% of the variance in AI capability.

Furthermore, we found that AI capability exerts a significant influence on both service innovation ($\beta = 0.654$, $p < 0.01$) and organizational performance ($\beta = 0.643$, $p < 0.01$). In addition, service innovation exerts a significant influence on organizational performance ($\beta = 0.237$, $p < 0.01$), with a stronger influence after controlling for six variables—firm size, firm age, industry type, age, gender, and job level—that demonstrated nonsignificance (see Table 2). Thus, H2a, H2b, and H4 are supported, with R^2 values of 42.8% and 44.6%, respectively.

Turning to the mediating effects of AI capability, we found that it has a significant mediating effect on the relationships between explorative learning and service innovation ($\beta = 0.296$, $p < 0.01$), between exploitative learning and service innovation ($\beta = 0.237$, $p < 0.01$), between explorative learning and organizational performance ($\beta = 0.291$, $p < 0.01$), and between exploitative learning and organizational performance ($\beta = 0.233$, $p < 0.01$). Therefore, H3a to H3d are supported (see Table 2). Overall, AI capability was found to have an important role in bridging the relationship between team learning (explorative and exploitative learning) and organizational outcome (service innovation and performance).

To ensure the robustness of our findings on the structural model, confirming the absence of any endogeneity was crucial [87]. To do so, we took the Gaussian copula approach [88]. The results in Table 2 show that the Gaussian copula terms are statistically insignificant ($p > 0.05$), suggesting that the tests do not indicate significant endogeneity concerns in the hypothesized relationships, thereby supporting the robustness of the model.

Finally, we assessed two other aspects of quality in the model: predictive validity and model fit criteria (see Table 2). We found that the $Q^2predict$ values [89] for AI capability (0.455), service innovation (0.205), and organizational performance (0.220) were all positive, indicating that the model has predictive validity. Our model fit results for standardized root mean squared residual (SRMR) (0.071) and Normed Fit Index (NFI) (0.901) were satisfactory, showing that our findings confirm that our proposed model is supported by the data.

Table 2
Results of the structural model for both Study 1 and Study 2.

Test	Relationship	Study 1 (n =600) Std Beta (p-value)	Study 2 (n = 276) Std Beta (p-value)
Direct	Explorative learning → AI capability	0.453 (0.000)	
	Exploitative learning → AI capability	0.362 (0.000)	
	AI capability → Service Innovation	0.654 (0.000)	0.525 (0.000)
	AI capability → Organizational performance	0.643 (0.000)	0.570 (0.000)
	AI capability → Team Creativity		0.769 (0.000)
	Service Innovation → Organizational performance	0.237 (0.000)	0.417 (0.000)
	Team Creativity → Service Innovation		0.291 (0.001)
	Team Creativity → Organizational performance		0.272 (0.000)
Indirect	Explorative learning → AI capability → Service innovation	0.296 (0.000)	
	Exploitative learning → AI capability → Service innovation	0.237 (0.000)	
	Explorative learning → AI capability → Organizational performance	0.291 (0.000)	
	Exploitative learning → AI capability → Organizational performance	0.233 (0.000)	
	AI capability → Team Creativity → Service innovation		0.224 (0.003)
	AI capability → Team Creativity → Organizational performance		0.209 (0.002)
Control Variable	Firm size → Service innovation	0.077 (0.111)	0.007 (0.913)
	Firm age → Service innovation	0.063 (0.195)	0.026 (0.651)
	Industry type → Service innovation	0.057 (0.212)	0.056 (0.419)
	Age → Service innovation	0.028 (0.532)	0.230 (0.721)
	Gender → Service innovation	0.038 (0.436)	0.164 (0.374)
	Job level → Service innovation	0.024 (0.859)	0.067 (0.199)
	Firm size → Organizational performance	0.062 (0.123)	0.004 (0.453)
	Firm age → Organizational performance	0.051 (0.205)	0.011 (0.385)
	Industry type → Organizational performance	0.025 (0.389)	0.005 (0.450)
	Age → Organizational performance	0.042 (0.292)	0.111 (0.057)
	Gender → Organizational performance	0.052 (0.398)	0.093 (0.097)
	Job level → Organizational performance	0.018 (0.887)	0.049 (0.431)
Endogeneity	GC (Explorative learning) → AI capability	-0.040 (0.361)	
	GC (Exploitative learning) → AI capability	-0.075 (0.729)	
	GC (AI capability) → Service innovation	0.031 (0.845)	0.202 (0.392)
	GC (AI capability) → Organizational performance	-0.085 (0.604)	0.216 (0.240)
	GC (AI capability) → Team creativity		0.010 (0.953)
	GC (Team creativity) → Service innovation		-0.244 (0.165)
	GC (Team creativity) → Organizational performance		-0.274 (0.074)

