Unveiling the impact of the congruence between artificial intelligence and explorative learning on supply chain resilience

Abstract

Purpose – Drawing upon socio-technical system theory, this study intends to investigate the effects of the congruence and incongruence between artificial intelligence (AI) and explorative learning on supply chain resilience as well as the moderating role of organizational inertia.

Design/methodology/approach – Using survey data collected from 170 Chinese manufacturing firms, we performed polynomial regression and response surface analyses to test our hypotheses.

Findings – We find that the congruence between AI and explorative learning enhances firms' supply chain resilience, while the incongruence between these two factors impairs their supply chain resilience. In addition, compared with low–low congruence, high–high congruence between AI and explorative learning improves supply chain resilience to a greater extent. Moreover, organizational inertia attenuates the positive influence of the congruence between AI and explorative learning on supply chain resilience, while it aggravates the negative influence of the incongruence between these two factors on supply chain resilience.

Originality/value – Our study expands the literature on supply chain resilience by demonstrating that the congruence between a firm's AI (i.e. technical aspect) and explorative learning (i.e., social aspect) boosts its supply chain resilience. More importantly, our study sheds new light on the role of organizational inertia in moderating the congruent effect of AI

and explorative learning, thereby extending the boundary condition for socio-technical system theory in the supply chain resilience literature.

Keywords: Supply chain resilience; artificial intelligence; explorative learning; organizational inertia; socio-technical system

1. Introduction

The increasingly uncertain and volatile environments in the past decade have rendered firms more vulnerable to the risks of supply chain disruptions (Sturm *et al.*, 2023). For example, the COVID-19 pandemic has triggered unprecedented disruptions in supply and demand, impeding the movement of materials and goods in the supply chain (Nikookar and Yanadori, 2022). The trade war between the U.S. and China has also immensely disrupted the supply chain, leading to significant delays in product delivery (Handfield *et al.*, 2020). These tumultuous supply chain disruptions have a detrimental impact on firms' operational and financial performance (Sturm *et al.*, 2023). As such, researchers and practitioners have underlined that it is crucial for firms to boost supply chain resilience to effectively mitigate the risks of supply chain disruptions (Dubey *et al.*, 2023).

Supply chain resilience refers to a firm's ability to remain alert to, adapt to, and respond promptly to supply chain disruptions (El Baz and Ruel, 2021; Wei *et al.*, 2023). A resilient supply chain can successfully deal with changes in uncertain and turbulent environments, thus enabling firms to alleviate the negative impact of supply chain disruptions (Mirzabeiki and Aitken, 2023). Researchers have identified technical and social factors that can help firms enhance their supply chain resilience (Eryarsoy *et al.*, 2022; Le and Behl, 2023), as emphasized by socio-technical system (STS) theory (Tong *et al.*, 2023). STS theory suggests that technical and social subsystems interact, and firms need to jointly optimize them to attain optimal performance (Bednar and Welch, 2020). In particular, with the rapid advancement of digital technologies, artificial intelligence (AI) has been glorified as an essential technical factor that promotes firms' supply chain resilience (Belhadi *et al.*, 2022a; Le and Behl, 2023). The implementation of AI is beneficial for firms to improve their predictive and data analytics abilities and facilitate the decision-making process, thereby allowing them to better anticipate, adapt to, and deal with unexpected supply chain disruptions such as supply shortages and delivery outages (Leoni *et al.*, 2022). Moreover, as an emerging technology, the adoption of AI necessitates a firm to have substantial new knowledge and capabilities (Le and Behl, 2023) that could be created by the firm's explorative learning. Explorative learning refers to the learning activities that generate novel knowledge and competencies by expanding the existing knowledge base (Patel *et al.*, 2012), which can assist firms in adapting to environmental changes and developing new ideas and solutions to handle unforeseen supply chain disruptions (Eryarsoy *et al.*, 2022).

In the current rapidly changing and evolving business environments, firms are expected to be highly innovative and adaptive, and thus explorative learning is deemed as a critical social factor that can boost firms' supply chain resilience (Belhadi *et al.*, 2022b). Nevertheless, STS theory advocates for an integrated and synergistic perspective, underscoring that the alignment between technical and social factors is an important prerequisite for achieving optimal organizational outcomes (Bostrom and Heinen, 1977). As such, it may be not sufficient to solely implement AI or explorative learning to achieve high supply chain resilience. Rather, firms that strike a balance between AI (i.e., technical aspect) and explorative learning (i.e., social aspect) and maintain a fit between them are more likely to improve supply chain resilience. Yet, so far, scant research has delved into how AI aligns with explorative learning to affect firms' supply chain resilience, which hampers a nuanced understanding of the complementary effect of these two factors.

To narrow this gap, our study adopts STS theory to investigate the influence of the congruence between AI and explorative learning on firms' supply chain resilience. STS theory highlights that technical subsystems provide a supporting structure for social subsystems and vice versa (Tong *et al.*, 2023). Specifically, in our context, AI can support explorative learning by offering real-time information for predictions and advanced decision-making that can help firms make better decisions in terms of responding to supply chain disruptions, thereby elevating their supply chain resilience (Yu *et al.*, 2023). In turn, explorative learning, which involves the acquisition, interpretation, and utilization of new knowledge (Patel *et al.*, 2012), can facilitate the effectiveness of AI implementation by providing valuable and novel insights that can help firms refine and optimize the algorithms employed in AI. The mutual reinforcement of AI and explorative learning enables firms to better cope with unanticipated disruptions or changes in supply chains and thus heightens their supply chain resilience.

Hence, based on STS theory, we posit that the congruence between AI and explorative learning improves firms' supply chain resilience. By contrast, the incongruence between these two factors impairs firms' supply chain resilience. Furthermore, different types of congruence (i.e., high–high vs. low–low) between AI and explorative learning may exert differential effects on firms' supply chain resilience, given that the synergic effects of the two elements could vary across different situations of congruence.

STS theory also holds that an organization constitutes a multifaceted system comprised of technical and social elements, where alterations in any single element can influence the entire system (Bostrom and Heinen, 1977). In this vein, the integration of AI and explorative learning is a system change, which might be impeded by organizational inertia that reflects an organization's resistance to changes (Hannan and Freeman, 1984). We therefore endeavor to unravel the role of organizational inertia in modifying the effects of the congruence and incongruence between AI and explorative learning on firms' supply chain resilience.

To accomplish the above research objectives, this study collected survey data from 170 Chinese manufacturing firms and conducted polynomial regression and response surface analyses. The results reveal that the congruence between AI and explorative learning enhances firms' supply chain resilience, while the incongruence between these two factors dampens their supply chain resilience. Moreover, compared with low–low congruence, high–high congruence between AI and explorative learning improves firms' supply chain resilience to a greater extent. Furthermore, organizational inertia weakens the positive influence of the congruence between AI and explorative learning on supply chain resilience, while it exacerbates the negative influence of the incongruence between these two factors on supply chain resilience.

This study makes several theoretical contributions. First, it expands the supply chain resilience literature by empirically unraveling the impacts of the congruence and incongruence between AI and explorative learning on firms' supply chain resilience. Prior studies have primarily investigated the effect of AI (Le and Behl, 2023) or explorative learning (Eryarsoy *et al.*, 2022) on supply chain resilience unilaterally, yet scant research has paid attention to their joint effect on supply chain resilience. We highlight the importance of the integration of a system's technical aspect (i.e., AI) and social aspect (i.e., explorative learning) to enhance its effectiveness and achieve better supply chain resilience. Moreover, we disentangle the varying effects of different types of congruence. That is, high–high congruence between AI and explorative learning facilitates supply chain resilience more than low–low congruence. Second, this research provides novel insights into how organizational inertia alters the impacts of the congruence and incongruence between AI and explorative learning on supply chain resilience, which echoes recent research that calls for more investigations of the boundary condition of supply chain resilience (Sturm *et al.*, 2023). Lastly, our research advances the literature on STS theory by theoretically elucidating the fit between the technical aspect (i.e., AI) and the social aspect (i.e., explorative learning) as well as the contingency effect of organizational inertia.

2. Theoretical background and literature review

2.1. Socio-technical system theory

STS focuses on the interaction between technical and social aspects of work systems to achieve optimal performance and worker satisfaction (Bednar and Welch, 2020; Bostrom and Heinen, 1977). Under this concept, the technical aspects include the machines and techniques that help transform inputs into outputs, while the social aspects feature human-related factors and social relations among organizations (Bednar and Welch, 2020; Chaudhuri and Jayaram, 2019). STS theory posits that it is necessary to adjust and balance technical and social subsystems to achieve superior performance (Shou *et al.*, 2021).

