Artificial Intelligence-Driven Strategies for Enhancing Operational Performance and Managing Uncertainties in Supply Chain Management

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Abstract

In a dynamic business environment, firms face numerous uncertainties that significantly impact operational effectiveness. Recently, artificial intelligence (AI) has become a powerful toolkit for identifying and managing known and unknown uncertainties. This study examines how AI technology enhances operational performance amid uncertainty, a key concern for firms seeking to gain a competitive edge through advanced technology. Grounded in dynamic capabilities theory (DCT), we developed a construct-based model that includes mediating, moderating, and direct relationships. An empirical analysis was conducted on a sample of 811 leading logistics firms, focusing on the implementation of AI in their operations. We employed partial least squares structural equation modeling (PLS-SEM) to test the proposed hypotheses among latent variables and constructs. The results demonstrate that both known and unknown uncertainties positively influence operational performance. Furthermore, AI provides stability and improvement in logistics operations, thereby enhancing competitive positioning. AI has significantly advanced the management of supply chain uncertainties, reducing operational errors and mitigating risks. The findings suggest that policymakers should consider adopting AI technologies in logistics operations to effectively address and navigate uncertainties.

Keywords: artificial intelligence; logistical operations; known uncertainties; unknown uncertainties; operational performance; uncertainties in the supply chain

1. Introduction

Business operations are increasingly vulnerable to disruptions caused by predictable and unpredictable shocks. Logistics operations provide an optimal context for examining AI-enabled responses to uncertainty, characterized by their significant temporal sensitivity, interconnected, networked nature, and the integration of physical and digital systems (Wang & Zhang, 2025). Policymakers have shown a growing interest in choosing the most suitable supply chain management (SCM) approach for complex competition and dynamic market conditions (Mokadem

& Khalaf, 2023; Li et al., 2022; Leung et al., 2020; Yang et al., 2024). Globally, technology is considered a vital enabler that allows firms to optimize their internal and external operations (Munir et al., 2020; Lima et al., 2022). It forms the foundation of the supply chain networks by reconfiguring firms' capabilities and tasks, thereby reducing costs and enhancing long-term performance and competitiveness (Koberg & Longoni, 2019; Li et al., 2022). A company's potential for success, development, expansion, and prosperity is governed by the operational procedures (Liu et al., 2023). Firms can accomplish strategic goals and secure long-term prosperity by concentrating on operational excellence (Fragapane et al., 2022; Lima et al., 2022). The rapid advent of advanced technology, such as blockchain and artificial intelligence (AI) has transformed the traditional idea of competitiveness for companies (Balsalobre-Lorente et al., 2023; Belhadi et al., 2024; Li et al., 2022) and highlighted the essential function of SCM in enhancing the competitive edge (Garcia-Buendia et al., 2023). However, rapid technological change in logistics operations has transformed the conventional concept of competition, highlighting the importance of advanced technology in SCM (Xu et al., 2023). Unlike many production settings, logistics operations must coordinate with carriers, suppliers, customers, and platform partners to manage disruptions in transportation, warehousing, inventory positioning, and last-mile fulfillment. Logistics unpredictability requires quick sensing, decision synchronization, and process reconfiguration. SCM members monitor day-to-day logistical operations in factories, warehouses, local shipping terminals, and other facilities by utilizing digital resources (Benzidia et al., 2021). Recently, Herold et al. (2024) argued that digital technologies are revolutionizing logistics operations today, enhancing the logistics capability mechanism. The most significant change in the logistics sector is the digital revolution, from an operational perspective, which poses a major challenge for many business partners due to the increasing complexity and globalization of the supply chain (Liu, 2023). For example, artificial intelligence is an emerging and transformative technology in logistics rapidly and has made significant progress in the field by expanding its range of uses and applications in running process (Loureiro et al., 2021; Song et al., 2022; Toorajipour et al., 2021), and AI has emerged as a key solution to formidable problems (Helo & Hao, 2022; Min, 2010). Furthermore, AI technology offers an inventory automation structure with a low error rate, safe employees, no shutdowns, less expensive, and faster (El-Haoud & Bachiri, 2019); a smart inventory management structure with high purchasing performance, stock availability, and lower transportation cost (Nawrocki & Jonek-Kowalska, 2016; Preil & Krapp, 2022); an automatic order picking structure with effective picking time and efficient procedure (Min, 2010); and transport transparency with better delay forecasting and optimization of delivery routes (Helo & Hao, 2022). However, the literature lacks research on AI technologies that address high-risk factors in logistics operations, such as disruptions, variability, unexpected events, and uncertainty. Given uncertainty factors, how can AI improve operational performance and gain a competitive edge? Current work conceptualized the role of artificial intelligence in operations (AIO) in shaping the effects of supply chain uncertainties on operational performance (OP). AIO integrates AI-driven computational systems alongside routine operations to improve decision-making, prediction, and process optimization (Al-Surmi et al., 2022). In logistics and supply chain operations, AIO involves machine learning algorithms, predictive analytics, intelligent automation, and data-driven decision-support systems.

Advanced technology helps predict and mitigate disruptions but cannot control everything in a business (Belhadi et al., 2024). The management of logistical operations is becoming increasingly complex due to frequent, unpredictable disruptions (Tan et al., 2023). The term "uncertainty impact" refers to the effects of a lack of knowledge, confusion, and volatility on organizational decision-making, planning, and outcomes (Ho et al., 2005). Uncertainties pose significant challenges for firms, leading to reduced productivity, disrupted operations, and damaged reputations. These challenges also include hazards and problems arising from unforeseen events (Wang, 2018). Uncertainties in operations can arise from various resources, including disruptions, natural disasters, changes in demand, and unexpected delays (Anne et al., 2009; Bai et al., 2021). Wessel & Aron (2017) concluded that unforeseen incidents can profoundly affect a firm's operations, with varied consequences. In any case, operational efficiency is significantly impacted by uncertainties across multiple industries, which can disrupt supply networks, delay production, increase prices, and reduce overall efficiency (Pereira et al., 2017). Wang (2018) suggested that operational uncertainties have substantial and diverse effects on business performance and that policymakers struggle to detect and manage them in their operating environments. Restuti et al. (2023) noted that managers suppress collaboration to drive operational improvements in response to uncertainty. In this work, given the uncertainty in the supply chain, the broader effects of uncertainty on operational performance can be divided into known and unknown categories. Known uncertainties (KUc) are specific risks, obstacles, or causes that have been identified and addressed. KUc refers to uncertainty arising from expected operational disruptions when the underlying event types are known, and businesses have response playbooks or procedures, such as variability and risk in a known situation. In contrast, unknown uncertainties (UUc) are risks or factors that are unpredictable or unfamiliar, which refers to new or unexpected disruptions where the types of events that will happen are not fully known in advance, there aren't many historical examples to draw on, and there aren't enough pre-planned responses, so people have to think on their feet and adapt quickly. The study analyzes how unknown and recognized uncertainty impacts OP, which demands careful uncertainty management.

Successfully navigating uncertainties requires strategic foresight, adaptability, and robust risk management practices (Belhadi et al., 2024; Fang & Shou, 2015). Navigating uncertainties depends on several strategies, such as scenario planning (developing multiple scenarios to anticipate disruptions), supplier diversification (using multiple sources of raw materials or services), increased visibility, fostering collaboration, and risk management (Ho et al., 2005). Firms can identify uncertainties, but require money and time to implement risk management strategies. In the digital era, technological resources are essential for firms to navigate risks and disruptions (Belhadi et al., 2024; Restuti et al., 2023). Researchers have discussed how AI and machine learning can optimize firm resources, logistics, supply chain management, and waste management in smart production to address critical issues for manufacturing operations by increasing the efficiency and effectiveness of business operations (Ameye et al., 2023; Belhadi et al., 2024; Weiser & Krogh, 2023; Yu et al., 2020). In a dynamic business environment, uncertainties are increasingly prevalent due to factors such as globalization, natural disasters, and geopolitical events (Suryawanshi & Dutta, 2022). Understanding the role of AI in mitigating these uncertainties is crucial to improving business operations. The research question can thus be framed as:

RQ: What is the role of artificial intelligence in managing uncertainties to improve operational performance in the supply chain?