(continued on next page)

5. Study 2: exploring the role of team creativity

In Study 2, we surveyed an additional sample of managers to examine whether and how team creativity mediates the relationship between an organization's AI capability and its service innovation and organizational performance.

5.1. Participants and procedures

Following the procedure described in Study 1, the first section of the Study 2 survey collected information about respondents and their firms in China, for example, the size of each firm and the gender and education level of each manager. In the second section, we used some of the same measurement items (i.e., AI capability, service innovation, and organizational performance) but extended the scope by including additional variables (i.e., team creativity). To measure team creativity, we adopted nine items from Ali et al. [90]. In this study, team creativity was operationalized through managers' assessments of their teams' creative behaviors; therefore, empirical references to team creativity should be interpreted as manager-assessed team creativity rather than as

Table 2 (*continued*)

Test	Relationship	Study 1 (n =600) Std Beta (p-value)	Study 2 (n = 276) Std Beta (p-value)
Quality Criteria			
R^2	AI capability	0.459	
	Team Creativity		0.591
	Service Innovation	0.428	0.596
	Organizational Performance	0.446	0.667
$Q^2predict$	AI capability	0.455	
	Team Creativity		0.572
	Service Innovation	0.205	0.536
	Organizational Performance	0.220	0.587
SRMR	Estimated Model	0.071	0.063
NFI	Estimated Model	0.901	0.934

Notes: GC: endogeneity tested using the Gaussian Copula; SRMR: standardized root mean squared residual; values must be below 0.08; NFI: normed fit index; values must be above 0.90 [84].

aggregated team member responses. This approach is consistent with key informant research, in which individuals occupying knowledgeable organizational roles are used to report on phenomena that they are well positioned to observe, particularly those with direct oversight of relevant activities, resources, and outcomes [76,77]. In our context, managers were appropriate informants because they had direct interaction with AI-enabled platforms and were responsible for observing team behaviors, coordination, creativity, and performance within their organizational units. All these items were measured on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) (see Appendix B on Study 2). The Study 2 survey questions were also translated using the back-translation procedure [79]. We again pretested the questionnaire on a panel of experts before pilot testing it on a different sample of 45 managers with AI experience to assess the questionnaire's clarity, content and suitability for the main study. Notably, in this case we did not need to refine any items on the basis of feedback after either the pretest stage or the pilot study.

5.2. Data collection and analysis

For data collection, we used the same database platform to select potential respondents, applying the same two sampling criteria: (1) employment at firms using AI and offering services and (2) holding a managerial position. We also adopted the procedural approach to CMV as in Study 1. After distributing our survey, we received responses from managers of 339 firms. Sixty-three responses were excluded owing to missing values or illogical answers (e.g., managers reporting a strong capability for change but claiming they could not anticipate or plan for change). The final sample included 276 managers, one from each firm (see Appendix A on Study 2). In particular, most of the firms had between 101 and 500 employees (50.4%) and had been in business for more than 15 years (38.0%). The majority of respondents were male (72.1%), three-quarters had an undergraduate degree (75.7%), and two-thirds were aged 26 to 35 years (65.6%). All respondents reported that their companies offered AI-smart services, and roughly one-half interacted directly with AI-enabled platforms multiple times daily (51.1%), primarily for analytics (55.1%) and research and development (25.0%). Among the sample firms, the largest share operated in “other” sectors (food and beverages, construction, manufacturing, security; 36.6%), and more than one-half offered both B2B and B2C services (53.3%).

