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Navigating across the uncertainty:
Investigating the impact of buyer firms' digital transformation on operational efficiency

Abstract

Purpose: Extensive literature and business consultants assert that digital transformation (DT) substantially enhances firm business operations, while there are significant counterarguments suggesting that DT may squander resources and fall short of delivering the anticipated benefits. Additionally, the impact of uncertainties arising the buyer-supplier relationship has been largely overlooked. Drawing upon information processing theory, we propose to decipher the relationship between DT and operational efficiency through the buyer-supplier perspective, and further examine how uncertainties at the task, source, and supply network levels moderate this relationship by influencing information processing capabilities.

Design/methodology/approach: Using secondary data derived from Chinese A-share listed firms, our study evaluated a total of 257 listed buyer firms with 892 firm-year observations.

Findings: The findings reveal that DT positively influences operational efficiency, with this effect being moderated by buyers' technological resources and supplier dependency. Interestingly, the supplier digitalisation level and buyer-supplier distance do not significantly moderate this relationship.

Originality/value: This study contributes to technology literature by empirically investigating the actual impacts of DT on operational efficiency and identifying how various uncertainties at different levels can be managed for improved performance. The distinctive application of IPT offers a novel perspective on addressing these uncertainties in technological advancements. Moreover, this research provides valuable practical insights for firms on effective digitalisation process and offer guidance to policymakers in supporting DT initiatives.

Keywords: Digital transformation, operational efficiency, information processing theory, text analysis, supply chain management

1. Introduction

In times of escalating technological advancement and fierce competition, the advent of digital transformation (DT) presents new prospects for firms to address operations issues (Pelletier, L'ecuyer and Raymond, 2025). DT positions it as a fundamental action than just digitalizing existing processes or work products. Specifically, its practises cover the management of new technologies in operations and a set of digital actions, such as informatisation, Internet Plus, and intellectual operations (Tian et al. 2023; Zhai, Yang, and Chan 2022). DT helps integrate different tiers of the supply chain through real-time data flow. The smart supply chain enables hardware applications such as 3D printing for rapid provision of spare parts (Delic and Eyers 2020), and advanced robotics for transportation and distribution (Enrique et al. 2022). Moreover, DT significantly enhances collaboration among supply chain partners by facilitating more effective information sharing and improving the coordination of activities (Dubey et al. 2024). In this sense, Firms anticipate enhancing their competitive edges through integrating DT into supply chain management to create new value and generate revenue (Guo et al. 2023). For instance, an increasing number of enterprises are embracing DT, evidenced by a forecast that the worldwide spending on technology to support AI will reach $337 billion in 2025 (IDC 2024).

However, practical evidence suggests that the increasing DT initiatives among firms does not always improve performance. Approximately 70% of DT efforts fall significantly short to meet their expected objectives (Priestley and Low 2023; Wade and Shan 2020). The unsuccessful projects are commonly caused by inadequate leadership, innovation hesitations, inability to develop information systems, or a lack of alignment between technology and organizational objectives (Oludapo, Carroll, and Helfert 2024). As the essential objective in the endeavour of DT, operational efficiency refers to the firm's operational performance relative to an efficiency frontier formed by best-practise firms that convert production inputs into outputs most efficiently (Lee and Johnson 2014). Unpacking the DT power to improve operational efficiency is critical for business organisations, given that such the association with short-term benefits, including cost and time savings as well as resources allocation, serves as a strong basis for competitiveness (Kortmann et al. 2014; H. Li et al. 2021). Although firms aspire to achieve greater output, a significant obstacle to this ambition lies in low operational efficiency, which is influenced not only by the stand-alone firms' structure, processes, and culture but more importantly by their actors along the supply chain (Ghafoori et al. 2024).

Prior research has attempted to ascertain whether DT engagement generally aids in improving organisational performance from various angles, such as DT's role in influencing sustainable performance (L. Li 2022), business process management (Baiyere, Salmela, and Tapanainen 2020) and innovation (M. Liu, Li, et al. 2023), which affects firms' operational efficiency ultimately. Nevertheless, the existing studies show inconsistent impact of DT on sustained performance improvement, especially considering the rising importance of DT in enhancing operations for firms and supply chain. One of the main reasons pertains that few research investigates the relationship between DT and operational efficiency in the context of supply chain, especially taking into account various uncertainties embedded in the buyer-supplier relationship. Based on the operations management literature, the expected transformation in an organisation depends on not only the stand-alone firms but their primary stakeholders like suppliers to facilitate major operational efficiency improvements. In this sense, we propose to entangle the effect of DT on operational efficiency via focusing on the buyers' perspective and uncertainties in their supply chain, given that buyers' proactive DT implementations drive the whole transformation process along the supply chain (Zhang et al., 2025). Moreover, it is surprising that limited empirical research has investigated the DT-OE relationship using a large-scale datasets (Tian et al. 2023). In practise, numerous firms have attempted to use DT to solve issues associated with low operational efficiency. The empirical evidence would bring answer to firms that whether optimize their business processes via DT can achieve operational efficiency.

To better explain the impact of DT on operational efficiency, this study utilized the lens of information processing theory (IPT). IPT posits that firms need to enhance their information processing capacity, especially under a variety of uncertainties, in order to achieve the fit between information processing needs and capacity (Galbraith 1974). Investment in DT is regarded as an effective approach to improve the information processing capacity by facilitating efficient data gathering, storing and transformation (Lu, Jiang and Wang 2024; Yu et al. 2021). Achieving this fit increases the likelihood of improved operational efficiency. Additionally, certain conditions may either diminish or reinforce the relationship between DT and operational efficiency. These conditions can be explained by the range of uncertainties firms encounter when adopting DT (Lu et al. 2023). According to IPT, uncertainties inherently trigger the need for information processing within firms. When faced with uncertainty, organizations must engage in thorough information processing to effectively resolve challenges.

If these uncertainties were not properly resolved, they might result in a decrease of operational efficiency (Tian et al. 2023). IPT stressed that organisations' uncertainty can be derived from (i) tasks, (ii)sources, and (iii) supply networks (Jia et al. 2020; Busse, Meinlschmidt, and Foerstl 2017). Therefore, this study examines four factors related to different types of uncertainty: buyers' technological resources, suppliers' digitalisation, buyer-supplier distance, and supplier dependency. At the task uncertainty level, with the advent of the digital economy, the buyer's technological resources enable the use of implicit information in a concrete manner and establish empirical data-based decision systems, thereby strengthening the buyer's competence in improving operational efficiency. At the source uncertainty level, the higher digitalisation level of the supplier can contribute to making communication more efficient and responsible, and ensuring that supply chain activities are more easily legally controllable (Gillani et al. 2024; Romero-Martínez and García-Muiña 2021). At the supply network level, geographic distance acts as a fundamental aspect of the social relationship dynamics between firms that influence the ways of information change and knowledge transfer in business (Rivera, Soderstrom, and Uzzi 2010). Supplier dependency, which reflects the proxy for a supplier's degree of dependence-based relational embeddedness (Kim and Henderson 2015), plays a significant role in increasing supplier participation in buyer-supported training (Carr et al. 2008). Building upon these considerations, the objective of this research is to address the following two research questions:

RQ 1: Can buyers' digital transformation enhance their operational efficiency?

RQ 2: How does the influence of DT on operational efficiency vary under different moderators (i.e., buyers' technological resources, suppliers' digitalisation level, buyer-supplier distance, and supplier dependency)?