This paper's objectives are threefold. The primary objective is to examine how Artificial Intelligence in Operations (AIO) can enhance logistics operations performance amid known and unknown uncertainties. Specifically, the direct, mediating, and moderating roles of AIO are examined to investigate the impact of uncertainties. By differentiating between known uncertainties (predictable disruptions) and unknown uncertainties (unexpected disruptions), the research seeks to provide a nuanced understanding of how AI can serve as both a strategic and operational capability. A comprehensive model grounded in dynamic capabilities theory (DCT) to clarify the role of AIO is proposed. Current work not only advances academic knowledge but also offers actionable insights for practitioners. Additionally, a research gap is identified that has not been explored in the operations management literature. Table 1 summarizes the literature and highlights existing research gaps in AIO, OP, uncertainty, and the application of structural equation modeling (SEM).

The paper is organized as follows: The theoretical background and hypothesis development are presented in Section 2; the research method is described in Section 3; the results are presented in Section 4; the discussion of the results is provided in Section 5; and conclusions are drawn in Section 6.

2. Literature Review

2.1 Theoretical Background

Previous research has highlighted the theoretical role of a firm's capabilities in determining business performance (Abdelaziz et al., 2023; Teece, 2018). According to Teece et al. (1997), dynamic capabilities theory (DCT) describes a firm's ability to combine, develop, and reorganize internal and external competencies to adapt quickly to unpredictable situations. The DCT approach highlights firms' ability to adapt, innovate, and respond to dynamic market conditions. Winter (2003) argued that dynamic capabilities encompass product development, strategic thinking, and partnerships. DCT expands, evolves, or generates regular capabilities, helping organizations survive in the short and long term by improving their competitive edge (Eisenhardt & Martin, 2000; Mudalige et al., 2018). Dynamic capabilities are essential for firms to enhance their operational performance by enabling them to respond proactively to uncertainties and changes in the competitive environment. In light of DCT, a construct-based model was developed to investigate the role of AIO in minimizing the effects of uncertainty on operational performance (see Figure 1).

To clarify the theoretical logic underpinning the subsequent dual role of AIO, which is conceptualized as an AI-enabled operational dynamic capability rather than as a purely contextual condition. In line with DCT, such capabilities are both (i) shaped by environmental dynamism and (ii) determine the firm's ability to convert turbulence into operational outcomes through sensing, seizing, and reconfiguring. Accordingly, AIO plays two analytically distinct roles that are consistent (not conflicting) within DCT (Abdelaziz et al., 2023). However, AIO, as a mediator, functions as a transmission mechanism because increased uncertainty motivates firms to strengthen information processing and decision support, thereby deepening the enactment and routinization of AI in operational processes. Second, AIO acts as a boundary condition (moderation) because firms vary in the maturity and strength of their capability base. Stronger AIO capabilities enable better sensing and faster operational reconfiguration, changing how strongly uncertainties affect operational performance. Mediation reflects capability enactment in response to uncertainty, whereas moderation reflects heterogeneity in capability strength/maturity that conditions the conversion of uncertainty into performance.

Although previous studies have examined the role of AIO and business performance, most research treats uncertainty as a single factor. Still, uncertainty is treated as an undifferentiated concept in the literature and is not explored in terms of how AI may respond differently to UUc and KUc. The current framework distinguishes between KUc and UUc by differentiating risk from uncertainty. KUc enables organizations to assess probability and establish organized response routines when disruption causes are recognized and historically recorded. In contrast, UUc need improvisational responses since the nature, timing, and impact of disruptions cannot be predicted (Suryawanshi & Dutta, 2022). The variation is crucial for DCT. Firms control variability using sensors, predictive analytics, and optimization processes under KUc. UUc activates exploration-oriented skills, forcing enterprises to sense in real time, seize emerging possibilities, and reconfigure operational processes. Thus, KUc and UUc are qualitatively different environmental situations that need fundamentally different capacity setups. Therefore, existing frameworks have not explained how AI adapts to varied uncertainties, which is a major theoretical gap of this work. Li et al. (2024) noted that DCT emphasizes organizations' ability to adapt and innovate in response to changing environments. In summary, dynamic capabilities theory and artificial intelligence are closely intertwined, with AI acting as a powerful enabler of organizational adaptation, innovation, agility, and resilience in dynamic environments (Pournader et al., 2021). AI allows organizations to generate, deploy, and preserve intangible assets that boost long-term company performance. By leveraging AI technologies to develop and enhance their dynamic capabilities, organizations can better position themselves to thrive.

Table 1: Key studies on the impact of AI, operational performance, and uncertainties in SCM

Authors	Artificial Intelligence in Operations	Operational Performance	Uncertainties	SEM Approach	Major Findings
(Belhadi et al., 2024)	✓		✓		Investigate the leverage of digital technologies for uncertainty
(Chen, 2024)	✓	✓		✓	Explored whether employees of high-tech firms can improve their operations by adopting AI applications and big data analytics
(Ameye et al., 2023)	✓		✓		Explores technology adoption to uncover important patterns in AI use.

(Ghaffarian et al., 2023)	✓		✓		A systematic literature review extracting for disasters and AI’s potential
(Ruel et al., 2023)	✓	✓		✓	Examine the digitalization and operational performance under the effect of organizational legitimacy.
(Al-Surmi et al., 2022)	✓	✓			Explored the strategic alignment for information technology to improve the operational performance
(Cadden et al., 2022)	✓			✓	Examines the organizational and behavioral factors that foster AI integration in supply chains
(Bai et al., 2021)			✓		Examines the impact of various operational risks on a firm's stock market performance.
(Munir et al., 2020)		✓	✓	✓	Explore the mediating effect of supply chain risk management among supply chain integration and operational performance
(El-Haoud & Bachiri, 2019)	✓				Explore the use of effective management techniques for competitiveness.
(Fang & Shou, 2015)			✓		Examine how the levels of uncertainty and competition intensity
(Ho et al., 2005)			✓		the uncertainty in supply chain was measured through a structural approach

2.2 Hypothesis Development

For hypothetical development, the proposed conceptual framework rely primarily on DCT to featured the role of AIO concept for operational performance. OP measures business processes, including regularity, production cycle time, and turnover of inventories (Garcia-Buendia et al., 2023). The literature highlights that the connection from known and unknown uncertainties to operational initiatives is crucial for firms striving to achieve their strategic goals (e.g., quality, cost, flexibility, and delivery), which can harm the operational performance (Ameye et al., 2023; Bai et al., 2021; Wang et al., 2023). Uncertainties are signposts in the landscape of business tasks that are marked by instability and a lack of understanding and can impede decision-making, strategic planning, and operational efficiency (Abdelaziz et al., 2023; Restuti et al., 2023). Known uncertainties indicate possible risks and opportunities that can directly affect business processes (Amayuelas et al., 2023; Atherton, 2003; Chua Chow & Sarin, 2002). However, unknown represent unpredictable factors in business that can pose unforeseen challenges, potentially disrupting operational performance (Hoti et al., 2021). The unpredictable nature of uncertainties makes it particularly daunting; however, understanding and effectively managing these uncertainties is crucial for sustaining operational excellence. The connection between uncertainties and operational success is deep and has several components (Ameye et al., 2023). A conceptual model is shown in Figure 1.

