Big data artificial intelligence to promote new product performance: the role of electronic-supply chain collaboration in B2B firms

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Abstract

Purpose – This study aims to examine how big data analytical intelligence (BDAI) assimilation promotes new product performance (NPP) in business-to-business (B2B) manufacturing firms. This study tests the intermediary role of artificial intelligence (AI) capabilities and the contingency impact of electronic supply chain collaboration (ESCC) in the relationship between BDAI assimilation and NPP.

Design/methodology/approach – Drawing on the dynamic capabilities theory (DCT), this study tests the moderated-mediation model using multi-wave, multi-source data collected from 291 Chinese B2B manufacturing firms. Structural equation modeling was applied to test the proposed hypotheses.

Findings – The results demonstrate that BDAI assimilation significantly promotes NPP, and AI capabilities act as an intermediary bridge – empowering B2B firms to convert BDAI assimilation into enhanced NPP. This study further found that this mediation model is strengthened through the contingency impact of ESCC and increases its indirect effect on NPP.

Practical implications – This study suggests that B2B managers and policy architects should recognize that investment in BDAI assimilation is not sufficient. However, building AI capabilities might fully support BDAI assimilation to gain innovation outcomes such as NPP. This study further suggests the practical implications of ESCC in achieving higher returns through AI capabilities in the B2B context.

Originality/value – This study has threefold contributions to the existing literature on big data innovation and B2B firms. This study contributes to extend DCT by emphasizing AI capabilities as an intermediary channel and ESCC as a vital contingency – strengthening the relationship between BDAI assimilation and NPP. We contributed and understand how Chinese B2B firms strategically used big data and AI strategies to reach firms' competitive advantage.

Keywords Big data analytical intelligence, Artificial intelligence capabilities, Electronic supply chain collaboration, New product performance

Paper type Research paper

1. Introduction

In the recent decade, business-to-business (B2B) firms have faced multifaceted challenges in innovating new product strategies to advance productivity and performance (Getnet *et al.*, 2024; Zouari *et al.*, 2025). In China, B2B manufacturing firms are at the forefront of industrial transformation. Thus, digital revolution has become not only an opportunity but also a strategic necessity (Huang *et al.*, 2025). To remain competitive, firms are seeking to adopt and apply innovative technologies to enhance operational efficiency and improve new product performance (NPP; Deng *et al.*, 2025; Lu *et al.*, 2025). Such technological support becomes a central driver for long-term survival and competitiveness in B2B markets (Maga and Bodlaj, 2025). However, despite this technological importance, several Chinese firms are still struggling to integrate emerging technological support into their innovation strategy, which may impact their inferior NPP, lower efficiency and productivity (Holmes *et al.*, 2023; Manzoor *et al.*, 2025).

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In this study, we focus on big data analytical intelligence (BDAI) assimilation, which is defined as the combination of large-scale data collection with the help of artificial intelligence (AI) tools to support and enhance organizational decision-making (Zhang *et al.*, 2020). Manyika *et al.* (2011, p. 1), demonstrated that "big data refers to data sets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze" while recently, Wang and Wang (2020, p. 12) noted that:

> [. . .] vast data sets are gathered from multiple platforms and resources such as social media networks, electronic websites, customer sales records, and mobile devices as the size can be as big as some terabytes to many petabytes.

A growing body of literature acknowledged the value of BDAI in various contexts, such as healthcare supply chain, market-based performance, market agility, alliance relationships, organizational competitiveness, and micro and small family business innovativeness (Hajli *et al.*, 2020; Mikalef *et al.*, 2021; Lin *et al.*, 2022; Bag *et al.*, 2023; Deng *et al.*, 2024; Nusrat *et al.*, 2025). However, evidence remains limited and underexplored on how BDAI, specifically the "assimilation" of BDAI (e.g. Zhang *et al.*, 2020), contributes to improving NPP in a B2B context. This crucial gap motivates this study investigation.

Drawing on the dynamic capability theory (DCT), this study emphasizes that a firm's ability to adapt to changing environments via technological expansion is crucial for cultivating sustainable growth and performance (Teece, 1990, 2017). DCT suggests a firm's capacity to reconfigure, regroup and rebuild internal resources – including firm-level knowledge and technological assets – in response to growing market environments and uncertainties (Teece, 2010, 2017). Building on this logic, we propose that the assimilation of BDAI, although necessary, is not sufficient in itself to promote NPP. Instead, B2B firms require AI capabilities – a particular type of dynamic capability that we theorize acts as an intermediary channel for fostering the deployment of BDAI assimilation. Prior research has demonstrated that AI capabilities help facilitate firms' ability to interpret machine learning methods and advanced algorithms related to significant data advancements (Wamba *et al.*, 2017; Zhang *et al.*, 2020; Wang and Wang, 2020; Mikalef *et al.*, 2021; Vitezić and Perić, 2024). In this vision, BDAI assimilation reflects the demand to which data-driven practices are embedded in firm processes, while on the other hand, AI capabilities enable firms to sense such opportunities, seize them and reconfigure resources accordingly (Dubey *et al.*, 2022; Di Vaio *et al.*, 2022). Characteristically, we explain the logic that these two constructs are interdependent, where BDAI assimilation provides the technological foundation, and AI capabilities ensure that data can be transformed into actionable strategies to develop NPP.

Drawing on the potential of our mediation model (e.g. BDAI assimilation, AI capabilities and NPP), this study further designs a moderated-mediation model. It proposes that this mediation pathway is contingent on the quality of intrafirm linkages, specifically firms' external supply chain digital alliance, hybrid relationships and AI linkages. We introduce and focus on electronic supply chain collaboration (ESCC), which strengthens the indirect effect on NPP through BDAI assimilation and AI capabilities. We explain that ESCC supports BDAI assimilation and AI capabilities by sharing digital knowledge, fostering alliances and coordination, and ensuring digital synchronization across worldwide supply chain partners (Al-Omoush *et al.*, 2023; Lenuwat *et al.*, 2025). For B2B businesses, ESCC facilitates digital knowledge exchanges, strengthens global supply chain alliances and provides a collaborative vision and visibility to achieve a firm's competitive advantage (Zhang *et al.*, 2024). B2B businesses lacking ESCC often face ineffective and fragmented information, as well as delayed responses to new market shifts, which limits the profitability of big data innovation strategies and decreases firms' ability to enhance NPP (Yu *et al.*, 2022; Wei *et al.*, 2023). Contrarily, B2B firms with well-organized ESCC are embedded in continuous networked settings that enable BDAI assimilation and AI capabilities to promote NPP strategically (Al-Omoush *et al.*, 2023).

This study has threefold contributions to the existing literature on big data innovation and B2B firms. First, we expand theoretical knowledge by demonstrating how BDAI assimilation improves NPP, while also contributing to the broader debate on data-driven innovation in B2B manufacturing firms. Apart from the prior studies' findings that have mainly investigated the direct impact of BDAI (Zhang *et al.*, 2020; Bag *et al.*, 2023; Huang *et al.*, 2025; Deng *et al.*, 2025; Lu *et al.*, 2025; Manzoor *et al.*, 2025), this study contributed to and underlined the synergistic effect of BDAI on NPP by unfolding how its assimilation transforms innovation performance. Second, we present and unpack AI capability as a vital dynamic capability acting as an intermediary bridge to transform and mediate between BDAI assimilation and NPP. Whereas preceding literature has increasingly focused on its multifaceted direct nature (e.g. Dubey *et al.*, 2022; Di Vaio *et al.*, 2022; Vitezić and Perić, 2024; Nusrat *et al.*, 2025), we contributed to and empirically tested its particular role as a potential mediator. Third, this study contributes and presents ESCC as a critical moderating factor that significantly and indirectly affects NPP via BDAI assimilation and AI capabilities. Drawing on the core tenets of DCT (Teece, 2010, 2017), we explore its interactive nature by illustrating how firms' external supply chain alliances support the provision of BDAI-driven insights into value-added NPP in the B2B context.