To answer these research questions, this study tested the hypotheses using panel data from Chinese A-share listed firms in both the Shanghai and Shenzhen Stock Markets. A-share listed firms are particularly keen to develop DT compared with state-owned firms (Duan, Wang, and Zhou 2020). China is deemed as an excellent country to examine these research questions for the following two reasons. First, the Chinese government has realized the strategic value of data since the emerge of technology and the country has continually conducted a pro-DT policy over several decades (Zhai, Yang, and Chan 2022). China raised the importance of big data to a national strategy and implement several action plans in 2014, including the construction of a massive national data centre the following year. In 2020, the Chinese government officially acknowledged data as one of the five fundamental factors of production, along with land, labour, capital, and technology in a core policy document (Yan 2021). Moreover, China's 2035

Vision Outline promoted to establish a digital economy through the creation of a “digital China” and fostering greater integration between real and digital economies. Second, China's digital economy is gradually growing, and the rate of DT has accelerated significantly. According to CAICT's white paper on the development of China's digital economy (CAICT 2021), the added value of China's digital economy exceeded 39.2 trillion yuan in 2020, marking a substantial rise from 14.2% of Gross Domestic Product (GDP) in 2005 to 38.6% of GDP in 2020, which is 2.4% higher compared to the same period in the previous year. (M. Liu, Li, et al. 2023). As a result, the operational impact of DT practise in Chinese firms offer valuable insights for emerging countries implementing similar DT initiatives.

The present study makes a distinct contribution to the supply chain and operations management literature by providing empirical insights into the application of DT for enhancing firm performance. To begin with, it is the first study to apply the theoretical framework of IPT to examine the impact of DT on operational efficiency in this specific context. This refined framework contributes to a deeper understanding of IPT in empirical business research. Unlike prior studies, this research extends the theoretical application of DT to inter-organizational relationship management in supply chain settings. While previous research has employed IPT to explore moderating effects, this study identifies new sources of uncertainty at different levels—specifically at the task, source, and supply network levels. These additional dimensions contribute to a more nuanced understanding of how uncertainty influences the alignment between information processing needs and capabilities. The study addresses the call from supply chain and operations management scholars for broader consideration of factors—at both the firm and supply chain levels—that affect the implementation of DT strategies (Plekhanov, Franke and Netland 2023; Whipple, Wiedmer, and Boyer, 2015). By highlighting the moderating roles of supplier dependency and buyers’ technological resources, the findings offer valuable insights into managing supply chain complexity while pursuing enhanced operational efficiency.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive overview of the literature on DT and IPT. Section 3 focuses on the formulation of the study hypotheses, which examine the impact of DT on operational efficiency, and the moderating role of the four factors. This is followed by a detailed description of the research design in Section 4. Section 5 provides the empirical results and robustness test. Lastly, Section 6 provides a discussion on the implications and limitations of this study, as well as suggestions for future research directions.

2. Literature review and theoretical underpinning

2.1 Digital transformation (DT) and operational efficiency in the supply chain management

DT is a process aimed at improving an organisation via triggering major improvements to its attributes using a mix of technologies such as information, computing, communication, and connectivity (Vial 2021). The rising importance of DT requires a clear definition in the academic literature. Recent studies described DT as the transformation of business operations, processes, and value creation by utilizing various digital technologies such as artificial intelligence, blockchain, machine learning, the Internet of Things, and cloud computing (Gillani et al. 2024; Sheng, Feng, and Liu 2023; Bharadwaj et al. 2013). DT consists of three key components including digital artifacts, infrastructure, and platforms (Culasso et al., 2024). DT uniquely changes operations and value creation for enterprises through the application of digital technologies. In more detail, DT empowers firms to implement a variety of agile responses by optimising existing processes and resource utilisation, therefore facilitating resource reconfiguration (Warner and Wäger 2019). Additionally, DT enables businesses to gather data related to the behaviours of their supply chain partners across various contexts using new digital devices and channels, like software platforms and network services, to enhance the ability to sense and seize business opportunities (Gillani et al. 2024; Nylén and Holmström 2015).

While DT alone does not generate extra returns, its proper implementation by firms aids in their growth and acquisition of supplementary benefits (Mikalef et al. 2019). In this regards, pioneering scholars delve into the various outcomes of DT in influencing business performance. For instance, Fang and Liu (2024) indicates that DT significantly stimulate the momentum of enterprise high-level innovation and can reduce costs, increase revenue, improve efficiency. Chiarini (2021) asserted that DT incurs better environmental performance through lessening energy consumption and carbon emissions. Sheng, Feng, and Liu (2023) used a survey to investigate the impact of DT on financial and carbon performance through low-carbon operations management, considering the moderating influence of CEO ambivalence. Besides, L. Li (2022) examined DT for sustainable development in both the economy and environment and discovered a curvilinear relationship between DT and sustainable performance.

Nevertheless, a thorough investigation of the extent of the literature yields limited evidence on the impact of DT on operational efficiency. Operational efficiency refers to the firm's operational performance relative to an efficiency frontier formed by best-practise companies that convert production inputs into outputs most efficiently (Lee and Johnson 2014). It is critical for business organisations due to its association with short-term benefits such as cost and time savings, as well as resources allocation, which serving as a strong basis for competitiveness (Kortmann et al. 2014; H. Li et al. 2021). Parviainen et al. (2017) demonstrates that digitizing information-heavy processes can lead to cost reductions of up to 90% and significantly enhance turnaround times by multiple orders of magnitude. Employing software to automate tasks enables firms to automatically gather data and gain deeper insights into process efficiency, cost drivers, and risk mitigation. However, industry-based evidence indicates that DT poses a heavy burden on firms' operations management, as 89% large firms undertook the DT journey while only 31% achieved improvements in revenue lifting and cost savings[1]. In this regards, there is still limited understanding of how firms' DT implementations directly influence operational efficiency within the supply chain perspective, given that DT redistribute power and resources across organizational layers in the digital economy (Plekhanov, Franke and Netland 2023). This void emphasises the need for an exploratory study in this particular field.

Moreover, anticipated DT also depends upon firms' internal and external conditions that fit their DT implementations. Most of the extant studies probe into such contingent factors from the stand-alone firm perspective. For instance, by comparing the practice of digitally mature firms from digitally developing organisations, Mugge et al. (2020) highlights that key investments, key investment focus, successful initiation strategies, design philosophy, digital leadership, communications, and functional unit characteristics are factors that drive the success of DT. Similarly, Omol (2024) utilised scoping review methodology to summarise strategies for successful DT, including leadership and vision stand, the establishment of a culture of adaptability, customer-centricity, data-driven decision-making, agile methodologies, technology integration, change management, ecosystem collaboration, continuous monitoring and optimization. Additionally, Ghafoori et al. (2024) emphasized the importance of organizational culture in enabling data-driven practices and supporting the success of organizational transformation. While another stream develops frameworks to guide the DT implementation process. The work of Butt (2020) provides a framework to support DT in manufacturing based on business process management approach and incorporates the factors into implementation including skills gap analysis, risk management, contingency planning, change management, and cost-benefit analysis. Additionally, Elia et al. (2024) proposed a conceptual framework for successful DT initiatives, emphasizing key dimensions of

[1] Source: https://www.mckinsey.com/featured-insights/themes/how-top-performing-companies-approach-digital-transformation

technology, processes, people, and value orientation. The framework further addresses critical considerations, including the need for change, performance orientation, process transformation, and impacts across multiple levels such as finance, society, environment. Nevertheless, there still exists a gap in identifying the inter-organisational factors that may influence the relationship between DT and operational efficiency. Specifically, we still can not decipher how the uncertainties of supply chain relevant factors influence the impact of DT on operational efficiency from the buyer-supplier relationship. Figure 1 visualises the relevant literature as well as existing research gaps that we propose to address in this research.