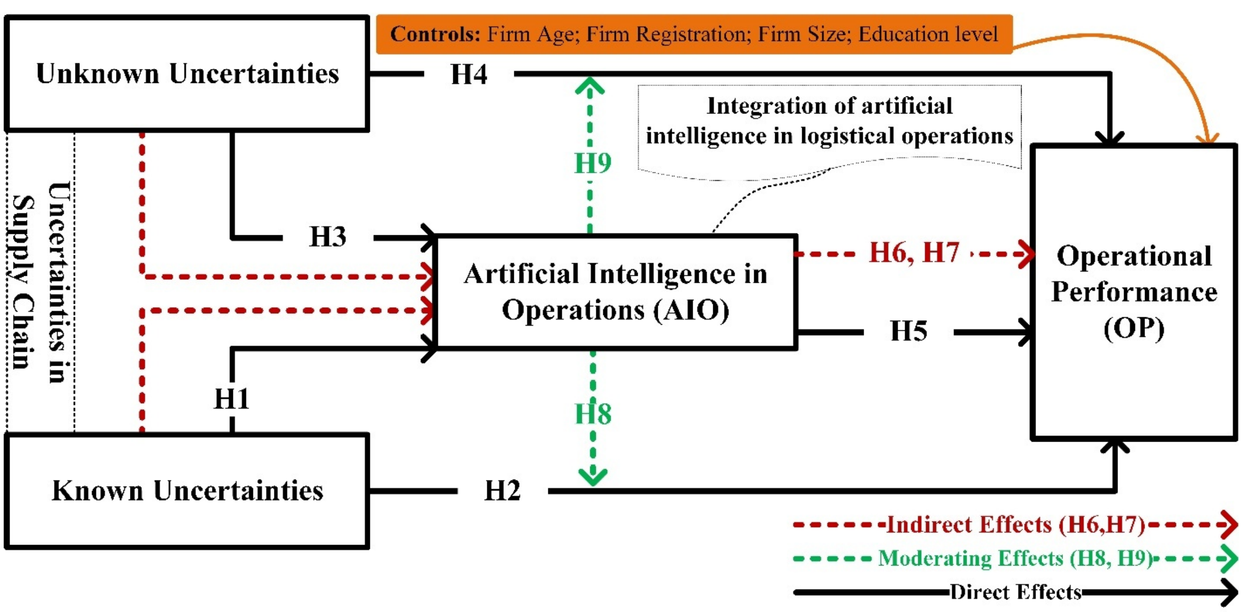

Figure 1: Conceptual Research Model

According to DCT, leveraging advanced technologies such as artificial intelligence and data analytics as a direct dynamic capability by enhancing resource allocation can help firms to reshape the competitiveness by anticipating and mitigating potential risks (Bai et al., 2021; Wessel & Aron, 2017). In literature, AI acts as a direct dynamic capability by enhancing resource allocation, decision-making efficiency, and reducing operational errors (Rana et al., 2024). AI is consistently demonstrated to positively impact operational outcomes through automation, predictive analytics, and process optimization (Sharma et al., 2022). For mediating role, AI serving as a mechanism that how uncertainties impact OP, the theoretical foundation is based on a resources capability of a firm directly integrated wth DCT (Li et al., 2024). Under proposed framework, uncertainties prompt firms to acquire new capabilities (AI) to manage disruptions effectively. Meanwhile, DCT suggests that there is no one-size-fits-all strategy; rather, organizational responses must align with specific environmental conditions. Known uncertainties can typically be addressed through predictive AI systems that enhance operational planning. In contrast, unknown uncertainties require more adaptive, real-time AI applications that support flexible decision-making. This study argues that AIO mediates and moderates these two forms of uncertainty (KU and UU) from complementary perspectives. Regarding the alteration of the relationship between uncertainties and OP, AIO plays a moderating role, suggesting that the effectiveness of organizational processes depends on specific internal and external capabilities of a firm. For example high uncertainties, advanced AI technologies (such as predictive analytics and real-time decision-making algorithms) help mitigate negative impacts, thus positively moderating the relationships. Known uncertainties are predictable risks or variations within the supply chain, such as demand variability or seasonal fluctuations. AI is adept at managing these uncertainties through predictive analytics, demand forecasting, and optimization techniques, enhancing decision-making (Ronchini et a., 2024).

Subsequently, unknown uncertainties include unpredictable disruptions such as natural disasters, pandemics, or abrupt regulatory changes. The adaptability of AI, enabled by real-time data processing and scenario analysis, can mitigate the adverse effects of uncertainty, thereby enhancing resilience (Belhadi et al., 2024). AI systems' performance, dependability, and efficiency may be affected by uncertainties (Ghahramani, 2015). To achieve operational objectives, firms must adjust the business procedures to efficiently handle uncertainties and customer requirements (Helm & Gritsch, 2014). Understanding the relationship between uncertainty and artificial intelligence is crucial for businesses and researchers to mitigate risks and enhance benefits (Bai et al., 2021; Ghouati et al., 2022; Özcan & Hüseyinoğlu, 2023). The relationship between uncertainties and operational performance is well documented; however, the role of AI remains underexplored (Helm & Gritsch, 2014; Rodrigues et al., 2024). The integration of AIO reveals that uncertainties, both known and unknown, can significantly impact operational activities across various industries, a topic that is underrepresented in the existing literature. In recent crises, supply chain disruptions have increased due to subsequent pandemics, and supply chains are increasingly adopting advanced information processing methods, such as AI applications, to improve supply chain performance (Min, 2010). In the context of the USC's effect, this research models two hypothetical relationships (see Figure 1):

H1: Known uncertainties positively affect the AIO.

H2: Known uncertainties positively affect the OP.

H3: Unknown uncertainties positively affect the AIO.

H4: Unknown uncertainties positively affect the OP.

To fully utilize AI technology, researchers and organizations must have a thorough understanding of how operational activities interact with advanced technology (Belhadi et al., 2021; Weiser & Krogh, 2023). The capacity of artificial intelligence technologies to imitate human intelligence has triggered fundamental changes in many sectors (Sharma et al., 2022). The relationship between uncertainties and artificial intelligence is dynamic and multifaceted (Rodrigues et al., 2024), with AI offering capabilities to address and manage them (Pournader et al., 2021; Toorajipour et al., 2021). The implementation of AI in business processes enhances performance by optimizing workflows, minimizing delays, and improving resource allocation. AI models for supply chain optimization enhance critical metrics, including delivery time and cost efficiency (Ikram & Sroufe, 2024). AI mediates the impact of unknown uncertainties on operational performance by providing strategic alternatives during unpredictable situations. The intermediatory role highlights AI's ability to maintain operational stability in volatile environments (Lomakin et al., 2022). Even the nature of work, decision-making, data processing, and the generation of new ideas could change as AI is incorporated into business processes (Ghahramani, 2015). To use AI effectively to address issues and uncertainties, firms need to understand the relationship between AI and OP (Ghaffarian et al., 2023). Charles et al. (2023) suggested that AI can enhance corporate creativity and performance, enabling innovation and addressing uncertainties in the creative process. The study shows how AI technologies manage financial market uncertainties and risks, boosting decision-making and ensuring stable economic growth, which was developed as an AI-based financial stability cognition model (Lomakin et al., 2022). How AI components and fuzzy regulators might optimize running tasks of a firm and solve entrepreneurial concerns is described by (Ali et al., 2023; Charles et al., 2023). Moreover, known uncertainties catalyze the integration of artificial intelligence (AI) into organizational processes, driving innovation and strategic decision-making (Atherton, 2003; Hoti et al., 2021). By recognizing operational challenges, organizations can strategically deploy AI technologies to address specific pain points and optimize performance. The integration of AIO ignites firms' strategies, which can spark uncertainties. Based on the current scenario, a construct, artificial intelligence in operations (AIO), is modeled and investigated. For AIO investigations, three novel relationships are proposed in this study:

H5: The integration of AIO positively affects the OP.

H6: AIO positively mediates the relationship between known uncertainties and OP.

H7: AIO positively mediates the relationship between unknown uncertainties and OP.

H8: AIO positively moderates the relationship between known uncertainties and OP.

H9: AIO positively moderates the relationship between unknown uncertainties and OP.