2. Theory and hypotheses development

2.1 BDAI assimilation through the lens of DCT

BDAI assimilation is fundamental for improving NPP when viewed through the lens of DCT (Mikalef *et al.*, 2021). Building on the DCT (Teece, 1990), this study argues that sustained competitiveness for B2B firms in an unpredictable environment is contingent on their ability to sense new opportunities, seize them effectively and reconfigure resources accordingly (Teece, 2010). BDAI assimilation refers to the extent to which a B2B firm integrates big data techniques into its production, operations and supply chain procedures (Chatterjee *et al.*, 2022). In consequence, B2B firms can develop an enormous volume of both structured and unstructured data to respond to market shifts and boost their production, operations and supply chain procedures (Holmes *et al.*, 2023). While BDAI assimilation implies the adaptation of predictive tools and techniques, at the same time, AI capabilities constitute a dynamic aptitude to design, deploy and regulate big data tools and techniques, such as machine learning techniques and predictive analytics (Di Vaio *et al.*, 2022; Bag *et al.*, 2023). This DCT extension is critical (Teece, 1990), where B2B firms may successfully assimilate BDAI tools and techniques (e.g. machine learning and predictive analytics); however, a deficiency in AI capabilities is less able to convert its success for promoting NPP (Zhang and Wu, 2017; Hajli *et al.*, 2020).

The concepts of BDAI and specifically its assimilation strengthen firms' dynamic capabilities by fostering real-time data insights into firm decision-making and strategic vision (Mikalef *et al.*, 2021). Such conceptions and expediency enable B2B firms to more commendably adapt, innovate and reach a firm's competitive advantage (Wamba *et al.*, 2017). The expediency of these firm-level dynamic capabilities is contingent mainly on the development of AI capabilities (Zahoor *et al.*, 2022). This strengthens the firm's ability to apply AI tools to solve big data challenges, as well as generate innovative solutions and foster creative decision-making, and improve NPP (Cetindamar *et al.*, 2022; Getnet *et al.*, 2024). Taken together, these organizational capabilities are more amplified in the presence of ESCC (Benzidia *et al.*, 2021). In the ESCC context, data-driven coordination serves as a strategic means of sharing digital knowledge among supply chain partners, effectively translating technological investments into superior NPP (Deng *et al.*, 2025). Drawing on the perspective of DCT (Teece, 1990), this study explains how dynamic capabilities are not only embedded within firms but also developed through digital alliances and relationships of ESCC, enabling firms to sense and seize new opportunities (Lin *et al.*, 2022). Therefore, we provide a nuanced understanding of how assimilation of BDAI, AI capabilities and ESCC extends DCT (Teece, 2017), core tenets by orchestrating resources to shape sustained innovation outcomes, such as NPP (Zahoor *et al.*, 2022).

2.2 BDAI assimilation and NPP

The advancement of BDAI into core organizational processes enhances a B2B firm's ability to identify market opportunities, anticipate risks and make informed strategic decisions (Hallikainen *et al.*, 2020). The specific "assimilation" of BDAI involves the systematic integration of data analytics into firm policymaking, empowering the handling of vast volumes of both structured and unstructured data and transforming raw information into actionable insights (Di Vaio *et al.*, 2022). In so doing, this strategic functionality not only increases the operational effectiveness of B2B firms but also rationalizes supply chain coordination and the formation of innovative and competitive products (Bag *et al.*, 2023; Lu *et al.*, 2025). Prior studies show that the application of BDAI in a number of contexts, including numerous performance and healthcare supply chain, agricultural growth and new product effectiveness (Bag *et al.*, 2023; Benzidia *et al.*, 2021; Hajli *et al.*, 2020). As a result, the assimilation of BDAI extends beyond the mere adoption of innovative technologies and digital transmission (Deng *et al.*, 2025). It entails cultivating a data-driven culture that helps foster innovation and sustain long-term value creation (Manzoor *et al.*, 2025).

Drawing on the DCT views (Teece, 2010), in highly competitive and resource-constrained environments, the assimilation of BDAI enables B2B firms to reconfigure and optimize resource allocation dynamically (Mikalef *et al.*, 2021). By facilitating analytics and intelligent decision-predictions, BDAI helps B2B firms to protect existing resources while simultaneously transforming them for new prospects of success in unpredictable markets (Wamba *et al.*, 2017). In addition, B2B firms function within the multifaceted nature of supply chain networks, where collaboration and responsiveness through data prediction and analytics are indispensable for launching new products and services (Getnet *et al.*, 2024). In particular, this assimilation of BDAI support and provision of such processes by fostering knowledge sharing, amplifying digital and predictive responsiveness, enables firms to adapt quickly in evolving markets (Zhang and Wu, 2017; Hajli *et al.*, 2020; Maga and Bodlaj, 2025). Collectively, these capabilities of BDAI and its assimilation strategically shape the dynamic foundation for superior NPP in B2B contexts (Wang and Wang, 2020). Therefore, we propose:

H1. BDAI assimilation is positively related to NPP.

2.3 BDAI assimilation and AI capabilities

In B2B firms, BDAI assimilation forms the groundwork for developing AI skills by inserting advanced data-driven tools into day-to-day operations (Benzidia *et al.*, 2021). The assimilation of BDAI motivates traditional organizational processes and transformation to use large-scale data sets, predictive analytics and automated decision-support systems (Bag *et al.*, 2023). In doing so, organizations develop their technical processes and managerial capabilities to enhance their flexibility and innovation objectives related to big data (Hajli *et al.*, 2020). With the help of such mechanisms, firms strengthen their dynamic capabilities to identify the assimilation of BDAI, interpret and execute large data patterns and insights, and use AI techniques to improve complex operational issues (Vitezić and Perić, 2024). Given that, we build on DCT (Teece, 1990) and elucidate that this process explains how organizations sense and seize new opportunities to shape continuous learning from BDAI assimilation (Teece, 2017; Mikalef *et al.*, 2021). In the present work, we define AI capabilities as a specific firm capability that enables the integration, mobilization and reconfiguration of digital transformation processes through big data insights into actionable strategies. This helps us understand and position AI capabilities not as an individual skill, but as managerial dynamic capabilities to enhance NPP (Dubey *et al.*, 2022).

Inside the B2B manufacturing, where operations are multi-dimensional and interdependent, AI capabilities are crucial (Cetindamar *et al.*, 2022). Accordingly, the combination and assimilation of BDAI equips organizational teams with the necessary technical infrastructure and analytical resources to experiment with AI applications (Hallikainen *et al.*, 2020; Zhang *et al.*, 2024). This AI capability empowers organizational development and learning, focusing on AI solutions for their supply chain activities (Bag *et al.*, 2023), refining forecast precision (Dubey *et al.*, 2022), mitigating uncertainties (Di Vaio *et al.*, 2022) and consolidating collaborative decision-making models to improve NPP (Getnet *et al.*, 2024). In so doing, we posit that BDAI assimilation both associates the B2B firm's technological infrastructure and cultivates AI capabilities to achieve strategic objectives. This process ensures that organizational learning and resources are diffused across managerial policies rather than at the individual level. Therefore, we propose that:

H2. BDAI assimilation is positively related to AI capabilities.

