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How do BDA-AI capabilities drive innovation, resilience and efficiency under risk concerns? A dynamic capabilities-contingency perspective

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Abstract

Purpose – This study investigates the role of big data analytics and artificial intelligence (BDA-AI) as an integrated digital sensing capability that enables logistics firms to enhance operational performance in risk-intensive environments. Drawing on dynamic capabilities theory and contingency theory, this research explains how BDA-AI capabilities enhance organisational resilience through service innovation and distribution efficiency, and how organisational resilience, in turn, improves operational performance, while also examining the moderating role of BDA-AI risk concerns.

Design/methodology/approach – Survey data were collected from 296 logistics firms in China and analysed using partial least squares structural equation modelling.

Findings – The results show that BDA-AI capabilities significantly enhance service innovation and distribution efficiency, which in turn strengthen organisational resilience. Organisational resilience also positively influences operational performance. In addition, BDA-AI risk concerns negatively moderate the relationship between BDA-AI capabilities and organisational resilience, indicating that heightened risk concerns weaken the extent to which BDA-AI capabilities are translated into resilience outcomes.

Originality/value – This study advances research on digital transformation and logistics by clarifying the theoretical positioning of BDA-AI and developing a process-oriented, capability-based explanation of digital value creation. It conceptualises BDA-AI as an integrated digital resource infrastructure that remains analytically distinct from the sensing–seizing–reconfiguring processes of dynamic capabilities theory. The findings demonstrate that service innovation, distribution efficiency and organisational resilience function as interdependent capability outcomes, and that BDA-AI risk concerns serve as a negative contingency condition that shapes capability development.

Keywords Big data analytics and artificial intelligence capabilities (BDA-AI), Service innovation, Organisational resilience, Distribution efficiency, Risk concerns, Operational performance

Paper type Research article

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1. Introduction

The rapid integration of big data analytics and artificial intelligence (BDA-AI) has reshaped logistics and supply chain operations by improving decision accuracy, responsiveness and execution efficiency in volatile environments (Ma and Chang, 2025; Majumdar and Mitra, 2024). As supply chains confront geopolitical disruptions, regulatory complexity and rising customer expectations, analytics-driven decision-making has evolved from a competitive advantage into a strategic necessity (Bag *et al.*, 2021). By leveraging predictive modelling, automated optimisation and real-time information processing, BDA-AI enables logistics firms to innovate service processes, enhance organisational resilience and improve distribution efficiency (Hwang *et al.*, 2026). These developments underscore the growing importance of data-driven systems in shaping operational performance.

Despite these advances, uncertainty remains regarding how and under what conditions BDA-AI contributes to improved operational performance. Prior research has predominantly examined BDA or AI as standalone technological resources and frequently modelled direct technology-performance relationships (Chen *et al.*, 2024; Narwane and Priyadarshinee, 2025). Such approaches provide limited insight into the organisational mechanisms through which digital sensing translates into capability development. Moreover, they often conflate technological infrastructure with dynamic capability processes, thereby obscuring the distinction between resource inputs and capability outcomes. This conceptual ambiguity constrains theoretical advancement in logistics analytics research. In light of this, the present study treats BDA-AI as an integrated digital resource infrastructure, analytically separating it from dynamic capability processes and explaining its value through the capability pathways of service innovation, distribution efficiency and organisational resilience under the boundary condition of BDA-AI risk concerns.

In practice, logistics firms face persistent challenges when deploying BDA-AI at scale, particularly in translating analytics insights into execution-level decisions across fragmented distribution networks, coordinating AI-driven recommendations with managerial judgement and maintaining system reliability under real-time disruption conditions (Culotta *et al.*, 2024; Öhman *et al.*, 2021). These implementation difficulties can lead to tangible operational consequences, including service delays, inefficient routing and weakened recovery capacity when analytics-driven decisions fail under disruption. Consequently, logistics firms increasingly struggle not with whether to adopt BDA-AI, but with how to deploy it effectively to strengthen resilience and improve operational outcomes under risk-intensive conditions.

These challenges call for an explanation that moves beyond direct technology–performance relationships and instead clarifies the organisational pathways through which BDA-AI contributes to performance. Accordingly, this study adopts a capability-based perspective in which service innovation and distribution efficiency are conceptualised as two complementary mechanisms by which BDA-AI capabilities enhance organisational resilience, thereby improving operational performance in logistics firms. Drawing on dynamic capabilities theory, BDA-AI is conceptualised as an integrated digital resource infrastructure that strengthens firms' sensing processes by enabling them to identify environmental changes, interpret emerging risks and opportunities, and support timely operational responses. Rather than constituting a dynamic capability itself, BDA-AI provides the technological foundation that enables capability development.

Through this digital sensing role, BDA-AI enables firms to redesign service offerings, enhance adaptability and optimise execution processes. For example, logistics firms can use predictive analytics to anticipate supply chain disruptions, dynamically reallocate resources and maintain service continuity during unexpected events such as port congestion, demand surges or regulatory interventions (Adewusi *et al.*, 2024; Ivanov and Dolgui, 2021). These challenges have been particularly pronounced in China's logistics sector, where firms have experienced pandemic-related shutdowns, last-mile delivery disruptions and heightened scrutiny over data governance. Accordingly, China provides a theoretically meaningful context for examining how analytics-enabled sensing capabilities operate under sustained exposure to operational and regulatory risks.

While BDA-AI enhances firms' sensing capacity, its effect on organisational resilience may depend on contextual conditions. Contingency Theory suggests that organisational outcomes depend on alignment with external conditions such as technological risk and governance requirements (Donaldson, 2001; Wadongo and Abdel-Kader, 2014). In this study, BDA-AI risk concerns, such as concerns over data security, system reliability, algorithmic transparency and regulatory compliance, are conceptualised as a boundary condition that may weaken the relationship between BDA-AI capabilities and organisational resilience. When such concerns are high, firms may become more cautious in relying on analytics outputs and less able to translate BDA-AI capabilities into adaptive and resilient responses.

Existing studies on digital transformation and logistics rarely explain how analytics-enabled sensing translates into multiple interdependent organisational capabilities within a unified capability system. Most studies treat innovation, efficiency and resilience as isolated outcomes, neglecting their systemic interactions and overlooking how risk governance conditions capability development at the process level. Specifically, limited attention has been paid to how AI-related risks, such as data security concerns, system reliability failures and regulatory compliance pressures, may constrain the use of BDA-AI in logistics decisions. This gap is crucial because logistics operations rely on time-sensitive and data-intensive decisions, including routing, delivery prioritisation and disruption response. Integrating dynamic capabilities theory with contingency theory, this study develops a framework explaining how logistics firms translate BDA-AI capabilities into organisational resilience and operational performance. The following research questions (RQs) are proposed:

RQ1. How do BDA-AI capabilities affect organisational resilience through service innovation and distribution efficiency, and how does organisational resilience influence operational performance in logistics firms?

RQ2. To what extent do BDA-AI risk concerns moderate the relationship between BDA-AI capabilities and organisational resilience?

To address these questions, this study empirically tests a capability-based, risk-contingent framework using firm-level survey data analysed through partial least squares structural equation modelling (PLS-SEM).

Consequently, this research advances the literature in three ways. *First*, it resolves conceptual ambiguity in prior BDA and AI research by analytically distinguishing digital resource infrastructure from higher-order dynamic capability processes. Whereas recent BDA-AI and logistics studies have often examined BDA and AI separately or treated them as direct technological drivers of performance, this study conceptualises BDA-AI as an integrated digital resource infrastructure that strengthens analytics-enabled sensing in logistics firms. *Second*, it develops a process-based capability framework that explains how BDA-AI capabilities translate into organisational resilience through two complementary organisational mechanisms: service innovation and distribution efficiency. This extends prior research, which has largely focused on direct technology–performance relationships, by explaining the intervening capability pathways through which BDA-AI creates operational value. *Third*, it extends Contingency Theory by conceptualising BDA-AI risk concerns as a negative boundary condition that constrains the extent to which BDA-AI capabilities are translated into organisational resilience. In doing so, the study responds to limited attention in prior research to how data security, system reliability, algorithmic transparency and regulatory compliance concerns may weaken digital capability deployment.

2. Theoretical underpinnings

2.1 Dynamic capabilities theory

Consistent with Teece's (2018) emphasis on sensing as the foundation of dynamic capability development, this study conceptualises BDA-AI as an integrated digital resource infrastructure that enhances firms' sensing processes. BDA-AI strengthens firms' ability to detect patterns, anticipate disruptions and interpret high-velocity environmental signals; however, it does not constitute a distinct dimension of dynamic capability. Instead, BDA-AI is defined as a composite digital infrastructure and analytics resource configuration that enables firms to continuously collect, analyse and interpret data to support adaptive decision-making.

BDA provides real-time data integration and diagnostic insight, while AI enables predictive, prescriptive and adaptive learning capabilities. When deployed together, BDA-AI enhances firms' ability to scan their environments, interpret emerging risks and opportunities, and update organisational understanding in real time. In this sense, BDA-AI functions as a digital enabler of sensing, seizing and reconfiguring processes that shape how firms initiate and coordinate organisational capabilities.

Sensing refers to the firm's ability to identify, interpret and evaluate changes in its external environment before they fully materialise into operational threats or strategic opportunities (Teece, 2007). In logistics contexts, this involves continuously monitoring demand volatility, delivery bottlenecks, supplier instability and emerging disruption signals across the supply network. BDA-AI strengthens this foundational process by integrating heterogeneous and high-velocity data, detecting anomalies and weak signals, and generating timely predictive insights that improve situational awareness and support early managerial response (Aslam *et al.*, 2018). Accordingly, BDA-AI should be positioned as a digital resource infrastructure that strengthens sensing by enhancing the firm's ability to scan, interpret and anticipate environmental change.

