Leveraging supply chain visibility for implementing just-in-case practices: The roles of knowledge and digital resources bundling

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Abstract

Purpose – This study aims to explore how bundling knowledge resources (i.e., knowledge integration mechanisms (KIMs)) and digital resources (i.e., big data-powered artificial intelligence (BDAI)) can enhance supply chain visibility (SCV) capabilities for implementing just-in-case (JIC) practices.

Design/methodology/approach – Analysis of survey data from Chinese manufacturers was conducted to test the proposed hypotheses.

Findings – The results reveal a significant positive effect of KIMs on BDAI, as well as positive effects of both BDAI and KIMs on SCV. Furthermore, the results suggest that SCV partially mediates the KIMs–JIC relationship and fully mediates the BDAI–JIC relationship.

Original/value – This study advances the digital SC and inventory management literature by proposing and empirically testing a digital JIC model that explores how to bundle knowledge and digital resources into SC capabilities for managing JIC inventory in uncertain and digital times.

Keywords: Just-in-case supply chain practices; Big data powered artificial intelligence; Knowledge integration mechanisms; Supply chain visibility; Resource orchestration theory

Paper type: Research paper

1. Introduction

Global supply chain (SC) disruptions and uncertainties caused by unforeseeable events such as the COVID-19 pandemic and Russo-Ukrainian war have challenged well-stablished just-in-time (JIT) approaches (Sodhi and Choi, 2022). As a result, firms are now considering shifting JIT to just-in-case (JIC), which operates by anticipating demand to reduce the risk of stockouts due to large-scale disruptions and complexities during uncertain times (Drakeley, 2022; Jiang *et al.*, 2022; Masters and Edgecliffe-Johnson, 2021). A McKinsey report by Alicke *et al.* (2021) indicates that about 61% of firms increased inventory of critical products, components, and materials during the COVID-19 pandemic. Even Toyota, who pioneered the JIT method, has broken its JIT inventory rule by securing "one to four months of stocks as necessary" for various components (e.g., semiconductor chips) (Trivedi, 2021). Although the JIC system has been discussed by researchers over decades, and more recently by practitioners in emerging reports, the understanding of JIC and its application, especially in the digital age, is still limited and ambiguous. Many firms have started adopting emerging technologies to quickly identify SC delays and implement better inventory management processes (such as classify stock accurately, forecast demand, and calculate optimal safety stock levels) (Drakeley, 2022). Recent research work on digital transformation has suggested that the adoption of digital technologies enables firms to deal with SC challenges through the enhanced implementation of SC practices such as visibility, resilience, and agility (e.g., Qader et al., 2022; Ye *et al.*, 2022). Despite this, how to adopt the JIC approach remains under-researched in the digital context and the literature calls for empirical studies that provide guidance for managers on the implementation of JIC-SC practices.

Specifically, according to the knowledge-based view (KBV), when organizational environments become increasingly complex and dynamic, firms typically need to adopt knowledge integration mechanisms (KIMs), referring to the formal processes and structures that enable firms to capture, interpret, and integrate different types of knowledge (such as market and technology knowledge) among different functional departments within the firms (De Luca and Atuahene-Gima, 2007; Zahra *et al.*, 2000). Although previous research has found the important role of KIMs in improving new product performance (e.g., De Luca and Atuahene-Gima, 2007; Tsai and Hsu, 2014) and product innovativeness (e.g., Tsai *et al.*, 2015), it is not clear how the integration of market and technological knowledge helps firms implement digital transformation projects and build SC capabilities during the COVID-19 crisis.

Emerging digital technologies (e.g., big data analytics and artificial intelligence) hold significant potential for firms to exploit an increasing abundance of SC information and extract key unstructured and structured data to implement SC practices (e.g., KIMs) (Ye *et al.*, 2022; Yu *et al.*, 2021). In the era of digital transformation, big data-powered artificial intelligence (BDAI) technology acts as a key technological enabler that ensure data-driven, smart problem solving, and decision making (Bag *et al.*, 2021a; Duan *et al.*, 2019; Dubey *et al.*, 2021). However, recent reports by McKinsey and KPMG indicate that 70-95% of digital transformation projects failed to deliver expected benefits (Block, 2021; Yu *et al.*, 2023a). While BDAI gained increased momentum in the COVID-19 crisis (Dubey *et al.*, 2021), further research is needed to determine if BDAI enables firms to develop SC capability for managing JIC inventory.

As noted above, not all digital transformation projects enable firms to achieve the expected benefits, and the success rate of digital transformation is still low (Block, 2021; Yu *et al.*, 2023a). The adoption of BDAI technology or KIMs may not be intrinsically valuable, and their value may be realized through SC visibility (SCV) capability, which refers to a firm's ability to effectively manage informational resources to ensure access to high quality information relevant to various factors of supply, demand, and market (Brandon-Jones *et al.*, 2014; Lafargue *et al.*, 2022; Williams *et al.*, 2013). After SCV capability is formed, leveraging it allows firms to create value for implementing JIC-SC practices (Sirmon *et al.*, 2007, 2011). Thus, we suggest it is the SCV capability that enables firms to quickly respond to the changing business environment for effectively managing JIC inventory.

We draw upon resource orchestration theory (ROT) to argue that SCV capability serves as the underlying mechanism for explaining the KIMs–JIC and BDAI–JIC relationships. Implementing SC practices in uncertain times needs effective resource management (Ye *et al.*, 2022) and ROT posits that firms operating in an uncertain environment need to better structure their resource portfolios; bundling organisational resources into capabilities and leveraging those capabilities to create business value (Sirmon *et al.*, 2007). Based on ROT, we view SCV as an orchestrating capability enabling firms to better manage JIC inventory in the COVID-19 crisis. To build this SCV capability, however, firms need to bundle knowledge (i.e., KIMs) and digital resources (i.e., BDAI) (Sirmon *et al.*, 2011). According to ROT, it is believed that ensuring precise and timely visibility into inventory levels and market demand information empowers more expeditious and improved decision-making processes around demand forecasting and tracking excess stock to prevent obsolescence (Williams *et al.*, 2013). However, the empirical link between SCV and JIC is still unclear.