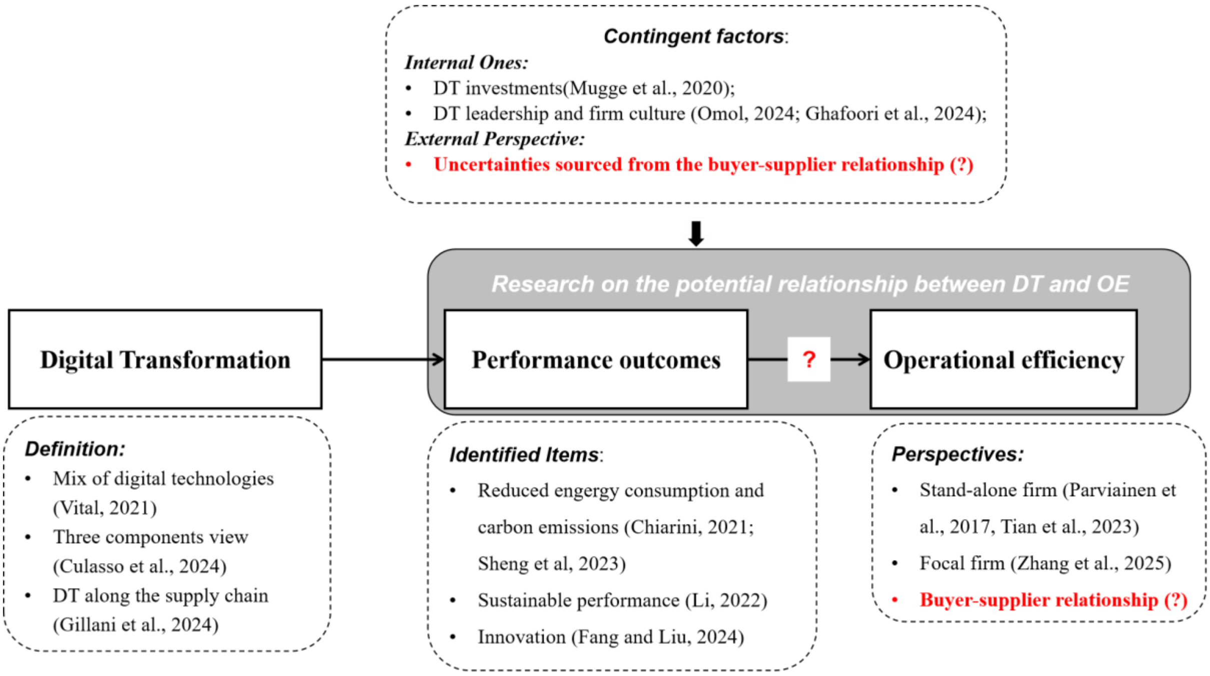

Figure 1. The visualisation of relevant literature and existing research gaps.

2.2 Information Processing Theory

Firms need to effectively organise and utilize information, particularly in situations characterised by a high degree of uncertainty (Lu et al., 2023; Srinivasan and Swink, 2018). ITP explains this phenomenon by looking into the link between environmental uncertainty and a firm's information processing needs, as well as the ways that firms can cope with these needs Galbraith (1974). The key components of IPT encompass information processing requirements, the capacity of information processing, and the congruence between information needs and capacity (X. Liu, Tse, et al. 2023; Tushman and Nadler 1978). Specifically, an organisation's information processing requirement is created by uncertainty and requires the management of the necessary amount of information requisite by the organisation for a particular set of objectives (Egelhoff 1991; Tushman and Nadler 1978; Galbraith 1974). Information processing capacity refers to an organisation's ability to effectively manage and structure information in a meaningful manner that facilitates decision-making.

According to IPT, uncertainty stems from tasks, sources, and supply networks (Busse, Meinlschmidt, and Foerstl 2017; Jia et al. 2020). Task uncertainty arises from the interdependent nature of organisation task performance (Cegielski et al. 2012). It emphasizes the distinction between the information needed to complete the task and the information already available within the organisation (Galbraith 1974). For example, the buyer firms may face task uncertainty because their limited technology capacities prevent them from effectively integrating and managing advanced digital tools, coordinating complex workflows, or responding promptly to technological disruptions. Meanwhile, source uncertainty generally arise from the aggregate of suppliers, including the uncertainties from the nodes and links to the buyer (Busse, Meinlschmidt, and Foerstl 2017). Source uncertainty considers the dyadic inter-organizational relationship between businesses and their suppliers. This type of uncertainty can stem from supplier-related factors, including the suppliers themselves; for instance, inadequate digital development of suppliers may lead to an inability to engage in digital communication with buyers, or issues such as opportunism or unethical practices. Additionally, source uncertainty can also arise from adversarial relationships caused by supplier behaviors. (Busse, Meinlschmidt, and Foerstl 2017). As a result, differences in a supplier's digitalisation level create source uncertainty, arising from potential gaps in communication, mutual understanding, and coordination capabilities (Pelletier, L'ecuyer and Raymond, 2025). Lastly, supply network uncertainty is defined as the uncertainty arising from the structural characteristics of the supply chain, including horizontal complexity, vertical complexity, and spatial complexity (Choi and Krause 2006). Supply network-related uncertainty often attributed to challenges in acquiring and managing vast amounts of data, the complex nature of supply chains facilitating information loss, and the difficulty in implementing mechanisms to oversee the entire chain. This study examines the supplier network uncertainty through two dimensions, horizontal complexity, reflecting by the extent of dependency on top suppliers, and spatial complexity, indicated by the physical distance between buyers and suppliers. Overall, as stated by Galbraith (1974), heightened uncertainties in these areas requires increased information processing. In order to address these uncertainties, organisations can either minimize their information requirements or enhancing their information processing capabilities.

Additionally, the fit between information processing needs and information processing capacity is another essential implication of IPT, and fitness would affect performance to a great extent (Lu, Jiang and Wang 2024; X. Liu, Tse, et al. 2023; Egelhoff 1991). In contrast to traditional perspectives like the resource-based view, dynamic capabilities, resource orchestration, or cumulative capabilities, which highlight the types of resources owned by organisations, or the evolutionary perspective, which focuses on changes in the firm's relationships and organisation (Pelletier, L'ecuyer and Raymond, 2025). ITP focuses on aligning information capabilities with needs to determine what is required to accomplish this fit (Enrique et al. 2022). The mismatch between information processing needs and available capacity can lead to problems such as schedule delays and budget overruns (Lu et al. 2023). When there is insufficient capacity for the required information processing, it hinders effective decision-making and can lead to delays in project timelines. On the other hand, excessive capacity can lead to unnecessary costs without providing any significant benefit (X. Liu, Tse, et al. 2023). The example of early failures of business-to-business (B2B) electronic marketplaces demonstrate that attempting to use technology in incompatible circumstances results in failure (Premkumar, Ramamurthy, and Saunders 2005). Empirical studies have provided evidence to support the importance of "fit". For instance, Srinivasan and Swink (2018) identified the positive impact of information-supporting analytics capability, complemented with organisational forms and systems to match the changing needs of customers (i.e., organisational flexibility) on operations performance.

3. Hypothesis development

3.1 Digital transformation and operational efficiency

According to IPT, organisations prioritize achieving the fit between their information processing needs and their capacity for information processing purpose, which indicate that firms can either improve their processing capacity or diminish their processing needs in efforts to mitigate uncertainty (Galbraith 1974; Tushman and Nadler 1978; Egelhoff 1991). This study argues that buyers, as an important supply chain actor, can develop their DT to increase their knowledge processing capacity through the combination of technologies, including information, computing, communication, and connectivity (Vial 2021).