Study 2 focused on team creativity as a mediating construct assessed through managers' reports of their teams' creative behaviors that required more detailed responses. To ensure the quality and reliability of this measure, stricter inclusion criteria were applied, resulting in a smaller but more targeted sample. The survey instrument was also more time-consuming, leading to a lower completion rate despite comparable outreach initiatives. Although sample size differed between Studies 1 and 2, both samples exceeded the recommended thresholds for PLS-SEM analysis using the gamma exponential (minimum 146) or inverse square root (minimum 160) methods [91], and both met the power analysis requirement of more than 114 respondents with a medium effect size at 95% power [84]. Thus, the variation in sample size reflects fit-for-purpose sampling aligned with the distinct aims and constructs of each study, without compromising the robustness of the findings.

5.3. Results

5.3.1. Measurement model

We assessed CMV using three complementary approaches. Initially, Harman's single-factor test demonstrated that the largest factor accounted for 31.40% of the variance, falling short of the 40% threshold [81]. Second, the full collinearity assessment demonstrated that all VIF values were below the conservative threshold of 3.3 [84] (see Appendix B and Appendix D(ii) for Study 2). Third, and more crucially, the marker variable technique was implemented [86] to explicitly model potential method variance. Incorporating this latent factor resulted in only slight increases in explained variance ($\Delta R^2 < 0.10$), with R^2 values of 0.608 for team creativity, 0.681 for service innovation, and 0.761 for organizational performance compared to the baseline values presented in Table 2 for Study 2 (0.596, 0.591, and 0.667, respectively). This minimal change suggests that controlling for a common method factor does not have a substantial impact on the model estimates. Taken together, these results suggest that CMV is unlikely to pose a serious threat to the validity of the findings of Study 2, although this cannot be ruled out entirely.

Subsequently, we assessed the validity and reliability of our construct measures (see Appendix B for Study 2). Although we removed several measurement items with loadings below 0.50, all variables had AVE values above 0.50 and CR values above 0.70 [84]. This established both convergent validity and internal consistency. In addition, the HTMT ratio yielded values below 0.85 for all variables, indicating discriminant validity (see Appendix C(ii) on Study 2).

Finally, we assessed the higher-order construct by following the same procedure as described for Study 1. This resulted in VIF values below the maximum of 3.33 (Appendix D(ii) on Study 2), which indicates that all the items and dimensions were distinct. The statistical test on the first-order constructs of AI capability yielded mixed results, with some significant and others nonsignificant; nonetheless, the statistical significance of the second-order constructs allowed us to establish the statistical significance of the third-order construct, AI capability ($p < 0.05$), which also showed statistical significance in all the second-order constructs or dimensions (i.e., tangible, human, and intangible AI capability) ($p < 0.05$). Therefore, the third-order construct of AI capability was also confirmed and established (see Appendix D(ii) on Study 2). Corroborating this result, the redundancy analysis yielded a path coefficient of 0.731, which exceeds the minimum of 0.70 [84]. This indicates convergent validity for the construct of AI capability.

5.3.2. Structural model

Similar to Study 1, we first estimated structural models to examine the proposed relationships. The results, shown in Table 2, reveal that AI capability was significantly related to team creativity. H5 is supported ($\beta = 0.769$, $p < 0.01$), with AI capability explaining 59.1% of the variance in team creativity ($R^2 = 0.591$).

Subsequently, we found that AI capability ($\beta = 0.525$, $p < 0.01$) and team creativity ($\beta = 0.291$, $p < 0.01$) exert a significant influence on service innovation. This supports H2a and H6a, with an explanatory power of 59.6%. In addition, AI capability ($\beta = 0.570$, $p < 0.01$), team creativity ($\beta = 0.272$, $p < 0.01$), and service innovation ($\beta = 0.417$, $p < 0.01$) exert a significant influence on organizational performance. Thus, H2b, H4, and H6b are also supported, with an explanatory power of 66.7%. The hypothesized relationships remained supported after accounting for six control variables: firm size, firm age, industry type,

respondent age, gender and job level, which demonstrated nonsignificant results (see Table 2).

Turning to team creativity, we found significant indirect effects through team creativity on the relationship between AI capability and service innovation ($\beta = 0.224$, $p < 0.01$) and the relationship between AI capability and organizational performance ($\beta = 0.209$, $p < 0.01$). Therefore, H7a and H7b are both supported (Table 2). As shown in Table 2, none of the results of the Gaussian copula tests were significant ($p > 0.05$), and thus we can conclude that in Study 2, the Gaussian copula tests did not identify statistically significant endogeneity concerns

We next assessed the model's predictive performance and fit (see Table 2). The $Q^2predict$ values [89] for team creativity (0.572), service innovation (0.536), and organizational performance (0.587) were all positive, meaning that the model has predictive validity. In addition, the SRMR (0.063) and NFI (0.934) values indicate satisfactory model fit. The significant indirect effects reported above support the mediating role of team creativity between AI capability and organizational outcomes (service innovation and performance).