In the field of operations and supply chain management (OSCM), STS theory has been employed to explicate how firms integrate technical and social subsystems to attain superior performance. For instance, from the STS perspective, Chaudhuri and Jayaram (2019) disentangled the complementary effect of social and technical integration on quality and sustainability performance. Tong *et al.* (2023) built on STS theory to examine how organizations balance their focus on different environmental projects while building their environmental management capabilities to acquire better environmental performance. Shou *et al.* (2021) leveraged STS theory to propose a matching traceability and supply chain coordination framework that helps firms achieve high operational performance and customer satisfaction.

The concept of congruence and incongruence in the context of STS theory is central to understanding the interaction between technical and social aspects for optimal performance in work systems (Tong *et al.*, 2023). In our context, we contend that firms can achieve optimal supply chain resilience by balancing AI (i.e., technical aspect) and explorative learning (i.e., social aspect). This congruence cultivates compatibility between technical and social elements, facilitates efficiency and effectiveness, and fosters a culture of continuous improvement, thereby boosting firms' supply chain resilience. Conversely, the incongruence between AI and explorative learning hinders effective functioning, eroding the supply chain's ability to handle supply chain disruptions and impairing supply chain resilience. As such, the degree of congruence or incongruence influences a system's efficiency, effectiveness, and overall resilience in response to supply chain disruptions. However, the effect of the congruence between AI and explorative learning as an integrated system on supply chain resilience remains largely underexplored in the extant literature, which falls short of the imminent need for firms to effectively align these two factors to achieve higher supply chain resilience. To this end, we strive to bridge this gap by invoking STS theory to examine the impact of the congruence between AI and explorative learning on firms' supply chain resilience. Moreover, we aspire to advance the existing literature by investigating the moderating role of organizational inertia, thus providing nuanced insights into the boundary condition that shapes the effectiveness of the STS composed of AI and explorative learning.

2.2. Supply chain resilience

The escalating uncertainties and disruption risks that grip the world have drawn considerable attention to the resilience of supply chains (Handfield *et al.*, 2020; Nikookar and Yanadori, 2022). Hence, supply chain resilience has emerged as a critical capability for firms to maintain operational continuity and a competitive edge in the face of supply chain disruptions such as supply failures, delivery delays, and demand fluctuations (Sturm *et al.*, 2023). In this study, supply chain resilience is defined as a firm's ability to prepare for, adapt to, and respond quickly to disruptions in its supply chain (El Baz and Ruel, 2021; Sturm *et al.*, 2023; Wei *et al.*, 2023). Firms with resilient supply chains can effectively deal with unanticipated supply chain disruptions and mitigate their detrimental effects, ensuring that they can continue to function, bounce back from disruptions, and meet customer demands promptly under adverse conditions (Dubey *et al.*, 2023).

Given the increasing importance of achieving supply chain resilience, scholars in OSCM have shown a keen interest in examining the factors that affect supply chain resilience. Particularly, in volatile and unpredictable environments, researchers have identified technical and social factors as enablers of supply chain resilience. For example, previous studies have shown that additive manufacturing technology (Belhadi *et al.*, 2022b), blockchain technology (Liu *et al.*, 2024), digital agility and digital adaptability (Dubey *et al.*, 2023), and entrepreneurial orientation (Sturm *et al.*, 2023) can enhance firms' supply chain resilience. Besides, recent research has documented that as an emerging digital technology, AI can boost firms' supply chain resilience by bolstering their data analytics and predictive capabilities for identifying vulnerabilities and handling unexpected supply chain disruptions (Le and Behl, 2023; Leoni *et al.*, 2022). Past research has also stressed that given the intensified turbulence in global business environments, explorative learning serves as a key social factor that helps firms develop new solutions to cope with supply chain disruptions and thus elevate their supply chain resilience (Eryarsoy *et al.*, 2022). Nevertheless, the extant studies have mainly examined the independent role of AI and explorative learning in building supply chain resilience, overlooking their complementary effect. As emphasized by STS theory (Bostrom and Heinen, 1977), technical factor (i.e., AI) and social factor (i.e., explorative learning) interact and need to be balanced to enable firms to achieve higher supply chain resilience. Thus, there is a significant lack of research that empirically unveils how AI aligns with explorative learning to influence firms' supply chain resilience, which warrants further exploration.

2.3. Artificial intelligence

Over the past decade, AI has developed dramatically and gained rapid popularity (Mithas *et al.*, 2022). AI can be considered as a capability to acquire knowledge by analyzing the data from the outside environment and applying the obtained knowledge to modify or develop new tasks against fast-changing environments (Gupta *et al.*, 2023). These tasks incorporate techniques and algorithms that allow humans to learn from input data, with or without prior knowledge regarding the eventual output formats (Yu *et al.*, 2024). Increased computational capabilities, the expansion of big data, and the widespread applications of AI in OSCM have recently led to a renewed focus on AI (Mithas *et al.*, 2022).

Researchers in OSCM have maintained that AI can help firms improve operational efficiency, lessen costs, and boost decision-making processes (Mithas *et al.*, 2022). Moreover, AI can overcome cognitive information processing constraints and therefore handle large quantities of data, detect patterns, and forecast customer demands (Yu *et al.*, 2024). This enables firms to optimize inventory levels, reduce waste from excess materials, and elevate customer satisfaction (Le and Behl, 2023).

Recently, researchers have studied the applications of AI in OSCM. For instance, Belhadi *et al.* (2024) explored AI-driven innovation from a supply chain dynamism perspective and found that it can enhance the resilience and performance of supply chains. Moreover, Gupta *et al.* (2023) discovered that AI can boost supply chains' financial resilience. However, Li and Li

(2022) compared the decision-making between AI and humans in the retail sector, and found that AI's decision-making leads to worse firm performance than humans.

2.4. Explorative learning

The existing literature underscores that organizational learning is critical in enhancing the competitiveness and performance of firms in turbulent business environments (Patel *et al.*, 2012). March (1991) developed a seminal framework of organizational learning that demonstrates the trade-off between two fundamental types of organizational ambidexterity: exploration and exploitation. Exploitative learning refers to the learning activities that make incremental improvements to current knowledge and capabilities. In contrast, explorative learning denotes the learning activities that create new knowledge and capabilities by extending the current core knowledge (Patel *et al.*, 2012). Different from exploitative learning, exploratory learning is especially relevant to radical innovation, enabling firms to search distant domains of knowledge and thus generate a broad set of novel ideas or knowledge (Azadegan and Dooley, 2010). Considering that AI is one of the disruptive digital technologies, which requires firms to possess considerable new knowledge and skills (Le and Behl, 2023), explorative learning would be a more complementary element to be considered. That is, firms' primary focus will be on the explorative learning activities to reconfigure their information technology competencies in response to advanced technologies such as AI.

In the field of OSCM, a significant stream of literature has concentrated on the impact of explorative learning on innovation and operational performance. For instance, Raymond *et al.* (2020) found that firms that engage more in explorative learning activities are likely to achieve higher innovation performance and competitive advantage. Patel *et al.* (2012) observed that firms with higher exploration learning capabilities are in a better position to enhance manufacturing flexibility to achieve superior performance. Belhadi *et al.* (2022b) uncovered that firms engaging in explorative learning are more likely to cultivate dynamic capabilities that enable them to respond to disruptions in volatile business environments.

3. Hypotheses development

3.1. The impact of the congruence and incongruence between AI and explorative learning on supply chain resilience

STS theory indicates that the technical and social aspects of the system need to be balanced to enhance the system's effectiveness and thus achieve optimal performance (Bostrom and Heinen, 1977). AI is considered as a technical aspect that can reinforce decision-making and enhance the efficiency and effectiveness of supply chain operations (Gupta *et al.*, 2023), and explorative learning refers to a social aspect that can enable adaptability and innovation in supply chain management (Raymond *et al.*, 2020). In this study, AI and explorative learning are considered as being congruent when they are at similar levels in an organization, regardless of whether the congruence level is high or low.

We postulate that the congruence between AI and explorative learning positively influences firms' supply chain resilience for several reasons. First, fit is an essential concept of STS theory that focuses on the degree of compatibility or congruence between technical and social aspects of the system (Tong *et al.*, 2023). When AI (i.e., technical aspect) is congruent with explorative learning (i.e., social aspect), firms are better able to cultivate dynamic capabilities that enable them to adapt to and react quickly to supply chain disruptions in highly uncertain and volatile business environments (Belhadi *et al.*, 2024). As such, the congruence between AI and explorative learning of the system would elevate firms' supply chain resilience by improving their abilities to forecast, prepare for, and respond to potential supply chain disruptions, such as disruptions in the procurement of critical materials and customer demands. Such competence derives from the data analytics ability of AI and the innovation and adaptation ability of explorative learning, which collectively contribute to a more resilient supply chain that can predict and handle unexpected supply chain disruptions.