Seizing refers to the firm's ability to mobilise resources and enact responses to opportunities identified through sensing. Prior literature linking analytics-enabled sensing to service redesign and opportunity mobilisation supports this positioning, demonstrating that AI- and data-driven insights facilitate structured experimentation, rapid service prototyping and data-informed reconfiguration of delivery processes (Eslami *et al.*, 2024). In logistics contexts, these capabilities enable firms to translate analytical insights into actionable service improvements and operational innovations.

Reconfiguring captures the firm's capacity to realign organisational structures, routines and resource combinations in response to environmental change. This capability is particularly critical in logistics operations, where firms must continuously adapt to demand volatility, disruption risks and regulatory pressures. AI- and data-enabled reconfiguration supports recovery from disruptions, enhances coordination between digital and physical processes and strengthens organisational resilience over time (Faro *et al.*, 2024). Through reconfiguration, firms institutionalise adaptive capacity by restructuring coordination mechanisms and reallocating resources in response to disruption.

Accordingly, dynamic capabilities theory provides a coherent explanation of how BDA-AI, as a digital resource infrastructure, strengthens organisational dynamic capability processes in logistics service operations (Tan *et al.*, 2025). Sensing, seizing and reconfiguring describe how organisations interpret environmental signals, mobilise resources and realign operational routines when deploying BDA-AI. Through these processes, firms develop strengthened organisational resilience. The three dimensions of dynamic capabilities operate as explanatory mechanisms, whereas service innovation and distribution efficiency represent capability outcomes enabled by these mechanisms.

Service innovation is strengthened by seizing processes triggered by analytics-enabled sensing, capturing firms' ability to mobilise resources, redesign service offerings and exploit opportunities identified through BDA-AI insights. Distribution efficiency is an execution-level capability informed by sensing and seizing processes, through which analytics-driven insights are operationalised into coordinated, reliable logistics processes. These capabilities illustrate how analytics-enabled sensing is translated into operational value through dynamic capability processes within logistics systems.

Dynamic capabilities theory, therefore, provides a process-level explanation of how BDA-AI influences resilience and operational performance through specific organisational capabilities. Through sensing–seizing–reconfiguring processes, firms develop service innovation and distribution efficiency as distinct but interdependent capability outcomes. Accordingly, dynamic capabilities theory provides the foundation for the hypothesised effects of BDA-AI capabilities on organisational resilience, mediated by service innovation and distribution efficiency. It also explains why organisational resilience is expected to improve operational performance.

2.2 Contingency theory

Rooted in the classical formulation of contingency theory (Donaldson, 2001), organisational effectiveness depends on alignment between internal capabilities and external contextual conditions. The theory posits that organisational capabilities are effective only when aligned with environmental conditions such as uncertainty, risk exposure and regulatory pressures (Coreynen *et al.*, 2020). In supply chain and logistics contexts, where operational disruptions, cyber risks and regulatory constraints are pervasive, such alignment is particularly critical (De Lima and Seuring, 2023; Hussain and Malik, 2022).

Digital transformation initiatives, including analytics- and AI-based systems, are especially sensitive to external contingencies. The effectiveness of advanced digital systems depends not only on technological sophistication but also on firms' ability to adapt deployment strategies to contextual conditions such as cybersecurity threats, data governance requirements and system reliability risks (Nguyen *et al.*, 2022; Rathore *et al.*, 2021). These contingencies influence both the depth of system integration and the extent to which decision-makers rely on analytics-driven insights.

Extending Donaldson (2001) contingency logic, this study conceptualises BDA-AI risk concerns as a contextual condition shaping how digital capabilities are deployed, governed and translated into performance outcomes. BDA-AI risk concerns are defined as logistics firms' perceptions and management approaches regarding data security, algorithmic transparency, system stability and regulatory compliance associated with analytics and AI deployment (Rana *et al.*, 2022). Importantly, risk concerns shape governance structures, security safeguards and decision rights surrounding BDA-AI implementation. Firms with heightened risk awareness are more likely to adopt structured governance and monitoring mechanisms that enhance trust, system reliability and disciplined use of analytics systems. Misalignment between BDA-AI deployment and risk governance may therefore constrain the extent to which BDA-AI capabilities support capability development and organisational resilience.

From a contingency perspective, the performance effects of dynamic capabilities depend on their alignment with contextual conditions such as technological risk, regulatory pressure and governance requirements. In the context of BDA-AI deployment, risk concerns shape governance structures, decision rights and implementation discipline. Although risk governance is necessary, heightened risk concerns may also constrain capability development when concerns over security, compliance and system reliability reduce the flexibility and speed with which BDA-AI capabilities are deployed. This logic provides the theoretical basis for conceptualising BDA-AI risk concerns as a moderating condition shaping the relationship between BDA-AI capabilities and organisational resilience, thereby grounding RQ2.

Dynamic capabilities theory and contingency theory explain complementary aspects of the proposed framework. Dynamic capabilities theory explains the internal capability-development process through which BDA-AI capabilities support service innovation, distribution efficiency, organisational resilience and operational performance. Contingency theory complements this logic by explaining how external and technological risk conditions shape the effectiveness of this process. Thus, BDA-AI risk concerns are positioned as the contingency that conditions the capability-development process.

To summarise, dynamic capabilities theory and contingency theory provide the analytical foundation for this study. Guided by dynamic capabilities theory, the study explains how

BDA-AI capabilities are translated into organisational resilience through service innovation and distribution efficiency, and how organisational resilience, in turn, contributes to operational performance. Service innovation reflects opportunity mobilisation (seizing), distribution efficiency represents execution-level deployment and organisational resilience captures adaptive reconfiguration in the face of disruption. Collectively, dynamic capabilities theory explains how BDA-AI-enabled sensing is transformed into organisational capabilities that drive performance (RQ1). Contingency theory explains how BDA-AI risk concerns condition the relationship between BDA-AI capabilities and organisational resilience (RQ2). Together, these perspectives inform the research model presented in Figure 1.

3. Hypothesis development

3.1 Effects of BDA-AI capabilities on resilience

Organisational resilience has been extensively studied as a firm's capacity to withstand disruptions, recover performance and adapt under uncertainty (Duchek, 2020; Linnenluecke, 2017). Recent studies highlight the role of digital technologies in improving visibility, coordination and response to disruptions. Increasingly, resilience is conceptualised as a reconfiguring capability, reflecting firms' ability to realign resources, routines and coordination mechanisms in response to sensed disruptions (Gallo *et al.*, 2023).

In this study, organisational resilience refers to a firm's capacity to maintain operations while adapting structures, routines and resources in response to unexpected disturbances. Its inclusion is grounded in the reconfiguring dimension of dynamic capabilities theory, as it captures how analytics-enabled sensing supports adaptive restructuring rather than only short-term recovery. Beyond recovery, resilience encompasses learning, adaptive resource reallocation and process renewal, enabling firms to evolve under persistent uncertainty (Lengnick-Hall *et al.*, 2011).

Consistent with dynamic capabilities theory, digital technologies that enhance sensing and analytical interpretation enable firms to develop organisational capabilities that support innovation, efficiency and resilience (Teece, 2018). In uncertain, data-intensive logistics environments, firms face the dual challenge of continuously innovating service offerings while maintaining operational efficiency and resilience against disruptions. Achieving these objectives increasingly depends on firms' ability to sense environmental changes, interpret complex signals and respond promptly, rather than relying on static operational routines. From

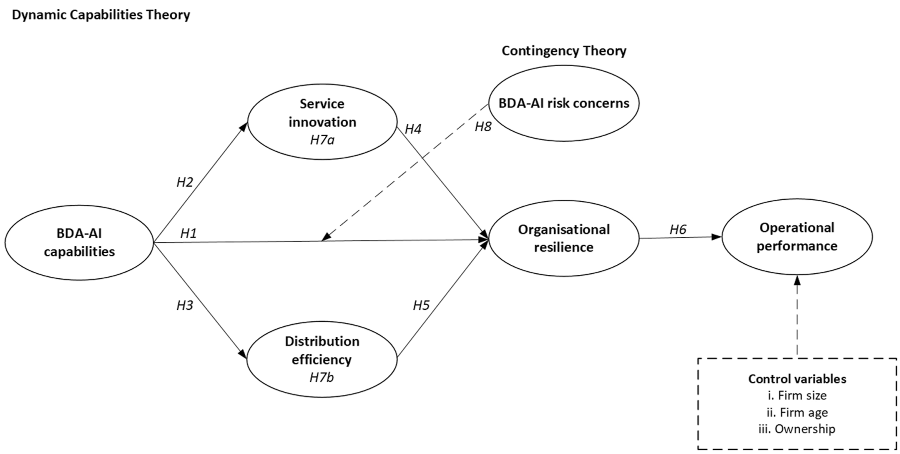

Figure 1. Research model. **Note(s):** BDA-AI capabilities = Big data analytics and artificial intelligence capabilities. **Source(s):** Authors' own work

a dynamic capabilities perspective, firm performance therefore depends on how effectively digital sensing inputs are transformed into adaptive organisational capabilities (Holland, 2006). In this context, BDA-AI functions as a digital sensing infrastructure that provides real-time visibility and predictive insights, but performance improvements materialise only when such sensing is translated into concrete capability outcomes.

BDA-AI provides logistics firms with advanced sensing mechanisms through large-scale data processing, pattern recognition and predictive decision-making. Unlike traditional information systems, BDA-AI enables continuous monitoring of demand fluctuations, traffic conditions, supplier performance and policy changes. This capability is particularly relevant in China's logistics sector, where firms have faced pandemic-related shutdowns, port congestion, regulatory tightening and last-mile delivery disruptions. Under such conditions, analytics-enabled sensing becomes strategically important for sustaining operational continuity and competitiveness.