Based on the above argument and using KBV and ROT as overarching theoretical views, we address the following research question: *how do firms implement JIC practices in uncertain times through bundling knowledge (KMIs) and digital resources (BDAI) into SC capabilities (SCV)?*

This study advances the knowledge base of JIC inventory management in several important ways. This study proposes an integrated JIC theoretical framework that investigates how to adopt a JIC approach through bundling knowledge and digital resources in uncertain times. The present study is one of the first studies to advance the conceptual understanding of JIC-SC in the digital age. The results from empirically testing the JIC model will provide managers with timely and useful guidance on how to leverage SCV capability for effectively adopting a JIC approach to cope with current and future global SC disruptions. Also, by investigating the effects of KIMs and BDAI on SCV, this study tests KBV and ROT within the context of digital JIC-SC management and advances our understanding of how to combine knowledge and digital resources to form SCV capabilities. Results of this study will help inform managers as they consider bundling firm resources relating to knowledge integration and digital assets into SC capabilities. Exploring the mediating role of SCV will reveal the important role of SC capabilities during the COVID-19 crisis.

2. Literature review

2.1. JIC-SC

Although the JIC system has been discussed by researchers for decades, the understanding of the JIC system is still limited and ambiguous. One reason for this is that the JIC system was developed prior to the 1980's under different contexts and the concept of JIC was a term used to generally describe the traditional (pre lean) western manufacturing system (Ebrahimpour and Schonberger, 1984; Lee and Ebrahimpour, 1984). JIC was employed to achieve high volume production of standardised products to enable firms to capture value through scale economies (Bramble, 1988). To guard against disruption (e.g., machine break down, defects), firms had to carry high levels of in-process inventory to ensure that manufacturing systems could function continuously.

Recent unexpected events such as the COVID-19 crisis and Ukraine conflict are disruptive; however, they are different from other disruptions in that they entail the availability of inputs to the transformation process. This has steered the focus of researchers and practitioner from JIT towards JIC (Drakeley, 2022; Jiang *et al.*, 2022; Sodhi and Choi, 2022). JIC delivers value by allowing firms to cope with unexpected disruptions through a set

of JIC approaches (e.g., larger inventories, diversified supplier base, and component standardization). We suggest this positions JIC systems as a special form of competitive advantage enabling firms to maintain critical operations and effectively explore alternative solutions for managing disruptive events (Koo, 2020; Masters and Edgecliffe-Johnson, 2021). Although JIC has been employed under differing contexts, the essence is to maintain business continuity, which is naturally extended to the SC. To do so, a firm's SC needs to prepare for and explore alternatives to assure material availability, manufacturing productivity, and product delivery during unexpected events (Martha, 2002). A JIC oriented SC incorporates techniques such as identifying essential items, frequently anticipating stockouts, building safety inventories, diversifying the supplier base, and accurate demand forecasting that enables a more effective push system (Drakeley, 2022; Koo, 2020).

2.2. BDAI

Firms are becoming increasingly data-oriented, acquiring considerable amounts of real-time data in structured, semi-structured and unstructured formats (Bag *et al.*, 2021b; Yu *et al.*, 2021). However, although modern firms regard big data as a valuable asset empowering decision-making processes, big data itself has no value without the presence of advanced analytical tools to derive useful insights (Dubey *et al.*, 2020). AI opens new approaches to analysing big data e.g., machine learning and automation (Toorajipour *et al.*, 2021). In this respect, some scholars use the term of BDAI to indicate the ability of a firm to use AI-based techniques and tools to advance big data analytics for prediction and optimization (Dubey *et al.*, 2020; 2021). While such a conceptualization captures the technical importance of BDAI, it fails to consider the implementation of BDAI as it is also a socially complex task. Hence, in this study we define BDAI as embracing AI to systematically exploit big data in a manner that is not only involved with acquiring tangible resources, e.g., Hadoop for data processing and data visualization tools, but also dependent on structuring intangible resources e.g., functional coordination and institutional collaboration (Bag *et al.*, 2021a). The exploitation of BDAI includes the management of large and complex datasets through orchestrating tangible resources as well as an orchestration of intangible resources to gain knowledge from the resulting information (Bag *et al.*, 2021a, 2021b; Duan *et al.*, 2019).

2.3. KIMs

KIMs are designed to encourage the exchange of information, for the purpose of continuous learning and innovation (Estrada *et al.*, 2016). KIMs refer to the structural

mechanisms that facilitate the ability to capture, synthesize, and integrate different types of information and knowledge from functional units within firms (De Luca and Atuahene-Gima, 2007; Zahra *et al.*, 2000). This definition is consistent with KBV, wherein competitive capabilities result from knowledge collection, integration, application, and protection through a knowledge management mechanism (Asiaei *et al.*, 2021). According to KBV, the actual knowledge value does not reside in knowledge itself, but rather in how it is integrated within firm functions which in turn creates competitive advantage (De Luca and Atuahene-Gima, 2007). KIMs emphasize an integration process through which firms internalize and transform externally acquired knowledge and make better use of internal knowledge (Tsai and Hsu, 2014). The integration is typically accomplished by the formal structures and processes, which are often related to information-sharing meetings, collective discussions, analyses of successful and failed projects, and formal reports (De Luca and Atuahene-Gima, 2007; Tsai *et al.*, 2015). Using KIMs, employees of a firm can share and process the increasing amounts of information within the context of organizational decision-making (Tushman and Nadler, 1978). KIMs encourage employees to critically evaluate past experiences and existing knowledge. This evaluation enables the systematic understanding of business processes, and improved understanding of performance implications (Tsai and Hsu, 2014; Zahra *et al.*, 2000). KIMs allow for codifying the knowledge within the firm through a set of written tools, e.g., memos and formal reports, which guides intra-firm dissemination of knowledge in an organised and structured manner (Tsai *et al.*, 2015).

2.4. SCV

SCV is a firm's ability to effectively manage informational resources to ensure access to high quality information relevant to various factors of supply, demand, and market (Brandon-Jones *et al.*, 2014; Williams *et al.*, 2013). High quality information is characterized by accuracy, usefulness, and completeness (Williams *et al.*, 2013) and its level is determined by the usefulness and meaningfulness of the information shared among SC partners (Barratt and Oke, 2007). With a high level of SCV, firms can obtain supply-related information, e.g., inventory levels, lead times/delivery dates, and advanced shipment notices, on an accurate and timely basis (Brandon-Jones *et al.*, 2014; Qader *et al.*, 2022). This enables more proactiveness (Christopher and Lee, 2004). SCV enables firms to quickly sense and act on demand changes by collectively acquiring and analysing actual sales data, demand forecasts, and customer inventory levels (Kalaiarasan *et al.*, 2022; Srinivasan and Swink, 2018). Through effectively managing resources (e.g., information-sharing and information-based

linkages), SCV assists firms with retrieving and aggregating market level information to better understand actual market trends (Wei and Wang, 2010; Williams *et al.*, 2013).