Second, firms can leverage the advanced analytics capabilities of AI to detect patterns and gain novel insights into supply and demand fluctuations. For example, firms can utilize AI techniques to conduct scenario planning and simulation exercises for better mitigating the risks of supply chain disruptions, which contributes to building supply chain resilience (Modgil *et al.*, 2022). AI can support explorative learning by providing real-time data for forecasting and decision-making that can assist firms in making better-informed decisions in response to disruptions or changes in the supply chain, thereby improving their supply chain resilience (Yu *et al.*, 2023).

Finally, by combining AI and explorative learning, firms can foster a culture of continuous improvement, which enhances their abilities to deal with unconventional emergency and disruption risks and thus elevates their supply chain resilience. Once the firms have such a culture in place, it further promotes the improvement of AI by providing valuable feedback and insights that can help refine and optimize the algorithms used in AI (Gupta *et al.*, 2023). This ensures that the adoption of AI is not only designed to optimize and automate current operations but is also geared toward improving the adaptive capability of the supply chain in the long term. The adaptive capability allows firms to rapidly respond to and recover from supply chain interruptions, thus playing a pivotal role in enabling firms to maintain continuity and enhance supply chain resilience (Dubey *et al.*, 2022; Modgil *et al.*, 2022).

H1a. *The congruence between AI and explorative learning has a positive impact on supply chain resilience.*

STS theory suggests that the misfit between technical and social factors could exert a negative impact on firm performance (Shou *et al.*, 2021). We propose that the incongruence between AI and explorative learning potentially harms firms' supply chain resilience. First, although AI can enhance decision-making processes, firms may need more explorative learning activities to develop capabilities to deal with unexpected disruptions in supply chains. Therefore, without engaging in explorative learning activities, firms could have very limited capabilities in using AI in their operations and supply chain processes and thus are less capable of handling supply chain disruptions, which erodes their supply chain resilience. Moreover, the incongruence between AI and explorative learning may lead firms to lack the necessary agility to respond quickly to supply chain disruptions. For instance, when firms rely heavily on AI but neglect explorative learning that is closely linked to innovation (Belhadi *et al.*, 2022b; Patel *et al.*, 2012), they may miss out on identifying innovative solutions and practices to cope with disruptions in supply chains. This will result in firms being technically advanced but unprepared for the dynamic nature of supply chain risks. As such, when supply chain disruptions occur, firms are unable to innovate beyond the data-driven insights provided by AI and have limited capacity to address such disruptions, which impairs their supply chain resilience.

Second, in rapidly changing business environments, developing supply chain resilience is critical. A lack of explorative learning may lead firms to encounter great difficulties in bouncing back from setbacks (Azadegan and Dooley, 2010), harming their readiness and agility in handling supply chain disruptions. Thus, firms with high AI usage but lack the accompanying ability to learn and innovate may be less resilient in the face of supply chain disruptions.

Third, the incongruence between AI and explorative learning implies that the technical and social aspects are mismatched. This could give rise to systems that must be better aligned and well-integrated to harmonize these two aspects to accomplish a common goal (Bednar and Welch, 2020). The misfit of systems can bring about a breakdown in communicating and coordinating within the supply chain, as explorative learning contributes to a shared understanding within the organization. For example, employees who need to be adequately trained in learning activities may need help in terms of collaborating with AI-based systems effectively. As such, the misfit between AI and explorative learning jeopardizes firms' ability to harness the benefits to deal with unpredictable supply chain disruptions, thus compromising their supply chain resilience.

In sum, building on STS theory, we postulate that the incongruence between AI and explorative learning hinders the supply chain's effective functioning and erodes its ability to remain alert to, adapt to, and respond promptly to unexpected supply chain disruptions, thus impairing firms' supply chain resilience.

H1b. *The incongruence between AI and explorative learning has a negative impact on supply chain resilience.*

3.2. The impact of different types of congruence: high–high vs. low–low congruence

While supply chain resilience generally tends to be in the high zone when AI and explorative learning are congruent, we propose that different types of congruence may offer additional insights into predicting variations in supply chain resilience. We postulate that high–high congruence between AI and explorative learning is associated with higher supply chain resilience than low–low congruence. First, fit, a crucial concept of STS theory, refers to the degree of compatibility between technical and social aspects of the system (Bostrom and Heinen, 1977). When AI and explorative learning are congruent at a high level, firms can better cultivate dynamic capabilities, allowing them to adapt to highly volatile business environments and build a more resilient supply chain. High–high congruence between technical and social aspects enables firms to better respond to unforeseen disruptions in supply chains, thus enhancing supply chain resilience to a greater extent. However, low–low congruence only implies a primary level of compatibility (Wang *et al.*, 2023), which is insufficient for the development of dynamic capabilities and thus limits the organization's ability to respond adeptly to changing circumstances. In the context of establishing supply chain resilience, high–high congruence between AI and explorative learning is considered more beneficial than low–low congruence because the former aligns with the development of dynamic capabilities, enables firms to better leverage the complementary benefits of technical and social aspects, and allows firms to respond to supply chain disruptions in a more effective manner. When AI and explorative learning are in the situation of low–low congruence, the supply chain may experience difficulties in handling unexpected disruptions beyond the capability of the entire STS, ultimately constraining its resilience (Bednar and Welch, 2020).

Second, analytical effectiveness is essential in navigating rapidly changing environments, contributing to superior supply chain resilience. In the low–low congruent situation where both AI and explorative are at low levels, the STS can only provide limited analytical effectiveness that hinders a firm's ability to anticipate and respond effectively to disruptions in supply chains. Consequently, the benefits of AI–explorative learning congruence for supply chain resilience may be constrained regardless of the compatibility between technical and social subsystems (Yu *et al.*, 2023). Nevertheless, as the congruence level rises, the benefits of AI–explorative learning congruence can be gradually released, as high–high congruence implies more advanced analytics capabilities that allow firms to detect patterns and gain novel insights as well as cultivate better learning capabilities to assimilate and leverage these insights. Simultaneously, a better explorative learning capability can further unfold the potential of AI and stimulate its evolvement. Collectively, compared with low–low congruence, high–high congruence can help firms better reap the benefits of the compatibility between technical and social subsystems (Bednar and Welch, 2020), which improves supply chain resilience to a larger extent.

Finally, high–high congruence refers to a high level of shared commitment that fosters a culture of continuous improvement (Wang *et al.*, 2023), enhancing firms' supply chain resilience to unexpected events and risks. This alignment promotes supply chain resilience to a greater extent by encouraging a proactive approach to handling supply chain disruptions. In contrast, low–low congruence may lead to a limited willingness to adapt to changes and thus a lower degree of the development of a culture that facilitates supply chain resilience. Therefore, firms with high–high congruence between AI and explorative learning are more likely to adapt to and respond to supply chain disruptions, elevating supply chain resilience to a greater extent.

H2. *Given that AI and explorative learning are congruent, high–high congruence is associated with higher supply chain resilience than low–low congruence.*

3.3. The moderating role of organizational inertia

STS theory indicates that a firm is a complex system comprising interacted technical and social aspects, and changes in one aspect have ripple effects throughout the entire system (Bostrom and Heinen, 1977). In this sense, the integration of AI and explorative learning is a system change and organizational inertia might hamper it. Previous research suggests that organizational inertia represents the consequence of the organizational evolution process, which encompasses internal cognition, resources, structures, and conventions (Liang *et al.*, 2017). In this sense, Hannan and Freeman (1984, p. 151) defined organizational inertia in relation to environmental changes as "structures of organizations have high inertia when the speed of reorganization is much lower than the rate at which environmental conditions change." Huang *et al.* (2013) pinpointed that inertia prevails in most organizations, and when a firm has strong inertia to retain the status quo, the firm tends to be slower in responding to environmental changes. The nature of organizational inertia represents resistance to an organization's changes and its tendency to maintain the status quo due to various factors, including bureaucratic structures, entrenched norms, and a lack of innovative culture (Huang *et al.*, 2013). Therefore, when inertia is high, firms are inclined to maintain existing routines and practices rather than integrate AI and explorative learning into supply chain management. Such hesitant changes make it hard for firms to fully reap the benefits of new technologies and learning activities, thus weakening the positive influence of the congruence between AI and explorative learning on supply chain resilience. For instance, Haier Group, a leading appliance manufacturer in China, implemented an AI-driven system to forecast volatile customer demands and optimize the replenishment of raw materials (Cheng and Xie, 2021). In principle, this technical change will improve supply chain resilience by elevating the firm's predictive abilities for navigating supply chain disruptions. However, when organizational inertia is high, employees are likely to persist with conventional processes. Thus, when unanticipated supply chain disruptions occur and request prompt responses, the firm encumbered by inertia may fail to respond to such disruptions by leveraging the insights derived from AI and explorative learning effectively, thus impairing its supply chain resilience.