As an important way of improving information processing capability, the buyer's DT enables them to achieve efficiency-based performance goals. Firstly, the deployment of appropriate digital technology improves corporate analysis capacity and communication (Gharoie Ahangar et al. 2025). The intelligence across organisations and speedy responding to the learning outcome considerably increase the effectiveness for daily operations or solving emerging situations in the supply chain network under competitive environment (Li et al., 2021). It is supported by Chien, Liu, and Chuang (2017) that DT diagnoses problem root causes before an incident happens and interrupts production. Secondly, DT allowed for a more effective and accurate distribution of resources across operational units, resulting in heightened flexibility in operational strategies overall (Fletcher and Griffiths 2020). DT usually migrates data into a centralized repository that can greatly improve data accessibility, and authorized engineers can retrieve information quickly for information analysis. Supported by the constant availability of data and its easy access, DT brings a holistic process change of the organisation which can replace fragility with flexibility continuously (Struijk et al. 2023). The buyer with sufficient strategic flexibility can then adapt to uncertainty and be operationally efficient by gaining traction, creating direction, and avoiding mistakes (Kortmann et al. 2014). Thirdly, DT bring chances to generate digital value in processes, products, and services. ((Baiyere, Salmela, and Tapanainen 2020). With trails, experiments and engineering efforts, firms attempt to re-conceptualise business models and brings to deep structure changes in business processes, such as radical re-engineering efforts. DT also enables the provision of digital services that customers can access conveniently anytime and anywhere (Culasso et al., 2024). These advancements generally necessitate leveraging digital technologies, and DT involves the ability to manage the generativity of those technologies. Accordingly, we propose:

H1. The buyer's digital transformation positively impacts the buyer's operational efficiency.

3.2 Moderating factors

As previously noted, DT may influence operational efficiency by strengthening information processing capabilities; nevertheless, a greater knowledge of how the buyer's DT might positively impact the buyer's operational efficiency is critical. Thus, we argue that the moderators – technological resources, supplier's digitalisation level, supplier dependency, and buyer-supplier distance– are activities that either increase or decrease information processing needs, and thus influence the extent to which buyer DT influences its operational efficiency.

3.2.1 Buyer's technological resources

Technological resources, such as patents, trade secrets, and know-how, have evolved into fundamental assets for firms. Technological resources are generated through research and development (R&D) investment, and the deployment of technological resources brings to a broad set of assets, including manufacturing capabilities, access to distribution channels, and exclusive partnership held by the organisation (Mattia Bianchi et al. 2014b). The accessibility of adequate technological resources accelerates the diffusion of new technologies, including digital technologies, which plays a crucial role in enhancing operational processes (Hughes et al. 2018). According to IPT, technological resources enable the execution of intelligent and autonomous operational tasks, ultimately leading to a decrease in uncertainty in task complexity (Anzoategui et al. 2019). Less complex tasks lead to easier in predictability, thus facilitating the fit between information processing needs and information processing capacity (Tushman and Nadler 1978). This implies that advanced technological resources are likely to decrease the knowledge processing need and strengthen the role of DT in improving operational efficiency accordingly. Thus, the second hypothesis is proposed as follows:

H2. The greater a buyer's technology resources, the more positive the influence of buyer digital transformation on its operational efficiency.

3.2.2 Supplier's digitalisation level

A supplier's digitalisation level refers to the extent to which that supplier has adopted and integrated digital technologies and processes into its business and operations practises. A supplier's digitalisation level acts as an indicator of the supplier's technological advantage and the ability to provide improved services and responsiveness. Different entities in the supply chain are interdependency and interconnected, therefore, the behaviour of one member can affect other members (Y. Yang and Jiang 2023a). The transformation of digital technology of supplier is affecting the processes and practices of buyer firm (Chen et al. 2025). When both suppliers and buyers have consistent strategy to expand the digital industrialization, the alignment of digital transformation level between them improve the supply chain transparency and reduce supplier opportunism (L. Yang et al. 2021; Chen et al. 2025). Aligned with IPT, a supplier with a high degree of digitalisation demonstrates an advanced information processing capacity. This capacity enables the supplier to provide its buyer with accurate, real-time data on the sourcing process, such as inventory levels, production status, and delivery timelines, through advanced IoT systems and blockchain technology (Struijk et al. 2023). This level of transparency and prompt communication allows buyers to anticipate and mitigate potential disruptions, align their production schedules more effectively, and make timely adjustments to their procurement strategies. Consequently, the enhanced visibility and reliability reduce uncertainties for the buyer in the sourcing process (Busse, Meinlschmidt, and Foerstl 2017). Besides, since buyers advance in their DT initiatives aimed at enhancing operational efficiency, suppliers with advanced digital capabilities can provide valuable assistance in addressing related challenges based on their expertise. Additionally, highly digitalized suppliers facilitate efficient knowledge transfer to buyers, thereby promoting enhanced collaboration (Yang et al. 2025). For instance, buyers may need to acquire new skillsets to improve communication during the digital transformation process, such as utilizing blockchain technology for document management. Suppliers with a high level of digitalisation can support buyers in this learning process. As buyers become proficient in these new techniques, the effectiveness of buyers' operations alongside with their collaboration with suppliers can be significantly enhanced. Therefore, the third hypothesis is postulated as follows:

H3. The greater a supplier's digitalisation level, the more positive the influence of buyer digital transformation on its operational efficiency.

3.2.3 Buyer-supplier distance

With increased geopolitical conflicts, serious challenges to supply chain security have taken place, therefore, many buyer firms searching for suppliers on a larger geographical scale to secure supply chains have become an important source of core competence (Bernard, Moxnes, and Saito 2019). The physical distance between buying and supplying firms is also understood as the spatial complexity of supply chain uncertainty in IPT. The increased uncertainty stemming from long distances diminishes the buyer's strategic flexibility, making it harder to adapt to unforeseen circumstances and a rapidly changing environment. In detail, geographical separation between buyers and suppliers brings challenges arising from cultural differences and diverse legal and regulatory compliance requirements (Wiengarten and Ambrose 2017). As buyers progress in their DT, supply chain members may face challenges such as alignment and communication issues. These obstacles can lead to delays, errors, and inconsistencies, which hinder the smooth integration of digital technologies across the supply chain. Consequently, these issues can disrupt workflows, prolong problem resolution, and decrease the overall responsiveness of the supply chain (Busse, Meinlschmidt, and Foerstl (2017). Thereby, the positive effect of the buyer DT on the buyer's operational efficiency is lessened. Hence, the fourth hypothesis is proposed as follows:

H4. The greater the buyer-supplier distance, the more negative the influence of buyer digital transformation on its operational efficiency.

3.2.4 Supplier dependency

Organisations are increasingly dependent on their supply chain partners to facilitate cost reduction, enhance processes, and ensure quality, thereby attaining a competitive edge

(Petersen et al. 2008). Supplier dependency refers to a buyer's dependency on its suppliers, and it acts as a key characteristic that influences the dynamic of the supply chain relationship. Buyers with high supplier dependency are more vulnerable and face greater sourcing uncertainty, as any disruptions, delays, or quality issues from these suppliers can directly affect their operations and competitiveness (Petersen et al. 2008). To mitigate these risks, buyers need to adopt problem-solving routines, such as advancing their digital transformation (DT) efforts, to strengthen their position within the supply network. Additionally, buyers with higher supplier dependency need to better utilize resources to enhance operational efficiency (Yang et al. 2025). Schiele and Vos (2015) explained that firms heavily reliant on suppliers tend to leverage supplier resources, including production capacity and innovation resources like personnel dedicated to new product development projects. As a result, buyers gain access to more external resources that can be organized to assimilate relevant knowledge, enabling them to explore potential alternatives in their operations (Fang and Liu 2024). Thus, DT-induced knowledge processing is well-align with the increased processing requirements of firms, ultimately resulting in enhancing operational efficiency. Given the information provided, we put forth our fifth hypothesis:

H5. The greater the supplier dependency, the more positive the influence of buyer digital transformation on its operational efficiency.