6. General discussion

AI is driving significant transformations across industries, changing business models, and enabling firms to develop novel products and services [92]. Consistent with the empirical design, our present findings should be interpreted as reflecting managers' assessments of team learning and team creativity rather than aggregated team member responses. Consistent with the cross-sectional design, the relationships tested in this study should be interpreted as theoretically informed associations rather than evidence of temporal ordering or causality. Despite increasing interest in human–AI collaboration for enhancing organizational performance [8,12,13,16,93,94], the knowledge of how team-level processes, particularly team learning and team creativity, mediate the relationship between AI capability and organizational outcomes remains limited. While previous research has focused largely on technological implementation or individual-level competencies [5,12,29,95], our study offers a novel perspective by examining how team learning and creativity, as assessed by managers, are associated with the success of AI in organizations. Our findings reinforce a sociotechnical view of AI in which technological capability alone is insufficient. The extent to which AI supports learning and creativity depends on enabling human conditions such as trust in AI, perceived autonomy, and psychological safety, which determine whether teams treat AI as a collaborative partner or a rigid control system.

Building on earlier work examining the effects of explorative and exploitative learning separately (e.g., [36,38]), our study shows that both types of learning make complementary contributions to the development of AI capability. These findings advance the research on organizational learning by positioning team learning as a dynamic process that balances innovation and refinement, aligning with but also extending previous frameworks on ambidexterity [30,41]. Our results demonstrate that team learning processes are not only relevant but also fundamental to developing the human and organizational dimensions of AI capability.

Drawing on research linking AI capability to service innovation and organizational performance (e.g., [4,49]), our study highlights the mechanisms through which this relationship unfolds. Rather than treating AI capability as a standalone technological asset, we show that it functions as a dynamic enabler, nurtured by team learning and further amplifying creative team processes. This underscores the importance of viewing AI capability not as a fixed resource but rather as a socially constructed and adaptable capability, embedded in ongoing team-level interactions.

A particularly novel contribution of this study is the identification of team creativity as a mediating mechanism between AI capability and key performance outcomes. While creativity has been widely studied at the individual or organizational level [5,68], our findings reveal that creativity at the team level, arising through collaboration, idea sharing, and mutual influence, is essential to translating AI capability into innovation and performance. This challenges the assumption that AI tools independently generate value and reinforces the importance of human collaboration in realising their full potential. This insight is especially salient in service-based contexts, where innovation frequently depends on co-creation and interpersonal dynamics.

Our two-study design also strengthens the reliability and theoretical clarity of our findings. Study 1 examines how team learning is associated with AI capability, while Study 2 unpacks how team creativity amplifies the downstream effects of that capability. This sequential structure avoids common methodological pitfalls and offers a layered understanding of the human–AI interface.

By integrating findings across team learning, AI capability, and team creativity, this study provides a more comprehensive view of how organizations can foster successful human–AI collaboration. It shifts the focus from technology-centred perspectives to a sociotechnical model in which team dynamics play a central role. This lens invites future research to explore other human-centric factors, such as trust, autonomy, and psychological safety, that may further shape how AI is integrated into teams and leveraged for innovation.

6.1. Theoretical contributions

This study provides several important theoretical contributions that extend and challenge current thinking on AI capability, dynamic capabilities, and team-level processes in organizations adopting AI. First, our work makes a novel contribution by conceptualizing and providing empirical evidence that manager-assessed team learning capabilities, both explorative and exploitative, serve as microfoundations of AI capability. While the dynamic capabilities literature recognizes the importance of organizational learning [22,23], most studies have remained at the organizational level. We contribute a finer-grained understanding by demonstrating that learning dynamics at the team level, and not just the firm level, are critical to developing AI capability in rapidly changing environments. Our findings build on and extend earlier work on ambidextrous learning [36–38], showing that both exploration (e.g., experimentation and discovery) and exploitation (e.g., refinement and efficiency) are essential for enabling teams to engage with AI as a dynamic capability enabler. This extends dynamic capability theory by grounding the development of AI capability in team-level, interactional learning processes.