2.4 AI capabilities and NPP

Recent research indicates that AI capabilities enhance digital knowledge, facilitate hybrid skills development, and increase efficiency, enabling organizations to apply AI tools in organizational decision-making and problem-solving effectively (Bag *et al.*, 2023; Maga and Bodlaj, 2025). For B2B firms, managers who adapt and execute AI models are more likely to understand global supply chain systems and foresee emerging customers and consumers' demands by anticipating new market conditions (Zhang *et al.*, 2020). The potential of AI enhances the accuracy of product development, and new products are consistently adapted to shifting technological and B2B landscapes (Hajli *et al.*, 2020). Similarly, AI-oriented environments cultivate organizational alliances, enabling teams to derive insights from real-time data and improve NPP (Lin *et al.*, 2022). From the lens of DCT (Teece, 1990), a possible transformation through AI capabilities reinforces sensing and seizing organizational aptitudes to augment B2B firms' adaptability, modernization and innovation (Sheng *et al.*, 2024).

Furthermore, AI capabilities enhance resource flexibility, a critical antecedent for achieving long-term NPP (Hallikainen *et al.*, 2020). Prior studies demonstrate that B2B organizations with advanced AI tools can apply predictive analytics, machine learning techniques and data-driven simulations to respond efficiently to supply chain disruptions in B2B contexts (Wei *et al.*, 2023; Lenuwat *et al.*, 2025). Notably, AI adaptability allows B2B firms to mitigate uncertainties successfully and help foster NPP (Hallikainen *et al.*, 2020). These dynamic capabilities are equally essential for organizations that are capable of integrating AI into daily workflows, raising strategic collaborations with supply chain partners, and significantly strengthening NPP (Di Vaio *et al.*, 2022). In consequence, we posit that AI capabilities not only help nurture B2B operational effectiveness with supply chain partners but also amplify the functions of NPP on a broader course. Therefore, we propose that:

H3. AI capabilities are positively related to NPP.

2.5 AI capabilities: a mediating role

By facilitating the growth of digital set-ups and predictive data solutions, BDAI and its assimilation enable B2B firms to respond more efficiently to increase NPP (Wang and Wang, 2020). This particular "assimilation" of BDAI alone does not guarantee improvements directly for NPP. However, it offers the technological substructure to process large-scale data; the translation of this "assimilation" into successful actions is ultimately contingent upon AI capabilities (Bag *et al.*, 2023). AI-skilled organizations are more proficient in predictive analytics, machine learning or data visualization, which can more effectively extract value from BDAI outputs (Vitezić and Perić, 2024). These organizational-level transformation helps enable the enhancement of new product design, supply chain networking and strategic planning (Dubey *et al.*, 2022). In this context, AI capabilities serve as the "strategic bridge" between the technical assimilation of BDAI and the organizational outcomes it is expected to thrive. From the perspective of DCT (Teece, 2010), BDAI assimilation provides the sensing mechanisms, but it is through the firms' AI skills and capabilities that B2B firms seize and reconfigure to unlock NPP.

In B2B settings, where operational proficiency is crucial during digital transformation and the integration of various stakeholders, the intermediary role of AI capabilities is vital. These AI capabilities empower organizations to interpret real-time data, identify new trends and collaboratively adapt NPP strategies to address customer-focused value creation (Holmes *et al.*, 2023; Maga and Bodlaj, 2025). In so doing, this intermediate mechanism confirms that insights generated via BDAI assimilation are not confined to a theoretical realm but are actively and efficiently supported through organizational AI capabilities (Dubey *et al.*, 2022). Lacking such intrafirm linkages and supporting mechanisms, B2B firms risk underutilizing BDAI investments, which can result in missing new market demands and limited innovation outcomes. Thus, in this study, we explain the logic of this mediation practice by highlighting that BDAI assimilation may create certain circumstances for innovation through AI capabilities, enabling NPP.

Moreover, AI capabilities deliver strategic flexibility by combining organizational learning and innovation into day-to-day decision-making (Di Vaio *et al.*, 2022). Drawing on the DCT (Teece, 1990), long-term competitive advantage cannot rely merely on retaining advanced technologies, but particularly on a firm's dynamic capabilities. Building on these significant verdicts, AI capabilities initially form a high-order dynamic capability, which is ultimately linked to the organization's dynamic capabilities at a higher level to achieve competitive advantage (Wamba *et al.*, 2017; Mikalef *et al.*, 2021). These high-order capabilities can transform, internalize and act on new insights, empowering firms to allocate resources more effectively and manage such resources to reach NPP (Teece, 2010, 2017). In so doing, our intermediate relationship clarifies that BDAI assimilation and NPP are not directly associated; however, AI capabilities build a foundation and act as a crucial mechanism that translates technical skills into sustainable innovation outcomes, such as NPP. Therefore, we propose that:

H4. AI capabilities mediate the relationship between BDAI assimilation and NPP.

2.6 ESCC: a moderating role

In recent decades, B2B businesses and their supply chains have confronted massive challenges due to the advancement of technology (Deng *et al.*, 2025). These advancements have also disrupted the flow of traditional supply chain strategies (Manzoor *et al.*, 2025). Al-Omoush *et al.* (2023, p. 1) stated that, "collaboration is a basic area in the study of supply chain management". Through supply chain collaboration, B2B firms can rapidly adapt to unpredictable market strategies and their supply chain landscapes by coordinating and deploying AI tools and techniques (Bag *et al.*, 2023). ESCC supports the relational and technological advancement necessary to effectively integrate BDAI assimilation into enhanced AI skills and capabilities (Dubey *et al.*, 2022). This suggests that when B2B firms possess strategic collaboration, they can more efficiently convert BDAI assimilation and firm AI capabilities with digital supply chain strategies (Al-Omoush *et al.*, 2023). In this study, the moderating role of ESCC aligned with BDAI assimilation and AI capabilities to enhance firm coordination and execute internal and external operational plans to enhance NPP. Lacking such strategic collaboration, the assimilation of BDAI remains scarce and limits firms' AI abilities to thrive in superior NPP. Therefore, such advancement through ESCC and the evolution of BDAI assimilation and AI capabilities facilitate supply chain actors and substantially transform B2B relationships to achieve a firm-level competitive advantage (Wei *et al.*, 2023; Zhang *et al.*, 2024).

Into the bargain, BDAI assimilation creates data-rich atmospheres; however, the extent of its foundation is determined by how these firms can access, disseminate and integrate information among supply chain partners (Yu *et al.*, 2022). Confirming the seamless flow of knowledge, dissemination of data and integration of real-time insights across organizational boundaries, ESCC provisions firms with crucial inputs to cultivate their AI capabilities and reach successful NPP (Dubey *et al.*, 2022; Al-Omoush *et al.*, 2023). Consequently, ESCC develops how BDAI assimilation forms firm-level AI assistances, supporting hands-on learning and strengthening NPP (Benzidia *et al.*, 2021). Such an enriched experience accelerates B2B business profits by enabling the sense of new business models (Teece, 2010), seizing them through adaptive AI models (Mikalef *et al.*, 2021) and converting them into innovative products and processes – reflecting the three core dimensions of DCT (Teece, 2017). Without ESCC, the assimilation of BDAI risks may remain a primarily technical process, with limited spillover for organizational learning, knowledge transformation and innovation practices to accomplish NPP and its success (Lenuwat *et al.*, 2025).