3. Theoretical framework and hypothesis development

3.1. Theory and research model

The resource-based view (RBV) posits the possession of resources that are valuable, rare, inimitable, and non-substitutable (VRIN) allows firms to advantageously outperform competitors (Barney, 2001). As an extension of RBV, the knowledge-based view (KBV) suggests that knowledge could be VRIN and thus a source of value and competitive advantage (Asiaei *et al.*, 2021; Grant, 1996). However, the possession of knowledge does not always ensure competitive advantage nor superior performance (Miao *et al.*, 2017). Especially in today's digital age, data has been viewed as a core resource by many firms, although its value has not been fully understood (Kristoffersen *et al.*, 2021; Ye *et al.*, 2022). While RBV and KBV provide useful lenses to steer focus towards the contributions of VRIN resources for firm performance, it has been argued that the mere possession of these resources cannot adequately engender competitive advantage without capability-building processes (Crook *et al.*, 2008; Kraaijenbrink *et al.*, 2010). In other words, there is a need to understand the channels and mechanisms through which knowledge can be leveraged (Asiaei *et al.*, 2021).

As an extension of RBV and KBV, resource orchestration theory (ROT) was proposed to describe the capability-building process, and posits that resource orchestration subsumes processes for structuring, bundling, and leveraging resources, which enables capabilities to be formed and applied to create specific value for firms (Sirmon *et al.*, 2007, 2011). In other words, the benefit of resources is associated with the effectiveness with which firms manage and orchestrate their resource portfolios rather than the value and rare nature of resources. Structuring is the process by which firms acquire e.g., purchasing from strategic factor markets, enhance e.g., internally developing resources, and divest e.g., shedding unproductive resources. Bundling is the process by which firms combine and integrate resources to form capabilities, and leveraging is involved with the application of capabilities to generate business value (Sirmon *et al.*, 2007, 2011).

ROT provides an opportunity to explain how to implement digital JIC-SC practices through building SCV capability based on digital and knowledge resources bunding (see Figure 1). The logic of ROT suggests that to build SCV capability, firms first need to structure their BDAI (digital resources) and KIMs (knowledge resources) resource portfolios

(Fawcett *et al.*, 2022). Although both BDAI and KIMs need to be structured initially, as per KBV, knowledge integration is more related to the accumulation of knowledge through continuous learning, knowledge transfer, and mobilization. This enables firms to later embrace AI to systematically exploit big data effectively. A central tenet of ROT is "resource mobilization" whereby resources are mobilised and integrated into a structure (through KIMs) for coordination, alignment, and direction (Miao *et al.*, 2017). As illustrated in Figure 1, firms need to bundle both knowledge and digital resources to build SC capabilities (Sirmon *et al.*, 2007). BDAI that directs the use of AI-based and informational resources increases the effectiveness and efficiency with which accurate and timely supply- and market-level information are collected and analysed. KIMs enabling intra-firm dissemination of knowledge assist with ensuring the quality of collected and shared information in the pursuit of SCV. After SCV is formed, the effective leveraging of SCV allows firms to create firm-specific value for implementing JIC-SC practices during disruptions.

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3.2. Hypotheses

3.2.1. Effect of KIMs

In harmony with the tenants of ROT (and extending KBV), KIMs can act as an established resource mobilization mechanism, which facilitates the collection, application, and integration of knowledge (Asiaei *et al.*, 2021) to fully utilize BDAI. This suggest that KIMs deepen knowledge flows within the firm and permit lateral forms of communication that enable the transfer, recombination, and use of knowledge across functional boundaries (Tsai *et al.*, 2015). More specifically, the implementation of BDAI builds on team members' diverse portfolios of know-how, skills, and information (Wamba and Akter, 2019). KIMs emerge thus as a formal structure or foundation mechanism to maximise knowledge transfer within a firm and among various functional units (Liao *et al.*, 2003), which includes knowledge reaching the appropriate team members to support them more effectively in cultivating insights and intelligence from data (Pauleen and Wang, 2017). Also, by forming regular patterns for knowledge integration, KIMs serve as a mechanism for fostering cross-functional coordination that can help in combining different knowledge elements (Bag *et al.*, 2021b). Thus, according to KBV, firms with established KIMs can enable firms to codify the best practices applied in their BDAI projects and periodically gain feedback. This is essential for embracing AI to systematically exploit big data (Bag *et al.*, 2021a; Tsai and Hsu, 2014). In other words, without existing knowledge resources, norms and specific resource channels

(e.g., KIMs), technologies such as big data predictive analytics cannot be effectively embraced, modified and transformed into competitive resources (Sodero *et al.*, 2019). Based on the above argument and consistent with KBV and ROT, we hypothesise that:

H1: KIMs have a significant positive effect on BDAI.

Structuring KIMs permit firms to increase the effectiveness and efficiency with which knowledge resources are communicated and assimilated, which in turn enables the creation of SCV capability. KIMs can function as integrative mechanisms for identifying, communicating, and assimilating newly acquired knowledge that could empower firms to enact well-designed knowledge exchange communications with suppliers and customers (De Luca and Atuahene-Gima, 2007; Turkulainen *et al.*, 2017). Mechanisms such as information sharing, failure analysis, and formal reports summarizing learning are structural devices that drive integration within a firm (Barratt and Oke, 2007; Jacobs *et al.*, 2016; Zahra *et al.*, 2000). These internal integrative mechanisms enable firms to better absorb and internalize externally acquired information from suppliers and customers (e.g., inventory levels and demand forecasts) (Williams *et al.*, 2013). Moreover, prior research has established internal integration across various functional departments to be a precursor to strategic collaboration with customers and suppliers (Jacobs *et al.*, 2016). This may be due to KIMs assisting team members with appreciating, understanding, and evaluating the merit of informational resources (Tsai and Hsu, 2014) from trading partners. Thus, as per KBV, firms with KIMs are more likely to build connectedness with suppliers and customers to acquire, assimilate and utilize outside informational resources (Mubarik *et al.*, 2021). This is critical to realizing the full value of a firm's knowledge and informational resources that create SCV. Therefore, we hypothesise that greater KIMs yield greater SCV.

H2: KIMs have a significant positive effect on SCV.