Second, we extend the RBV by showing how team creativity functions as a mediating mechanism that transforms AI capability into service innovation and performance gains. Prior research, most notably Mikalef and Gupta [4], conceptualized AI capability as an organizational-level strategic resource that directly influences innovation and performance. While this work established the importance of AI capability, it largely treated it as a firm-level asset and left the internal processes through which it is built and activated undertheorized. Our study advances this stream of research by unpacking the team-level microfoundations through which AI capability is developed (via explorative and exploitative learning) and the team-level mechanisms through which it is realized (via team creativity). In contrast to prior RBV-based models that link AI capability directly to performance, we show that value creation depends on how teams learn, adapt, and creatively recombine AI with human expertise. Prior studies have often conceptualized AI capability as a static technological resource [4], with limited exploration of the relational and interactive conditions under which it creates value. Our study challenges this assumption by proposing that AI capability becomes strategically valuable only when embedded in socially cohesive and creatively enabled teams. In particular, we highlight that team creativity is not simply an outcome of AI tools but is shaped by human–AI collaboration [17,20], in which team dynamics, communication quality, and diversity of thought are

essential. This reconceptualization advances RBV by positioning team creativity as a dynamic, socially embedded resource through which AI capability is enacted.

Third, our study provides a new theoretical synthesis by integrating team learning, team creativity, and AI capability into a unified socio-technical framework. While previous studies examined human–AI interaction primarily from a technological or leadership perspective [11, 14], few studies have examined team-level processes as mechanisms linking AI capability to organizational outcomes. Our framework demonstrates that AI capability does not operate in isolation, but rather that its performance and innovation effects are amplified by team-level learning and creative dynamics. This is especially relevant in the service context, where innovation is co-produced by human and technological actors [8,96,97]. Our findings thus contribute to closing a major gap in the literature, enhancing the understanding of how team processes support the operationalization and value realization of AI technologies.

Fourth, we challenge the narrative that AI implementation is primarily a technological integration issue by showing that team-related factors often have a more decisive role than technological factors in enabling or impeding AI capability [12,13]. AI adoption failures remain high [15], owing in part to underdeveloped frameworks for understanding how human capabilities interact with AI. Our research addresses this by theorizing how teams, through cycles of learning and creativity, enable adaptive responses to technological complexity—offering a more nuanced understanding of AI success and failure.

Finally, our contribution is reinforced by our two-study empirical design, which separately examines team learning (Study 1) and team creativity (Study 2) to unpack their distinct and interrelated roles. This structure enables us to examine complementary aspects of our theoretical framework and examine the proposed relationships linking team learning, AI capability development, and innovation outcomes. By grounding our findings in both RBV and dynamic capability theory, we offer an enriched and actionable perspective on human–AI collaboration that situates teams as central to the adaptive and creative use of intelligent technologies.

Taken together, these contributions show how AI capability is not merely possessed but also built through team-level learning microfoundations and realized through team-level creative resource complementarities. This study's framework moves beyond prior work treating AI capability as either a static resource (RBV) or an abstract organizational capability (dynamic capabilities). It integrates dynamic capability theory and the RBV in a novel way by theorizing team learning as a microfoundation of AI capability (a dynamic capability) and team creativity as the value-realizing mechanism (an RBV concept) through which AI capability positively affects service innovation and organizational performance.

6.2. Managerial implications

Our findings offer several practical implications for managers seeking to maximize the value of AI capability through team-level strategies. First, when deploying AI systems, organizations should invest in customizable and user-centric AI tools. These systems need to allow flexibility so that employees can tailor AI outputs to their specific tasks and workflows. Managers should also implement structured onboarding processes for AI tools, including clear role definitions, standard operating protocols, and safeguards such as human override mechanisms. Supervised training, quality control procedures, and transparent communication around AI capabilities and limitations are essential to ensure alignment with business goals and employee trust.

Second, to support the development of AI capability, managers should actively promote both explorative and exploitative learning within teams. This can be achieved by establishing a culture in which employees are encouraged to reflect on past processes and outcomes, experiment with new approaches, and share lessons learned from using AI tools. Alongside continuous improvement of established practices, managers should create opportunities for innovation by supporting team-led pilots, AI experimentation workshops, and regular forums for feedback and adaptation. Recognition and incentives for adaptive learning behavior can further motivate teams to engage in meaningful collaboration with AI.