3. Research Method:

3.1 Data collection

The data collection instrument was a well-designed questionnaire developed by modifying the wording of selected items from literary works. A well-designed questionnaire was developed, including 24 scales and 5 demographic questions (see Tables 2 and 3). For example, in the final questionnaire, six items were adapted from (Belhadi et al., 2021; Cadden et al., 2022) were used for artificial intelligence in a firm's operations. The key themes are appropriate technological capabilities, trust in technology adoption, an appropriate cybersecurity structure, and technological experience from the AIO construct. Nine items were adapted to measure the uncertainty subconstructs, which show that complete information about something is intuitively lacking. Five items were revised to measure known uncertainties, and four items were modified to measure unknown uncertainties (Ho et al., 2005; Sreedevi & Saranga, 2017). Finally, eight items were adapted and included to observe the operational performance concept in the logistics sector

(Mlambo et al., 2024). A five-point Likert scale (1= strongly not consider (SU), 2= not consider (U), 3= neutral (N), 4= consider (C), 5= strongly consider (SC)) was used for each construct.

A team of research experts and scholars was invited to verify the final questionnaire and revise it on the basis of the team's suggestions. The questionnaire's content was evaluated to improve its clarity. After multiple revisions, a final questionnaire was obtained, which included two sections; the first section of the questionnaire was based on demographic information (gender, firm age, firm size, firm registration, and education level), and the second section was based on scale items linked with the KUc, UUc, OP, and AIO constructs. Furthermore, to ensure the quality of the questionnaire, a team of native English and Chinese speakers reviewed and verified the meaning and wording of the questionnaire. A translation procedure was adopted to translate the entire survey from English to Chinese. For translation, a familiar scholar (proficient in Chinese and English) in the logistics field translated the original (English) version of the questionnaire. The consistency of the English and Chinese versions was examined by a practitioner proficient in both Chinese and English.

A cross-sectional design was considered suitable for the current work, as this survey approach allows for testing a hypothetical model, thereby enhancing data validity and generalizability. Different survey phases were employed to collect data from the target sample. In this study, we used the Chinese national database, Tian Yan Cha, to evaluate logistics companies. This work took registered and operationalized logistics companies as survey objects. A convenience sampling method was employed to collect data from respondents associated with logistics companies. The data was gathered from different cities in Guangdong Province, China, to enhance the final data. The reason for choosing the Guangdong region is that Shenzhen, Guangzhou, Foshan, and Shantou are well-known business cities with numerous registered logistics companies. Therefore, research data were collected through a survey between 1st June 2023 and 31 August 2023 to explore the role of AIO in businesses and unexpected actions. Before conducting the survey, we calculated the sample size as 779 by using G*power software with a two-tailed test, a significance level of $\alpha = 0.05$, and statistical power $(1 - \beta)$ of 0.80 (Faul et al., 2007; Gefen et al., 2011). In total, 845 samples were gathered in the survey, and 811 samples were deemed valid for data analysis after the mining process was performed on the collected data. According to the data (see Table 2), the total number of respondents was divided into four categories by education level: 399 had bachelor's degrees, 190 had master's degrees, 182 had college degrees, and 29 had Ph.D. degrees. In terms of firm age, 253 respondents worked at 10-year-old firms, 126 at 8-year-old firms, 176 at 6-year-old firms, 142 at 4-year-old firms, and 114 at new or 2-year-old firms. According to demographic information, most of the 811 respondents were educated, young, and employed by companies with fewer employees. The multidimensional relationships among survey indicators and respondents' demographics are visualized in Figure 2, which shows varying levels of consideration towards AI adoption.

Table 2: Summary of demographics (n=811)

Attributes	Preferences	Frequency	%
Age	Under 20 years	253	31.20
	20-25 years	126	15.54
	26-30 years	176	21.70
	31-35 years	142	17.51
	36-35 years	35	4.32
	Above 35 years	79	9.74

Education	College	182	22.44
	Bachelor	399	49.20
	Master	190	23.43
	Ph.D	29	3.58
	Other	11	1.36
Income	<5k RMB	128	15.78
	5k-10k RMB	375	46.24
	10k-15k RMB	135	16.65
	15k-20k RMB	99	12.21
	20k RMB	74	9.12

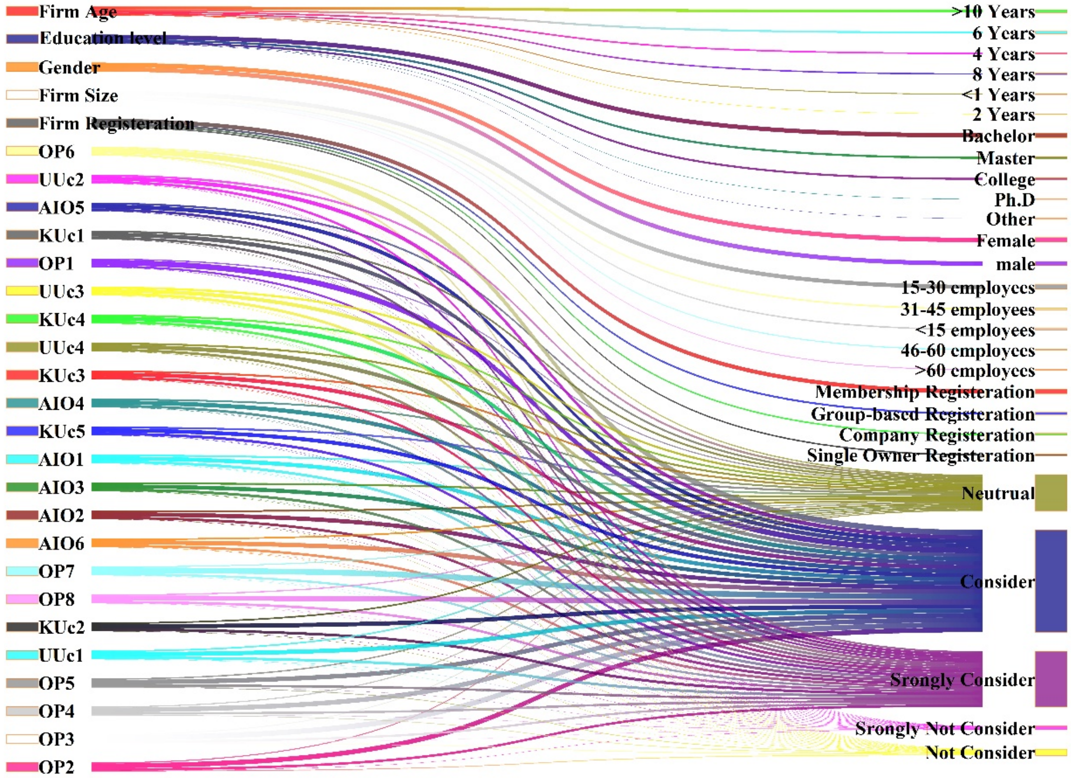

Figure 2: Visualization of the dataset with the Sankey graph. where values in brackets are observations, AIO= artificial intelligence in operation, KUc= known uncertainties, UUc= unknown uncertainties, and OP= operational performance.

3.2 Structural Equation Modeling (SEM)

For the data analysis, the current work employed descriptive statistics, confirmatory factor analysis (CFA), and structural equation modeling (SEM) to achieve the research objectives. To confirm theoretical expectations, CFA is an appropriate method to examine the dataset for a structural model (Schmitt, 2011). The SEM method is suitable for SmartPLS 4.0, and SPSS 25 is an eminent statistical package used throughout the analysis.

4. Results

4.1 Descriptive Analysis

The mean, skewness, and standard deviation values were calculated to clarify the descriptive statistics (see Table 3). The normality of all factors was assessed using skewness and kurtosis. The kurtosis values for each factor were within limits and adequate according to the standards of minus 7 to plus 7 (Black & Babin, 2019; Hair et al., 2010). The skewness values demonstrate that the normality of each factor was between -2 and +2, which meets the standards for a normal distribution. Moreover, three scale items were excluded from the final analysis due to low factor loadings. The final analysis is based on four different structural models.