Moreover, organizational inertia might induce a misfit between the socio-technical aspects and the organizational culture, which diminishes firms' flexibility and adaptability in integrating new technologies such as AI into the existing system. The reason is that organizational inertia often leads to rigid structures and processes that resist adaptation (Liang *et al.*, 2017). Therefore, although firms are aware of the congruence between AI and explorative learning, they still cannot commit to adapting it to their operations and supply chains and take full advantage of the combined benefits. This could impair the organization's capability to adapt to changing circumstances and respond to supply chain disruptions, thus attenuating the positive influence of the congruence between AI and explorative learning on supply chain resilience. For instance, Lenovo, a high-tech manufacturer, utilized AI techniques to forecast shortages or oversupplies of electronic devices, thus enhancing its supply chain resilience to unexpected disruptions (China Daily, 2022). Yet, if the firm's culture is embroiled in inertia, the evolution to AI-guided decision-making can be suppressed. Consequently, higher organizational inertia intensifies the firm's resistance to leveraging the insights generated by AI and explorative learning, ultimately compromising its supply chain resilience.

In addition, organizational inertia impedes learning and knowledge sharing in the firm (Yamoah *et al.*, 2022), thereby restricting communication and collaboration across different functions and departments. This lack of cross-functional communication and collaboration limits the organization's capability to integrate AI and explorative learning activities. As such, organizational inertia induces a low level of common understanding and cross-functional collaboration, which restrains the benefits of the congruence between AI and explorative learning, attenuating the positive impact on supply chain resilience.

H3a. *Organizational inertia weakens the positive impact of the congruence between AI and explorative learning on supply chain resilience.*

We further predict that organizational inertia exacerbates the negative influence of the incongruence between AI and explorative learning on supply chain resilience. Specifically, in a setting where AI is high but explorative learning is low, firms with high inertia not only struggle to adopt AI through learning processes but also exhibit heightened resistance to embracing the intrinsic benefits of AI, such as enhanced decision-making and automation capabilities for handling supply chain disruptions. This dual challenge stems from the deeply ingrained resistance within the organizational culture and structure (Liang *et al.*, 2017). High levels of inertia imply a rigid adherence to existing practices and a reluctance to embrace innovative technologies (Mikalef *et al.*, 2021), even when their potential benefits, such as improved supply chain resilience, are apparent. For example, Intel, a semiconductor company, utilized AI techniques for defect classifications in its production lines and supply and demand predictions, aiming to enhance its supply chain resilience (Desineni and Tuv, 2024). Nevertheless, when organizational inertia is high, it adds to entrenching dependency on outdated practices and impairs the effectiveness of AI adoption for addressing supply chain disruptions. As such, organizational inertia exacerbates the incongruent effect of AI and explorative learning, leading to lower supply chain resilience.

Moreover, in a setting where AI is low but explorative learning is high, organizational inertia aggravates the negative impact of the incongruence between these two factors on supply chain resilience. The reluctance to adopt AI, coupled with organizational inertia (Yamoah *et al.*, 2022), creates a compounding effect that hinders a firm's ability to effectively prepare for, adapt to, and respond to disruptions in supply chains, thus resulting in a greater reduction in supply chain resilience. For instance, supply chain managers who have worked for firms for an extended period may engage in explorative learning activities but still resist implementing AI, as they may feel that AI jeopardizes their job security and challenges their existing knowledge and expertise. The misfit between AI and explorative learning harms firms' ability to handle supply chain disruptions and thus compromises their supply chain resilience. In this situation, when organizational inertia is high, it aggravates the challenges posed by the incongruence between AI and explorative learning, because firms with high inertia are loath to embrace new technologies and ideas and prefer to maintain existing routines and practices (Liang *et al.*, 2017). As such, organizational inertia impairs the effectiveness of leveraging AI and explorative learning to anticipate, adapt to, and respond to disruptions in supply chains, thereby exacerbating the adverse effect of the incongruence between these two factors on firms' supply chain resilience.

H3b. *Organizational inertia exacerbates the negative impact of the incongruence between AI and explorative learning on supply chain resilience.*

The conceptual model is shown in Figure 1.

[Insert Figure 1 here]

4. Method

4.1. Data collection and sample

We conducted a survey of Chinese manufacturing companies to test the proposed model. We focused on Chinese manufacturing companies for several reasons. First, China is known as the world's factory, yet due to intensified global uncertainties and turbulences, Chinese manufacturers confront mounting risks of supply chain disruptions, which emphasizes the urgent need for them to build supply chain resilience (Jiang *et al.*, 2023). Thus, China offers a suitable and rich context in which to examine manufacturers' supply chain resilience. Second, in response to the Chinese government's policies stimulating the development and application of digital technologies such as AI, Chinese manufacturers have dedicated significant efforts to the adoption of AI (Yu *et al.*, 2024). Moreover, owing to increased market competition, Chinese manufacturers have proactively engaged in explorative learning activities. As such, it is important and meaningful to investigate how AI aligns with explorative learning to affect supply chain resilience within Chinese manufacturing industries.

According to established survey measures in the literature, we developed the questionnaire in English and then translated it into Mandarin. A third party subsequently translated the Mandarin version back into the English version to verify precision, and no semantic discrepancy was detected. Before gathering data, we invited four academic professionals and two industry experts who had extensive experience regarding operations and supply chain management to assess the content validity of the scales (Deng *et al.*, 2022). This process can help us verify the meaningfulness, wording, clarity, interpretability, structural accuracy, and relevance of each item. Based on the assessments and suggestions of these academic professionals and industry experts, a few slight adjustments on the translation from English to Chinese in terms of the wording and sentence structures were made to improve the clarity and interpretability of the scales.

We targeted the operations or supply chain managers as key informants, given that they possess a comprehensive understanding of their firms' supply chains (El Baz and Ruel, 2021). A professional survey company was employed to help us collect data. The company randomly distributed the questionnaire to 948 Chinese manufacturing firms. Eventually, we received 246 responses, among which 66 responses were excluded due to missing data. This results in a response rate of 17.9% with 170 valid responses. Table 1 presents the demographic information of our sample regarding type of ownership, annual revenue, number of employees, and firm age.

[Insert Table 1 here]

4.2. Assessment of bias

First, the potential nonresponse bias was checked (Hair *et al.*, 2010). The *t*-test indicates no significant differences across all constructs between the first 25% and last 25% responses. Thus, nonresponse bias is not a severe concern in our research.

Second, we made the following efforts to alleviate the impact of common method bias (CMB). Specifically, as information reliability can lower the likelihood of CMB (Deng *et al.*, 2022), we targeted respondents who are supply chain professionals with a strong knowledge base. Moreover, we performed the Harman's single-factor test (Podsakoff *et al.*, 2003). Compared with our measurement model, the results (χ^2=484.181, d.f.=102, p=0.000, RMSEA=0.149, GFI=0.704, CFI=0.620, NFI=0.570, IFI=0.626) are significantly worse. Additionally, to assess the influence of CMB, we utilized a marker variable (i.e., the lowest bivariate correlation among the manifest variables) (Williams *et al.*, 2010). We computed the adjusted correlations and found that they are significant after the adjustment. Collectively, these results suggest that CMB is not a serious issue for our study.

Finally, we took the following measures to mitigate possible social desirability. Specifically, we adopted well-established multi-item scales used in previous studies (e.g., Azadegan and Dooley, 2010; Belhadi *et al.*, 2024) and elaborately worded the Mandarin version of the questions to ensure neutrality. We also assured the respondents that their responses would remain anonymous. Moreover, key constructs involved in this study were presented discretely in the original survey, which makes them less subject to social desirability bias because it is unlikely that informants will respond based on a connected mindset. Additionally, following Deng *et al.* (2022), we conducted an independent sample *t*-test for key variables to assess possible bias, which indicated no significant difference between the first and last quarter of the responses (e.g., $t=-1.29$ for supply chain resilience).

4.3. Measurement and validity

All measures for the constructs in our conceptual model were adopted from established multi-item scales in the extant literature. Specifically, we used five items to measure AI (Belhadi *et al.*, 2024) and three items to measure explorative learning (Azadegan and Dooley, 2010). The measure of supply chain resilience was derived from El Baz and Ruel (2021). Our measure of organizational inertia was derived from Li *et al.* (2019). These items were measured with a 5-point Likert scale that ranges from 1 (strongly disagree) to 5 (strongly agree). Table 2 presents the survey items we used.