Hence, BDA-AI strengthens organisational resilience by enabling real-time monitoring of risk indicators, early detection of anomalies and enhanced coordination across organisational units (Gallo *et al.*, 2023; Shobhana, 2024). In logistics contexts, analytics-enabled information sharing reduces siloed decision-making and supports rapid cross-functional responses during disruptions such as transport restrictions, demand shocks or supply interruptions. Through data-driven feedback loops and continuous learning, BDA-AI enhances reconfiguring capability by enabling firms to adjust operational structures, decision rules and coordination mechanisms over time. Thus, this study proposes the following hypothesis:

H1. BDA-AI capabilities have a significant positive influence on organisational resilience.

3.2 Innovation and efficiency as mediators

Drawing on dynamic capabilities theory, this study argues that firms must convert analytics-enabled insights into concrete organisational actions that support both external adaptation and internal coordination (Teece, 2007). In logistics settings, these actions are most directly manifested in two domains, as logistics firms operate under a dual imperative: they must continuously adapt service offerings to changing customer and market requirements while also maintaining efficient execution across distribution and fulfilment processes (Vakulenko *et al.*, 2019). Service innovation represents a market-facing mechanism through which firms redesign service processes, delivery arrangements and customer interaction models in response to changing demand and operational conditions (Barrett *et al.*, 2015). Distribution efficiency represents an operations-facing mechanism through which firms embed analytics-enabled insights into fulfilment, coordination and resource deployment routines (Abideen *et al.*, 2023). Together, these two mechanisms represent complementary organisational pathways through which BDA-AI capabilities are transformed into organisational resilience.

In the service and logistics literature, service innovation is commonly defined as the redesign of service processes, delivery mechanisms and customer interfaces to create new value propositions and improve responsiveness (Barrett *et al.*, 2015; Snyder *et al.*, 2016). Prior research also indicates that digital technologies and data integration support service modularity, flexible fulfilment and adaptive customer interaction in time-sensitive service settings (Opazo-Basáez *et al.*, 2022; Sjödin *et al.*, 2021). However, service innovation is often treated as a direct outcome of digitalisation or as a strategic orientation, rather than as a seizing capability that emerges from analytics-enabled sensing.

In this study, service innovation is conceptualised as an organisational capability reflecting a firm's ability to redesign service processes, delivery mechanisms and customer interaction models in response to sensed market and operational changes. Its effectiveness depends on firms' ability to interpret customer needs and adapt to evolving market conditions (Opazo-Basáez *et al.*, 2022). BDA-AI strengthens this capability by enabling real-time analysis of heterogeneous customer and operational data, allowing firms to identify service bottlenecks, emerging preferences and latent opportunities more rapidly than traditional systems (Ladeira *et al*., 2024; Thayyib *et al*., 2023). In addition, AI-supported automation and algorithmic configuration facilitate personalised service design and adaptive customer interaction mechanisms, which are increasingly important in platform-based and time-sensitive logistics services (Inavolu, 2024; Sjödin *et al*., 2021). Thus, BDA-AI enhances seizing processes by enabling firms to convert sensed information into redesigned and improved service offerings. Accordingly, this study proposes:

H2. BDA-AI capabilities have a significant positive influence on service innovation.

Distribution efficiency has been widely examined as an operational outcome associated with delivery timeliness, cost control and asset utilisation (Pan *et al*., 2019). While studies on routing optimisation, warehouse coordination and delivery planning often emphasise technological solutions and algorithmic models, efficiency can be more appropriately conceptualised as an execution-level organisational capability, reflecting how effectively firms embed analytics-driven insights into routinised coordination and resource allocation processes.

In this study, distribution efficiency is defined as the extent to which logistics firms achieve timely, reliable and cost-efficient delivery through effective coordination, allocation and utilisation of distribution resources. It captures the firm's ability to translate analytical insights into consistent execution performance across logistics operations. Distribution systems involve interdependent activities, including routing, warehousing, inventory positioning and vehicle scheduling, all of which are sensitive to demand volatility, traffic congestion and capacity constraints (Ross, 2004). Traditional optimisation approaches often rely on static assumptions and historical averages, limiting their effectiveness in environments characterised by real-time variability and disruption.

Hence, BDA-AI enables logistics firms to integrate operational data across distribution nodes, apply predictive models for demand forecasting and dynamically adjust routing and scheduling decisions in response to changing conditions (Rashid *et al*., 2025; Shobhana, 2024). For example, machine learning algorithms can anticipate peak demand periods, optimise inventory replenishment cycles and mitigate congestion-related delays – challenges that are particularly salient in China's urban logistics systems. Through analytics-enabled coordination, optimisation and automation, BDA-AI strengthens this execution-level capability by embedding predictive and prescriptive insights into routinised distribution workflows. Accordingly, this study proposes the following hypothesis:

H3. BDA-AI capabilities have a significant positive influence on distribution efficiency.

Dynamic capabilities theory emphasises that organisational capabilities rarely operate in isolation; performance emerges from the alignment and coordinated deployment of complementary capabilities through ongoing reconfiguration. In dynamic environments, organisations must continuously adjust structures, routines and coordination mechanisms to remain adaptive and robust over time. Service innovation often involves redesigning workflows, coordination arrangements and digital interfaces, thereby strengthening flexibility and responsiveness to environmental change (Devi *et al*., 2023; Vendrell-Herrero *et al*., 2021; Yaroson *et al*., 2021). Innovative service configurations, such as flexible delivery options and real-time customer interaction platforms, help firms respond more effectively to demand volatility and uncertainty (Khuntia *et al*., 2024).

As a result, the hypothesised relationships among these capabilities reflect complementarities and capability interdependencies rather than a sequential mediation chain. From a capability perspective, service innovation supports organisational resilience by strengthening adaptive capacity, response speed and continuity in the face of disruption. Firms that continuously redesign service processes are better positioned to absorb shocks, adjust routines and sustain performance in uncertain environments. Accordingly, this study hypothesises that:

H4. Service innovation has a significant positive influence on organisational resilience.

In logistics settings, where service continuity depends on the reliable movement of goods, information and operational resources, distribution efficiency is a critical organisational capability that supports resilience (Sawyerr and Harrison, 2020). Efficient distribution systems reduce delays, minimise coordination failures and improve the visibility and responsiveness of logistics operations, thereby enabling firms to maintain performance under conditions of disruption and uncertainty (Mohammed and Mandal, 2023).

Distribution efficiency strengthens a firm's ability to reconfigure operational processes and maintain coordinated operational action during disruptions by embedding adaptive responses into everyday fulfilment and distribution routines (Yang *et al*., 2009). When logistics firms operate more efficiently, they can reallocate transport capacity, adjust schedules, coordinate with partners and restore service flows more rapidly in response to unexpected disturbances. In this sense, distribution efficiency enhances both the absorptive and adaptive dimensions of resilience, as firms are better able to withstand shocks and continue delivering core services.

Moreover, efficient distribution processes improve operational reliability and reduce the vulnerability of logistics systems to external and internal disturbances (Yang and Lirn, 2017). Firms with higher distribution efficiency are more likely to possess streamlined workflows, stronger coordination mechanisms and better resource utilisation, all of which contribute to faster recovery and greater continuity during periods of disruption. Therefore, distribution efficiency should positively influence organisational resilience by enabling logistics firms to respond more effectively, recover more quickly and sustain performance in turbulent environments. Accordingly, this study proposes that:

H5. Distribution efficiency has a significant positive influence on organisational resilience.

Drawing on dynamic capabilities theory, this study argues that BDA-AI capabilities strengthen resilience by enabling firms to translate analytics-enabled insights into capabilities that support external adaptation and internal coordination. In logistics contexts, service innovation and distribution efficiency represent two complementary pathways through which this transformation occurs. Service innovation enables firms to convert analytics-based insights into redesigned service processes, flexible delivery arrangements and adaptive customer interaction mechanisms (Lehrer *et al*., 2018), thereby enhancing responsiveness and continuity under disruption (Dovbischuk, 2022). Distribution efficiency enables firms to embed predictive and prescriptive insights into fulfilment, routing, scheduling and resource allocation routines, thereby improving coordination, reliability and recovery capability in turbulent operating environments (Dubey *et al*., 2018). Both capabilities help firms respond more effectively, maintain continuity and recover more rapidly under disruption. They therefore serve as mechanisms linking BDA-AI capabilities to organisational resilience. Accordingly, we propose:

H6a. Service innovation mediates the relationship between BDA-AI capabilities and organisational resilience.

H6b. Distribution efficiency mediates the relationship between BDA-AI capabilities and organisational resilience.

3.3 Effect of resilience on operational performance

Operational performance is conceptualised as a multidimensional outcome reflecting efficiency, reliability, responsiveness and service quality in logistics operations. In logistics firms, operational performance captures the ability to deliver services reliably, control operational costs, optimise inventory utilisation and achieve high customer satisfaction in time-sensitive environments (Bhattacharya and David, 2018; Pan *et al*., 2019). As the operational interface between market demand and supply execution, the distribution system plays a pivotal role in shaping overall performance outcomes.

Accordingly, operational performance in logistics firms reflects firms' ability to execute efficiently in stable environments and to maintain continuity and recover operational functionality when disruptions arise (Essuman *et al.*, 2020). Resilient firms are better able to absorb shocks, reallocate resources, maintain coordination across operational activities and recover from disruption without prolonged deterioration in delivery reliability, responsiveness, cost efficiency and service quality. In logistics settings, where performance is highly sensitive to demand volatility, transport interruptions and fulfilment delays, resilience enables firms to preserve operational continuity while adapting routines and resource deployment to changing conditions. Empirical evidence further shows that resilience-related capabilities improve firm performance in the liner shipping industry, that operational resilience positively affects operational efficiency and that organisational resilience contributes to multidimensional business performance, including process-related outcomes (Beuren *et al.*, 2022; Liu *et al.*, 2018). Accordingly, we propose:

H7. Organisational resilience has a significant positive influence on operational performance.