In addition, ESCC can line up worldwide supply chain actors and share innovation goals to amplify the applications of AI and big data (Deng *et al.*, 2025). Mutual planning, benefits and digital trust help empower B2B firms to reduce operational uncertainties, enabling them to achieve NPP (Lu *et al.*, 2025). This strategic roadmap helps B2B firms to incorporate AI into new product development, market forecasting and healthy supply chain relationships, thereby positioning ESCC as a high-order organizational resource rather than an immediate sales tool (Manzoor *et al.*, 2025). This justifies that the benefits of ESCC extend beyond efficiency to drive sustainable growth and competitiveness (Bag *et al.*, 2023). According to the DCT sights (Teece, 2010), ESCC extends the firm's dynamic capabilities by supporting managerial dynamic capabilities and enabling uninterrupted reconfigurations of organizational resources (Mikalef *et al.*, 2021; Sheng *et al.*, 2024). Therefore, we propose the following hypotheses, and in Figure 1, we present our conceptual model:

H5. ESCC moderates the relationship between firms' BDAI assimilation and AI capabilities such that the relationship is stronger when ESCC is higher vs. lower.

H6. ESCC moderates the mediating effect of AI capabilities in the relationship between firms' BDAI assimilation and NPP, such that the mediating effect is stronger when ESCC is higher vs. lower.

3. Research methods

3.1 Sampling and procedure

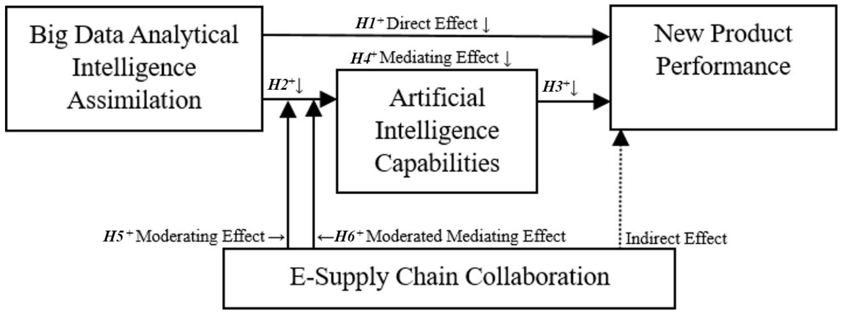
China's rapid industrial development translates its ascendancy as a worldwide leader in B2B manufacturing, offering an ideal context for this study (Deng *et al.*, 2025). As Chinese B2B firms rapidly adapt AI tools and techniques and engage in collaborative innovation networks, offering a valuable setting to explore our proposed constructs, such as BDAI assimilation and NPP (Nusrat *et al.*, 2025; Lu *et al.*, 2025). More importantly, Chinese B2B firms are a highly relevant focus for this proposed research, as they play a pivotal role in global supply chains and consistently pursue advanced industrial technologies (Maga and Bodlaj, 2025; Manzoor *et al.*, 2025). China has solidified its potential role as a global manufacturing powerhouse (Wamba *et al.*, 2017). To increase B2B tasks, Chinese firms within their borders are increasingly turning to big data transformational systems and AI innovative manufacturing structures (Zhang *et al.*, 2024). For these reasons, the present study draws on a sample of 291 B2B manufacturing firms from three core provinces that are known for their significant contributions to both national and international manufacturing contexts (Zhang *et al.*, 2020; Lu *et al.*, 2025).

In the first phase of the study, participants were identified through confidential sources, which included the official Yellow Pages published by China Telecom and directories provided by the Provincial Economic and Information Technology Commission (Yu *et al.*, 2022). An initial sample of 500 firms was designated from each province. Key data, including firm type, size, location, industry specification, key products and official contacts, was collected. These selected B2B firms represent a diverse range of manufacturing sectors that include information technology, chemicals, plastics, and rubber production. These industries are characterized by a high reliance on big data and AI to transform and operationalize supply chain operations, driving new product development (Lin *et al.*, 2022; Deng *et al.*, 2024).

Building on the first phase, we started our second phase of data collection. We contacted and secured the participation of key decision-makers, namely, the chief executive officers (CEOs) and senior marketing managers of each selected firm. These decision-makers provide holistic understandings of their firms' B2B strategy for using big data and AI tools. A multichannel communication strategy, combining phone calls and emails, was used to cover the study's objectives transparently (Lu *et al.*, 2025; Muneeb *et al.*, 2025). The third phase involved designing a questionnaire survey of proposed constructs, which was structured into three distinct waves (Podsakoff *et al.*, 2003). Each survey was strategically designed to address essential aspects of our research variables. Particularly, the questionnaires administered at Times 1, 2 and 3 each included measures for each proposed construct. A six-week interval was maintained between each data collection point to ensure reliability and validity (Deng *et al.*, 2025). This data collection strategy establishes the time-lagged nature of our design (Huang *et al.*, 2025).

The six-week interval was determined based on two considerations. First, BDAI assimilation is a gradual process that requires firms to adapt, integrate and operationalize big

Figure 1 The conceptual model



Source: Authors' own work

data tools over an extended period to improve NPP (Wamba et al., 2017). Prior research suggests that a short interval may not adequately capture the implementation of big data and AI transformations in firms' regular innovation process (Zhang et al., 2024; Bag et al., 2023). Second, our choice is aligned with recent scholarship on big data, which suggests a 4–8-week interval is optimal for observing the evolving patterns in digital transformation (Chatterjee et al., 2022; Nusrat et al., 2025). In this context, the six-week interval is an optimally balanced organizational dynamic and digital transformation to mitigate common method bias (Podsakoff et al., 2003).

Moving toward the fourth phase, our team of 22 interviewers, comprising 2 full professors, 13 PhD students and 7 master's students, was assigned specific tasks. This helps us to understand and conduct on-site interviews and ensure the uniformity, accuracy and appropriateness of the data collection process (Dubey et al., 2022). During the data collection process, this research team was consistently voluntarily available to address additional questions from participants (Muneeb et al., 2025). A total of 291 firms from the initial pool of 1,500 firms across three key provinces provided consistent and complete responses at all three times, forming the final matched sample (refer to Table 1). This regional distribution revealed a well-balanced representation across the three provinces, with 37.11% firms from Liaoning, 31.95% from Guangdong and 30.92% from Shandong. Any surveys with missing data, including those with three-time points, were excluded from the final sample due to incomplete information (Lenuwat et al., 2025).

The final sample collected for the present study shows 291 B2B firms, meeting the suggested and recommended sampling size to interpret through structural equation modeling (SEM; Zhang et al., 2024). According to Hair et al. (2017), a minimum sample size of 200–300 respondents is required for SEM analysis with a complex model, ensuring adequate statistical power for hypothesis testing. In addition, this study's sample size adheres to the heuristic proposed by Kline (2023), which suggests that a minimum of 10 cases per observed indicator for models with 5–7 latent constructs. Thus, our collected sample of 291 B2B firms exceeds the threshold. Consequently, we proceeded with the chosen sample size to ensure the parameters of reliability and statistical validity (Hair et al., 2017).