The validity and reliability of the constructs used in this study were evaluated in the following ways. First, we evaluated the convergent and discriminant validity of the four latent variables (i.e. AI, explorative learning, supply chain resilience, and organizational inertia) in our conceptual model through a confirmatory factor analysis (CFA) in AMOS. Table 2 displays factor loadings, Cronbach's alpha, average variance extracted (AVE) values, and composite reliability. To assess discriminant validity, we followed the method outlined by Hair *et al.*

(2010), which involves comparing the correlation between all possible construct pairs with the square root of the AVE value of each construct. Table 3 depicts that the square root of the AVE value of each construct is higher than its correlations with other constructs. This offers strong evidence of discriminant validity. Besides, the results of CFA (χ^2=165.771, d.f.=84, p=0.000, RMSEA=0.078, GFI=0.872, CFI=0.912, NFI=0.842, IFI=0.913) suggest an adequate model fit.

[Insert Table 2 here]

4.4. Polynomial regression and response surface analyses

Following previous literature (Deng *et al.*, 2022), we employed polynomial regressions coupled with the response surface analyses (RSA) to test the proposed hypotheses. Polynomial regression incorporates the linear and quadratic terms for AI and explorative learning in addition to their linear interaction term, as shown in Eq. (1). It offsets the methodological shortcomings such as oversimplification and inaccuracy of traditional difference scores and thus serves as an ideal approach to study the congruence effects (Edwards and Cable, 2009).

$$SCR = b_0 + b_1AI + b_2EL + b_3AI^2 + b_4(AI \times EL) + b_5EL^2 + e \qquad (1)$$

In Eq. (1), SCR represents supply chain resilience, AI stands for artificial intelligence, and EL denotes explorative learning. To further investigate the moderating effect, we included organizational inertia (OI) and the product of OI with each term in Eq. (1) to generate Eq. (2). To enhance the interpretability of the results, we mean-centered AI, EL, and OI.

$$SCR = b_0 + b_1AI + b_2EL + b_3AI^2 + b_4(AI \times EL) + b_5EL^2 + b_6OI + b_7(AI \times OI) + b_8(EL \times OI) + b_9(AI^2 \times OI) + b_{10}(AI \times EL \times OI) + b_{11}(EL^2 \times OI) + e \qquad (2)$$

Then, the estimated coefficients can be explained by using the RSA which provides a precise visualization and evaluation of a three-dimensional surface corresponding to the above polynomial regressions (Wang *et al.*, 2023). Specifically, the interpretation of the results relies on the slopes and curvatures of the surface along the congruence (where $AI = EL$) and incongruence (where $AI = -EL$) lines (Edwards and Cable, 2009). To derive the response surfaces, we substituted $AI = EL$ and $AI = -EL$ for the congruence and incongruence lines in Eq. (1) and developed Eq. (3) and Eq. (4), respectively.

$$SCR = b_0 + (b_1 + b_2)AI + (b_3 + b_4 + b_5)AI^2 + e \qquad (3)$$

$$SCR = b_0 + (b_1 - b_2)AI + (b_3 - b_4 + b_5)AI^2 + e \qquad (4)$$

Hence, $b_1 + b_2$ and $b_1 - b_2$ represent the slopes along the congruence and incongruence lines, respectively; $b_3 + b_4 + b_5$ and $b_3 - b_4 + b_5$ represent the corresponding curvatures along the congruence and incongruence lines (Shanock *et al.*, 2010). Similarly, to inspect the slopes and curvatures along the congruence and incongruence lines in the moderated model, we transformed Eq. (2) into the following models.

$$SCR = b_0 + (b_1 + b_2 + b_7OI + b_8OI)AI + (b_3 + b_4 + b_5 + b_9OI + b_{10}OI + b_{11}OI)AI^2 + b_6OI + e \qquad (5)$$

$$SCR = b_0 + (b_1 - b_2 + b_7OI - b_8OI)AI + (b_3 - b_4 + b_5 + b_9OI - b_{10}OI + b_{11}OI)AI^2 + b_6OI + e \qquad (6)$$

where $(b_1 + b_2 + b_7OI + b_8OI)$ and $(b_1 - b_2 + b_7OI - b_8OI)$ represent the slopes along the congruence and incongruence lines, respectively; $(b_3 + b_4 + b_5 + b_9OI + b_{10}OI +$

$b_{11}OI$) and $(b_3 - b_4 + b_5 + b_9OI - b_{10}OI + b_{11}OI)$ stand for the curvatures along the congruence and incongruence lines, respectively.

5. Results

The descriptive statistics and correlation coefficients of all variables are presented in Table 3. We calculated the values of variance inflation factors (VIFs). All VIF values are lower than the recommended threshold of 10, indicating that multicollinearity is not a concern in our study.

[Insert Table 3 here]

Before generating the interaction and curvilinear terms, we centered the scores of AI and EL by deducting the scale mid-point from the measured values (i.e., 3) to reduce multicollinearity and promote their interpretation (Paulraj and Blome, 2017). We initially controlled for four demographic features (shown in Table 1) of the sample firms, including ownership, annual revenue, number of employees, and firm age. The control variables did not show significance in the models. Consequently, we dropped them to generate response surfaces that reflect the combined effect of AI and EL (Paulraj and Blome, 2017).

H1a (H1b) posits that the congruence (incongruence) between AI and explorative learning enhances (impairs) supply chain resilience, which can be verified after satisfying two conditions. First, it is expected that the incongruence line exhibits an inverted U-shape, suggesting that the curvature along the incongruence line should be significantly negative. Moreover, the slope and intercept of the first principal axis of the concave surface should not be significantly different from one and zero, respectively (Edwards and Cable, 2009). This would indicate that the first principal axis does not deviate from the projection of the congruence line in the "AI−EL" plane.

Hence, the downward trend would be minimal along the congruence line but maximal along the incongruence line. Table 4 demonstrates the results of polynomial regressions and response surface features. We discovered that the curvature along the incongruence line is significantly negative ([$b_3 - b_4 + b_5$]=−0.55, p<0.01), thereby satisfying the first condition of the congruence effect. Furthermore, we utilized the bootstrapping approach to derive 10,000 subsamples and constructed the 95% bias-corrected confidence intervals (CI) for the slope and curvature of the first principal axis, respectively. The slope of the first principal axis is not significantly different from one (95% bias-corrected CI=[−1.77, 3.45]) and the intercept is not significantly different from zero (95% bias-corrected CI=[−4.41, 25.38]), which meets the second condition of the congruence effect (Edwards and Cable, 2009). Hence, in together, H1a and H1b are supported. We also plotted the response surface in Figure 2(a) and found that it curves downward along the incongruence line, such that supply chain resilience is higher when AI and explorative learning are more congruent.

H2 predicts that high–high congruence between AI and explorative learning leads to higher supply chain resilience as compared to low–low congruence. In Model 1 of Table 4, we found that the slope along the congruence line is significant and positive ([$b_1 + b_2$]=0.41, p<0.05). This indicates that under the condition of congruence, supply chain resilience will be higher when AI and explorative learning are congruent at a higher level. Hence, H2 is supported.

H3a (H3b) proposes that the positive (negative) impact of the congruence (incongruence) between AI and explorative learning on supply chain resilience will be weakened (exacerbated) when organizational inertia increases. In Table 4, we observed that the addition of OI and its interactions with other polynomial terms into Model 1 will lead to significant increases in R-squared in Model 2 and Model 3, respectively (Model 2: ΔR^2=0.03, p<0.05; Model 3: ΔR^2=0.08, p<0.001). In Model 3, the curvature along the incongruence line becomes −1.40 (p<0.001). Moreover, we estimated the response surface parameters at the mean of OI, and mean minus and plus one standard deviation of OI, as shown in Table 5. We further plotted the corresponding surfaces in Figure 2(b)-(d). This displays that the inverted U-shaped curvilinear surface along the incongruence line is steepened significantly at higher levels of OI, implying that the positive (negative) effect of the congruence (incongruence) between AI and explorative learning on supply chain resilience is weaker (stronger) when organizational inertia is higher. Collectively, H3a and H3b are supported.

[Insert Tables 4 and 5 here]

[Insert Figure 2 here]

Power analysis was also conducted to ensure the power of our estimations. We adopted an R^2 method that computes power given the sample size and R^2 of the models (Chau *et al.*, 2020). All our models have a power value over 0.9, which exceeds the prescribed threshold (Chau *et al.*, 2020).