3.4 BDA-AI risk concerns as a moderator

Contingency Theory suggests that the effectiveness of technological capabilities depends on their fit with contextual conditions, such as environmental uncertainty, regulatory pressures and organisational governance arrangements (Coreynen *et al.*, 2020; Donaldson, 2001; Rana *et al.*, 2022). In this study, BDA-AI risk concerns are defined as firms' perceptions of risks related to data security, system reliability, algorithmic transparency and regulatory compliance associated with analytics and AI deployment (Rana *et al.*, 2022). In China's logistics sector, heightened regulatory scrutiny and recurrent cybersecurity incidents have made risk governance an integral component of digital transformation initiatives.

Recent research on AI governance and digital risk management indicates that the organisational value of AI-enabled systems hinges not only on technical capabilities, but also on a firm's ability to ensure transparency, accountability, system reliability, cybersecurity and regulatory compliance (Albulayhi and Alkhalifah, 2026; Polemi *et al.*, 2024). In logistics operations, where AI-assisted decisions can affect routing, delivery prioritisation, resource allocation and responses to disruptions, unresolved issues with algorithmic opacity, data misuse, system failures and compliance risks may undermine managerial trust and limit the effective use of BDA-AI capabilities.

Thus, this study argues that BDA-AI risk concerns are not merely adoption barriers, but important contextual conditions that shape how BDA-AI capabilities are deployed and utilised in organisational routines. From a contingency perspective, heightened risk concerns may lead firms to adopt more cautious and restrictive approaches to data use, system integration and analytics-enabled decision-making (Cheong, 2024; Papagiannidis *et al.*, 2025). In logistics operations, where speed, coordination and information sharing are critical, such caution may reduce experimentation, slow digital integration and constrain the flexible deployment of BDA-AI capabilities.

As a result, even firms with strong BDA-AI capabilities may struggle to translate these capabilities into organisational resilience when risk concerns are great. Concerns over data security, compliance and system reliability may limit collaboration, reduce trust in analytics-supported decisions and hinder rapid responses to disruptions (Cheong, 2024). In disruption-prone logistics environments, these constraints may undermine the extent to which BDA-AI capabilities support situational awareness, coordinated response and adaptive reconfiguration. Therefore, BDA-AI risk concerns are expected to weaken the positive effect of BDA-AI capabilities on organisational resilience. Accordingly, the following hypothesis is proposed:

H8. BDA-AI risk concerns negatively moderate the relationship between BDA-AI capabilities and organisational resilience.

4. Research methodology

4.1 Research context

China's logistics industry provides a highly appropriate empirical context for examining how BDA-AI is translated into operational performance through organisational capabilities. The sector is characterised by large scale, high operational complexity, rapid digitalisation and sustained exposure to environmental volatility. In recent years, logistics firms in China have faced repeated disruptions, including pandemic-related lockdowns, port and inland transport congestion, instability in last-mile delivery and increasingly stringent data security and regulatory requirements. These conditions create substantial variation in the deployment of digital capabilities and performance outcomes, thereby providing a theoretically rigorous setting for examining capability-based mechanisms while mitigating concerns about contextual homogeneity.

At the same time, China has actively promoted digital transformation in logistics through national initiatives such as the Digital Silk Road and Internet Plus (Xu, 2024). While these initiatives have accelerated the diffusion of BDA-AI technologies, logistics firms differ substantially in their ability to convert such technologies into service innovation, organisational resilience and distribution efficiency. This cross-firm variation is essential for empirical identification, as it reduces the risk that observed relationships are artefacts of uniform policy exposure or industry-wide digital mandates.

Accordingly, the Chinese logistics sector offers a theoretically meaningful and practically relevant context for assessing how BDA-AI operates as a digital sensing capability under heightened operational and regulatory risk. The combination of large-scale logistics networks, frequent exposure to disruption and stringent data governance requirements provides a rigorous empirical setting for understanding how analytics-enabled capabilities support reliable, efficient and resilient logistics operations.

4.2 Sample and procedure

China is one of the world's largest logistics markets, underpinned by its role as a global manufacturing hub and the rapid expansion of E-Commerce. Industry statistics indicate that in 2023, China's logistics sector generated approximately 13.2 trillion yuan, while the social logistics cost-to-GDP ratio declined to 14.4%, reflecting ongoing efficiency improvements.

Accordingly, the target population comprises medium- and large-sized logistics firms in China that have adopted, or are in the process of adopting, BDA-AI in their operations. The sampling frame targeted logistics firms with operational and managerial involvement in digital transformation. This included firms engaged in transportation, warehousing, distribution and logistics service provision. To enhance representativeness and reduce sampling bias, stratified screening criteria were applied based on firm size, ownership type and years of operation. The sampling frame was designed to ensure coverage across privately owned, state-owned and mixed-ownership enterprises, as well as firms with varying operational tenure and workforce size. To enhance the suitability of respondents, participants were screened to confirm they held middle- or senior-level managerial positions and possessed direct knowledge of their firm's BDA-AI deployment, operational decision-making or risk governance practices. Firm size, ownership structure, internationalisation level and operational tenure were examined descriptively to assess distributional balance and potential subgroup concentration. No single subgroup dominated the sample to an extent that would bias the estimation of aggregate parameters. Given subgroup imbalance in certain ownership and internationalisation categories, multi-group analysis was considered but not pursued, as highly uneven group sizes may reduce statistical power and yield unstable PLS-SEM estimates. This decision aligns with methodological guidance on subgroup analysis in variance-based SEM.

Furthermore, a purposive sampling strategy was used to ensure that respondents possessed sufficient knowledge of analytics-enabled operational practices. In addition to purposive selection, screening questions were embedded in the survey platform to verify managerial seniority, functional responsibility and direct involvement in deploying digital systems or in operational decision-making.

The study targeted middle- and senior-level managers, as these individuals are typically involved in decisions related to digital system deployment, operational coordination, risk governance and performance management. This key-informant approach strengthens construct validity by ensuring that responses reflect firm-level strategic and operational processes rather than individual perceptions of technology usage.

To further enhance data rigour, respondents were required to confirm at least three years of managerial experience within their firm and familiarity with BDA-AI implementation practices before proceeding with the questionnaire. By ensuring that respondents possessed decision-making authority and implementation experience, the study reduces potential endogeneity concerns arising from uninformed or temporally misaligned reporting.

While the cross-sectional survey design is suitable for testing the proposed theory-driven associations, it limits causal inference. Therefore, several design features were implemented to reduce, though not completely eliminate, potential endogeneity concerns. First, the structural model follows a theory-driven, temporally ordered logic grounded in dynamic capabilities theory, specifying directional relationships from digital resource infrastructure (BDA-AI) to organisational capabilities and, subsequently, to operational performance. Second, reciprocal or simultaneous relationships were not modelled, thereby reducing the risk of simultaneity bias. Third, key informants were required to report on established organisational practices rather than anticipated outcomes, reducing the risk of reverse causality. While longitudinal data would provide additional causal leverage, the present design is consistent with established capability-based survey research in logistics and digital transformation contexts.

4.3 Data collection

Data were collected in 2024 using a structured questionnaire administered through Wenjuanxin (https://www.wjx.cn), a widely used Chinese online survey platform comparable to Qualtrics. Wenjuanxin was selected for its support of industry-specific respondent recruitment, screening filters and controlled survey distribution, enabling access to qualified managerial respondents in the logistics sector while enhancing data quality and traceability.

Screening questions ensured that respondents (1) held middle- or senior-level management positions and (2) worked in firms that had adopted, or were actively using, BDA-AI-enabled operational practices. To enhance response validity, multiple quality-control mechanisms were implemented. First, attention-check items were embedded to identify inattentive responses. Second, response-time thresholds were applied to eliminate surveys completed in unrealistically short durations. Third, duplicate IP addresses and identical response patterns were screened and removed to prevent repeated submissions or automated responses. Fourth, straight-lining and low-variance response patterns were assessed during data cleaning to identify and exclude potentially careless responses.

To encourage candid responses, participants were assured of anonymity and confidentiality. The questionnaire also included brief explanations of key concepts and instructed respondents to answer based on their firm's actual operational experience. After applying eligibility checks, attention filters, response-time screening, duplicate detection and pattern-consistency diagnostics, 296 usable responses were retained for subsequent analysis. These procedures increase confidence that the final dataset reflects informed and high-quality managerial responses.

An *a priori* statistical power analysis was conducted using G*Power (Faul *et al.*, 2009). Assuming a significance level of 0.05, a statistical power of 0.80 and a medium effect size

(f^2 = 0.15), the minimum required sample size was estimated at 118 observations. The final sample substantially exceeds this threshold, indicating adequate statistical power to estimate the proposed model and detect the hypothesised relationships and moderation effects.

Table 1 summarises respondent and firm characteristics. The sample comprised 57.4% male and 42.6% female respondents, with the largest age group being 36–45 years (47.0%). Middle managers accounted for 79.7% of respondents. Most firms were privately owned enterprises (79.1%) and had been operating for 16–25 years. Firms with 100–500 employees represented 33.8% of the sample. Regarding internationalisation, 41.2% of firms reported foreign sales of 1%–25%, while 2.7% reported foreign sales of 76%–100%.