Table 1 Sample characteristics

Sample characteristics	Frequency	%	Sample characteristics	Frequency	%
Firm age			*Firm ownership*		
0–20	69	23.71	Private	81	27.83
21–30	156	53.60	State-owned	159	54.63
31–40	46	15.80	Other	51	17.52
41–50	11	3.78	*Industry type*		
Above 50	9	3.09	IT manufacturing	108	37.11
Firm size			Chemical manufacturing	65	22.33
21–50	59	20.27	Electronic manufacturing	92	31.61
51–100	63	21.64	Plastic and rubber manufacturing	26	8.93
101–500	112	38.48	*Firm area*		
501–1,000	39	13.40	Liaoning Province	108	37.11
Above 1,000	18	6.18	Guangdong Province	93	31.95
Revenues (in million RMB)			Shandong Province	90	30.92
0–10	65	22.33	*Total questionnaire surveys*	*1,500*	
11–30	103	35.39	Time 1	456	30.4
31–50	69	23.71	Time 2	340	22.66
51–100	23	7.90	Time 3	295	19.66
Above 100	31	10.65			

Source(s): Authors' own work

3.2 Measurements

In the present work, the measurement Likert scale was chosen to provide participants a greater range of expression; therefore, we used a seven-point Likert scale (1 > strongly disagree to 7 > strongly agree). This study's constructs were operationalized with established scales from the existing literature. Particularly, BDAI assimilation was measured using a three-item scale validated by Zhang *et al.* (2020), and AI capabilities were measured using a four-item scale established by Dubey *et al.* (2022). Next, ESCC was measured using an eight-item scale developed by Al-Omoush *et al.* (2023), while a three-item scale of NPP was adapted from the existing research by Jin *et al.* (2019).

3.3 Control variables

In this study, three control variables were included: firm age, size and ownership. These controlling variables are widely identified in the prior literature as key factors that either have a theoretical relationship or a previously stated empirical relationship with one or more of our focal variables (Dubey *et al.*, 2022; Hallikainen *et al.*, 2020; Deng *et al.*, 2024; Getnet *et al.*, 2024; Nusrat *et al.*, 2025; Huang *et al.*, 2025). We control firm age because it translates to organizational experience, learning and adaptability in response to technological shifts. Prior scholarship demonstrates that older firms may have well-established strategies but could be less agile in adapting to technological shifts (Zhang and Wu, 2017; Holmes *et al.*, 2023). Conversely, younger firms may have more strength but lack the necessary strategies to fully adapt to such a technological shift (Zhang *et al.*, 2020; Bag *et al.*, 2023). Therefore, we calculated firm age based on the founding year of each firm identified and then applied a natural logarithm transformation.

Second, firm size is controlled, as prior studies have established that firm size is a critical determinant of resource availability, technological investment, and the ability to implement advanced data analytics tools (Hajli *et al.*, 2020; Lin *et al.*, 2022). Larger firms typically have more enriched human resource systems and financial resources; on the other hand, smaller firms may face the opposite (Deng *et al.*, 2024; Muneeb *et al.*, 2025). Consequently, we calculated firm size using a three-year average of the number of employees and applied a natural logarithm transformation to the data. Third, firm ownership has been controlled in this study, as prior studies show that ownership structure is a key factor, such as decision-making autonomy and risk tolerance (Mikalef *et al.*, 2021; Dubey *et al.*, 2022). Accordingly, state-owned firms often benefit from resources, while private firms and partnership firms are generally more agile in their technological transformation and their adaptation strategies (Nusrat *et al.*, 2025; Lu *et al.*, 2025). For those reasons, we calculated firm ownership as our third controlling variable by identifying whether they are state-owned firms, private firms or partnership firms.

4. Results

4.1 Common method bias

In this study, we used several steps to mitigate the potential for common method bias (CMB). First, we collected a multi-source data collection approach by gathering information from two informants (i.e. CEOs and senior marketing managers) at each identified B2B firm (Nusrat *et al.*, 2025). This multi-source approach provides us with an understanding that enhances data collection procedures and helps reduce CMB that can arise from a single source (Podsakoff *et al.*, 2003; Zhang *et al.*, 2020). Next, we temporally separated the measurement of constructs by administering our surveys in three distinct phases (Getnet *et al.*, 2024; Huang *et al.*, 2025). This separation helps us minimize CMB by reducing the likelihood that transient B2B business situations involving big data usage may or may not influence any related bias (Bag *et al.*, 2023). We also applied a time-lagged strategy by spacing out the data collection over six weeks (Deng *et al.*, 2025). This time-lagged gap between the three phases helps reduce the risk of CMB caused by respondents' temporal influences (Podsakoff *et al.*, 2003). To ensure the consistency of our data collection, we estimated Harman's single-factor test, a common method for detecting CMB (Dubey *et al.*, 2022). We implemented a single-factor analysis by loading all the latent variables. The results illustrate that the first factor accounted for only 29.68% of the variance, well below the 50% threshold of the total explained variance of 67.96% (Wamba *et al.*, 2017). This suggests that CMB is not a significant issue in our data sets, as the variance is distributed across multiple factors (Podsakoff *et al.*, 2003).

4.2 Confirmatory factor analysis

In the present study, we applied confirmatory factor analysis (CFA) through Mplus software version 8.0, adapting the guidelines of Muthén and Muthén (2017). The results demonstrate a robust fit for our four-factor model (χ^2 = 703.89, df = 165, χ^2/df = 4.266, CFI = 0.91, TLI = 0.921, RMSEA = 0.071, SRMR = 0.041), affirming its adequacy. On the other hand, we also calculated a three-factor CFA model, which revealed a significantly worse fit compared to the four-factor CFA model. These results support the construct validity and reliability, and are presented in Table 2.

4.3 Descriptive statistics and correlations

The descriptive statistics and correlation results show that BDAI assimilation is positively correlated with AI capabilities ($r = 0.12$, $p < 0.001$) and is significantly associated with ESCC ($r = 0.15$, $p < 0.001$) and NPP ($r = 0.28$, $p < 0.001$). Likewise, PPI is positively associated with ESCC ($r = 0.26$, $p < 0.001$) and NPP ($r = 0.12$, $p < 0.05$). Finally, NPP is positively linked to ESCC ($r = 0.33$, $p < 0.001$). The descriptive statistics and correlation results are presented in Table 3. To reinforce our findings, we assessed the convergent reliability and validity of our latent variables. We examined standard factor loadings and reliability tests to check Cronbach's alpha (α), average variance extracted (AVE) and composite reliability (CR). All factor loadings of measurement items were statistically significant ($p < 0.01$), indicating satisfied convergent validity, presented in Appendix. The AVE scores were taken in the square root form, which is higher than any focal variable coefficient correlations (see Table 3), supporting the validity and reliability of each variable coefficient (Fornell and Larcker, 1981).

4.4 Hypothesis testing

We test our proposed hypotheses by using Mplus v. 8.0 and SPSS v.24.0 (Muthén & Muthén, 2017). The results are

Table 2 Confirmative factor analysis (CFA)

Factor models	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Four-factor model – hypothesized model	703.89	143	4.922	0.091	0.921	0.071	0.041
Three-factor model – BDAI assimilation and ESCC into one-factor	1501.59	157	9.564	0.824	0.814	0.101	0.112
Three-factor model – BDAI assimilation and AI capabilities into one-factor	1678.71	157	10.692	0.714	0.654	0.192	0.141
Three-factor model – ESCC and AI capabilities into one-factor	1984.43	158	12.559	0.695	0.621	0.190	0.130
Two-factor model – BDAI assimilation and ESCC into one-factor, AI capabilities and NPP into one-factor	2139.08	159	13.453	0.651	0.600	0.189	0.125
One-factor model – All latent variables into one-factor	3245.87	191	16.994	0.411	0.561	0.127	0.162

Note(s): df = degree of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean squared residual between departments
Source(s): Authors' own work