6. Discussion and conclusion

6.1. Theoretical contributions

Our study makes several theoretical contributions. First, it extends the supply chain resilience literature by empirically untangling how the congruence and incongruence between AI and explorative learning affect supply chain resilience. Previous studies have mainly examined the unilateral effect of AI (Le and Behl, 2023; Leoni *et al.*, 2022) and explorative learning (Belhadi *et al.*, 2022b; Eryarsoy *et al.*, 2022) on supply chain resilience, yet the joint effect of these two factors on supply chain resilience remains largely underexplored in the existing body of work. Our study takes an initial step in examining how AI aligns with explorative learning to influence supply chain resilience, thus responding to a recent call for more research investigating the synergic effect of different factors on supply chain resilience (Jiang *et al.*, 2023). We emphasize the importance of the balance between a system's technical aspect (i.e., AI) and social aspect (i.e., explorative learning) to enhance its effectiveness and achieve better resilience in the supply chain. Our results confirm that when AI and explorative learning are congruent, they complement each other and enable firms to boost supply chain resilience. In contrast, the incongruence between AI and explorative learning signifies a lack of fit and compatibility between the technical capabilities of AI and the social processes of explorative learning within the organization. Such incongruence hinders the organization's ability to leverage the full potential of AI in enhancing supply chain resilience. This phenomenon may be due to inefficiencies when AI, the technical capability, is not seamlessly integrated with explorative learning, the social process. Therefore, achieving supply chain resilience requires a harmonious blend of technical capability and social process, underscoring the significance of the congruence between AI and explorative learning in the modern supply chain landscape.

Our study also engages in dialog with previous research which underlines the importance of the integration of technical and social aspects. Although the extant literature has highlighted the advantage of the fit between technical and social aspects (Chaudhuri and Jayaram, 2019;

Shou *et al.*, 2021; Tong *et al.*, 2023), rare efforts have been devoted to unpacking how the fit between AI and explorative learning promotes supply chain resilience. Our results imply that only pursuing technological advancements, such as AI, without sufficient attention to aligning them with explorative learning, may lead to unintended consequences and even backfire. Issues such as lack of adaptability to changes and disruptions in communication and collaboration may arise. Hence, the incongruence between AI and explorative learning compromises the organization's capacity to prepare for, adapt to, and respond effectively to supply chain disruptions, resulting in weakened supply chain resilience.

Moreover, we broaden the understanding of how different types of congruence between AI and explorative learning exert distinct effects on supply chain resilience. We uncover that compared with low–low congruence, high–high congruence between AI and explorative learning can better facilitate supply chain resilience. This result supports the idea that the benefits reaped from a low-level congruence between AI and explorative learning could be inherently limited. That is, the supply chain might experience difficulties in coping with unexpected disruptions beyond the capability of the entire STS, regardless of the potential complementary effect between the system's technical and social aspects, which ultimately constrains supply chain resilience. Nevertheless, as the level of congruence escalates, the advantages of the compatibility between technical and social subsystems can gradually manifest (Bednar and Welch, 2020), which elevates firms' supply chain resilience to a greater extent. This finding adds knowledge to prior research by offering a more fine-grained understanding of factors affecting the magnitude of supply chain resilience (El Baz and Ruel, 2021; Mirzabeiki and Aitken, 2023).

Second, our study provides novel insights by disentangling that organizational inertia weakens the positive influence of the congruence between AI and explorative learning on supply chain resilience, while exacerbating the negative influence of the incongruence between these two factors on supply chain resilience. This finding lends support to the notion that an organization's resistance to changing regular operating routines and the current status quo impairs its willingness and capability to fully utilize resources and leverage emerging digital technologies effectively (Mikalef *et al.*, 2021). Consequently, organizational inertia acts as a barrier that undermines the benefits of the congruence between AI and explorative learning for building supply chain resilience. Meanwhile, it aggravates the adverse impact of the incongruence between these two factors on supply chain resilience. Despite that prior studies have examined the influence of organizational inertia on circular economy practices (Yamoah *et al.*, 2022), organizational agility (Liang *et al.*, 2017), and dynamic capability (Mikalef *et al.*, 2021), little is known about how organizational inertia alters the joint effect of AI and explorative learning on supply chain resilience. Recently, OSCM scholars have called for more research to explore the boundary condition of supply chain resilience (Eryarsoy *et al.*, 2022; Sturm *et al.*, 2023). Echoing this call, our research sheds light on the supply chain resilience literature by investigating the important yet neglected role of organizational inertia in modifying the effect of the congruence and incongruence between AI and explorative learning on supply chain resilience.

Finally, this research enriches the literature on STS theory by theoretically elucidating the interplay of AI, explorative learning, and organizational inertia in shaping firms' supply chain resilience. Previous studies have primarily employed the resource-based view (Eryarsoy *et al.*, 2022), practice-based view (Dubey *et al.*, 2022), dynamic capability theory (Sturm *et al.*, 2023; Wei *et al.*, 2023), panarchy theory (Mirzabeiki and Aitken, 2023), and information processing theory (Yu *et al.*, 2024) to examine the antecedents of supply chain resilience. Nonetheless, the literature has offered limited knowledge regarding the use of STS theory as the theoretical lens to explicate how firms balance technical and social subsystems to boost supply chain resilience. In this sense, our research contributes to the theoretical advancement of STS theory by adopting it to illuminate how the alignment between AI (i.e., technical aspect) and explorative learning (i.e., social aspect) influences firms' supply chain resilience. More importantly, our research introduces a boundary condition to STS theory by articulating how organizational inertia alters the system change induced by the integration of AI and explorative learning, thus resonating with previous research which highlights that organizational characteristics affect the effectiveness of STS (Soliman *et al.*, 2018). Overall, our study sheds new light on the STS literature by delineating the congruent effect of AI and explorative learning on supply chain resilience and the role of organizational inertia as the boundary condition.

6.2. Managerial implications

This research provides several insightful implications for operations and supply chain managers. First, our findings reveal that the congruence between AI and explorative learning boosts supply chain resilience, while the incongruence between them impairs supply chain resilience. This highlights that when AI and explorative learning are at similar levels (i.e., low–low or high–

high), firms can achieve higher supply chain resilience. This also informs managers that the imbalance between AI and explorative learning (i.e., low–high or high–low) is undesirable because it is detrimental to firms' supply chain resilience. Thus, we strongly suggest that firms should strive to align AI with explorative learning rather than simply focusing on either AI or explorative learning in isolation. Moreover, by showing that low–low congruence is better than low–high and high–low incongruence, our study provides insights regarding why some firms fail to succeed with AI, as failure to understand firms' balanced STS may lead to an incomplete or even biased assessment of the benefits derived from AI. When firms are in a balanced low–low STS, they can maintain stable operations and leverage the synergic effect of AI and explorative learning to build supply chain resilience. Yet, once either system is alert, the imbalanced STS would disrupt existing stable operations and harm supply chain resilience. For example, firms invest considerable resources in developing a high level of AI but underinvest in explorative learning. In this situation, employees will find it challenging to adapt quickly to such technologically innovative environments enabled by AI, which ultimately would negatively influence established supply chain resilience. Hence, we advise that firms should be mindful of the potential dark side of the incongruence between AI and explorative learning and make efforts to harmonize them to elevate supply chain resilience. For instance, firms can arrange regular meetings between different departments to promote communication and coordination and put more emphasis on timely evaluation of the current levels of AI and explorative learning. In doing so, firms can better detect incongruent situations and balance their resource allocations to ensure that AI and explorative learning are aligned and complement each other effectively.

Second, managers need to recognize the importance of fostering high levels of both AI and explorative learning, because high–high congruence is better than low–low congruence. Our results indicate that compared with low–low congruence, high–high congruence between AI and explorative learning can enhance supply chain resilience to a greater extent. Therefore, we highly recommend that firms invest resources in developing AI and explorative learning capabilities simultaneously to maximize their complementary effect on supply chain resilience. For example, firms can increase the use of AI techniques in their operations and supply chain processes, such as developing AI-based systems and utilizing AI techniques to predict supply and demand changes and advance decision-making. Meanwhile, they can make dedicated efforts to cultivate high explorative learning capabilities, such as undertaking frequent training programs to nurture employees' creativity and conducting experiments to generate new ideas or products.

Finally, managers need to be alarmed that organizational inertia attenuates the positive influence of the congruence between AI and explorative learning on supply chain resilience, while it exacerbates the negative effect of the incongruence between these two factors on supply chain resilience. Given this, managers should be cautious about the potential downside of organizational inertia and carefully oversee the level of organizational inertia. Hence, it is suggested that when engaging in AI and explorative learning simultaneously, firms should be vigilant about analyzing the change in organizational inertia and proactively take actions to lower the level of organizational inertia to alleviate its adverse impact. For example, firms can empower the workforce, reward the efforts of employees, and promote cross-functional collaboration and mutual trust to mitigate organizational inertia.