To evaluate potential non-response bias, early and late respondents were compared on key characteristics at both the individual and firm levels, including gender, age, position, firm size, firm age, ownership and degree of internationalisation. Utilising Armstrong and Overton's (1977) extrapolation approach, late respondents were treated as proxies for non-respondents. The analysis revealed no significant differences between early and late respondents across

Table 1. Characteristics of participants and firms (N = 296)

Category	Item	Frequency	Percentage (%)
Gender	Male	170	57.4
	Female	126	42.6
Age	18 – 25	2	0.7
	26 – 35	132	44.6
	36 – 45	139	47.0
	46 – 55	16	5.4
	55 and above	7	2.4
Position	Senior managers	60	20.3
	Middle managers	236	79.7
Firm size (number of employees)	Below 100	13	4.4
	100–500	100	33.8
	501–1,000	91	30.7
	1,001–5,000	64	21.6
	5,001–10,000	15	5.1
	10,001–30,000	8	2.7
	30,000 and above	5	1.7
Firm age (years)	Below 3	1	0.3
	3–6	7	2.4
	7–15	119	40.2
	16–25	121	40.9
	26–40	40	13.5
	40 and above	8	2.7
Ownership	State-owned or state-controlled enterprises	31	10.5
	Private enterprise	234	79.1
	Sino-foreign joint ventures	22	7.4
	Wholly foreign-owned enterprises	9	3.0
Internationalisation degree (the proportions of clients from different countries, specifically, foreign sales)	No internationalisation (0% of foreign sales)	47	15.9
	Small internationalisation degree (1% – 25% of foreign sales)	122	41.2
	Medium internationalisation degree (26–75% of foreign sales)	119	40.2
	Large internationalisation degree (76–100% of foreign sales)	8	2.7

Source(s): Authors' own work

these characteristics, indicating that non-response bias is unlikely to materially impact the findings.

4.4 Measures of the study

All constructs were measured using multi-item scales adapted from established literature (see Table 2). Minor wording adjustments were made to ensure contextual suitability for logistics operations and BDA-AI deployment. All items were assessed using a seven-point Likert scale.

BDA-AI capabilities was measured using seven items adapted from Bag *et al*. (2021). Service innovation was measured using five items adapted from Wang *et al*. (2022). Organisational resilience was measured using seven items adapted from Yu *et al*. (2024). Distribution efficiency was operationalised using eight items adapted from El Bhilat *et al*. (2024), while operational performance was measured using five items from the same source. BDA-AI risk concerns were captured using six items adapted from Rana *et al*. (2022).

Questionnaire development followed a staged validation process. First, a pre-test with logistics practitioners and academic experts was conducted to refine item clarity and contextual relevance. Second, a back-translation procedure was used to minimise translation bias: the questionnaire was translated from English into Chinese and then independently back-translated into English, with discrepancies resolved through iterative discussion (Brislin, 1970). Third, a pilot test involving 50 respondents was conducted to assess item clarity and scale reliability. Composite reliability values for all constructs exceeded the recommended threshold of 0.70 (Hair and Alamer, 2022), indicating satisfactory internal consistency.

4.5 Common method bias evaluation

Given the use of a single survey instrument, potential common method bias (CMB) was addressed using a combination of procedural and statistical remedies, following established recommendations (MacKenzie and Podsakoff, 2012). In response to recent methodological guidance advocating more rigorous diagnostics, additional statistical techniques were applied to directly assess and control for potential method variance.

Procedurally, respondents were assured that participation was voluntary and anonymous, reducing evaluation apprehension and social desirability bias. Psychological separation of predictor and criterion constructs was achieved by organising questionnaire sections with neutral transitions and avoiding construct clustering that might cue hypothesised relationships. Different scale anchors and item formats were used across sections to further mitigate response pattern consistency. The questionnaire also avoided leading language and included reverse-coded items to reduce acquiescence bias. Overall, the instrument was designed with clear instructions, neutral wording and context-specific items to minimise ambiguity and reduce the risk of systematic response patterns arising from item interpretation.

Statistically, two complementary approaches were implemented. First, a full collinearity test was conducted by examining variance inflation factors (VIFs) for all latent constructs (Kock, 2015). All VIF values ranged from 1.016 to 1.372 (see Table 2) and were well below the conservative threshold of 3.3, indicating that neither vertical nor lateral collinearity is problematic and that CMB is unlikely to materially bias the structural estimates.

Second, a measured latent marker variable (MLMV) approach was used to assess and control for CMB (Chin *et al*., 2013). A theoretically unrelated marker construct was included in the survey and linked to all substantive constructs before re-estimating the structural model. The marker paths were statistically non-significant and showed negligible effect sizes. Essentially, the inclusion of the marker variable did not materially alter the magnitude, direction, or statistical significance of the hypothesised relationships, with differences in structural path coefficients remaining minimal (<0.02). Changes in explained variance were also negligible. As shown in Table 3, R^2 differences ranged from 0.005 to 0.008, corresponding

Table 2. Assessment of loading, composite reliability and convergent validity

Constructs/Items	Loadings	CA	CR	AVE	VIF	Source
BDA-AI capabilities		*0.917*	*0.934*	*0.669*	*1.028*	Bag *et al.* (2021)
BAI1: Using BDA-AI, our company can easily integrate information from different data sources	0.756					
BAI2: Our firm routinely uses data visualisation techniques to assist users or decision-makers in understanding complex information	0.796					
BAI3: Our firm dashboards allow us to decompose information to help root cause analysis and focus on continuous improvement	0.830					
BAI4: Our firm has optimised resource usage and utilised assets better by leveraging BDA-AI	0.811					
BAI5: Recycling options have increased by leveraging BDA-AI	0.829					
BAI6: The BDA-AI project is led by experts, and everyone follows the timelines strictly	0.826					
BAI7: BDA-AI project goals are reviewed regularly based on the dynamic business environment	0.870					
Service innovation		*0.882*	*0.914*	*0.680*	*1.372*	Wang *et al.* (2022)
SEI1: Our firm has introduced many new services to the market	0.763					
SEI2: Our firm has introduced many modifications to the existing services	0.835					
SEI3: Our firm constantly seeks find new services	0.860					
SEI4: Our firm has introduced more new services than other firms that offer similar services	0.864					
SEI5: The new services our firm introduced have caused significant changes in the industry	0.796					
Organisational resilience		*0.924*	*0.939*	*0.688*	*1.016*	Yu *et al.* (2024)
ORR1: Given other firms' business partnerships, our firm has developed appropriate ways for the unexpected	0.780					
ORR2: Our firm engages in frequent practice and testing of our emergency plans to ensure their effectiveness	0.779					
ORR3: Our firm focuses on our ability to respond to uncertain situations	0.857					
ORR4: Our firm actively monitors our industry to identify the early warning signs of crises	0.851					
ORR5: Our firm has sufficient resources to withstand the impact of unexpected emergencies	0.817					
ORR6: If primary responsible persons are unavailable, our firm can always find other stakeholders to fill their roles	0.861					
ORR7: Our firm has strong leadership to lead us to sustain future crises	0.857					

(*continued*)

Table 2. Continued

Constructs/Items	Loadings	CA	CR	AVE	VIF	Source
Distribution efficiency		*0.943*	*0.953*	*0.717*	*1.205*	
DIE1: Our firm is able to improve inventory accuracy to track stock levels in real-time	0.878					El Bhilat *et al.* (2024)
DIE2: Our firm can easily modify warehouse space	0.873					
DIE3: Our firm offers sustainable packaging that is physically designed to optimise materials and energy	0.867					
DIE4: Deliveries in our firm are able to adjust/modify their routes based on changes in customer demand	0.881					
DIE5: Our firm can manage outbound transportation by reducing empty miles	0.794					
DIE6: Our firm is able to efficiently manage the return of goods	0.791					
DIE7: Our firm is able to respond to customer requests without delay	0.859					
DIE8: Our firm is able to ship different types of high-quality products in good condition	0.827					
Operational performance		*0.890*	*0.919*	*0.696*	*1.342*	El Bhilat *et al.* (2024)
OPP1: Ability to reduce manufacturing operating costs	0.858					
OPP2: Ability to execute a perfect order (i.e. complete, without delay and damage)	0.887					
OPP3: Improvement in sales share	0.862					
OPP4: Improvement in market share	0.793					
OPP5: Improvement of the product image	0.763					
BDA-AI risk concerns		*0.919*	*0.937*	*0.712*	*1.109*	Rana *et al.* (2022)
RIC1: Our firm does not have enough technology competency to fully adopt an AI-integrated business analytics solution	0.860					
RIC2: Our firm thinks AI cannot be used for important decision-making purposes	0.862					
RIC3: Our firm believes AI-integrated business analytics solutions may not be a technology risk for our firm	0.799					
RIC4: AI-integrated business analytics solutions may not pose security challenges to our firm	0.809					
RIC5: Appropriate security should not be in place before our firm can fully adopt an AI-integrated business analytics solution	0.891					
RIC6: Our firm does not have the appropriate security mechanism to adopt AI-integrated business analytics solutions in our firm fully	0.837					

Note(s): CA = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted; FC = Full collinearity

Source(s): Authors' own work

to percentage changes between 1.72% and 8.70% across the endogenous constructs. These small variations indicate strong structural stability and provide further evidence that CMB does not meaningfully influence the model estimates.

Overall, the convergence of procedural remedies and two independent statistical diagnostics provides triangulated evidence that the findings are unlikely to be artefacts of CMB.