Table 3 Descriptive statistics and correlations

Latent variables	M	SD	AVE	CR	α	1	2	3	4	5	6	7
1. Firm age[a]	5.81	1.42	–	–	–	–						
2. Firm size[a]	2.53	0.81	–	–	–	0.32**	–					
3. Firm ownership	3.32	0.88	–	–	–	0.02	0.13	–				
4. BDAI assimilation	4.25	0.71	0.92	0.97	0.96	0.12	−0.11	0.02*	*(0.96)*			
5. AI capabilities	4.98	0.63	0.86	0.96	0.95	0.01*	0.14	−0.12	0.12***	*(0.93)*		
6. ESCC	4.22	0.85	0.60	0.92	0.81	0.02	0.15**	0.04*	0.15***	0.26***	*(0.92)*	
7. NPP	4.84	0.82	0.79	0.91	0.86	0.14	−0.13	0.12	0.28***	0.12*	0.33***	*(0.88)*

Note(s): $n = 291$; BDAI = big data analytical intelligence; AI = artificial intelligence; ESCC = electronic-supply chain collaboration; NPP = new product performance;[a]Log-transformed. $^{*}p < 0.05$; $^{***}p < 0.001$; The italic elements represent AVE square root
Source(s): Authors' own work

Table 4 Bootstrapped results of all hypotheses

Path	Effect	s.e.	95% CI
1. BDAI assimilation on AI capabilities	0.43***	0.06	[0.22, 0.49]
2. AI capabilities on NPP	0.27**	0.07	[0.23, 0.37]
3. BDAI assimilation × ESCC on AI capabilities	0.21**	0.05	[0.12, 0.38]
4. Total effect of BDAI assimilation on NPP	0.24***	0.06	[0.15, 0.29]
5. The direct effect of BDAI assimilation on NPP	0.16*	0.08	[0.01, 0.31]
6. Indirect effect of BDAI assimilation on NPP	0.15*	0.06	[0.06, 0.22]

Note(s): Bootstrap samples = 5,000; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; Covariates includes > Firm age, size, ownership
Source(s): Authors' own work

Table 5 Moderated mediation effects

Coefficient of ESCC	Conditional indirect effect	SE	95% CI
3.49	0.06	0.04	[0.01, 0.16]
4.26	0.10	0.04	[0.02, 0.20]
4.99	0.13	0.06	[0.08, 0.25]
Moderated mediating effect			
0.07		0.05	[0.03, 0.17]

Note(s): Bootstrap samples = 5,000
Source(s): Authors' own work

presented in Tables 4 and 5. Table 4 shows that the total effect of BDAI assimilation on NPP yielded a statistically significant outcome (β = 0.24, s.e. = 0.06, p < 0.001, 95% CI = [0.15, 0.29]), thereby substantiating the foundational support of *H1*. These results align with prior research studies, which have shown that BDAI has a positive impact on NPP (Hajli *et al.*, 2020; Wang and Wang, 2020). Next, we proposed *H2*, which posits a positive relationship between BDAI assimilation and AI capabilities. The statistical analysis supports this assertion (β = 0.43, s.e. = 0.06, p < 0.001, 95% CI = [0.22, 0.49]). This evidence supports the notion that BDAI assimilation plays a crucial role in fostering and strengthening AI capabilities (Wamba *et al.*, 2017; Yu *et al.*, 2022).

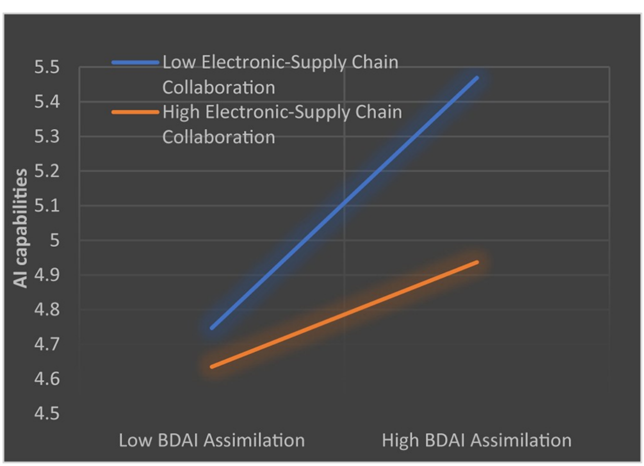
In addressing *H3*, which posits a positive association between AI capabilities and NPP, our empirical findings substantiate this conjecture. The statistical analysis reveals a significant and positive relationship (β = 0.27, s.e. = 0.07, p < 0.01, 95% CI = [0.23, 0.37]). These results underscore that AI capabilities contribute significantly to the augmentation of NPP. These results also suggest that as AI capabilities increase, there is a higher likelihood of strengthening the provision of NPP aligned with prior studies (Cetindamar *et al.*, 2022; Di Vaio *et al.*, 2022; Makarius *et al.*, 2020). We propose *H4* and suggest that AI capabilities significantly mediate the relationship between BDAI assimilation and NPP. The results provide robust support for this with a substantial effect (β = 0.15, s.e. = 0.06, p < 0.05, 95% CI = [0.06, 0.22]). This mediation effect implies that AI capabilities play a strategic role in enhancing the impact of BDAI assimilation on the ultimate achievement of NPP in B2B firms (e.g. Zhang *et al.*, 2020; Huang *et al.*, 2025).

In extending our examination, *H5* assumes that ESCC moderates the positive association between BDAI assimilation and AI capabilities, with a stronger association when ESCC is higher. As presented in Table 4, the statistical results reveal a significant interaction effect between BDAI assimilation and ESCC ($\beta = 0.21$, s.e. = 0.05, $p < 0.01$, 95% CI = [0.12, 0.38]). The results imply that the relationship between BDAI assimilation and AI capabilities is more pronounced and robust in the presence of higher levels of ESCC. To enhance interpretability, Figure 2 shows the simple moderation slope, providing a clear representation of the contingency influence of ESCC on the association between BDAI assimilation and AI capabilities.

Building on the earlier moderation hypothesis, *H6* has been investigated, which suggests the moderated-mediation outcome of ESCC on the link between BDAI assimilation and NPP. We posit that the intermediating role of AI capabilities is reinforced when ESCC is higher. The results, as depicted in Table 5, affirm this when ESCC is 1 SD below the mean, the effect is ($\beta = 0.13$, s.e. = 0.06, 95% CI = [0.08, 0.25]), and it is more pronounced to the lower levels (β = 0.06, s.e. = 0.04, 95% CI = [0.01, 0.16]). The moderated mediating effect is further conferred as significant (index = 0.07, s.e. 0.05, CI = [0.03, 0.17]). Together, these results are allied with preceding research conclusions (Hallikainen *et al.*, 2020; Lytras *et al.*, 2021; Wang and Wang, 2020; Deng *et al.*, 2025; Manzoor *et al.*, 2025) and interdependencies within B2B manufacturing firms linking big data and collaborative supply chain practices (Dubey *et al.*, 2022; Zhang *et al.*, 2024).

Our moderated-mediation findings suggest that B2B firms with stronger ESCC networks benefit more from BDAI assimilation, as higher levels of digital collaboration enhance the ability of AI-driven insights to translate into effective NPP. Specifically, ESCC facilitates real-time data sharing, cross-organizational knowledge transfer and decision-making (Bag *et al.*, 2023; Zhang *et al.*, 2024), which collectively optimize AI capabilities for predicting market trends and accelerating NPP (Hajli *et al.*, 2020). Consequently, aligning with prior research studies, our findings highlight that ESCC complements BDAI adoption and acts as an external enabler that amplifies its impact on firm-level innovation outcomes (Al-Omoush *et al.*, 2023). Unlike previous studies that focus on internal firm capabilities, such as agility and technological readiness, our analysis reveals that ESCC fosters organizational innovation process.