Organizations should also recognize that building AI capability requires more than just investing in technology. Managers must ensure that their approach is balanced across tangible infrastructure (such as data and technical platforms), human skills (including both technical proficiency and business acumen), and intangible factors like coordination across departments, openness to change, and support for experimentation. Establishing cross-functional implementation teams that bring together IT specialists, data analysts, and business managers can help integrate technical and organizational priorities.

Finally, our study shows that team creativity has a crucial mediating role in translating AI capability into innovation and performance. Consequently, managers should focus on enabling creativity within AI-enabled teams. This involves carving out space and time for collaborative ideation, encouraging co-development of AI-based solutions to service problems, and fostering an environment in which new ideas are welcomed, especially those that extend or challenge AI-generated output. Investing in AI literacy programs as part of team development can also enhance confidence, encourage creative exploration, and help teams better understand how to interact with intelligent systems as co-creators.

In summary, the successful deployment of AI for innovation and performance is not a technical challenge alone; it requires a holistic and systems-level approach that integrates team learning, creativity, organizational culture, and technology infrastructure. Managers who adopt this integrated perspective will be better positioned to unlock the full potential of human–AI collaboration and drive long-term value for their organizations.

6.3. Limitations and future research

Building on our findings, several research questions emerge that warrant further investigation. First, future studies could examine the conditions under which team creativity becomes a stronger or weaker mediator between AI capability and innovation. Potential moderators, such as team psychological safety, diversity, and task complexity, could shed light on these dynamics. Similarly, investigating how different forms of AI literacy or training interventions influence the relationship between team learning and AI capability development over time is another promising avenue.

Second, unpacking the sequence and feedback loops between explorative and exploitative learning in high-AI environments could clarify whether these processes are mutually reinforcing or if one precedes the other. In addition, researchers could explore how human–AI collaboration dynamics evolve at different stages of AI maturity within firms, focusing on the role of team-level trust and autonomy in shaping long-term performance outcomes.

Third, although this study draws on managers as knowledgeable key informants, the use of one manager per firm means that team learning and team creativity were captured through managerial assessments rather than through aggregated responses from multiple team members. This limited our ability to assess within-team variability, shared perceptions, and fully emergent team-level dynamics. Future research should use multi-informant and multilevel designs, collecting data from multiple members within the same team, to validate whether the relationships identified here hold when team learning and team creativity are measured as aggregated team-level constructs. Expanding data collection beyond managers to include employees could provide richer insights into the dynamics of AI adoption. Multisource and multilevel approaches would help address potential single-source bias and offer a

more nuanced understanding of how different organizational perspectives influence AI capabilities and outcomes.

Overcoming the temporal limitations of this study is another key area for future research. Although dynamic capability theory conceptualizes team learning, AI capability, and team creativity as evolving, path-dependent processes, our study's cross-sectional design could not capture these dynamics comprehensively or determine temporal precedence. Therefore, the observed relationships should be interpreted as associative rather than causal. Future research should prioritize longitudinal and time-lagged designs to trace capability development and rigorously test the proposed sequencing. Experimental and quasi-experimental approaches would further strengthen causal inference by isolating the effects of team learning on capability development and creative outcomes. In particular, longitudinal studies of organizations in the early stages of AI adoption would provide valuable insights into how capabilities emerge and generate value over time, and would improve the generalizability of the findings to other organizational and institutional contexts.

Fourth, cross-cultural validation is important. Differences in managerial practices, cultural norms, and AI regulatory environments may affect the applicability of our findings beyond Chinese service firms. Replicating this study in other regions, including Western and emerging economies, would help assess the robustness and cross-cultural validity of the proposed framework linking AI capability to organizational performance.

CRediT authorship contribution statement

Nisreen Ameen: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Jun-Hwa Cheah:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Shlomo Tarba:** Writing – review & editing, Conceptualization. **Margherita Pagani:** Writing – review & editing, Conceptualization. **Eleonora Pantano:** Writing – review & editing, Conceptualization. **Senmao Xia:** Writing – review & editing, Data curation, Conceptualization.

Declaration of competing interest

No conflict of interest

Supplementary materials

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