Table 3. Assessment of CMB using the MLMV technique

Endogenous construct	R^2 Without marker	R^2 With marker	Difference	% Difference
Service innovation	0.109	0.116	0.007	6.42%
Distribution efficiency	0.092	0.100	0.008	8.70%
Organisational resilience	0.335	0.341	0.006	1.79%
Operation performance	0.291	0.296	0.005	1.72%

Source(s): Authors' own work

4.6 Control variables

In this study, control variables including firm size, firm age and ownership structure were incorporated to minimise potential spurious explanations for the hypothesised relationships. Firm size was controlled because larger firms typically possess greater technological infrastructure and organisational resources, which may influence operational performance (Szász *et al.*, 2023). Firm age was included to account for accumulated organisational experience and learning that may affect the development and utilisation of technological capabilities (Amaya *et al.*, 2024). Ownership structure was also controlled, as differences among state-owned, privately owned and foreign-invested firms may influence resource allocation and strategic priorities (Tarzijan *et al.*, 2020). The results (see Table 5) indicate that firm size, firm age and ownership structure do not exhibit significant relationships with operational performance ($p > 0.05$), suggesting that the variance in operational performance is primarily explained by the focal constructs included in the equation.

5. Results

5.1 Data analysis

This study employed SmartPLS 4 to test the proposed hypotheses using partial least squares structural equation modelling (PLS-SEM). Consistent with the study's capability-based theoretical framing, the analysis examined directional relationships among digital resource infrastructure (BDA-AI), organisational capabilities and operational performance outcomes. PLS-SEM is well-suited to the study's research objectives for three reasons (Chin *et al.*, 2020; Hair *et al.*, 2024).

First, the study adopts a theory-driven capability framework specifying directional relationships among multiple interdependent organisational constructs, making PLS-SEM an appropriate analytical approach. Second, the framework includes several latent constructs and moderating relationships, which PLS-SEM can estimate efficiently without imposing restrictive distributional assumptions. Third, the use of PLSpredict enables an assessment of out-of-sample predictive performance, complementing explanatory analysis and providing additional insight into the practical relevance of the findings. This combined emphasis on explanatory adequacy and predictive assessment strengthens the overall robustness of the empirical evaluation.

5.2 Measurement model

The measurement model was evaluated in terms of internal consistency reliability, convergent validity and discriminant validity (Hair and Alamer, 2022). As reported in Table 2, composite reliability values ranged from 0.914 to 0.953, and Cronbach's alpha values ranged from 0.882 to 0.943, exceeding the recommended threshold of 0.70. Convergent validity was supported, as all indicator loadings exceeded 0.70 and average variance extracted (AVE) values were above the recommended minimum of 0.50.

Next, discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio (Table 4). All HTMT values were below the conservative threshold of 0.85 (Reinartz *et al.*, 2009), indicating satisfactory discriminant validity and suggesting that the constructs are empirically distinct.

5.3 Structural model

After confirming the absence of multicollinearity among predictor constructs (maximum VIF = 1.517; Table 5), the structural model was evaluated using bootstrapping with 10,000 subsamples. The hypothesised relationships were developed based on dynamic capabilities theory, where BDA-AI capabilities act as a sensing mechanism that enables firms to build operational capabilities and enhance performance outcomes.

The results support all hypothesised direct relationships (H1–H5 and H7). Specifically, BDA-AI capabilities have a significant positive effect on organisational resilience (H1: $\beta = 0.270$, $p < 0.001$), service innovation (H2: $\beta = 0.331$, $p < 0.001$) and distribution efficiency (H3: $\beta = 0.303$, $p < 0.001$), supporting H1–H3. Among these, the strongest effect is observed for service innovation, suggesting that analytics-enabled capabilities primarily translate into service redesign and innovation-oriented activities.

Service innovation also positively influences organisational resilience (H4: $\beta = 0.226$, $p < 0.001$), indicating that continuous service renewal enhances firms' adaptive capacity. Similarly, distribution efficiency has a significant positive effect on organisational resilience (H5: $\beta = 0.170$, $p < 0.01$), thus supporting H4 and H5. These results highlight the role of operational coordination and logistics efficiency in strengthening resilience.

Organisational resilience, in turn, exerts a strong positive effect on operational performance (H7: $\beta = 0.537$, $p < 0.001$), representing the most substantial relationship in the model. This finding indicates that organisational resilience is strongly associated with operational performance in the proposed model.

The coefficients of determination (R^2) indicate that the model explains 10.9% of the variance in service innovation, 9.2% in distribution efficiency, 33.5% in organisational resilience and 29.1% in operational performance. The relatively higher explanatory power for organisational resilience suggests that the combined effects of service innovation and distribution efficiency meaningfully contribute to firms' adaptive capabilities.

In addition, predictive relevance was established, as all Q^2 values are above zero (service innovation = 0.095; distribution efficiency = 0.080; organisational resilience = 0.199; operational performance = 0.136), indicating that the model has out-of-sample predictive capability (Cohen, 1988).

Effect size analysis (f^2) shows that the strongest effect is organisational resilience on operational performance ($f^2 = 0.399$), indicating a large effect. The remaining effects are

Table 4. Assessment of discriminant validity using the heterotrait–monotrait (HTMT) and Fornell–Larcker criterions

Construct	1	2	3	4	5	6
1. BDA-AI capabilities	*<u>0.818</u>*	*0.313*	*0.313*	*0.313*	*0.313*	*0.313*
2. BDA-AI risk concerns	−0.307	*<u>0.844</u>*	*0.325*	*0.325*	*0.325*	*0.325*
3. Distribution efficiency	0.303	−0.311	*<u>0.847</u>*	*0.425*	*0.425*	*0.425*
4. Operational performance	0.359	−0.254	0.394	*<u>0.834</u>*	*0.583*	*0.583*
5. Organisational resilience	0.377	−0.286	0.416	0.537	*<u>0.829</u>*	*0.480*
6. Service innovation	0.331	−0.212	0.420	0.526	0.440	*<u>0.825</u>*

Note(s): The HTMT result is highlighted in italics and falls above the diagonal value, while the result below (italic and underline) belongs to the Fornell–Larcker criterion

Source(s): Authors' own work

Table 5. Result of direct, indirect and interaction effects

Effect	Relationship	Std beta	Std error	*t*-value	*p*-value	BCCI 95% LB	UB	VIF	f^2
Direct	H1: BDA-AI capabilities → Organisational resilience	0.270	0.068	3.994	0.000	0.160	0.384	1.444	0.076
	H2: BDA-AI capabilities → Service innovation	0.331	0.062	5.295	0.000	0.220	0.426	1.000	0.123
	H3: BDA-AI capabilities → Distribution efficiency	0.303	0.066	4.599	0.000	0.186	0.405	1.000	0.101
	H4: Service innovation → Organisational resilience	0.226	0.066	3.448	0.000	0.115	0.330	1.341	0.057
	H5: Distribution efficiency → Organisational resilience	0.170	0.065	2.604	0.005	0.455	0.604	1.393	0.031
	H6: Organisational resilience → Operational performance	0.537	0.045	12.010	0.000	0.455	0.604	1.021	0.399
Indirect	H7a: BDA-AI capabilities → Service innovation → Organisational resilience	0.075	0.027	2.778	0.005	0.029	0.134		
	H7b: BDA-AI capabilities → Distribution efficiency → Organisational resilience	0.052	0.024	2.143	0.032	0.011	0.103		
	H8: BDA-AI risk concerns*BDA-AI → Organisational resilience	−0.109	0.050	2.194	0.014	−0.182	−0.022		
Control variable	Firm size → Operational performance	0.012	0.061	0.198	0.843	−0.111	0.132		
	Firm age → Operational performance	0.002	0.056	0.040	0.968	−0.111	0.108		
	Ownership → Operational performance	−0.054	0.054	1.016	0.310	−0.159	0.052		
		R^2	Q^2						
	Service innovation	0.109	0.095						
	Distribution efficiency	0.092	0.080						
	Organisational resilience	0.335	0.199						
	Operational performance	0.291	0.136						

Note(s): BDA-AI = Big data analytics and artificial intelligence. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Std Beta = Standard beta; Std Error = Standard error; BCCI = Bias-corrected bootstrap confidence interval; LB = Lower bound; UB = Upper bound; VIF = Variance inflation factor; R^2 = Coefficients of determination; Q^2 = Predictive relevance; Effect size (f^2): T = Trivial (<0.02), S = Small (0.02–0.15), M = Medium (0.15–0.35), L = Large (>0.35) (Cohen, 1988)

Source(s): Authors' own work

smaller, including the effects of BDA-AI capabilities on service innovation (f^2 = 0.123), distribution efficiency (f^2 = 0.101) and organisational resilience (f^2 = 0.076), as well as the effects of service innovation (f^2 = 0.057) and distribution efficiency (f^2 = 0.031). These results suggest that BDA-AI capabilities make modest but meaningful contributions to capability development, while organisational resilience is the strongest mechanism through which capability development contributes to operational performance.

Subsequently, predictive validity was assessed using PLS*predict* and Stone–Geisser's Q^2 (Chin *et al.*, 2020; Shmueli *et al.*, 2019). As reported in Table 6, all endogenous constructs exhibited Q^2predict values greater than zero (ranging between 0.028 and 0.176), indicating satisfactory predictive relevance. These results suggest that the model outperforms a naïve benchmark in predicting observed values. To further evaluate predictive performance, the root mean squared error (RMSE) values generated by the PLS-SEM model were compared with those obtained from a linear model (LM) benchmark. The results indicate that the PLS-SEM model consistently yields lower prediction errors than the LM across all indicators, suggesting high predictive power. Following established PLS*predict* guidelines, a model is considered to have high predictive power when the prediction errors of the PLS-SEM model are lower than those of the LM for most or all indicators. Therefore, the findings confirm that the study's model exhibits strong out-of-sample predictive capability.