Table 3: Descriptive statistics of this study

Questionnaire items	Mean	Standard deviation	Excess kurtosis	Skewness
Firm Age	2.774	1.605	-0.715	0.546
Firm Registration	2.527	1.165	-0.336	0.736
Education level of employee	2.122	0.842	0.733	0.673
KUc1: Our firm identifies and monitors known uncertainties (risks and challenges) effectively	3.932	0.900	1.279	-0.923
KUc2: Our firm has employed methods to assess the impact of known uncertainties	3.999	0.885	1.425	-1.003
KUc3: Our firm has well-defined protocols for addressing known uncertainties	3.959	0.892	0.908	-0.838
KUc4: Our firm is proactive in anticipating and preparing for known uncertainties.	3.951	0.881	1.225	-0.9
KUc5: Our firm has the ability to respond to expected operational disruption.	3.969	0.895	0.857	-0.827
UUc1: Our firm has strategies to manage unforeseen changes and disruptions.	3.988	0.903	1.737	-1.102
UUc2: Our firm has a technological process for monitoring and evaluating unforeseen hazards and risks.	3.916	0.893	0.739	-0.752
UUc3: Our firm slows down or stops normal business activities for unforeseen emergencies.	3.961	0.893	0.413	-0.693
UUc4: Our firm is agile in responding to unexpected events that may pose unknown uncertainties	3.965	0.872	1.101	-0.849
AIO1: AI technology is effectively integrated into our operational processes.	3.974	0.900	1.233	-0.936
AIO2: The implementation of AI technology in operations has improved efficiency and productivity.	3.977	0.889	1.425	-0.978
AIO3: AI-driven insights have enhanced decision-making processes.	3.978	0.892	0.959	-0.864
AIO4: AI technologies have effectively optimized resource allocation and utilization.	3.962	0.892	1.523	-0.999
AIO5: The integration of AI has resulted in improved quality and accuracy of services.	3.931	0.898	1.118	-0.877
AIO6: AI-powered inventory management system can easily monitor and update the status of products.	3.979	0.875	1.660	-1.022
OP1: Our firm's operations run smoothly and efficiently with advanced technology.	4.035	0.694	2.445	-0.888

OP2: Technology integration has significantly boosted productivity in our operations	3.98	0.864	0.653	-0.904
OP3: AI-powered inventory management system promotes service quality.	3.956	0.866	1.372	-1.101
OP4: AI-powered inventory management system promotes improve capacity utilization	3.912	0.945	1.339	-1.141
OP5: AI-powered inventory management system improves delivery time.	3.937	0.883	0.614	-0.847
OP6: AI-powered inventory management system improves product availability	4.026	0.696	2.76	-0.916
OP7: AI-powered inventory management system helps to reduce errors in operations.	4.067	0.697	3.202	-1.053
OP8: AI-powered inventory management system reduces wastage.	4.075	0.750	2.94	-1.107

4.2 Confirmatory Factor Analysis (CFA)

For the measurement analysis, the CFA method was implemented via the covariance-based structural equation modeling (CB-SEM) technique on the AIO, OP, UKc, and UUc constructs to assess the internal validity and reliability of the structural designs (see Table 3 and Figure 3). In CFA, the model fit measurement was assessed through chi-square (value=114.769), degree of freedom (value=224.000), RMSEA (value= 0.071), GFI (value= 0.894), AGFI (value=0.870), SRMR (value= 0.054), NFI (value= 0.894), TLI (value=0.902), CFI (value= 0.913), factor loadings, average variance extracted (AVE), scale composite reliability (SCR) for both the single factor (rho_c) and average (rho_a), Cronbach's alpha, correlations among variables, and variance inflation factor (VIF) values. Additionally, the VIF method was used to account for the potential of common method bias (CMB). All VIF values were below the recommended threshold of 3.3 (Browne & Cudeck, 1993; Leguina, 2015), indicating that CMB is not a serious concern in our model. The results of the CFA concerning the VIFs, AVEs, SCRs, and factor loadings are shown in Table 3. The EFA results indicate that the SCR values for rho_a and rho_c indicate the ideal position of the models in terms of inherent quality. The above 0.70 values of the SCR for all the constructs indicate good internal consistency of the model (Browne, M. W., and Cudeck, 1993). According to the CFA results, all the factor loadings were acceptable (the acceptance criterion was greater than 0.50), whereas the minimum factor loading was 0.647 in the current analysis, and factor overlap did not exist.

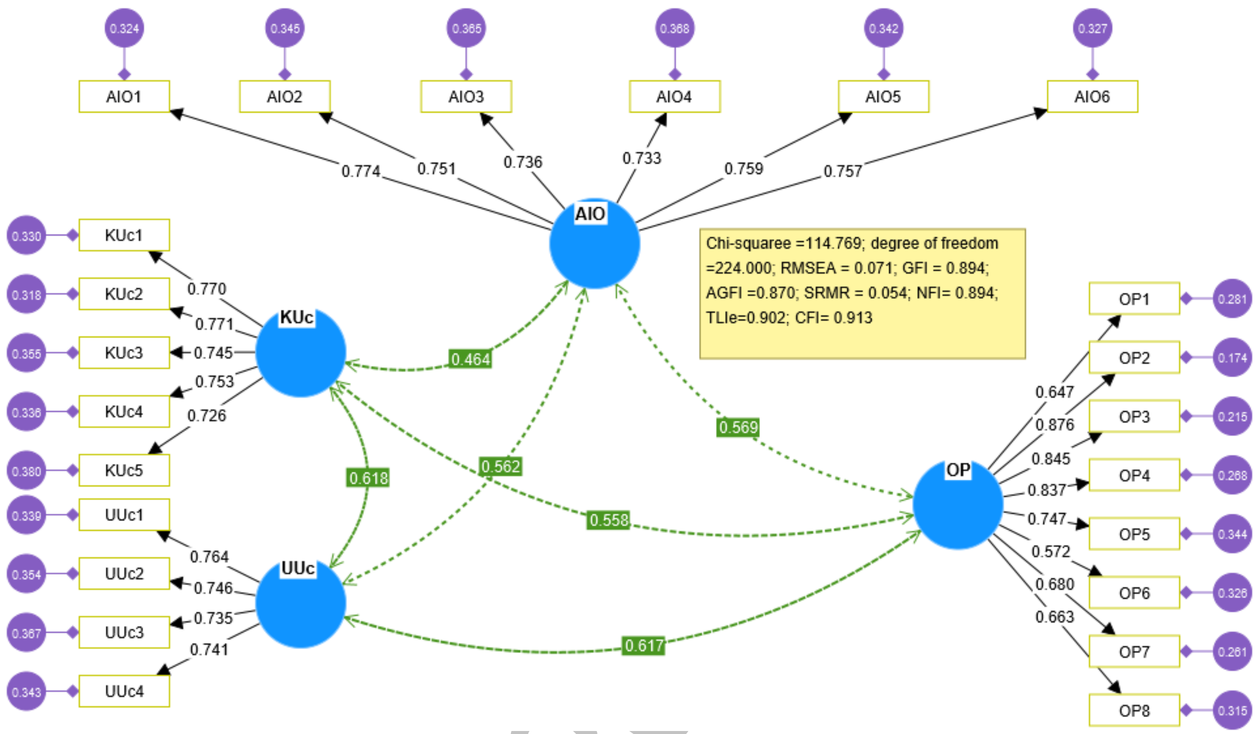

Figure 3: CFA analysis following CB-SEM. where KUc= known uncertainties, UUc= unknown uncertainties, AIO=artificial intelligence in operations, and OP=operational performance.

The quality of data validity was assessed through convergent validity (CV) and discriminant validity (DV) approaches (Leguina, 2015; Ringle et al., 2023). AVEs and SCR (rho_c) values were extracted and confirmed through factor loadings. Inclusively, the calculated AVEs were above 0.50, indicating high-quality convergent validity. Next, two popular criteria, the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion, were used for DV (see Table 4). For the Fornell-Larcker criterion, the DV was observed and confirmed through an assessment of the intercorrelations and the square roots of the AVEs. For the HTMT criteria, the HTMT values were below 0.9, thereby establishing the DV (Franke & Sarstedt, 2019). In the factor analysis, all square roots of the AVEs exceeded the intercorrelations, confirming the DVs.