Figure 2 Moderation effect of ESCC on the relationship between BDAI assimilation and AI capabilities. The steeper slope under low ESCC suggests a stronger impact of BDAI assimilation on AI capabilities when ESCC is low, indicating a compensatory rather than amplifying role



Source: Authors' own work

5. Discussion

Drawing on the DCT (Teece, 1990, 2010), this study makes valued contributions to the evolving understanding of BDAI assimilation, AI capabilities, ESCC and NPP. This study demonstrates how B2B firms integrate the assimilation of BDAI and build the agility needed to succeed in today's multidimensional and technologically advanced B2B settings. Our work highlights that developing AI capabilities is a crucial strategy for B2B firms to address these challenges. This study distinguishes between BDAI assimilation and AI capabilities and shows that the assimilation of BDAI is a firm technical foundation for creating infrastructure and data resources. However, AI capabilities are the dynamic processes a firm uses to sense opportunities, seize them and reconfigure resources into actionable strategies. Next, we explore a critical contingency factor that influences BDAI assimilation and the development of AI capabilities. We posit that ESCC enhances the development process of AI capabilities by supporting digital trust, facilitating real-time knowledge sharing and orchestrating collaborative decision-making across B2B firms. Our work thus demonstrates a unique perspective on NPP, revealing how B2B firms can use ESCC to boost both innovation and production efficiency. This study contextualized the Chinese B2B manufacturing setting to unfold how institutional drivers, such as state-led digitalization policies and government support for smart manufacturing and innovation.

Our findings align with prior research, which shows that the transformative potential of BDAI and AI capabilities in fostering firm innovation (Wang and Wang, 2020; Zhang *et al.*, 2020; Hajli *et al.*, 2020; Mikalef *et al.*, 2021; Lin *et al.*, 2022; Dubey *et al.*, 2022; Deng *et al.*, 2025). However, earlier scholarships have primarily examined AI's role in broader digital transformation efforts (Benzidia *et al.*, 2021; Bag *et al.*, 2023; Di Vaio *et al.*, 2022; Vitezić and Perić, 2024; Nusrat *et al.*, 2025). This study extends this by specifying how AI capabilities mediate this relationship between BDAI assimilation and NPP, offering a more nuanced understanding of the mechanisms through which AI capabilities foster NPP. This intermediary distinctive mechanism is critical; without well-developed AI capabilities, BDAI remains merely a technical resource with limited spillover to promote NPP. Next, building on prior studies (Dubey *et al.*, 2022; Bag *et al.*, 2023; Deng *et al.*, 2025; Manzoor *et al.*, 2025), our moderated-mediation model confirms that B2B firms with strong ESCC significantly impact BDAI assimilation, AI capabilities and NPP. Our findings provide empirical support to recent B2B literature (Zouari *et al.*, 2025; Huang *et al.*, 2025), which posits that post-digital collaboration and AI integration are essential pathways to achieving innovation outcomes. Importantly, this study serves as a warning that creating a high BDAI is not a strategic roadmap for Chinese B2B firms. Conjoining ESCC with BDAI assimilation and AI capabilities returns to covert strategic improvement for superior NPP.

5.1 Theoretical contributions

This study has threefold contributions to the existing literature on big data innovation and B2B firms. First, we contributed and showed that BDAI assimilation acts as a modern engine for enhancing NPP in Chinese B2B contexts. We advance DCT extension (Teece, 2010, 2017) by illustrating that BDAI is a crucial organizational enabler, empowering Chinese B_2B firms to continuously sense, seize and reconfigure organizational resources in response to changing market shifts. We contribute to clarifying that BDAI constitutes the organizational, technological and analytical infrastructure for collecting, storing and processing large data patterns (Hajli *et al.*, 2020; Bag *et al.*, 2023). On the other hand, AI capabilities represent the organizational strategic capability to transform those data patterns into strategic innovation (Vitezić and Perić, 2024). We posit that integrating BDAI assimilation assists AI capabilities to anticipate customer needs with greater accuracy and accelerate real-time decision-making for superior NPP (Mikalef *et al.*, 2021). Building on the learning orientation central to DCT (Teece, 2010), we present BDAI assimilation as a robust adaptive learning process for Chinese B2B firms. This aligns with the work of Mikalef *et al.* (2021), which leverages diverse data patterns to drive continuous innovation, empowering firms to modify their innovation strategies to achieve a competitive advantage increasingly. This organizational learning is vital for Chinese B2B firms, as it offers the rapid responsiveness needed to sustain a competitive advantage in changing and volatile market shifts (Dubey *et al.*, 2022; Di Vaio *et al.*, 2022). Our study further affirms the relevance of DCT (Teece, 2010) by demonstrating how hybrid tools like BDAI enhance organizational resource flexibility. This flexibility, as a core dimension and extension of dynamic capabilities (Mikalef *et al.*, 2021), enables and empowers firms to spur resource reallocations and promote NPP.

Second, this study extends DCT visualization (Teece, 1990) by describing AI capabilities as an essential intermediate mechanism that converts BDAI assimilation and transformation into improved NPP. Grounding on the core DCT (Mikalef *et al.*, 2021) tenets of integrating, developing and adapting new business models, we contribute and define AI capacities as a dynamic process that empowers firms to improve NPP. In this context, this study provides a novel understanding and catalyzes AI capabilities as an organizational driver assisting BDAI assimilation and NPP. Unlike traditional business models, this study contributes to understanding how AI's ability to transform multifaceted data patterns and generate predictive analytical solutions can benefit B2B firms by reinforcing, reconfiguring, and reestablishing new insights for improved NPP. AI capabilities empower Chinese B2B firms to make real-time decisions, which directly boost their operational and production efficiency and fuel strategic innovation (Dubey *et al.*, 2022; Bag *et al.*, 2023). In this vision, we contribute to and advance DCT (Teece, 2010, 2017) by describing how AI capabilities can power firms' competitive advantage by serving a learning orientation and developing interactive product development cycles (Cetindamar *et al.*, 2022).

Third, this study contributes to DCT (Teece, 2010) by introducing a vital contingency impact of ESCC that strengthens BDAI assimilation and AI capabilities and has a significant indirect effect on NPP. According to DCT (Teece, 1990), we understand and explain that firms need internal capabilities and dynamically leverage external relationships to enhance existing resources and their re-combination to achieve competitive advantage. Significantly, our findings position and contribute ESCC as essential boundary conditions for Chinese B2B firms, which assist in accessing external knowledge and sharing technological expertise to accelerate big data innovation (Al-Omoush *et al.*, 2023; Lenuwat *et al.*, 2025). While traditional DCT viewpoints (i.e. Zhang and Wu, 2017) often focus on the development of internal capabilities, we extend this lens by describing ESCC as a vital external enabler of resource reconfiguration and technological diffusion. Notably, the present work contributes to how ESCC fosters digital trust, mutual planning and benefits, and systematic joint data platforms which help enable BDAI assimilation and AI capabilities be more effectively supported and provision NPP. The synergy between ESCC, BDAI and AI capabilities created a strategic co-innovation environment to push Chinese B_2B firms to align their NPP success dynamically. This finding aligns with prior established research contributions that focus on digital collaborations in the supply chain as a driver of innovation outcomes (Dubey *et al.*, 2022; Bag *et al.*, 2023; Deng *et al.*, 2025; Manzoor *et al.*, 2025). This broader conceptualization and contributions advance the theoretical understanding of how Chinese firms dynamically reconfigure internal (e.g. BDAI assimilation and AI capabilities) and external (e.g. ESCC) resources to sustain competitive advantage in B2B contexts.