5.4 Mediating effects

The mediating effects were evaluated using bootstrapping and bias-corrected confidence intervals. The results indicate that BDA-AI capabilities exert significant indirect effects on

Table 6. Results of PLS*predict*

	Item	Q^2predict	PLS-SEM_RMSE	LM-RMSE
Service innovation	SEI1	0.044	0.044	1.019
	SEI2	0.071	0.071	0.868
	SEI3	0.069	0.069	0.831
	SEI4	0.082	0.082	0.914
	SEI5	0.066	0.066	1.222
Organisational resilience	ORR1	0.128	0.128	0.899
	ORR2	0.045	0.045	1.110
	ORR3	0.150	0.150	0.745
	ORR4	0.176	0.176	0.753
	ORR5	0.140	0.140	0.820
	ORR6	0.148	0.148	0.745
	ORR7	0.149	0.149	0.799
Distribution efficiency	DIE1	0.049	0.049	0.972
	DIE2	0.069	0.069	0.932
	DIE3	0.082	0.082	0.927
	DIE4	0.057	0.057	0.955
	DIE5	0.028	0.028	1.166
	DIE6	0.030	0.030	1.130
	DIE7	0.047	0.047	0.982
	DIE8	0.091	0.091	0.946
Operational performance	OPP1	0.122	0.122	0.798
	OPP2	0.123	0.123	0.921
	OPP3	0.069	0.069	1.078
	OPP4	0.084	0.084	0.872
	OPP5	0.072	0.072	0.978

Source(s): Authors' own work

organisational resilience through both service innovation and distribution efficiency. Specifically, the indirect effect via service innovation is positive and significant (H6a: $\beta = 0.075$, $p < 0.01$; CI = [0.029, 0.134]), suggesting that BDA-AI capabilities enhance resilience by enabling firms to innovate and reconfigure service offerings. Similarly, the indirect effect via distribution efficiency is also significant (H6b: $\beta = 0.052$, $p < 0.05$; CI = [0.011, 0.103]), indicating that improvements in operational efficiency and coordination contribute to resilience development. These findings confirm partial mediation, where BDA-AI capabilities influence organisational resilience both directly and indirectly through operational capabilities.

5.5 Moderating effects

The moderating effect of BDA-AI risk concerns was examined using the two-stage approach recommended for PLS-SEM interaction testing (Becker *et al.*, 2023). The interaction effect was statistically significant (H8: $\beta = -0.109$, $p < 0.05$; 95% CI = [−0.182, −0.022]), thereby supporting H8 (see Table 5). The negative coefficient indicates that BDA-AI risk concerns weaken the positive relationship between BDA-AI capabilities and organisational resilience.

To facilitate interpretation, an interaction plot was generated (see Figure 2). The plot shows that the relationship between BDA-AI capabilities and organisational resilience is stronger when risk concerns are low and weaker when risk concerns are high. Specifically, the slope flattens under high-risk conditions, suggesting that concerns about data security, regulatory compliance and system reliability reduce firms' ability to translate BDA-AI capabilities into resilience outcomes.

6. Discussion

6.1 Key findings

This study yields four key findings that clarify how BDA-AI capabilities create operational value in logistics firms. First, the results indicate that BDA-AI should not be interpreted as a direct performance driver, but as an integrated digital resource infrastructure whose value is realised through capability development. The significant positive effects of BDA-AI on service innovation, distribution efficiency and organisational resilience suggest that analytics and AI primarily strengthen firms' sensing and capability-building processes. However, the relatively small effect sizes for several BDA-AI-related paths indicate that these capabilities may deliver practical value gradually rather than through large, immediate effects. This pattern is consistent with prior empirical studies showing that BDA and AI often create value indirectly through organisational routines, innovation processes, coordination mechanisms and resilience capabilities rather than through direct technological effects alone (Bag *et al.*, 2021; Lehrer *et al.*, 2018; Wamba-Taguimdje *et al.*, 2020). Thus, the modest effect sizes should not be interpreted as weak practical relevance. Instead, BDA-AI creates incremental value when analytics-enabled insights are embedded in service redesign, coordination routines and disruption-response mechanisms. This interpretation is consistent with Dynamic Capabilities Theory, which emphasises that digital resources create strategic value when mobilised through organisational processes and capability reconfiguration (Teece, 2018). It also aligns with prior studies showing that analytics-enabled service redesign and coordination mechanisms generate value when embedded in organisational routines (Lehrer *et al.*, 2018).

Second, service innovation and distribution efficiency emerge as two complementary pathways through which BDA-AI capabilities strengthen organisational resilience. The relatively stronger effect of BDA-AI on service innovation, together with the significant indirect effect through service innovation, suggests that, in logistics settings, analytics-enabled sensing is first translated into market-facing adaptations, such as redesigned service processes, flexible delivery arrangements and improved customer interactions. This pattern is consistent with prior research showing that big data analytics can enable service innovation through the

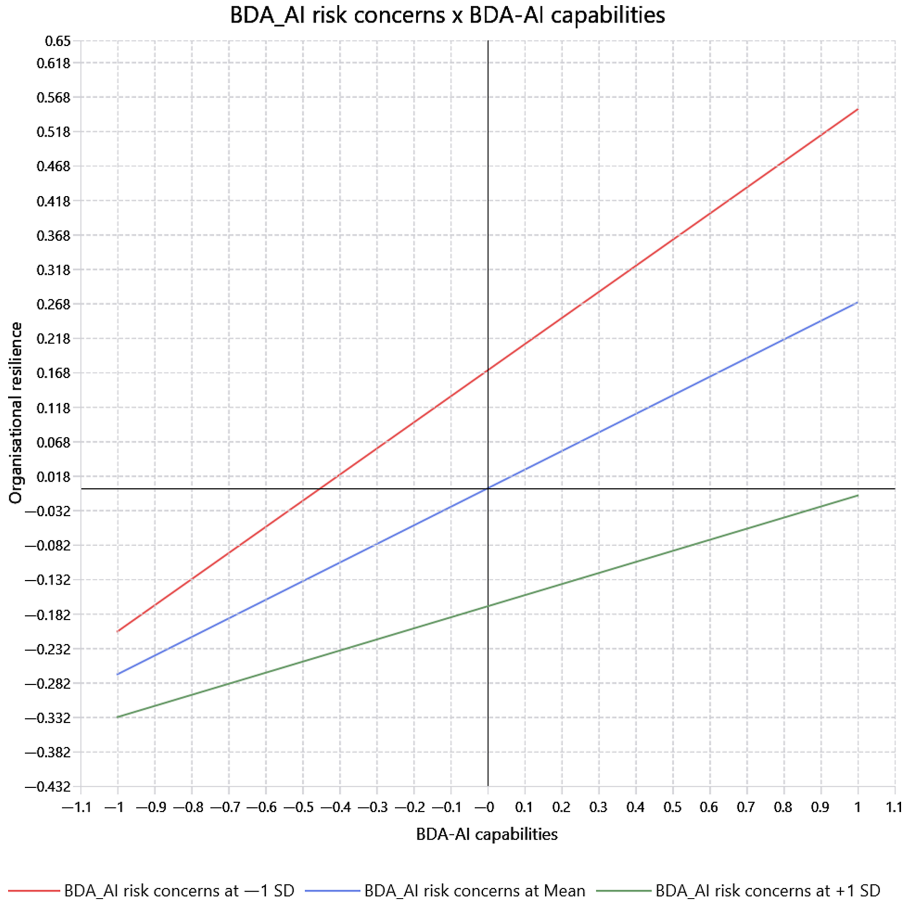

Figure 2. Moderating effect of BDA-AI risk concerns on the relationship between BDA-AI capabilities and organisational resilience. **Source(s):** Authors' own work

reconfiguration of service offerings and customer interfaces (Lehrer *et al.*, 2018), and with evidence indicating that innovation-oriented dynamic capabilities reinforce adaptive response under turbulent conditions (Dovbischuk, 2022). At the same time, the significant effects on distribution efficiency indicate that resilience is also built through stronger coordination, more reliable execution and greater operational visibility, which aligns with prior evidence on the role of analytics in improving coordination and decision quality in complex logistics systems.

Third, the results show that organisational resilience positively influences operational performance. Notably, this relationship has the strongest effect in the model, indicating that organisational resilience is the most practically important mechanism linking BDA-AI-enabled capability development to operational performance. This suggests that for logistics firms, the ability to absorb disruptions, maintain service continuity, reallocate resources and recover operational functionality has more immediate performance implications than BDA-AI capabilities alone do. The result is consistent with prior research showing that resilience supports efficiency and firm performance in disruption-prone environments (Essuman *et al.*, 2020), as well as more recent evidence that digitally enabled resilience contributes positively to operational performance outcomes (Yu *et al.*, 2024).

Fourth, although BDA-AI capabilities generally strengthen organisational resilience, this positive effect weakens when firms face heightened concerns about data security, system reliability, algorithmic opacity and regulatory compliance. This result is consistent with research on the dark side of AI-integrated analytics, which shows that perceived risk, opacity and weak governance can contribute to operational inefficiency and constrain value realisation (Rana *et al*., 2022). In this sense, risk concerns act not merely as background conditions but as active boundary conditions that shape whether BDA-AI-enabled sensing can translate into resilient organisational outcomes.

6.2 Theoretical implications

This study offers several theoretical implications for understanding how BDA-AI capabilities shape organisational resilience and operational performance in logistics firms. By integrating dynamic capabilities theory and contingency theory, the findings provide a more nuanced explanation of how digital capabilities generate value under risk-intensive conditions.