Correlations among variables were calculated between +1 and -1. The degree of multicollinearity was examined through the variance inflation factor (VIF), which influences issues among constructs during multiple-factor analysis. The calculated VIF values were ranged from 1.889 to 2.047 for AIO, 1.670 to 2.024 for KUc, 1.670 to 3.634 for OP, and 1.794 to 1.862 for UUc. Therefore, the VIF results indicate that multicollinearity is not present. The correlation matrix indicates that all constructs are significantly associated in the expected directions, with correlation coefficients below the threshold for multicollinearity concerns, thereby supporting the constructs' distinctiveness (see Table 5).

Table 3: Factor analysis

Constructs	**AIO**	**KUc**	**OP**	**UUc**
Factor loadings	≥0.733***	≥0.726***	≥0.647***	≥0.735***
Cronbach's α	0.937	0.926	0.974	0.904
Reliability	Established	Established	Established	Established
SCR (rho_c)	0.941	0.932	0.981	0.914
AVE	0.728	0.732	0.872	0.726
Convergent Validity	Established	Established	Established	Established
VIF	1.889 to 2.047	1.670 to 2.024	1.670 to 3.634	1.862 to 1.794

Note: KUc= known uncertainties, UUc= unknown uncertainties, AIO=artificial intelligence in operations, and OP=operational performance, AVE= average variance extracted, SCR= scale composite reliability, VIF= variance inflation factor.

Table 4: Discriminant Validity

Constructs	**AIO**	**KUc**	**OP**	**UUc**
Fornell-Larcker criterion				
AIO	**0.853**			
KUc	0.464	**0.855**		
OP	0.569	0.558	**0.934**	
UUc	0.562	0.618	0.617	**0.852**
Heterotrait-monotrait ratio (HTMT) - Matrix				
AIO	**1**			
KUc	0.465	**1**		
OP	0.583	0.578	**1**	
UUc	0.562	0.619	0.640	**1**

Scale Items	6	5	8	4
Discriminant Validity	**Established**	**Established**	**Established**	**Established**

Note: KUc= known uncertainties, UUc= unknown uncertainties, AIO=artificial intelligence in operations, and OP=operational performance.

Table 5: Correlation Matrix of Study Constructs

Constructs	**AIO**	**KUc**	**OP**	**UUc**
AIO	1	0.464	0.569	0.562
KUc	0.464	1	0.558	0.618
OP	0.569	0.558	1	0.617
UUc	0.562	0.618	0.617	1

Note: KUc= known uncertainties, UUc= unknown uncertainties, AIO=artificial intelligence in operations, and OP=operational performance.

This study builds stepwise empirical paths to investigate the provided hypothesis for direct and mediated effects via an empirical approach (Chen et al., 2022). Current research uses operational performance (OP) as an explanatory construct, unknown uncertainties (UUc), and known uncertainties (KUc) as core explanatory constructs, and artificial intelligence in operations (AIO) as an intermediary construct.

$$OP_{it} = c_0 + c_1 UUc_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (1)$$

$$OP_{it} = g_0 + g_1 KUc_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (2)$$

$$OP_{it} = e_0 + e_1 AIO_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (3)$$

$$AIO_{it} = b_0 + b_1 UUC_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (4)$$

$$AIO_{it} = d_0 + d_1 KUC_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (5)$$

$$OP_{it} = h_0 + h_1 KUC_{it} + h_1 AIO_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (6)$$

$$OP_{it} = d_0 + d_1 UUC_{it} + d_1 AIO_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (7)$$

$$OP_{it} = g_0 + g_1 AIO_{it} * UUc_{it} + controls_{it}[firmage + firmsize \ + firmregisteration + education\ level] + \acute{\varepsilon}\ (8)$$

$$OP_{it} = r_0 + r_2 AIO_{it} * KUc_{it} + controls_{it}[firmage + firmsize + firmregisteration + education\ level] + \acute{\varepsilon} \ (9)$$

where equations (1) and (2) represent the empirical paths for classifying the effects of known and unknown uncertainties toward the OP. Equation (3) expresses the direct effect of AIO on OP, and equations (4) and (5) represent the effects of known and unknown uncertainties, respectively, on AIO. The intermediary effect of AIO with the inclusion of equations (4) and (5) is represented in equations (6) and (7). The moderating effects of AIO are presented in equations 8 and 9. Furthermore, in the equations, the castoff of the subscripts *i and t* is the classification of the firm and year.

4.3 Structural Equation Modeling Analysis

In SEM analysis, the smartPLS bootstrapping technique with 5,000 subsamples is employed to generate p-values, β values, t-values, and standard deviations for assessing significance and evaluating the proposed hypothesis. Consistently, the coefficient of determination, known as R-squared, was measured by examining the proportion of the total variance in the dependent variable that is explained by the variation in the independent variable. According to Figure 4, the calculated R-squared values for OP as the dependent variable and AIO as the mediating variable are r2 = 0.489 and r2 = 0.268, respectively. Additionally, the age, size, registration, and educational level of the respondents were controlled for throughout the analysis. SEM analysis indicated that all the hypotheses were significantly supported by the SEM structural design. The examination of the structural design's fitness was completed before proceeding to SEM analysis (see Table 6).

Table 6: Model structural design fit indices

Fit Indices	Results
SRMR (standardized root mean square residual)	0.058
d_ULS (the squared Euclidean distance)	1.173
d_G (the geodesic distance)	0.352
Chi-square	1603.123

NFI (normed fit index)	0.854

We assessed the fit using the standardized root mean square residual (SRMR), the squared Euclidean distance (d_ULS), the geodesic distance (d_G), the chi-square statistic, and the normed fit index (NFI). where SRMR represents the difference between the correlation matrix and the observed correlation, which could be used for misspecification issues, whereby the results should be less than 0.08 for a good fit (Bentler & Bonett, 1980; Henseler et al., 2016). A threshold as low as 0.80 has been anticipated in the literature. However, the NFI fit index is an incremental degree that compares the chi-square value of the structural design, which should be between 0 and 1, and values close to 1 indicate a good fit (Bentler & Bonett, 1980; Henseler et al., 2016). For NFI, the calculated value was 0.854. Overall, the results of the fitness tests established for the SDs were acceptable and well suited for further analysis. The SEM results, presented in Table 7 and Figure 4, indicate that the coefficients provide insight into the relationships and interactions among the variables in the structural equation model, highlighting their significance and magnitude of effects on OP.

Table 7: SEM results for hypothesis testing

	Effects				Confidence intervals	
Paths	**Coefficients**	**Standard deviation (STDE)**	**T statistics (|O/STDEV|)**	**P values**	**2.50%**	**97.50%**
AlO -> OP	0.308	0.035	8.898	<0.001	0.24	0.376
KUc -> AlO	0.213	0.04	5.275	<0.001	0.13	0.289
KUc -> OP	0.24	0.036	6.68	<0.001	0.173	0.313
UUc -> AlO	0.372	0.049	7.556	<0.001	0.279	0.472
UUc -> OP	0.348	0.036	9.713	<0.001	0.283	0.423
AlO x UUc -> OP	0.109	0.034	3.203	<0.01	0.03	0.159
AlO x KUc -> OP	-0.085	0.042	2.004	<0.05	-0.169	-0.004
UUc -> AlO -> OP	0.115	0.022	5.188	<0.001	0.077	0.165
KUc -> AlO -> OP	0.066	0.015	4.363	<0.001	0.04	0.099

Note: KUc= known uncertainties; UUc= unknown uncertainties; AIO=artificial intelligence in operations; OP=operational performance; Significance levels are $p < 0.05$, $p < 0.01$, and $p < 0.001$.