5.2 Managerial implications

This study provides B2B leaders with actionable strategies to enhance their NPP significantly. First, leaders must prioritize the assimilation of BDAI as a fundamental managerial strategy to improve organizational agility and capitalize on rapidly changing B2B shifts (Benzidia *et al.*, 2021; Bag *et al.*, 2023). Leaders should assimilate modern data analytics and systems as a core section of their operations and productions – a shift that directly aligns with the DCT (Teece, 2010) tenet of constantly constructing technological resources. Cultivating a culture of constant learning and data-driven decision-making sharpens a firm's core technological competencies to accomplish multifaceted challenges in data patterns, anticipate market shifts and formulate evidence-based data strategies (see Sheng *et al.*, 2024; Wamba *et al.*, 2017). Hence, assimilation of BDAI increases support in B2B innovation and efficiencies that are crucial for sustaining a competitive edge. Consequently, leaders must treat BDAI assimilation as a strategic investment that not only improves NPP but also their firm's dynamic capabilities to proactively anticipate and address market changes and customer demands (Maga and Bodlaj, 2025).

Moreover, we provide key insights that can significantly influence firms' strategic decision-making and digital initiatives to help foster NPP. At the forefront is the importance for managers to understand how BDAI serves as a core enabler of organizational agility, enabling their firms to respond rapidly to emerging opportunities (Zhang *et al.*, 2020; Wang and Wang, 2020). Building on the core premise of DCT (Teece, 2010, 2017), managers should embed innovative data analytics into their managerial policymaking to enhance their ability to achieve a firm's competitiveness (Dubey *et al.*, 2022). Managers must prioritize how data-driven processes build organizational learning into innovation outcomes (Wamba *et al.*, 2017). Managers must extend digital upskilling programs, establish cross-departmental AI teams and develop an AI integration set-up that aligns with organizational objectives to improve new product development and processes (Bag *et al.*, 2023; Zhang *et al.*, 2024).

Besides such practical implementations, B2B leaders should consider regional and industry-specific dynamics when developing collaborative supply chain alliances (Al-Omoush *et al.*, 2023). For instance, in B2B Chinese markets, forecasting digital ecosystems that support strategic information exchange across supply chain manufacturers and logistic partners is crucial (Deng *et al.*, 2025). For Chinese managers, successfully implementing these strategies requires navigating challenges, including regulatory restrictions on data exchanges, fragmented organizational digital infrastructure and diverse cultural barriers to AI transformation. To address such loopholes, Chinese managers should understand the role of ESCC in mitigating operational efficiency through AI knowledge sharing and cross-border data sharing (Manzoor *et al.*, 2025). Introducing ESCC as a predictive tool for risk management and deploying real-time monitoring tools can further enhance supply chain networking, resilience and performance (Yu *et al.*, 2022).

5.3 Limitations and future implications

This study provides essential limitations for future consideration. First, the generalizability of our findings is somewhat limited by the study's emphasis on key categories of Chinese B2B firms, specifically, information technology, chemicals, electronics and plastics/rubber manufacturing. At the same time, these specific industries provide a clear context for analyzing technology's effect and its transformation on B2B firms, their operations, and production effectiveness. The generalizability of our findings to other diverse sectors in Chinese regions may be limited. For instance, sectors like healthcare, agriculture and local food services (Bag *et al.*, 2023; Lin *et al.*, 2022; Muneeb *et al.*, 2023) are more likely to determine technological variation and patterns and locally rooted competitive dynamics, which would differ from this study's findings. Future investigation should therefore examine these underrepresented regions in China. This would not only provide a more granular understanding of BDAI and NPP but also allow researchers to explore a comparative analysis of the impact of Chinese foreign direct investment and BDAI association (Muneeb *et al.*, 2025).

Furthermore, the cross-sectional nature of our data limits causal inference between the constructs. While our time-lagged design with a six-week interval fosters temporal precedence, this relatively short duration may be insufficient to observe the full, long-term dynamics of BDAI assimilation and AI capability development, organizational processes and competitive growth. Future investigations should experiment with alternative intervals and longitudinal panel data to better account for temporal changes. Next, while this study's focus on CEOs and senior marketing managers helps mitigate CMB (Podsakoff *et al.*, 2003), it may exclude critical technical insights from operations managers and information technology managers in Chinese B2B firms. Therefore, future research should incorporate these perspectives to reduce key informant bias and enhance the validity of the findings.

While this work provides broad empirical insights, its quantitative nature inherently lacks the deep contextual understanding that qualitative approaches, such as in-depth interviews or case studies, can offer. Future researchers could incorporate case studies and in-depth interviews to add a nuanced understanding of how these technological transformations are applied in B2B contexts. In addition, this study focuses on ESCC as a critical moderator in the relationship between BDAI assimilation and AI capabilities. The forthcoming investigations could explore other potential contingencies, such as a corporate entrepreneurship-based strategy to build promising future research (Muneeb *et al.*, 2020). Notably, firm agility and supply chain resilience are increasingly recognized factors that could provide more insights into how B2B firms leverage BDAI to maintain policy-making (Hajli *et al.*, 2020; Deng *et al.*, 2025). We also invited future researchers to unpack the public sector association with BDAI explorations, as public sector investigation could offer new pathways in B2B contexts (Di Vaio *et al.*, 2022). A further limitation of our study is its inability to explore deviant case studies. For instance, firms with high BDAI assimilation but low NPP. Investigating such anomalies through qualitative studies could unpack crucial boundary settings and causal mechanisms missed by quantitative models.

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Appendix

Table A1

Construct items	Loadings
Big data artificial intelligence assimilation: Source: Zhang *et al.* (2020)	
1. BDAI is used as an important tool in every department	0.95
2. BDAI is used for decision making in every functional area	0.97
3. BDAI is used in developing new products and other marketing-related activities	0.96
Artificial intelligence capabilities: Source: Dubey *et al*. (2022)	
1. Our organization has invested in cognitive computing technologies and infrastructure, which has assisted us in improving our strategic domains across all functional domains	0.92
2. Our organization has its own proprietary data analytics and machine learning algorithms for extracting information and making cognitive interpretations of the collected data (from multiple sources) in the event of a process interruption	0.94
3. Our organization has developed a dashboard that helps process administrators in understanding the cognitive computing outputs of multifaceted information to make informed decisions	0.96
4. Our organization has provisions for installing dashboard applications on our managers' communication devices to ease access to critical information	0.91
E-supply chain collaboration: Source: Al-Omoush *et al.* (2023)	
To what extent does your company use e-business applications, digital platforms and other IT tools to:	
1. Build long-term relationships with business partners?	0.71
2. Integrate processes and activities of the supply chain?	0.76
3. Maintain close communications with supply chain members?	0.83
4. Support information sharing and exchanging with business partners?	0.86
5. Empower supply chain planning and forecasting?	0.85
6. Share and coordinate supply chain resources and capabilities?	0.60
7. Collaborate with supply chain partners in managing inventory levels according to market supply and demand?	0.77
8. Collaborate with supply chain partners in managing uncertainties, market risks and fluctuations?	0.82
New product performance: Source: Jin *et al.* (2019)	
1. Compared to major competitors, our overall new product program is far more successful	0.80
2. Compared to major competitors, our overall new product development cycle time has been relatively shorter	0.94
3. The overall quality of our new products is higher than that of our competitors	0.92

Source(s): Authors' own work

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