KIMs facilitate knowledge and information distribution within firms and interpreting and identifying trends (De Luca and Atuahene-Gima, 2007). This played a vital role in enabling firms to adopt JIC approach during the COVID-19 pandemic. Cross-functional collaboration facilitates the analysis of SC operations, generates a consensus for resource requirements, and the planning and operationalization of suitable approaches to create competitiveness (Oliva and Watson, 2011). Internal integration efforts encourage inter-firm goal alignment, cross-functional collaboration, and the creation of information processing capabilities (e.g., information sharing and information quality) that enable the absorption and

integration of external knowledge for the purpose of reacting to and coping with changing environments (Schoenherr and Swink, 2012; Yu *et al.*, 2022). KIMs enable the navigation of knowledge among different functional units from the point where knowledge is obtained to the point where it is needed (Foss et al., 2013), which helps in developing real-time understanding of unexpected changes and delivering critical knowledge when and where needed to maintain business continuity (Van Doorn *et al.*, 2017; Yu *et al.*, 2023b). As per KBV, with KIMs, information acquired from suppliers (e.g., delivery dates and inventory availability) and customers (e.g., demand forecasts and market levels) enables firms to better anticipate stockouts, prepare safety inventory, and identify customer trends during the COVID-19 crisis (Gurbuz *et al.*, 2023). Through enhanced knowledge flows, KIMs aid responses to disruptions like the COVID-19 crisis, through fostering early awareness of sudden changes and maintaining communication channels during the pandemic (Ngo et al., 2023). As such, firms with KIMs may be better positioned as they are able to transform acquired knowledge resources into actions in uncertain environments, e.g., anticipating stockouts, building safety inventories, diversifying supplier base (Drakeley, 2022). Therefore, we hypothesise that:

H3: KIMs have a significant positive effect on JIC.

3.2.2. Effect of BDAI

Rooted in ROT, our argument is that firms can develop SCV capability through effectively managing digital resources (i.e., BDAI). The adoption of BDAI technology enables firms to explore large datasets derived from SC processes (Dubey *et al.*, 2020; 2021). More specifically, BDAI helps firms fully leverage digital and informational resources (e.g., sales information, market demand, and inventory levels) to gain a better understanding of suppliers' and customers' operational activities (Barratt and Barratt, 2011). From this, they can identify supply and demand patterns and anticipate market trends (Zamani *et al.*, 2023), thereby enabling the development of a high level of SCV capability (Williams *et al.*, 2013). Through an improved data-driven decision-making process, BDAI can provide firms with insights concerning ways to seek and identify useful and meaningful information (such as market, supply, and demand data) relevant to business partners' SC activities, thereby building SCV capability (Bag *et al.*, 2021a; Barratt and Barratt, 2011). According to ROT, as a crucial digital resource in the big data era, the adoption of BDAI techniques helps in the removal of noise from datasets and facilitates improved data structures for analysis. This

improves the efficiency with which insights are accumulated and interpretated (Oliveira and Handfield, 2019), rendering a higher level of SCV. We therefore propose that:

H4: BDAI has a significant positive effect on SCV.

Consistent with ROT, we contend that BDAI enhances resource mobilization and management that forms a viable response mechanism to environmental factors and thereby enable firms to effectively implement a JIC system. (Zamani *et al.*, 2023). JIC implementation requires an abundance of real-time information on various SC activities to orchestrate resources empowering the push system. For example, as a response to volatile environments, BDAI provides reliable and updated forecasts of supply and demand patterns and near real-time visibility of inventory stock (e.g., raw materials and finished products) (Bag *et al.*, 2021a, 2021b), which contributes toward monitoring stock levels and reconfiguring and aligning associated resources (Gurbuz *et al.*, 2023; Modgil *et al.*, 2021). By doing so, BDAI can inform managers and prioritize the further course of action through production and inventory planning to sustain business operations and cope with unexpected customer demand (Modgil *et al.*, 2021). Digital technologies such as BDAI increase firm level ability and adaptability by anticipating and mitigating risk in highly uncertain environments (Ngo *et al.*, 2023). Through real-time big data, BDAI can timely mitigate misinformation while simultaneously examining the correlation with possibilities of risks and their causes (Bag *et al.*, 2021b; Modgil *et al.*, 2021), which enables firms to proactively reconfigure and repurpose existing resources, and integrate new resources to make decisions (e.g., make changes to stock levels and manufacturing scheduling). We therefore propose that:

H5: BDAI has a significant positive effect on JIC.

3.2.3. Roles of SCV (direct and mediation)

In line with principles of ROT, once SCV capability is built, it can be leveraged to create firm-specific value for effectively implementing JIC-SC practices (Sirmon *et al.*, 2011). The fundamental need for the JIC system emanates from unexpected disruptions along the SC. Leveraging SCV can help a firm gain transparency of its SC partners' operational activities (e.g., stock availability, distribution, and demand forecast) and a better understanding of its own supply and demand conditions, which in turn allows it to dynamically adjust SC practices (Brandon-Jones *et al.*, 2014). For example, SCV enabled Toyota to identify and prepare for the chip shortage in 2021. At the beginning of the pandemic, Toyota quickly informed its suppliers to increase the stock levels of

semiconductors and updated its production plans based on supply conditions (e.g., suppliers' available capacities and resources) (Trivedi, 2021). Building SCV capability can help firms collectively acquire sales data and demand forecasts offered by customers, which is critical to correcting distorted demand signals and to align inventory with actual customer trends (Williams *et al.*, 2013). The increase in information thus leads to fewer stockouts (Brandon-Jones *et al.*, 2014). We therefore propose that SCV enables firms to adopt JIC approach.

H6: SCV has a significant positive effect on JIC.

ROT provides a robust perspective of the potential mediating role of SCV in the KIMs / BDAI–JIC relationship in that it suggests that knowledge-based resources (e.g., KIMs) must be bundled into capabilities and such capabilities must be leveraged in effective ways to generate firm-specific value (Sirmon *et al.*, 2011). According to KBV, KIMs indicate a process of knowledge integration that can produce improvements of knowledge flows and communications across different functional entities (Asiaei *et al.*, 2021; Tsai and Hsu, 2014). The leveraging of SCV can help direct team members' activities around retrieving and sharing knowledge throughout the firm with the purpose of understanding demand and supply conditions (Williams *et al.*, 2013; Ye *et al.*, 2022). Meanwhile, information shared between SC partners that enhances visibility is more likely to result in improved salience toward decisions associated with implementing JIC-SC practices during disruptive events (Gurbuz *et al.*, 2023; Ye *et al.*, 2022).