First, this study extends dynamic capabilities theory by empirically demonstrating how BDA-AI capabilities support capability development in logistics firms (Teece, 2018). Specifically, the findings show that BDA-AI capabilities strengthen service innovation and distribution efficiency, which, in turn, enhance organisational resilience and that organisational resilience, in turn, positively influences operational performance. In doing so, the study provides empirical support for a capability-chain explanation in which digital resource deployment enables firms to sense environmental changes, mobilise responses and reconfigure operational routines in volatile environments (Wamba-Taguimdje *et al*., 2020; Yu *et al*., 2024). This contribution extends dynamic capabilities theory into analytics-enabled logistics settings by showing how BDA-AI capabilities are linked to measurable organisational and performance outcomes.

Second, this study advances contingency theory by conceptualising BDA-AI risk concerns as a negative boundary condition on capability development (Donaldson, 2001). Rather than strengthening the performance effects of BDA-AI capabilities, heightened concerns over data security, system reliability, algorithmic transparency and regulatory compliance may weaken firms' ability to translate BDA-AI capabilities into organisational resilience (Rana *et al*., 2022). This finding refines contingency theory by showing that digital capability development is not uniformly beneficial, but depends on whether firms can manage risk conditions without constraining adaptive response and operational flexibility (El Bhilat *et al*., 2024).

Third, this study contributes to the digital transformation and supply chain management literature by offering a more process-oriented explanation of how BDA-AI creates value in logistics firms. Rather than treating analytics or AI as direct drivers of performance, the findings show that BDA-AI capabilities are positively associated with service innovation, distribution efficiency and organisational resilience within a unified capability-based framework. This differs from recent BDA-AI and logistics studies that have primarily emphasised direct technology-performance relationships or examined digital technologies as separate technological resources (Bag *et al*., 2021; Wamba-Taguimdje *et al*., 2020). The results further indicate that service innovation and distribution efficiency represent two distinct organisational capability pathways through which BDA-AI capabilities contribute to organisational resilience. In addition, the positive effect of organisational resilience on operational performance is consistent with prior research showing that resilience supports firm performance in disruption-prone environments (Duchek, 2020; Essuman *et al*., 2020). Taken together, these findings extend prior research that has often examined innovation, efficiency and resilience in isolation by showing how these constructs can be theorised and tested as analytically connected capability domains in logistics contexts.

Fourth, while prior logistics and operations studies report positive effects of big data analytics or AI on performance outcomes (Bag *et al*., 2021; Wamba-Taguimdje *et al*., 2020), these studies typically model technology as a direct driver of performance. In contrast, the present study demonstrates that performance gains are associated with interdependent organisational capabilities, namely service innovation, distribution efficiency and organisational resilience, rather than with direct technological effects alone. This process-oriented explanation offers a more granular account of digital value creation and addresses a key limitation in the extant literature.

Fifth, the present study advances the literature by theorising integrated BDA-AI as a resource infrastructure that enables capability development. It models service innovation, distribution efficiency and organisational resilience as interdependent capability outcomes. Additionally, it demonstrates that risk-related concerns can hinder the transformation of digital capabilities into resilient outcomes.

Finally, by integrating dynamic capabilities theory and contingency theory, this study challenges the traditional efficiency–resilience trade-off that dominates the fields of logistics and operations research. The findings suggest that BDA-AI can enable logistics firms to enhance distribution efficiency and organisational resilience simultaneously by strengthening information-processing capacity, predictive insight and adaptive coordination. This integrated perspective contributes to the literature by showing how analytics-enabled systems may support cost efficiency and robustness concurrently, rather than sequentially or at the expense of one another.

Ultimately, this study contributes by demonstrating how BDA-AI creates value through capability development rather than solely through direct technological impacts. By framing BDA-AI as an integrated digital resource infrastructure, the study elucidates how analytics-enabled insights translate into service innovation, enhanced distribution efficiency and organisational resilience. Moreover, it highlights that this transformation is influenced by concerns about BDA-AI risks, offering a more nuanced perspective on the development of digital capabilities amid risk.

6.3 Practical implications

By clarifying how BDA-AI capabilities contribute to operational performance through service innovation, distribution efficiency and organisational resilience, the findings provide concrete direction for implementing analytics-driven transformation in logistics operations.

For logistics managers, the findings highlight the importance of viewing BDA-AI capabilities as a strategic investment in capability building, rather than merely a standalone technological tool. This approach entails embedding AI-enabled predictive analytics, real-time data integration and intelligent decision-support systems into the core logistics processes. For instance, DHL exemplifies how AI can enhance last-mile delivery through route optimisation, utilising real-time data on traffic, weather, urban density and delivery priorities (DHL Group, 2025). This showcases how BDA-AI can facilitate operational decision-making when integrated into everyday logistics activities, rather than being treated as an isolated technological experiment. Consequently, managers should incorporate BDA-AI into functions such as demand forecasting, routing optimisation, inventory planning, exception management and delivery prioritisation. A phased implementation approach may prove beneficial: managers can first identify operational pain points, then pilot BDA-AI applications in select processes, assess system reliability and decision-making efficacy, and finally, scale successful applications across broader service and distribution operations. This gradual approach is crucial, as prematurely scaling BDA-AI systems without adequate reliability assessment, user training or governance measures may elevate operational risk rather than enhance resilience.

The results also suggest that BDA-AI capabilities are associated with stronger organisational resilience, driven by service innovation and distribution efficiency. In practice, this means that managers should not view resilience as an isolated outcome to be pursued separately from operational improvement. Instead, firms should enhance resilience by investing in service redesign, execution efficiency and cross-functional coordination, so that analytics-enabled insights can translate into more adaptive and reliable operational responses during disruption. For instance, Maersk exemplifies how AI and predictive analytics can enhance logistics resilience by refining planning, optimising routes and responding effectively to weather fluctuations, policy changes and unforeseen events (Maersk, 2025). This illustrates that analytics-driven insights can bolster both service continuity and distribution reliability when integrated into operational decision-making processes. Achieving this may require developing cross-functional analytics teams, establishing clear decision protocols for addressing disruptions, training managers to interpret AI-generated recommendations and ensuring operational staff are equipped to translate analytical insights into timely service and distribution modifications.

Furthermore, the findings underscore the need to manage risks associated with BDA-AI. Elevated concerns regarding data security, system reliability, algorithmic transparency and regulatory compliance can undermine the effectiveness of BDA-AI capabilities in fostering organisational resilience. Therefore, managers should ensure that risk governance promotes, rather than hinders, capability development. For example, in the context of AI-supported route optimisation or delivery prioritisation, firms must ensure that managers understand how recommendations are generated, who is accountable for overriding automated decisions, and how data access protocols are defined across logistics partners. Achieving this necessitates balanced governance frameworks, including well-defined accountability structures, transparent decision-making protocols, robust cybersecurity measures, routine system audits, explainability assessments, data access controls and comprehensive employee training. Such mechanisms can help firms build trust in their BDA-AI systems while ensuring that risk controls do not impede analytics-enabled responsiveness and adaptability.

From a policy and industry development perspective, the findings suggest that regulatory clarity, data governance standards and industry-wide interoperability frameworks are important for supporting the responsible and effective deployment of BDA-AI in logistics. Policymakers can facilitate digital transformation by establishing governance mechanisms that reduce uncertainty without imposing excessive compliance burdens, thereby helping firms translate digital capabilities into resilient, high-performing operations.

6.4 Limitations and directions of future research

Despite its contributions, this study has several limitations that provide opportunities for future research. First, the empirical context is limited to logistics firms operating in China. Although China provides a theoretically relevant context because of its large-scale logistics sector, rapid digitalisation and heightened regulatory scrutiny, digital infrastructure maturity, institutional conditions and risk governance requirements may differ across countries. Therefore, the findings support analytical generalisation to theory rather than statistical generalisation to all logistics firms. Future studies could test the proposed framework across different institutional settings, such as Europe, the United States and other emerging economies, to assess its cross-country applicability. Cross-industry comparisons across manufacturing, retail, healthcare and platform-based service sectors could also examine whether the capability pathways identified in this study operate similarly across different operational environments.

Second, although firm-level heterogeneity, such as firm size, ownership structure and internationalisation level, may influence the strength of the proposed relationships, formal multi-group analysis was not conducted due to substantial subgroup imbalance, particularly in ownership structure and among highly internationalised firms. Conducting MGA with highly unequal group sizes may reduce statistical power and yield unstable parameter estimates in PLS-SEM. Future research using more balanced samples, permutation-based MGA techniques or stratified research designs could examine whether firm characteristics shape the relationships among BDA-AI capabilities, service innovation, distribution efficiency, organisational resilience and operational performance.

Third, this study employs a cross-sectional design, which restricts the ability to make stronger causal inferences. Although the model is grounded in theory, cross-sectional data cannot adequately capture the evolution of BDA-AI capabilities, organisational routines and resilience capabilities over time. Future research could benefit from employing longitudinal or panel designs to explore how BDA-AI capabilities influence service innovation and distribution efficiency over time, how these mechanisms contribute to organisational resilience and how organisational resilience, in turn, impacts operational performance. Additionally, future studies might utilise multi-source data, such as managerial surveys combined with operational records or secondary logistics data, to mitigate concerns regarding same-source bias and enhance causal inference.

Lastly, while this study emphasises BDA-AI risk concerns as the primary contingency, other contextual factors may also influence the development of digital capabilities. Future research could investigate additional moderators, such as organisational culture, leadership support, inter-firm collaboration, digital maturity, industry standards or regulatory intensity, to ascertain when BDA-AI capabilities are more or less likely to enhance resilience and performance. Furthermore, future studies may also explore whether complementary digital technologies, such as blockchain, the Internet of Things (IoT) and cloud platforms, amplify or diminish the effects of BDA-AI capabilities on service innovation, distribution efficiency and organisational resilience.

Data availability statement

The data supporting this study are available from the corresponding author, CNLT, upon reasonable request.

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