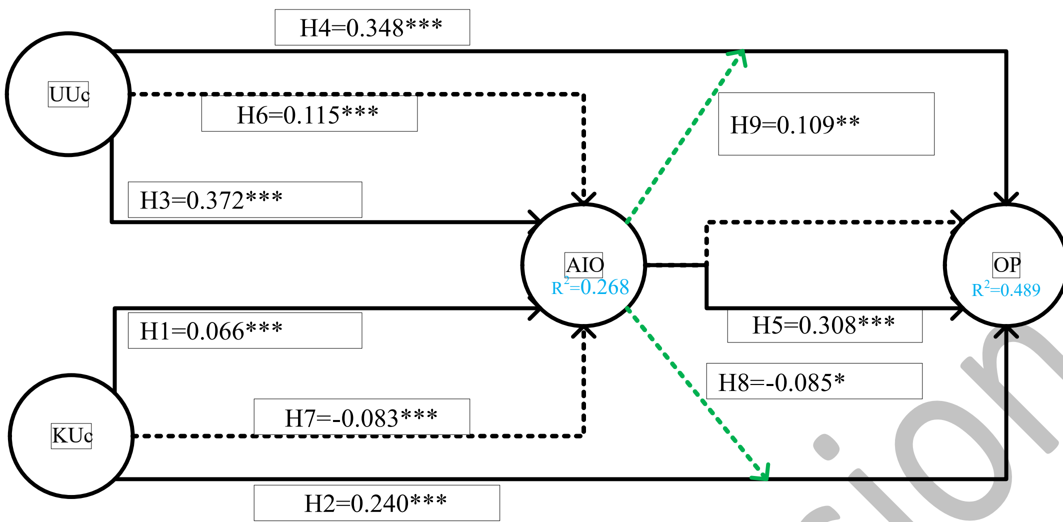

Figure 4: SEM results for hypothesis testing where KUc= known uncertainties, UUc= unknown uncertainties, AIO=artificial intelligence in operations, and OP=operational performance. Significance levels are (*)= $p < 0.05$, (**)=$p < 0.01$, and (***)=$p < 0.001$.

Figure 4 shows that the direct effects of uncertainties in the supply chain, both known and unknown, on OP were positive and significant. For example, SEM results show that known uncertainties (KUc) strengthen a firm's OP, with β = 0.240, t-value = 6.680, and p < 0.001, indicating that firms are aware of specific uncertainties. The results verified that known uncertainties enable firms to operate within target risk levels, prepare contingency plans, and develop more agile processes for rapid response. According to the current results, input known uncertainties have a significant effect on integrated AIO, with β = 0.213, t-value = 5.275, and p <0.001, indicating firms' support and readiness to increase operational elasticity and reduce disruptions when known challenges arise. Similarly, the effects of unknown uncertainties on OP and AIO were positive and significant, with β = 0.372, t-value = 7.556, p <0.001, and β = 0.348, t-value=9.713, p <0.001. The results for UUc indicate that the firm needs to prepare for unexpected changes and develop a resilient strategy for flexible logistics operations that can quickly adapt to new developments and challenges. For example, a firm might diversify its supply chain or invest in cross-training employees to ensure that operations can continue smoothly under various scenarios. Unknown shocks prompt firms to devise innovative ways to improve or develop new services to mitigate disruptions.

Next, the effect of artificial intelligence in operations (AIO) on OP was positive, with β = 0.308, t-value = 8.988, and $p<0.001$, which is supportive and indicates that logistical operations are enhanced by integrating AI technology. Specifically, the results support the use of AI technology, which reduces human error, increases service levels, and frees up firm resources to focus on more complex activities. Furthermore, the mediating role of AI technology among known and unknown uncertainties and operating performance was identified as positive and significant, with β =0.066, t-value = 4.363, and $p<0.001$, and β = 0.115, t-value = 5.188, and $p< 0.000$. SEM revealed that the moderating effect of AIO on the relationship between KUc and OP was significant and negative, with β=-0.085, t-value=2.004, and p-value< 0.05, whereas AI can lead to decisions that fail to account for the complexities of As uncertainties as risk, flawed outcomes. AI systems are often opaque, making it challenging to comprehend their decision-making processes and intervene effectively when necessary. There is also a risk of misalignment between AI outputs and human expertise, which is crucial in managing uncertainties. On the other hand, the moderating effect of AIO on the relationship between UUc and OP was positive, with β = 0.109, t-value = 3.203, and $p < 0.01$. The outcome for AIO explained that AI has a positive influence on operational performance in the face of unknown uncertainties by enhancing predictive capabilities, enabling adaptive learning, and automating decision-making. The ability of AI to analyze vast datasets allows AI technology to identify hidden patterns, predict potential issues, and suggest proactive measures.

5. Discussions

This study contributes to the existing body of knowledge on the logistics sector and AI integration through an empirical behavioral approach. The findings indicate a positive effect of UUc and Kuc on AI in logistics operations, thereby confirming hypotheses H1 and H2 and reinforcing existing research on technology adoption (Ali et al., 2023; Belhadi et al., 2024; Fragapane et al., 2022). Scholars have verified that the potential of AI and digital technologies to enhance supply chain resilience and performance is particularly beneficial for technology-based firms, especially in dynamic, uncertain environments (Ameye et al., 2023; Han et al., 2025; Pham et al., 2023). In alignment with existing literature, our findings demonstrate that the adoption of AI substantially enhances operational performance and strengthens firms' capacities to navigate both known and unknown uncertainties. This study contrasts with the existing literature by highlighting that previous research primarily addresses known risks, whereas this study explicitly distinguishes between known and unknown uncertainties. It empirically analyzes the direct and indirect impacts of AI on operational performance. Moreover, this study examines the role of AI in mitigating the effects of supply chain uncertainty on operational performance, as well as the effects of UUc and KUc on AI integration. In addition, numerous studies have investigated operational performance for risk/uncertainty factors in the supply chain, such as Pham et al. (2023) and Jajja et al. (2018); however, a few components of uncertainties were investigated for the moderating role of high integration among supply chain partners with a limited scope regarding technology. Therefore, firms' operational performance is always threatened by risk (Pham et al., 2023), and understanding the links identified in the current analysis positions companies strategically to extract considerable advantages, according to the investigation.

Furthermore, this study enhances the current understanding of digitalization's role in supply chain management amidst uncertainty. This study differentiates and empirically examines the various roles of AI, including direct, mediating, and moderating effects, in relation to the impact of known and unknown uncertainties on logistical operations, contrasting with prior research that primarily addressed the advantages of AI technology. AI (H6, H7, H8, and H9) plays a critical role in operations, as confirmed by the results. The reasoning behind its role is the process of installing AI algorithms. AI algorithms enable firms to operate autonomously by providing options for different courses of action and recommending solutions to problems (Chen, 2024). These findings are likely to encourage firms to adopt AI in their logistical operations. Further, findings reveal that AIO enhances operational performance (H5), which is consistent with previous research (Pournader et al., 2021; Ruel et al., 2023; Sharma et al., 2022). It means AI can be employed in firms if leaders want to innovate their operations by developing and transforming new software for services (Rana et al., 2024). Therefore, with a load of advanced technologies such as AI, logistical operations are more innovative and faster. Next, Pham et al. (2023), Hotrawaisaya & Jermsittiparsert (2020), Pereira et al. (2017), Munir et al. (2020), Wiengarten et al. (2016), and Wang (2018) have investigated the connections between uncertainties and operational performance, but have not proven the effects of KUc and UUc. Wang (2018) argued that uncertainties affect logistic performance, but did not clarify the performance indicators, such as financial/operational/sustainable, or environmental. The evaluation shows that UUc and KUc uncertainty affect the operational performance of logistics firms. Logistics organizations confront supply chain disruptions, market fluctuations, and technology developments. Companies could implement AI-driven supply chain analytics tools to better understand and mitigate known risks, such as supplier delays or demand fluctuations. Even firms can develop adaptive AI systems that are capable of learning from unforeseen events and dynamically adjusting business operations to mitigate the impacts of UUc and KUc.