From the ROT perspective, structuring BDAI is a necessary but insufficient condition to sustaining the business continuity (Sirmon *et al.*, 2007, 2011). While BDAI is critical for harnessing a considerable amount of data to inform a firm's JIC-SC practices through inventory planning and demand forecasting (Zamani *et al.*, 2023), BDAI itself might not be effective in terms of implementing JIC inventory management practices. Successful deployments of various inventory strategies, inclusive of JIC, require communication (Jacobs *et al.*, 2016). BDAI and KIMs form a corpus of sharable information and SCV facilitates the timeliness and accuracy of the information (Ye *et al.*, 2022). As such SCV is the mechanism through which a JIC strategy can be effective. Considered from a slightly different perspective, it has been established that JIT is an integration and trust building mechanism and that integration reduces uncertainty (Droge *et al.*, 2012); however, JIC tactics such as building inventory through rationing order fulfilment may instead exacerbate uncertainty, as gaming behaviours from buyers induce heightened bullwhip effect (Lee *et al.*, 1997). Enhanced SCV as enabled by KIMs and BDAI might help mitigate this. To act in response to

disruptions, it is also important to make use of BDAI to renew its digital resource base that can be used to building SCV capability. This will help the firm recognise the value of its existing resources and re-align its activities (Wei and Wang, 2010). As such, BDAI, through SCV, can support the adoption of JIC approaches in the event of disruptions with the availability of information provided by KIMs. Therefore, we hypothesize the mediating role of SCV between KIMs / BDAI and JIC models.

H7: SCV significantly mediates the relationships (a) between KIMs and JIC and (b) between BDAI and JIC.

4. Methodology

4.1. Survey data collection and bias assessment

Due to China's zero-COVID policy, we conducted an online questionnaire with the help of a professional survey firm. A random sample of 800 manufacturing firms were selected from the list provided by the survey firm. We then sent the questionnaires along with a cover letter that indicates the research objectives and completion guidelines to the targeted manufacturers via emails and WeChat. Finally, a total of 207 useable responses were obtained through two waves of data collection over four months, which suggests a response rate of 25.88%.

The characteristics of the respondents and their firms are reported in Table 1. All respondents held senior-level positions, and many of them have been working for their positions for about 10 years. Thus, it can be expected that our respondents were knowledgeable to answer the questions about AI-driven SC and inventory management practices their company implemented during the COVID-19. Table 1 also indicates that the respondents' firms were in the wide variety of manufacturing sectors (such as electronics and electrical, industrial machinery and equipment, and fabricated metal products) and geographic regions (such as Yangtze River delta, Bohai Sea economic area, and Pearl River delta).

---------- Insert Table 1 ----------

Non-response bias and common method bias (CMB) can occur in survey-based research and thus both were assessed in this study. We examined non-response bias by carrying out a t-test and found there is no significant differences between the early and late responses in terms of number of employees and annual sales. Thus, the result suggest that non-response bias is not a critical issue in this study.

We used two approaches to examine CMB. First, confirmatory factor analysis (CFA) approach to Harman's single-factor test were performed, and the CFA results show a poor model fit (χ^2 / df = 5.507; CFI = .664; IFI = .666; RMSEA = .148; SRMR = .114). Second, the marker variable technique was used to further test for CMB by selecting the respondents' shoe sizes as a method variance marker that is theoretically unrelated to at least one scale in the analysis (Lindell and Whitney, 2001; Ye *et al.*, 2022). As shown in Table 3, the lowest positive correlation (r = .007) between the marker variable and other variables was used to adjust the inter-construct correlations and statistical significance (Lindell and Whitney 2001). After adjustment, no significant correlations became insignificant. Therefore, it can be concluded that CMB does not appear to be a serious concern in this present study.

4.2. Questionnaire design and measures

Several approaches have been employed to enhance the content validity and reliability of the questionnaire for collecting high-quality survey data. First, to ensure the theoretical constructs' content validity, we conducted a comprehensive review of the existing literature to conceptualize each construct and formulate its initial measurement items. Second, the scales used in this study were initially developed based on English-language literature. The initial formulation of the scale occurred in English, and it was then translated into Chinese to ensure the questionnaire's reliability. To maintain conceptual equivalence, a back-translation process was employed (Yu *et al.*, 2023b). Certain questions were rephrased to enhance translation accuracy and to align with relevant practices in China. Third, before conducting data collection, we pre-tested our questionnaire by obtaining feedback from both academics and practitioners. We conducted formal and informal interviews with senior executives to gain insights into industry practices in China, ensuring that the survey questions are easily comprehensible and free from potential confusion. Additionally, we sought comments from SC and information systems experts regarding the appropriateness of the terminologies used. The measurement items appear in Table 2. All items were scored on a seven-point scale, ranging from "strongly disagree" to "strongly agree".

---------- Insert Table 2 ----------

As there are no available measures for JIC-SC in the existing literature, we developed new measurement items for JIC-SC mainly based on the interviews with senior managers in manufacturers in China, case studies using secondary data (e.g., firm annual reports), and the reports by McKinsey, BCG, and KPMG. The scale assessed how firm managed JIC inventory during the COVID-19 crisis, for example, diversifying the supply base, emphasizing accurate

demand forecasting, holding sufficient safety stock, using ABC inventory analysis to categorize stock items, and tracking excess stock to prevent obsolescence. The data analysis results reported in the following section confirmed reliability and validity of the newly developed scale.

Items adapted from De Luca and Atuahene-Gima (2007) were used to measure KIMs, which focused on the extent to which a firm uses a set of formal processes (e.g., information sharing meetings and formal analysis of product development projects) to capture and integrate knowledge. The measures for BDAI were adapted from Bag *et al.* (2021a), which captured the extent to which firms adopt BDAI technology to process large and complex data sets for making better informed and smart decisions. The SCV scale was measured using items that addressed the sharing of timely and accurate sales information, demand forecast information, and inventory information with suppliers and customers, as well as gathering timely market-level demand information (Williams *et al.*, 2013; Ye *et al.*, 2022). The measurement items span the upstream, downstream, and market dimensions of SCV identified by Williams *et al.* (2013). This operationalization of the SCV construct has also been utilized in recent empirical research (e.g., Ye *et al.*, 2022). We considered two statistical controls, including firm age (measured by number of years a firm has been established) and firm size (measured by number of employees).

5. Results

5.1. Measurement model: reliability and validity assessment

We conducted several tests to assess reliability and validity of the variables (Hair *et al.*, 2010). The results appear in Tables 2 and 3. First, the composite reliability (CR) and Cronbach's alpha (α) values of all theoretical construct were above the .70 threshold (see Table 2), which suggests that our constructs have adequate reliability. Second, we conducted confirmatory factor analysis (CFA). The results indicate that the measurement model had a good fit (χ^2 / df = 2.260; CFI = .909; IFI = .910; RMSEA = .078; SRMR = .058), which confirms the unidimensionality of each construct (Hair *et al.*, 2010). We also found that all measurement items had large (> .70) and significant (p < .001) factor loadings, and the average variance extracted (AVE) values of each construct were higher than .70, which demonstrates convergent validity of the measurement scales (Fornell and Larcker, 1981; Hair *et al.*, 2010). Third, the square root of the AVE of each latent variable was greater than the corresponding inter-construct correlations in the same row and column (see Table 3), which

confirms the latent constructs have sufficient discriminant validity (Fornell and Larcker, 1981).