The proposed research framework that summarises the previously mentioned hypotheses is shown in Figure 2.

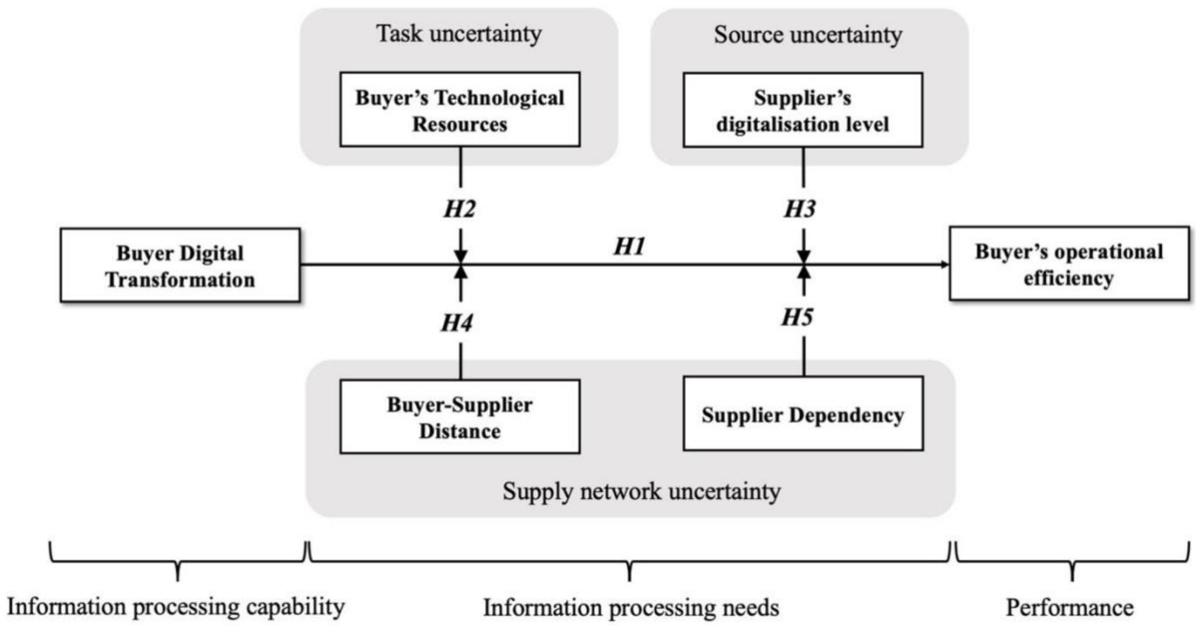

Figure 2. A research framework of DT and operational efficiency

Methodology

4.1 Data and sample

We collected sample data of Chinese A-share listed firms in Shanghai Stock Exchange and Shenzhen Stock Exchange (SHSE and SZSE) over 2010 to 2021 from multiple data sources. Specifically, we acquired listed firms' buyer-supplier dyadic relationship data as well as their annual financial reports from the China Stock Market Accounting Research (CSMAR) platform, which has been widely adopted by the studies investigating the buyer-supplier relationship in a Chinese context (Y. Yang and Jiang 2023a, 2023b). We also followed prior studies (Gu et al. 2024; Huo, Liu, and Tian 2022; Zhu, Yeung, and Zhou 2021) to exclude sample firms in the financial industry, labelled with special treatment (ST and ST*), and with missing data. We set our observation period to start in 2010, when a few sample firms began to disclose their DT strategies. After acquiring other firm-level data and financial data from China Research Data Service (CNRDS) and Wind, we finally obtained a data set containing 257 listed buyer firms with 892 firm-year observations from 2010 to 2021.

4.2 Variable Measurements

The dependent variable in this study is buyer firms' operational efficiency. Following existing studies on the measurements of operational efficiency, we adopted the stochastic frontier estimation (SFE) approach to quantify the sample buyer firms' comprehensive operational efficiency from the input-output perspective. The SFE method is widely utilised by operations management scholars to measure a firm's overall operational efficiency by establishing a stochastic production function. This approach can not only transform various operational input resources into the expected operational outcome, but also take industrial and other heterogeneous factors into consideration, which reduces the errors in operational efficiency estimation significantly (Lam, Yeung, and Cheng 2016). In this sense, we utilised the SFE method and constructed a typical stochastic production function of a buyer firm i of industry j in year t with input resources and the expected outcome as follows:

$$\begin{aligned}\ln(Operating\ Income)_{ijt} = \beta_0 + \beta_1 \ln(Number\ of\ Employees)_{ijt} \\ + \beta_2 \ln(Cost\ of\ Goods\ Sold)_{ijt} \\ + \beta_3 \ln(Capital\ Expenditure)_{ijt} \\ + \varepsilon_{ijt} - \eta_{ijt}\end{aligned} \quad (1)$$

The right side of the stochastic production function above indicates all the operating input resources, such as employee numbers, goods selling costs, and capital expenditures, whereas the left hand includes the expected operating output of operating incomes. ε_{ijt} in the function captures random and uncertain factors that influence a firm's production process, while η_{ijt} represents the operational inefficiency of a firm. Therefore, we can further calculate the operational efficiency of a buyer firm *i* of industry *j* in year *t* by deducting the inefficiency item as follows:

$$Operational\ Efficiency_{ijt} = 1 - \widehat{\eta_{ijt}} \quad (2)$$

With the aim of measuring the extent of a buyer firm's DT, we adopted the cutting-edge text analysis approach by following (Tian et al. 2023). Different from collecting primary data regarding DT through the application of surveys and/or questionnaires, more nascent studies strive to quantify a structured variable that measures a firm's DT degree through utilising text mining techniques to extract relevant but unstructured information from its annual reports and announcements. Such a method turns out to be more objective and provides more general findings. In this sense, we follow Tian et al. (2023) procedures to construct the variable that measures a buyer firm's DT extent. Specifically, we first utilised DT-related seed words sourced from Tian et al. (2023) to identify whether a buyer firm's annual report contains information about DT or not. These seed words constitute five main dimensions of DT strategy, including emerging digital technology, digital management, informatization, internet plus actions, and intellectual operations. Second, we match these seed words with sample buyer firms' annual reports to confirm word frequencies. After acquiring the seed words frequencies in each dimension, we further applied the entropy method to calculate the weights of each seed words. Finally, we employed the weight coefficients to measure the DT degree of a buyer firm i in year t as BDT_{it}.

Through the theoretical lens of IPT, this study also aims to examine the boundary conditions that influence the effect of buyer DT on buyer operational efficiency. In particular, we proposed four uncertainties that could potentially moderate the DT-operational efficiency relationship, including buyer technological resources, supplier's digitalisation level, buyer-supplier distance and supplier dependency. We utilised a buyer firm's R&D investments to proxy its technological resources, given that R&D investments represent a firm's access to technological development resources (Son and Zo 2023; M. Bianchi et al. 2014a). We also applied the text analysis method to quantify suppliers' DT degree. Buyer-supplier distance is measured by the direct geographic distance between a buyer and its supplier. Finally, we identify the supplier dependency as a buyer's dependency on its main suppliers by the calculation function as follows:

$$\mathrm{SD_{it}} = \frac{\mathrm{Procurements\ from\ Buyers'Top\ 5\ Suppliers_{it}}}{\mathrm{Total\ procurements_{it}}} \tag{3}$$

A high value SD_{it} delineates that buyers rely heavily on their suppliers. In this sense, buyers would form a close relationship with their suppliers (Zhu, Yeung, and Zhou 2021). Additionally, to exclude other variables that may influence a buyer firm's operational efficiency, we controlled firm size ($Size_{it}$), leverage (Lev_{it}), firm profitability (ROA_{it}) and growth ($Growth_{it}$) from the firm-level characteristics. We also controlled corporate governance factors, including board size ($board_{it}$), independent director ratio ($IndRatio_{it}$) and ownership concentration extent (OC_{it}). Finally, the industry fixed effect as well as the time fixed effects are controlled in the form of two dummy variables, avoiding the industrial and temporal heterogeneity effect on buyer firms' operational efficiency. Table 1 presents the names, definitions, and measurements of all variables in this study.