Data from China's logistics sector, which includes numerous supply chain members, provides a comprehensive assessment of AI technology's capabilities for managing uncertainty. Investment in AI technologies is key for organizations trying to boost operational performance. The positive coefficients associated with AI adoption indicate its potential to drive efficiency, productivity, and decision-making across various operational functions. Therefore, the logistics sector of an economy should invest in AI to develop predictive maintenance systems that minimize downtime, reduce maintenance costs, and improve overall operational performance. Furthermore, to allocate resources strategically, firms can leverage AI to streamline processes and optimize utilization. Thus, suggesting that mitigating methods are even more important when considering supply chain concerns. Furthermore, the adoption of AI and operational performance highlights opportunities for firms to utilize AI technologies to better understand and mitigate uncertainties in their supply chains. While known uncertainties can be anticipated and addressed through robust risk management strategies, positive relationships among them may exist. The significant impact of unknown uncertainties on both AI adoption and operational performance underscores the need for firms to increase their adaptive capabilities and invest in AI systems. Strategic decision-making also emerges as a critical imperative for firms as they navigate the complexities of AI adoption and uncertainty management. Negative AIO moderation of the KUc-OP connection indicates that AI does not always improve operational performance in uncertain situations. High levels of AI intervention may partially replace established human coordination routines and introduce decision-making frictions in the face of known uncertainties, reducing the performance benefits of routinized organizational responses. Current work does not contradict DCT; rather, it suggests that the value of dynamic capability depends on task–capability fit and on AI-enabled workflow alignment with operational procedures. By leveraging the insights from SEM findings, firms can make more informed decisions about AI investments, resource allocations, and operational strategies.

5.1 Theoretical Implications

The current empirical analysis aims to summarize the positive role of AIO in addressing unexpected events affecting the operational performance of China's logistics sector. The results in Figure 4 show that AIO's positive effect helps decrease uncertainty shocks by increasing competitiveness, operational resilience, cost efficiency, resource allocation, enhanced innovation, and stakeholder confidence. Based on these results, the current research has valuable implications for managers and policymakers seeking to strengthen business operations. First, when firms effectively use AI to manage uncertainty and optimize operations, they can gain a significant competitive advantage by increasing responsiveness. The logistics sector in China has faced significant challenges due to the lack of comprehensive policies for implementing AI technology. Firms that exhibit greater responsiveness and adaptability can capitalize on opportunities more swiftly and effectively than those with lower levels of technological integration. Organizations can ensure continuity across various scenarios, safeguarding against potential disruptions arising from both known and unknown uncertainties. The ability of AI to predict, adapt, and respond to changes ensures greater operational resilience. Third, with AI's predictive analytics and real-time decision-making, resources can be allocated more efficiently. Fourth, the optimization capabilities of AI can lead to substantial cost savings. By predicting and mitigating potential issues before they occur, organizations can avoid expensive emergency interventions and reduce waste, thereby improving their overall financial health.

5.2 Managerial Implications

Firms are increasingly adopting AI as a strategic imperative by recognizing AI potential to enhance competitiveness. AI has evolved from being merely a technological tool to becoming a core component of enterprise strategy. The findings indicate that policymakers should be apprehensive to formulate business operation with an effective strategy which neccessay for competitive advantage seeking frims. To attain practical benefits, firstly, managers should be organized in implementing AIO and attempt to find effective ways to minimize errors that can enhance the effect of uncertainties on a firm's operations. AI is enabling logistics innovations like automated documentation, route planning, warehouse layout optimization, and customer communication. Firms can use AI to accelerate delivery process and enhance operational perfroance under disruptive environment which is verified by current analysis. Secondly, the operational efficiency results indicate that for uncertainties, manager should adopt AI technology when the impact rate of uncertainty is high, which cannot be easily maintained, findings show that automated technology/highly skilled resources can maintain that bearing. Third, managers should learn about AIO's operational activities to improve the capabilities of their firms. Because in the logistics sector, this necessitates the continuous refinement of AI-driven strategies, targeted investments in scalable and adaptive technological infrastructure such as intelligent transportation systems and automated warehousing, and the cultivation of an organizational culture that embraces innovation, agility, and continuous learning. Therefore, outcomes show that critical learning is important for capability development to enhance operational issues, especially when companies are connected with logistics partners. Fourth, this work projected an early development of AIO capability for firms to enhance operational performance against unexpected disruptions. The projected developments in a firm's capabilities are adjusted to address forthcoming logistical problems. Furthermore, the findings of this study indicate that AI plays a significant role in mediating and moderating the relationship between supply chain uncertainties and logistics operational performance. Therefore, it is essential for managers to prioritize implementing AI systems with both predictive and adaptive capabilities. For known uncertainties, AI tools demand planning and inventory control systems, which can enhance forecasting accuracy. For unknown uncertainties, real-time data analytics and autonomous decision-making tools can enable quicker, more flexible responses to disruptions. Next, AI in operations negatively moderates the uncertainty–performance connection (H8), suggesting that enhanced AI intervention in routine and familiar variability, where reaction playbooks might cause coordination issues or over-automation. In routine scenarios, managers should not use AI to replace experienced planners. Consider AI as an augmentation tool for decision support, human oversight during final execution, and contextual knowledge exceptions. An effective strategy involves establishing automation boundaries, distinguishing between decisions suitable for automation and those resulting in human approval. It is essential to maintain rule-based fallbacks and to regularly assess AI recommendations to ensure alignment with operational practices. Lastly, firms should establish cross-functional AI. To strengthen internal capabilities, managers should focus on developing employees' skills in AI applications, integrating digital infrastructure across departments, and fostering collaborative environments in which operational and technical staff co-develop and apply AI strategies.

6. Conclusions

This study examined how Artificial Intelligence in Operations (AIO) affects logistics performance under uncertainty, demonstrating AIO's substantial direct, mediating, and moderating influences in fulfilling the research objectives. The findings indicate that AIO positively influences operational performance. In the context of the AI for sustainability matrix, findings suggest novel directions for scholars by proposing that integrating sustainability metrics into AI-enabled logistics and operations frameworks would provide a more holistic understanding of performance (Sánchez et al., 2023; Liu, 2023). Logistics firms can enhance operational efficiency, accuracy, and decision-making capabilities with AIO, thereby drastically improving business operations. This study presents a novel framework, grounded in dynamic capabilities theory, that examines the role of AI in mediating and moderating the relationship between known and unknown uncertainties and operational performance. This research systematically examines both forms of uncertainty, enhancing understanding of AI-driven dynamic capabilities and identifying new opportunities to improve competitiveness through strategic AI implementations. This work demonstrates that AIO plays a crucial role in mitigating supply chain uncertainties by offering advanced capabilities for data analysis and decision-making in the logistics sector. The current study showed that UUc and KUc have positive effects on logistics operations, indicating that the logistics sector is complex, has unified processes and stakeholders, and is susceptible to various sources of uncertainty. In conclusion, integrating AI technologies into logistics operations enables organizations to operate effectively in complex, ever-changing, and uncertain environments. Uncertainties are natural in logistics operations and create challenges that require proactive management and strategic thinking. The solution is that firms may enhance their resilience, efficiency, and agility in unexpected situations by using AI tools and algorithms.

6.1 Limitation and future rsearch directions

While this study makes significant managerial and theoretical contributions, it has several limitations that warrant careful consideration. The study's capability-based perspective emphasizes internal strategies and technological solutions but may understate external institutional, cultural, and environmental factors. The current approach has limited explanatory value in highly regulated or culturally diverse environments, where institutional or stakeholder theory may offer more nuanced insights. Although this lens provides valuable explanatory power, it may insufficiently capture the influence of external contingencies such as regulatory frameworks, cultural norms, and broader institutional environments. In contexts characterized by strong regulatory pressures or high cultural heterogeneity, alternative theoretical perspectives may yield a more comprehensive understanding of organizational behavior and performance outcomes. Next, while this study provides strong empirical evidence on the impact of AI in controlling operational uncertainty in the Chinese logistics sector, the conclusions are limited by a single country's geography and institutions. So, future research could conduct comparative cross-country analyses to examine whether the observed relationships hold. Lastly, the current work relies on self-reported questionnaire data, which may introduce common method bias (CMB), despite measures taken to mitigate this risk. To strengthen the robustness and validity of future investigations, scholars should consider adopting mixed-method approaches that integrate objective data sources, such as system-generated logs and operational performance indicators, alongside qualitative insights derived from interviews or case-based analyses. Such methodological triangulation would enhance both the depth and credibility of empirical findings.

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