---------- Insert Table 3 ----------

5.2. Structural model: hypothesis testing

We tested the proposed research hypotheses using structural equation modelling, and the results are presented in Table 4. The fit indices suggest a satisfactory model fit (χ^2 / df = 2.147; CFI = .904; IFI = .905; RMSEA = .075; SRMR = .058). We found a significant positive effect of KIMs on BDAI (β = .477, p < .001), SCV (β = .676, p < .001), and JIT (β = .538, p < .001), which supports H1, H2 and H3. The results also provide support for H4 that predicts a positive effect of BDAI on SCV (β = .191, p < .01), but no support to H5 (BDAI → JIC; β = -.043, *n.s.*). H6, positing the positive effect of SCV on JIC, is also supported (β = .332, p < .001).

---------- Insert Table 4 ----------

We tested H7 and H8 that posit the mediation effect of SCV using a bias-corrected bootstrapping approach. As shown in Table 6, the indirect effect of BDAI on JIC through SCV is positive and significant (β = .063, p < .05; 95% CI [.009–.168]) and the indirect effect of KIMs on JIC through SCV is also positive and significant (β = .234, p < .05; 95% CI [.047–.458]), in support of H7a and H7b. The mediation hypotheses are also supported by the Sobel test: the BDAI–JIC relationship is fully mediated by SCV (z = 2.113, p < .05), and the KIMs–JIC relationship is partially mediated by SCV (z = 2.944, p < .01).

---------- Insert Table 5 ----------

6. Discussion

6.1. Theoretical contributions

From a resource orchestration perspective, this study advances the digital SC and inventory management literature by proposing and empirically testing a digital JIC model that explores how to bundle knowledge resources (i.e., KIMs) and digital resources (i.e., BDAI) into SC capabilities (i.e., SCV) for managing JIC inventory in uncertain times. The results of this study suggest that knowledge integration and digital transformation, as essential organisational resources, have a significant positive effect on building SCV capability in the digital era. Consistent with ROT, we also find that SCV capability partially mediates the KIMs–JIC relationship, and fully mediates the BDAI–JIC relationship. These empirical results provide new insights for JIC research in the digital age in four important ways.

First, the findings of the important roles of KIMs shed new light to the SC literature in the era of digital transformation. Our findings of the significant positive effects of KIMs on BDAI, SCV, and JIC are important because such effects have not been empirically tested in the literature, especially in the context of the COVID-19 pandemic. Although previous research has demonstrated the important role of KIMs in improving new product performance (e.g., De Luca and Atuahene-Gima, 2007; Tsai and Hsu, 2014) and product innovativeness (e.g., Tsai *et al.*, 2015), it is still not clear how effective integration of knowledge helps firms implement BDAI projects and digital SC practices during the COVID-19 crisis. From the KBV perspective, the results of this study fill the gap by confirming the important roles of KIMs in building SCV capability for the implementation of JIC-SC practices. According to KBV, by sharing and integrating different types of knowledge such as technological and market across various functional units within an organisation, KIMs help organizations reorganize what they have learned from successful and failing product development and digital transformation projects, and effectively exploit the knowledge through SC innovation (De Luca and Atuahene-Gima, 2007; Tsai and Hsu, 2014).

Second, we find that exploiting existing technological knowledge enables firms to successfully carry out the BDAI projects (Bag *et al.*, 2021a). This study contributes to the ROT perspective by illuminating how bundling KIMs and BDAI resources to build a firm's SCV capabilities contributes to implementing JIC inventory management practices during the COVID-19 crisis. Specifically, KIMs enable BDAI by facilitating an understanding of what data and information are available and can be used, which in turn leads to enhanced SCV to empower a JIC-SC. In other words, the key to successfully orchestrating a firm's resources toward developing new competitive capabilities lies in understanding the specific sequences of developing multi-tiered foundational and supporting capabilities. Our finding complements previous studies (e.g., De Luca and Atuahene-Gima, 2007; Tsai *et al.*, 2015; Tsai and Hsu, 2014) by demonstrating the importance of KIMs in facilitating digital transformation. Effective knowledge integration enables a firm and its BDAI project team members to pay much more attention to the exploitation of digital technologies and technological knowledge, which will generate new and novel perspectives, ideas, and analytics techniques that more effectively embrace AI to systematically exploit big data in an intelligent way (Bag *et al.*, 2021a; Dubey *et al.*, 2021).

Third, we also find the importance of KIMs in building SCV capability and implementing JIC-SC practices. Our empirical findings contribute to an emerging resource orchestration perspective (ROT) on knowledge-driven SC practices (KBV) (Asiaei *et al.*,

2021). Effective integration of specific market and technological knowledge enhances visibility of supply chains because it ensures a long-term strategic relationship with specific contexts, which generates highly idiosyncratic insights for sharing accurate and timely market, supply, and demand data with SC partners (e.g., upstream suppliers and downstream customers) (Williams *et al.*, 2013). More specifically, while KIMs have a direct positive effect on JIC-SC, BDAI does not. This finding reinforces reports from consulting companies that many digital transformation projects failed to achieve expected benefits (Block, 2021). Our study indicates that it is knowledge resources (KIMs) rather than digital resources (BDAI) that directly influence the implementation of JIC-SC practices. This finding is also consistent with the principle of KBV, effective integration of knowledge such as technological and market information, data, and ideas enable organizations to gain broader and insightful perspectives (De Luca and Atuahene-Gima, 2007; Tsai and Hsu, 2014), thereby leading to the implementation of JIC-SC practices to deal with global SC disruptions caused by conflicts such as the COVID-19 pandemic and Ukraine conflict.

Fourth, another important finding generated from this study is the mediation effect of SCV, which supports ROT. The findings of this study contribute to a more comprehensive view of how SCV capability enables firm to implement digital JIC-SC practices to deal with global SC disruptions. We found that SCV fully mediates the BDAI–JIC relationship and partially mediates the KIMs–JIC relationship. First, the findings provide an interesting extension to the recent work of SCV that has demonstrated the importance of SCV in strengthening SC agility (Ye *et al.*, 2022) and responsiveness (Williams *et al.*, 2013). SCV, as an important SC capability, enables firms to effectively deal with environmental uncertainty. This may have been what drove the adoption of a JIC approach during the COVID-19 crisis. Consistent with ROT, firms that collect and share timely and high-quality information about demand and supply conditions with SC partners are more likely to implement JIC-SC practices during the COVID-19 pandemic, such as holding sufficient safety stock, anticipating essential stock items, and making accurate demand forecasting.