Table 1 Variables definition

Variable	Definition	References
Buyer Operational Efficiency (*BOE*)	Applying Stochastic Production Functions to evaluate a buyer firm's operational efficiency	Lam, Yeung, and Cheng (2016)
Buyer Digital Transformation (*BDT*)	Utilizing text analysis to quantify the degree of a buyer firm's digital transformation	Tian et al. (2023)
Buyer Technological Resource (*BTR*)	The R&D investment of a buyer firm	M. Bianchi et al. (2014a); Son and Zo (2023)
Supplier Digital Transformation (*SDT*)	Utilizing text analysis to quantify the degree of a supplier firm's digital transformation	Tian et al. (2023)
Buyer-Supplier Distance (*BSD*)	The direct geographic distance between a buyer and its suppliers	Wiengarten and Ambrose (2017)

Supplier Dependency (*SD*)	The proportion of total procurement from a buyer's top 5 suppliers	Zhu, Yeung, and Zhou (2021)
Firm Size (*Size*)	The natural log of a sample firm's total assets	
Leverage (*Lev*)	The ratio of a sample firm's total debts to its total assets	
Firm Profitability (*ROA*)	A sample firm's return on its total assets	
Firm Growth (*Growth*)	The ratio of a sample firm's total operating income growth in *t* year to operating incomes in t-1 year	
Board Size (*Board*)	The natural log of directors number in a sample firm's board	
Independent Director Ratio (*IndRatio*)	The ratio of independent directors number to the total number of directors in a sample firm's board	
Ownership Concentration (*OC*)	The shareholding ratio of top 10 shareholders in a sample firm	

4.3 Regression model specification

We built two groups of panel data regression models to examine all the hypotheses we proposed before. Specifically, we proposed model (4) as the baseline regression model to testify the effect of buyer DT on buyer operational efficiency:

$$BOE_{it} = \beta_0 + \beta_1 BDT_{it} + \sum_{i=1}^{n} \beta_i Control_i + \varepsilon \tag{4}$$

Further, we expect to examine H2-H5 regarding the potential moderators in the DT-operational efficiency relationship by proposing the other group of models as follows:

$$BOE_{it} = \beta_0 + \beta_1 BDT_{it} + \beta_2 Moderators_{it} + \beta_3 BDT_{it} \times Moderators_{it} + \sum_{i=1}^{n} \beta_i Control_i + \varepsilon \tag{5}$$

5. Analysis results

4.1 Descriptive statistics

Table 2 shows the descriptive statistics of all variables before putting into regression models. According to Table 2, BDT ranges from 0.109 to 0.326, representing different extents of DT that exist in sample buyer firms. Similarly, BOE also significantly differs from 0.697 to 0.934. Meanwhile, the results of all variance inflation factors (VIF) are 2.75, which is much lower than the reference value of 5, avoiding the concern of multicollinearity.

Table 2 Descriptive statistics

VarName	Obs	Mean	SD	Min	Max
BOE	892	0.782	0.221	0.697	0.934
BDT	892	0.283	0.062	0.109	0.326
Size	892	21.779	1.121	20.996	22.366

Lev	892	0.420	0.202	0.262	0.567
ROA	892	0.029	0.064	0.012	0.059
Growth	892	0.147	0.379	-0.028	0.249
Board	892	2.319	0.261	2.197	2.485
IndRatio	892	0.373	0.069	0.333	0.417
OC	892	0.325	0.139	0.221	0.416

4.2 Regression results

Table 3 demonstrates the results of both main regression and moderating examination models. Specifically, the coefficient of DT in Model 1 is 0.462*** (t-value = 2.66, P<0.01), representing that a buyer's DT has a significantly positive effect on its operational efficiency. This result supports H1. Afterwards, we added the interactions between DT and four moderators to further examine the moderating effects on DT-operational efficiency relationship. The coefficient of interaction term between buyer's DT and buyer technological resources in Model 2 is significantly positive (β=0.536***, t-value=2.75, P<0.01), suggesting that buyer technological resources strengthen the DT-operational efficiency relationship. Therefore, H2 is supported. However, the results in Models 3 and 4 indicate that both supplier digitalisation (β=0.392，t-value =1.31) and buyer-supplier distance (β=0.442，t-value=1.44) fail to enhance the buyer DT-buyer's operational efficiency relationship, as the coefficients of these two interaction terms are not statistically significant. Hence, the regression result cannot support H3 and H4. Finally, the coefficient of interaction between BDT and SD in Model 5 is significantly positive (β=0.618***，t=2.67, P<0.01), which supports H5.

Table 3 Main regression results

	Model 1	Model 2	Model 3	Model 4	Model 5
	BOE	BOE	BOE	BOE	BOE
BDT	0.462***	0.313	0.347*	0.352*	0.407**
	(2.66)	(1.63)	(1.74)	(1.81)	(2.01)
BTR		0.693			
		(1.52)			
BDT*BTR		0.536***			
		(2.75)			
SDT			0.572*		
			(1.85)		
BDT*SDT			0.392		
			(1.31)		
BSD				0.560**	
				(2.08)	
BDT*BSD				0.442	
				(1.44)	
SD					0.476
					(1.33)
BDT*SD					0.618***
					(2.67)

Size	0.017	-0.029	0.042	0.007	-0.051*
	(0.83)	(-0.92)	(1.24)	(0.22)	(-1.80)
Lev	-0.263***	-0.179	-0.307**	-0.363**	-0.143
	(-2.77)	(-1.12)	(-2.49)	(-2.29)	(-1.21)
ROA	0.294**	0.221	0.890***	0.162	0.647***
	(2.07)	(0.81)	(4.75)	(0.83)	(4.09)
Growth	0.010	0.003	0.011	0.011	-0.019
	(0.81)	(0.13)	(0.91)	(0.68)	(-1.13)
Board	-0.022	-0.062	-0.009	0.017	0.001
	(-0.67)	(-1.20)	(-0.19)	(0.33)	(0.02)
IndRatio	-0.124	-0.042	0.062	-0.340**	-0.177**
	(-1.38)	(-0.30)	(0.55)	(-2.21)	(-1.99)
	(0.30)	(-0.33)	(-0.79)	(0.30)	(1.51)
OC	0.052	-0.114	-0.043	0.120	-0.349
	(0.29)	(-0.42)	(-0.19)	(0.48)	(-1.37)
_cons	0.573	1.619**	-0.029	0.814	2.107***
	(1.25)	(2.38)	(-0.04)	(1.20)	(3.31)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	892	892	892	892	892
Adjuested-R^2	0.058	0.040	0.053	0.062	0.083

Note. The t-values are in parentheses. Statistical significance levels: *** p <0.01, ** p <0.05, *p < 0.10.

4.3 Robustness Check

To ensure the robustness of our analysis results above, we also conduct a battery of robustness check to address the concerns of measurement error, sample selection bias, and reverse causality. Table 4 reports the results of the robustness check in this study. Particularly, we first retain sample buyer firms with high-quality of information disclosure to guarantee the reliability and authenticity of annual reports. Each year, SHSE and SZSE in China announce whether a listed firm violates information disclosure regulations or not. In this respect, we retain sample buyer firms that do not violate regulations over the observation period in Model 1. Further, SHSE and SZSE also rated the disclosure quality of listed firms, and we also retained sample buyer firms with high disclosure ratings in Model 2. The results of Models 1 and 2 in Table 4 are consistent with our main analysis result, suggesting that DT has a positive effect on its operational efficiency.