6.3. Limitations and future research

Our research has a few limitations, which point out the avenues for future research. First, our study centers on the Chinese context, which might hinder the generalizability of our results in the context of other countries. Future studies are encouraged to gather data from other countries to verify our results. Second, drawing upon STS theory, we unearth how the congruence between AI and explorative learning enhances firms' supply chain resilience. Future research could contribute to the relevant literature by unpacking the synergic effect of AI and other social factors (e.g., human capital) on supply chain resilience. Third, we examine the critical role of organizational inertia in shaping the impact of the congruence between AI and explorative learning on supply chain resilience, yet there might be other contingent factors (e.g., supply chain complexity and uncertainty) that reinforce or attenuate this impact. Hence, a promising pathway for future research is to investigate other potential contingency factors, which can provide more implications regarding the boundary conditions of supply chain resilience. Finally, our study uses a traditional definition of supply chain resilience, which mainly denotes a firm's ability to respond quickly to supply chain disruptions and bounce back to the original or desired status (El Baz and Ruel, 2021; Sturm *et al.*, 2023). Complementing this traditional view, recent research has drawn on social-ecological systems theory to elucidate supply chain resilience, highlighting the evolutionary adaptation and radical transformation of the system in response to supply chain disruptions (Wieland *et al.*, 2023). Future research can build on this theory to further augment our understanding of how to build supply chain resilience.

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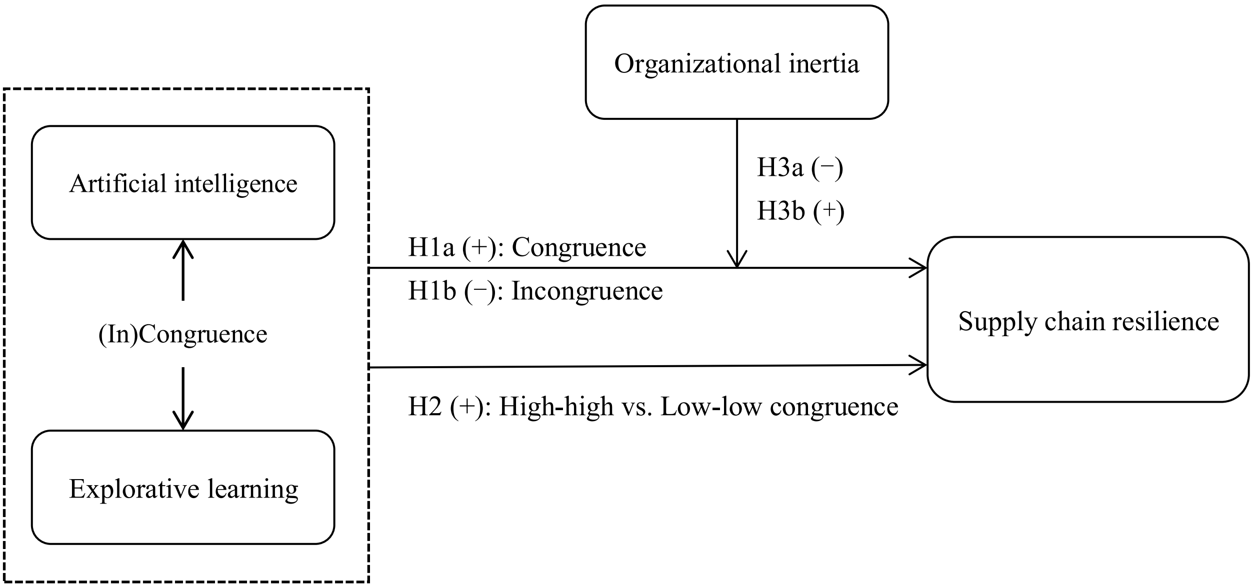
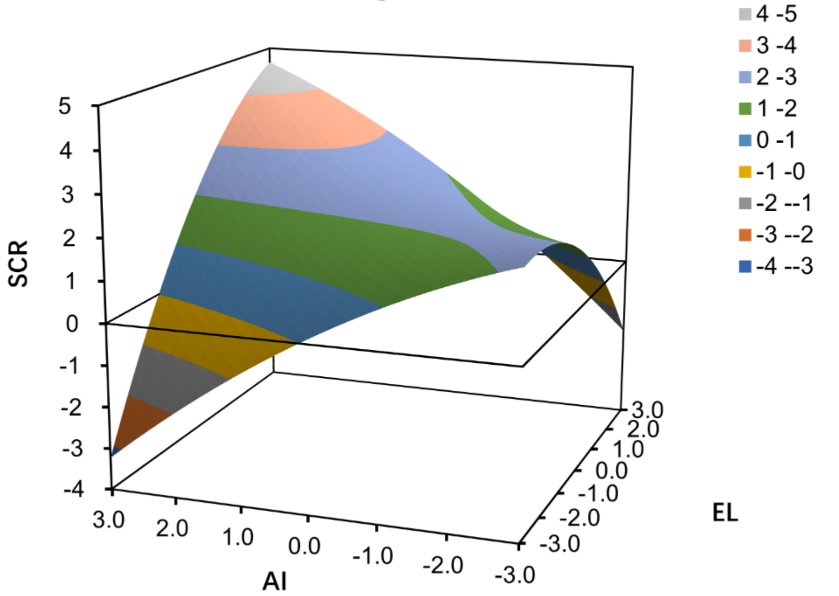
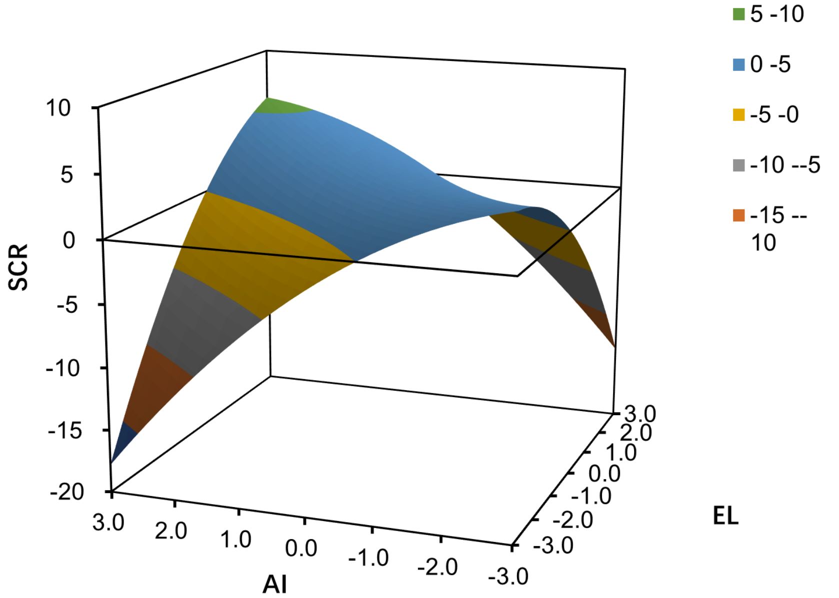