In a SC setting, the adoption of BDAI technology may not be intrinsically valuable, and their value may be realized through SCV. These important empirical findings can be considered a refinement and extension of the SCV literature. This study indicates that SCV converts BDAI into the successful implementation of JIC-SC practices, and the effectiveness of BDAI should be realized through SCV. This is an important finding as there is increasing debate among researchers and practitioners about whether firms can achieve full benefit of digital transformation (Block, 2021; Yu *et al.*, 2023a). The adoption of BDAI technology

does not directly influence JIC inventory management, and SCV serves as the underlying mechanism to explain the BDAI–JIC relationship. The results also indicate that SCV plays an important role in JIC by partially mediating the effects of KIMs on JIC. Consistent with ROT, these new insights imply that the important role of SC capabilities such as visibility should be considered when examining how knowledge and digital transformation facilitate the implementation of JIC-SC practices in the digital age. Ignoring the role of SCV, researchers may not assume visibility requited by JIC and thus may reach a premature and perhaps overly optimistic view of the importance of KIMs and BDAI for JIC.

6.2. Practical contributions

The study results provide insightful implications for managers. The integrated digital JIC-SC model proposed in this study provides managers with a useful guidance on which corporate resources to apply during times of disrupted demand and materials flow. Specifically, managers may need to adopt a JIC approach when there is difficulty conducting accurate demand forecasting or substantial surges in demand. For such a strategy to be effective, managers will need to leverage the data that is captured by the firm. This data should be analysed to determine optimal courses of action and then shared with relevant actors within the firm. Capturing this data into a "walled garden" and analysed using sophisticated analytical techniques such as machine learning should prove valuable in deploying changes to materials strategy. Such analyses will further help interpret signals from the environment and be a basis for cross-functional teams to rally around for decision-making. The more coordinated these teams can be, the more effective they will be.

The above paragraph demonstrates the importance of databases that are well designed and current. Although practitioners are likely to be aware of the importance of market knowledge in creating business values, our results provide a more fine-grained view. Existing firm processes can leverage novel technologies to enhance visibility and, ultimately, develop new SC processes. Specifically, our study calls on managers to consider leveraging market and firm knowledge with advanced analytical technologies to enhance SC capabilities. This will enable managers to effectively leverage JIC inventory approaches in highly uncertain environments. The effective integration of knowledge through organising regular information sharing meetings and reviewing project successes and failures will enable managers to learn from experience and exploit relevant market and technological knowledge.

Importantly, our study suggests that BDAI does not directly enhance a firm's implementation of JIC-SC practices; it is SCV capability that enables the translation of BDAI

into better implementation of JIC inventory management practices. The implications for managers are that adopting advanced and novel analytical technologies can be often disappointing, especially first-generation technologies. At this point, the BDAI may be in the initial phase of the Gartner Hype Cycle as expectations for gains are significant and growing. However, our study suggests that the BDAI offers real gains. As such managers do not need to wait for the technology to be proven or further developed. This study is the beginning of a mature understanding of the technology and how it can be deployed (Dedehayir and Steinert, 2016). Our study suggests that to implement JIC-SC practices successfully, e.g., conducting accurate demand forecasting, keeping sufficient safety stock levels, and tracking excess stock to prevent obsolescence, more effectively, managers will need to invest time and resources into capturing and sharing inventory, sales, and demand related information. Building such capability will enable managers to obtain the full benefit of adopting advanced analytical technologies.

6.3. Limitations and future research

The study has some limitations that could provide potential directions for future research. First, in this study we focused on BDAI technology and examined its effect on the implementation of JIC-SC practices. Future research might examine other advanced digital technologies such as blockchain, IoT and machine learning and the impacts on the JIC inventory management. Second, we investigated two essential firm resources in terms of knowledge and technology (i.e., KIMs and BDAI). Future research is encouraged to consider other tangible and intangible resources (e.g., human capital, organization learning, etc) and examine their impacts on the adoption of the JIC approach. Third, this study investigates the process of the implementation of JIC-SC practices. Adopting the JIC inventory might help firms improve business performance at unpredictable times. We encourage future research to explore the consequences of JIC, for example, financial performance and/or operational performance.

Fourth, while some researchers have criticised the effectiveness of the JIT method especially during the COVID-19 pandemic, others have argued that JIT has been proven as an effective inventory management strategy that helps firms improve productivity and lower operations costs (Sodhi and Choi, 2022). Thus, we encourage future research to examine if it is a time to abandon JIT and embrace JIC or adopt a hybrid model of JIT-JIC in the contexts of digital transformation and environmental uncertainty. Fifth, in this study we empirically tested the digital JIC-SC model by collecting survey data in China, one of the world's largest

investors and adopters of digital technologies. Future research could gather information from other countries and gather primary and/or secondary data to further test the JIC-SC model proposed in this study, which will also further generalize the results of this study. Finally, despite our meticulous efforts to address potential CMB and endogeneity issues, we acknowledge that achieving the complete elimination of endogeneity is improbable. This limitation is inherent in our study, attributable to its survey-based research design.

7. Conclusion

This study proposes and empirically tests the digital JIC-SC model that scrutinizes how bunding knowledge (i.e., KIMs) and digital resources (i.e., BDAI) to build SCV capability for implementing JIC inventory management practices. By doing so, this study makes contributions to theory and practice. Consistent with ROT, an extension of RBV and KBV, our findings indicate a direct positive effect of KIMs and BDAI on SCV. Another interesting finding generated from this study is that SCV, acting as an important SC capability, fully mediates the BDAI–JIC relationship and partially mediates the KIMs–JIC relationship. From a practical perspective, these empirical findings provide a useful digital JIC-SC model that helps managers better understand how to manage JIC inventory in the digital age.