Second, we also adopt the regression based on propensity score matching (PSM) method to address sample selection bias. Model 3-5 show the results achieved by implementing different matching strategies (i.e., 1:1, 1:2, 1:3 matching), which are also consistent with our main regression result. Finally, we employ instrumental variables to address the reverse causality issue. Specifically, we identify the digitalisation degree of the city wherein each sample buyer firm is located as the instrumental variable for BDT. Models 6-7 demonstrate the results of a two-stage regression approach, which ensures consistency with previous results.

Table 4 Robustness check

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Disclosure Quality No violation	**Disclosure Quality** High quality	**PSM** 1:1 matching	**PSM** 1:2 matching	**PSM** 1:3 matching	**2SLS** Instrumental Variable	**2SLS** Instrumental Variable
	BOE	BOE	BOE	BOE	BOE	BDT	BOE
BDT	0.396**	0.453**	0.522***	0.480***	0.490***		0.988*
	(2.09)	(2.55)	(2.83)	(2.74)	(2.95)		(1.71)
Digital_City						0.428***	
						(5.94)	
Size	-0.007	0.027	-0.020	-0.013	-0.020	0.017***	0.007
	(-0.28)	(1.16)	(-0.53)	(-0.44)	(-0.77)	(2.75)	(0.30)
Lev	-0.273***	-0.325***	-0.256	-0.231*	-0.195*	0.010	-0.273***
	(-2.69)	(-3.12)	(-1.54)	(-1.70)	(-1.73)	(0.51)	(-2.97)
ROA	0.619***	0.711***	0.408	0.371*	0.370**	0.001	0.295**
	(3.07)	(3.51)	(1.56)	(1.87)	(2.27)	(0.05)	(2.13)
Growth	0.006	-0.001	0.009	-0.008	0.003	-0.003	0.012
	(0.45)	(-0.06)	(0.30)	(-0.49)	(0.19)	(-1.48)	(0.99)
Board	-0.027	-0.015	-0.059	-0.056	-0.070*	0.002	-0.023
	(-0.66)	(-0.39)	(-1.06)	(-1.24)	(-1.69)	(0.31)	(-0.71)

IndRatio	-0.138	-0.111	-0.049	0.056	0.029	0.001	-0.128
	(-1.24)	(-1.17)	(-0.33)	(0.45)	(0.27)	(0.09)	(-1.42)
OC	-0.239	-0.110	-0.148	-0.160	-0.233	-0.000	0.055
	(-1.52)	(-0.63)	(-0.42)	(-0.63)	(-1.14)	(-0.00)	(0.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	673	634	253	361	432	892	892
Kleibergen-Paap rk Wald F statistic						35.276	
Adjuested-R^2	0.071	0.087	0.070	0.068	0.077	0.389	0.278

5. Discussion and conclusion

Building upon the IPT, this research empirically examines the effect of buyers' DT on their operational efficiency in China. Additionally, it analyses how their relationship varies according to four moderators. The results of the empirical analysis provide instructive insights. Specifically, buyers' DT enables operational efficiency, and the relationship between DT and operational efficiency strengthens with greater buyer's technological resources and supplier dependency. Surprisingly, it is not influenced by the supplier's digitalisation level or buyer-supplier distance. The following is the theoretical and practical discussion and implications of the results.

5.1 Theoretical implications

Despite numerous attempts to scrutinize the potential impact of DT, there exists a scarcity of empirical studies investigating the connection between DT and operational efficiency. Grounded in IPT, our results affirm the positive influence of DT on operational efficiency, highlighting the crucial role of DT in ensuring the survival of buyers within highly competitive environments. This research enhances the existing knowledge of the DT's literature by expanding upon it (Yang et al. 2025). DT assists firms achieve superior operations efficiency by improving firms' information processing capability. This finding aligns with the argument raised by X. Liu, Tse, et al. (2023) that the firms' performance can be improved through increased processing capability, as the dynamic nature of environment demands higher knowledge processing needs. The present study is also consistent with existing knowledge that emphasizes the pivotal role of digital technologies in facilitating the operations of firms (Tian et al. 2023; Holmström et al. 2019; Zhai, Yang, and Chan 2022). Furthermore, it extends this understanding by adopting a supply chain management perspective rather than focusing solely on firm level. Additionally, employing the lens of IPT provides novel insights by examining how various uncertainties influence DT, which is distinctly differ from Tian et al. (2023)'s practice based view. It is worth mentioning that the present study focuses on the context of China. The country has maintained a pro-DT stance over the years, evident in its government's initiatives, including the establishment of national policies to enhance internet infrastructure and promote e-business (Zhai, Yang, and Chan 2022). This commitment has resulted in a significant surge in firms actively undergoing DT (Yan 2021). Consequently, the research findings aptly capture and support the ongoing discourse on DT studies in China. Additionally, being an emerging market, the operational impacts of DT practises within Chinese firms, along with the factors influencing these dynamics, offer valuable lessons for other emerging markets contemplating similar DT strategies.

As mentioned, this study further delves into four moderation effects that could impact the influence of DT on operational efficiency. Firstly, the findings reveal that buyer's technological resources strengthen the relationship. We posit that a high level of technological resources enables firms to cultivate technological competence in related domains through the R&D process, leading to a stronger impact of DT. This finding bring into line with the view of Gharoie Ahangar et al. (2025) and Mattia Bianchi et al. (2014b), who suggest that technological advancements achieved through R&D efforts can produce a greater flow of new information technologies within the firm and allow the organisation to remain current with the latest technical developments. Different from previous studies focusing on the direct influence on operational efficiency (Mattia Bianchi et al. 2014b; Hughes et al. 2018), this study offers a unique viewpoint by considering technological resources as a potential factor and exploring their interaction with DT. Secondly, the results of the digitalisation level of suppliers show that it does not have an impact on the buyer's operational efficiency. Some researchers have been dedicated to exploring the effect of the digitalisation level of suppliers on organisational outcomes, given the crucial role of suppliers in the supply chain (Matthess et al. 2022; Colombari et al. 2023). There is an anticipation of knowledge sharing within the supply chain, thereby facilitating buyer's DT (Fletcher and Griffiths 2020). However, the knowledge possessed by the firm is often idiosyncratic and context specific. Leveraging the knowledge to improve operational efficiency requires firms to apply what they have learned within their own context, and the knowledge requires a degree of customization (Maritan and Brush 2003). It is crucial to note that a widely dispersed supplier network complicates the application of knowledge, making it challenging for focal firms to tailor knowledge based on a large supplier base. In such cases, the positive impact of buyer DT on operational efficiency may not be amplified by the digitalisation level of suppliers. Thirdly, this study also delves into the impact at the supply chain level, which was relatively less discussed in the previous study. Contrary to the expectations, the empirical evidence revealed that buyer-supplier distance does not diminish the effect of buyer DT on operational efficiency. The result can be explained by the findings of Elking, Cantor, and Hofer (2022), whose research posits that increased geographic separation between buyer and supplier accelerates the effective transfer of information and capabilities across organisational boundaries. This is supported by the fundamental principles of the geographic propinquity mechanisms, which assert closer spatial proximity fosters heightened levels of interaction (Rivera, Soderstrom, and Uzzi 2010). Boyd and Spekman

(2008) also claimed that cross-border agreements between buyers and suppliers necessitate increased communication to overcome cultural and language differences. Therefore, firms endeavour to create an environment to conducive to the seamless flow of information and external feedback through established communication routines, which foster cross-organisational knowledge transfer and the cultivation of innovative ideas. Fourthly, the results highlight a positive moderating effect of supplier dependency, supporting with previous studies that emphasised the possible influence of heavy dependency on suppliers regarding sourcing uncertainty (Schiele and Vos 2015). This outcome implies that buyers with higher dependency on their suppliers are more likely to engage in extensive communication and involve multiple actors within the supply chain to a greater extent. Consequently, the dissemination of valuable information and knowledge is facilitated through DT. Given that a firm's operations depend on transactions revenues (X. Liu, Tse, et al. 2023), the influence of suppliers is substantial, and acquiring information from them to sustain flexible operations.