Figure 1. Conceptual model

a. Original model



b. -1SD of OI



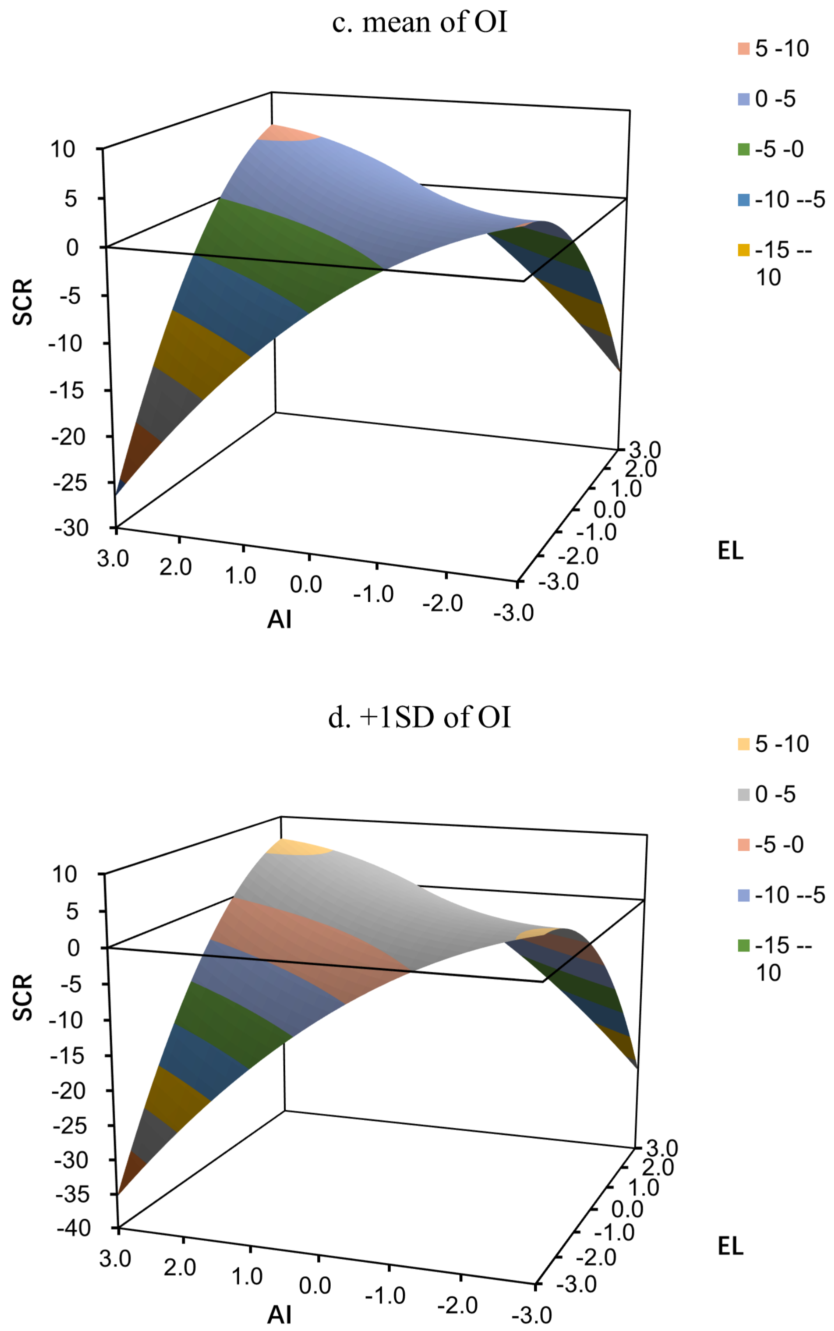


Figure 2. Response surfaces

Table 1. Demographic information of the sample

		Frequency	Percentage (%)
Ownership	State-owned firms	40	23.5
	Privately owned firms	105	61.8
	Foreign controlled firms	25	14.7
Annual revenue (million CNY)	<3	3	1.8
	3 to 20	25	14.7
	20 to 100	58	34.1
	100 to 400	35	20.6
	400 to 1000	19	11.2
	>1000	30	17.6
Number of employees	<100	17	10
	100 to 299	43	25.3
	300 to 499	21	12.4
	500 to 999	40	23.5
	1000 to 4999	41	24.1
	>5000	8	4.7
Firm age (years)	≤5	3	1.8
	6-10	15	8.8
	11-20	73	42.9
	21-30	52	30.6
	>30	27	15.9

Table 2. Measurement validity and reliability

Constructs	Items	Factor loadings	Cronbach's alpha	AVE	CR
Artificial intelligence (Belhadi *et al.*, 2024)	Please complete the following set of items by indicating to what extent your company has ever taken the following action (1=strongly disagree; 5=strongly agree):			0.52	0.85
	AI1. We possess the infrastructure and skilled resources to apply AI information processing system.	0.69			
	AI2. We use AI techniques to forecast and predict environmental behavior.	0.70			
	AI3. We develop statistical, self-learning, and prediction using AI techniques.	0.72			
	AI4. We use AI techniques at all levels of the supply chain.	0.79			
	AI5. We use AI outcomes in a shared way to inform supply chain decision-making.	0.72			
Explorative learning (Azadegan and Dooley, 2010)	Please complete the following set of items by indicating your level of agreement on each of the statements below (1=strongly disagree; 5=strongly agree):			0.48	0.74
	EL1. Frequently experiments with important new ideas or ways of doing things.	0.71			
	EL2. Employees frequently come up with creative ideas that challenge conventional ideas.	0.68			
	EL3. Compared to competition, a high percent of sales come from new products launched in the past three years.	0.69			
Supply chain resilience (El Baz and Ruel, 2021)	Please complete the following set of items by indicating your level of agreement on each of the statements below (1=strongly disagree; 5=strongly agree):			0.40	0.73

	SCR1. We are able to cope with changes brought by the supply chain disruption.	0.56		
	SCR2. We are able to adapt to the supply chain disruption easily.	0.70		
	SCR3. We are able to provide a quick response to the supply chain disruption.	0.68		
	SCR4. We are able to maintain high situational awareness at all times.	0.58		
Organizational inertia (Li *et al.*, 2019)	Please complete the following set of items by indicating your level of agreement on each of the statements below (1=strongly disagree; 5=strongly agree):		0.60	0.82
	OI1. Massive changes or adjustments to mechanisms in our company are very difficult.	0.75		
	OI2. Communication and coordination in our company are expensive and time-consuming.	0.82		
	OI3. We cannot change and adjust our mechanisms quickly to adapt to changing environments.	0.76		

Note: All estimated loadings are significant at $p<0.001$; AVE=average variance extracted; CR=composite reliability.

Table 3. Descriptive statistics, correlations matrix, and discriminant test

Constructs	Mean	S.D.	1	2	3	4	5	6	7	8
1. Artificial intelligence	3.90	0.66	*0.72*							
2. Explorative learning	3.87	0.67	0.60**	*0.69*						
3. Supply chain resilience	3.99	0.58	0.53**	0.59**	*0.63*					
4. Organizational inertia	2.81	0.99	-0.06	-0.12	-0.23**	*0.78*				
5. Ownership	1.91	0.61	-0.03	0.03	0.15	-0.05	/			
6. Annual revenue	3.78	1.37	0.18*	0.05	0.11	0.01	-0.10	/		
7. Number of employees	3.41	1.46	0.20**	0.18*	0.07	-0.04	-0.17*	0.73*	/	
8. Firm age	3.50	0.93	0.17**	0.06	0.03	0.00	-0.19*	0.43**	0.41**	/

Note: *p<0.05; **p<0.01 (two-tailed test); The values along the diagonal are the square root of the AVE values.

Table 4. Results of polynomial regressions

Variables	Model 1	Model 2	Model 3
Constant	2.32***	2.87***	2.93***
AI	0.09	0.08	0.19
EL	0.32**	0.26*	0.11
AI^2	-0.07	-0.08	-0.13$^+$
$AI \times EL$	0.33**	0.35*	0.36**
EL^2	-0.14$^+$	-0.13	-0.06
OI		-0.11**	-0.09
$AI \times OI$			-0.22
$EL \times OI$			0.16
$AI^2 \times OI$			-0.17*
$AI \times EL \times OI$			0.45**
$EL^2 \times OI$			-0.22+
Response surface features			
Congruence line ($AI = EL$)			
Slope ($b_1 + b_2$)	0.41*	0.34*	0.25
Curvature ($b_3 + b_4 + b_5$)	0.11	0.14	0.23+
Incongruence line ($AI = -EL$)			
Slope ($b_1 - b_2$)	-0.23	-0.18	-0.30
Curvature ($b_3 - b_4 + b_5$)	-0.55**	-0.56**	-1.40***
F-value	24.57	23.17	14.82
R^2	0.43	0.46	0.51
ΔR^2		0.03*	0.08***
Observations	170	170	170

Note: +p<0.1; *p<0.05; **p<0.01; ***p<0.001 (two-tailed test).

Table 5. Results of moderating analyses

	Congruence line (AI=EL)						Incongruence line (AI=−EL)					
	Slope			Curvature			Slope			Curvature		
	Observed coefficient	Bootstrap 95% CI		Observed coefficient	Bootstrap 95% CI		Observed coefficient	Bootstrap 95% CI		Observed coefficient	Bootstrap 95% CI	
		LLCI	ULCI		LLCI	ULCI		LLCI	ULCI		LLCI	ULCI
OI -1SD	0.20	-0.70	1.11	0.28	-0.19	0.75	-0.61	-1.99	0.77	-2.08	-3.96	-0.20
OI mean	0.15	-1.21	1.51	0.34	-0.34	1.01	-0.99	-3.07	1.08	-2.92	-5.70	-0.14
OI +1SD	0.09	-1.74	1.92	0.40	-0.49	1.28	-1.38	-4.17	1.42	-3.76	-7.47	-0.05

Note: bootstrap with 10,000 replications; +p<0.1; *p<0.05; **p<0.01 (two-tailed test); LLCI=lower limit confidence interval, ULCI=upper limit confidence interval.