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Table 1: Profiles of sample firms

	%		%
Industry type		**Firm location**	
Automobile	8.7	Pearl River Delta	14.0
Building materials	5.3	Yangtze River Delta	18.8
Chemicals and petrochemicals	6.8	Bohai Sea Economic Area	16.4
Electronics and electrical	19.3	Northeast China	4.8
Fabricated metal products	14.0	Central China	30.4
Food, beverage and alcohol	8.2	Southwest China	7.2
Industrial machinery and equipment	14.0	Northwest China	8.2
Pharmaceutical and medical	6.3	**Job title**	
Publishing and printing	1.4	President / Chief executive officer (CEO)	5.8
Rubber and plastics	5.8	Vice president	.5
Textiles and apparel	3.4	Director	6.3
Wood and furniture	.5	Manager	70.0
Others	6.3	Other senior executive	17.4
Number of employees		**Job tenure**	
≤ 100	13.0	≤ 10	62.3
101 – 500	43.0	11-20	34.3
501 – 1000	21.7	> 20	3.4
> 1000	22.2		
Firm age (years)			
≤ 20	51.2		
21 – 40	42.0		
41 – 60	5.8		
> 60	1.0		

Source: Author's own creation

Table 2: CFA results: reliability and validity assessment

Measurement Items	Factor loadings	Cronbach's alpha	Composite reliability	AVE
1. Knowledge integration mechanisms		.876	.877	.589
We make regular formal reports and memos that summarize learning	.783			
We conduct information sharing meetings	.779			
We organise face-to-face discussions by cross-functional teams	.736			
We conduct formal analysis of failing product development projects	.755			
We conduct formal analysis of successful product development projects	.783			
2. Big data powered artificial intelligence		.902	.903	.650
We use computing techniques (e.g., Hadoop) for processing of large data sets	.760			
Our management have approved budget for big data and artificial intelligence (BDAI) project	.843			
We collaborate with universities and other research centres for implementing BDAI projects	.786			
Our BDAI team coordinate effectively with other departments and stakeholders	.806			
AI chatbots can assist sales team by automating certain steps of sales and improving capabilities of sales force	.834			
3. Supply chain visibility		.879	.882	.599
The sales information we receive from our major customers is timely	.796			
The inventory level information we receive from our major customers is timely	.781			
The demand forecast information we receive from our major customers is accurate	.797			
The inventory information we receive from our major suppliers is timely	.755			
The market level demand information we gather is timely	.738			
4. Just-in-case supply chain		.887	.888	.531
We seek to find diverse suppliers closer to home to stock up on our inventories during COVID-19	.734			
We work closely with our existing suppliers while diversifying the supply base during COVID-19	.722			
We emphasize accurate demand forecasting during COVID-19	.747			
We hold sufficient safety stock during COVID-19	.700			
We anticipate stock outs, especially of essential stock items during COVID-19	.743			
We use ABC inventory analysis to categorize our stock items and assign different stocking policies to each group during COVID-19	.701			
We track excess stock to prevent obsolescence during COVID-19	.750			
Goodness-of-fit indices: $\chi^2 = 458.835$; df = 203; χ^2 / df = 2.260; CFI = .909; IFI = .910; RMSEA = .078; SRMR = .058				

Source: Author's own creation

Table 3: Descriptive statistics and correlations

	Mean	S.D.	KIMs	BDAI	SCV	JIC
Knowledge integration mechanisms (KIMs)	5.887	.943	**.767**[a]	.415**	.677**	.691**
Big data powered artificial intelligence (BDAI)	5.001	1.158	.419**	**.806**	.455**	.342**
Supply chain visibility (SCV)	5.631	.870	.679**	.459**	**.774**	.641**
Just-in-case supply chain (JIC)	5.629	.875	.693**	.347**	.644**	**.728**
Shoe sizes (marker variable)	2.310	.952	-.055	-.290**	-.007	-.069

Note: [a] Square root of AVE appear on the diagonal; unadjusted correlations appear below the diagonal; adjusted correlations for potential CMV appear above the diagonal; Source: Author's own creation

Table 4: Results of direct effect

Linkages in the model	Unstandardized coefficient	Standardised coefficient	t-value	Hypothesis testing outcome
KIMs → BDAI	.506***	.477***	5.922	H1: Supported
KIMs → SCV	.610***	.676***	8.092	H2: Supported
KIMs → JIC	.528***	.538***	4.940	H3: Supported
BDAI → SCV	.162**	.191**	2.828	H4: Supported
BDAI → JIC	-.039	-.043	-.658	H5: Not supported
SCV → JIC	.360**	.332**	3.171	H6: Supported
Controls				
Firm age → JIC	.0001	.0001	-.001	
Firm size → JIC	.038	.045	.739	
Variance explained	R^2			
BDAI	.227			
SCV	.615			
JIC	.651			
Goodness-of-fit indices: χ^2 = 521.758; df = 243; χ^2 / df = 2.147; CFI = .904; IFI = .905; RMSEA = .075; SRMR = .058				

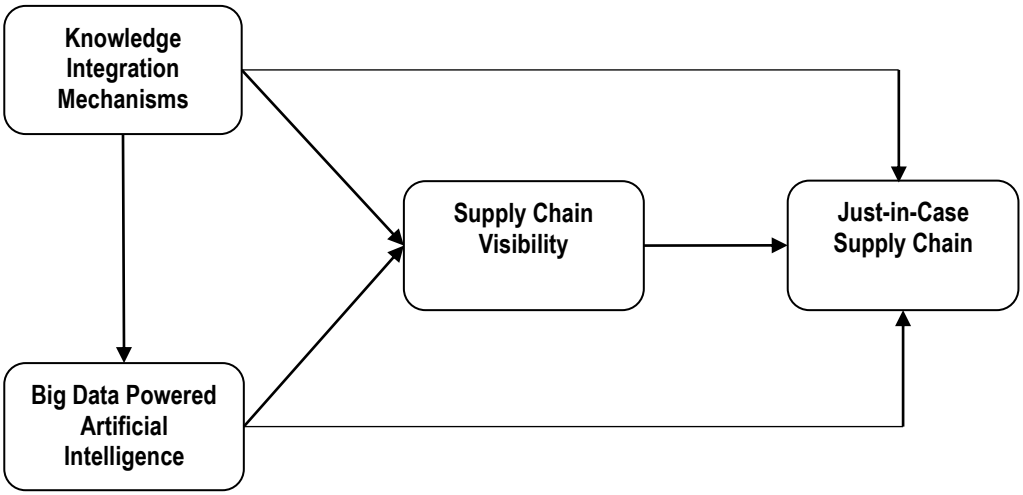
*** $p < .001$; ** $p < .01$; Source: Author's own creation

Table 5: Results of mediation effect

Structural paths	Direct effect	Indirect effect	SE of indirect effect	95% CI for indirect effect	Sobel test	Hypothesis testing outcome
KIMs→SCV→JIC	.538***	.234*	.104	.047–.458	z = 2.944**	H7a: Partial mediation
BDAI→SCV→JIC	-.043	.063*	.037	.009–.168	z = 2.113*	H7b: Full mediation

Note: SE = bootstrap standard error; CI = bootstrap confidence interval; Standardized effects; 2,000 bootstrap samples; *** $p < .001$; ** $p < .01$; * $p < .05$; Source: Author's own creation

Figure 1: Proposed research framework



Source: Author's own creation