Last but not least, this research extends prior studies by affirming the theoretical underpinnings of IPT and demonstrating its suitability as a framework for understanding DT in operations and supply chain management (H. Li et al., 2021; Srinivasan & Swink, 2018; Busse, Meinlschmidt, & Foerstl, 2017). Specifically, the study adopts an IPT lens to examine how DT enhances operational efficiency and how contextual factors shape this relationship. From this perspective, DT serves as a means to augment firms' information processing capabilities, thereby enabling them to address increased processing demands in highly dynamic and competitive environments—ultimately contributing to superior operational outcomes. Importantly, this research contributes to IPT by identifying how organizations process uncertainty at multiple levels—task, source, and supply network. It introduces novel moderating variables such as buyers' technological resources (task level), suppliers' digitalisation (source level), and buyer-supplier distance and supplier dependency (supply network level). These extensions provide a more nuanced understanding of how firms align their information processing needs with their capabilities to achieve performance gains, reinforcing the core principle of IPT (Gharoie Ahangar et al., 2025; Lu, Jiang and Wang, 2024). Furthermore, this study advances IPT by applying it beyond the boundaries of a single firm, focusing instead on inter-organizational relationships in supply chain contexts (Lu, Li and Yuen, 2023). While prior IPT research has primarily focus on internal organizational process (Lu et al., 2023; Li et al., 2021), our study emphasize that information processing challenges also arise from inter-organizational dynamics, particularly under conditions of environmental uncertainty from both upstream suppliers and downstream buyers. These uncertainties create substantial information processing needs that firms should address to achieve operational objectives. This broader application supports emerging views that DT plays a critical role in enabling supply chain collaboration and integration. Thus, the application of IPT in this research not only broadens the theoretical foundations of DT but also contributes meaningfully to the evolving knowledge base in digital transformation and supply chain theory.

5.2 Managerial implications

Beyond its research implications, this study contributes substantially to managerial understanding. Firstly, it demonstrates the pivotal role of DT as an information processing capability in enhancing firm performance (Pelletier, L'Ecuyer, and Raymond, 2025; Lu, Jiang, and Wang, 2024; X. Liu, Tse et al., 2023). By leveraging digital technologies, firms can access more accurate, timely, and trustworthy information, which can be transformed into actionable insights and improved decision-making (Gillani et al., 2024; Sheng, Feng, and Liu, 2023; Nylén and Holmström, 2015). To capitalize on these benefits, managers must fully grasp the importance, intricacies, and necessity of DT, ensuring that this understanding permeates the organisation through diverse communication channels. Such concerted efforts foster a shared commitment, enabling the collective navigation of complexities and collaborative risks in the transformation process, ultimately mitigating organisational inertia (L. Li 2022). In line with previous research findings, firms seeking to maximize the positive outcomes of DT should strategically employ various digital technologies. This strategic approach enhances the organisation's information processing capacity, facilitating a prompt response to uncertainties. The significant positive correlation between DT and operational efficiency serves as a crucial reference point for policymakers. Policymakers should focus on fostering technological advancement in firms, offering various forms of support, including financial subsidies or technical assistance, to incentivize investments in DT. Acknowledging and addressing the inherent complexity and uncertainty in the DT process is crucial for policymakers, providing support as a complement for firms navigating highly competitive environments.

Secondly, the study's outcomes offer valuable managerial insights into uncertainty factors that can contribute to the pursuit of high operational efficiency through DT. By identifying and addressing uncertainties at different levels, this study helps firms better align their information processing needs with their capabilities, ultimately enabling more effective management of DT initiatives. Particularly noteworthy is the positive impact of a buyer's technological resources when organisations embark on DT initiatives. Given that the effect of DT on operational efficiency varies based on technological resources, managers should deepen their understanding of internal knowledge capabilities. In competitive environments, firms armed with abundant knowledge-based resources are better positioned to pursue breakthrough innovations that demand novel combinations (Fang and Liu 2024; Srivastava and Gnyawali 2011). Consequently, managers are encouraged to allocate more technological resources to DT initiatives and actively participate in activities that yield superior outcomes for the organisation. Furthermore, managers should recognize the strategic importance of supplier dependency, acknowledging its role in driving cost reduction, process improvement, and quality to attain a competitive advantage (Petersen et al. 2008). Strengthening interaction and collaboration with suppliers becomes imperative, prompting firms to proactively establish dependency relationships. This proactive stance streamlines information processing needs, fostering an environment where less information processing is required. However, our findings also underscore that a supplier's digitalisation level and buyer-supplier distance do not influence the positive relationship between DT practises and firms' operational efficiency. In such scenarios, firms need not prioritize a supplier's digitalisation level or geographical proximity when selecting suppliers. This nuanced understanding guides managers in making informed decisions about resource allocation and supplier relationships within the context of DT initiatives.

Finally, this study advances the practical application of IPT within the supply chain domain. As a critical enabler of information processing capabilities, DT not only enhances internal operational efficiency but also facilitates collaboration and information exchange among supply chain partners (Vial, 2021). In highly uncertain environments, it is essential for supply chain members to develop digital capabilities that improve data visibility, enable system integration, and support real-time responsiveness (Dubey et al., 2024; Elia et al., 2024; Guo et al., 2023). However, the effectiveness of DT in such contexts is shaped not only by technological investment but also by the information processing needs arising from both buyers and suppliers. For example, supplier dependency can heighten information processing uncertainty in sourcing activities, thereby increasing the need for more sophisticated information systems to ensure the accurate interpretation and timely transmission of critical information. Therefore, these findings suggest that managers should reconceptualize the supply chain as an integrated information-processing system rather than merely a logistical network.

5.3 Limitations and future research

Similar to the majority of studies, this paper is not without its limitations. Firstly, the measurement of DT practises relies on the textual analysis method due to the constrains of data availability and sample objectivity. While questionnaire surveys and interviews are essential sources for collecting primary data and have been widely employed in existing studies, future research could consider incorporating first-hand data or multi-source data for result comparison. Secondly, operational efficiency of firms is results from multiple factors like information visibility, absorptive capacity, or supply chain learning. This study, which focuses on DT practises and related moderators from the perspective of IPT, could be benefit from the consideration of additional relevant factors in future studies. Thirdly, expanding the scope of this study might involve examining how DT affects other constructs at the firm or supply chain level. While the current study primarily examines the impact of DT on firms' operational efficiency and the conditions under which this occurs, future research might explore the relationship between DT and other outcomes, such as productivity or the triple bottom line. Fourthly, to broaden the applicability of the findings, future study could explore how firms from other developed countries implement DT and its subsequent impact on their operational efficiency. Although China shares certain similarities with other developing economics, future studies should delve into these aspects to enhance the generalizability of our results. Finally, this study investigates the impact of DT on firms’ operational efficiency through examining uncertainties embedded in the supply chain context. Building on this, future studies could extend our findings by exploring diverse inter-organisational structures within firms’ business networks, such as ecosystems, parent-subsidiary relationships, strategic alliances, and mergers & acquisitions. Such explorations would extensively validate and extend our understanding of the DT-OE relationship across varying organisational contexts.

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