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The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view

Meng Tian [a,b], Yang Chen [a], Guanghao Tian [c], Wei Huang [a,*], Chuan Hu [d]

[a] School of Economics and Management, Hubei University of Technology, No. 28 Nanli Road, Wuhan, Hubei Province, China
[b] Hubei Circular Economy Development Research Center, Hubei University of Technology, No. 28 Nanli Road, Wuhan, Hubei Province, China
[c] School of Artificial Intelligence, Nanchang Jiaotong Institute, No. 111 East Huangjiahu Road, Nanchang, Jiangxi Province, China
[d] School of Business Administration, Zhongnan University of Economics and Law, No. 182 Nanhu Avenue, Wuhan, Hubei Province, China

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ABSTRACT

Digitalization has become increasingly crucial for manufacturing firms to optimize their production processes and improve operations management. However, the role of digital transformation practices in firms' operations improvement is still debated in the extant research. Moreover, there is little quantitative research on analyzing their associations using large data sets. Therefore, a theoretical framework is developed in this study based on a practice-based view (PBV) to demonstrate the relationships between digital transformation practices and firms' operational efficiency from three aspects of workforce productivity, physical asset efficiency, and working capital efficiency. Then, the role of industry competition in their relationships is examined. Besides, digital transformation practices are measured using the text analysis method targeting authoritative annual reports to enhance the objectivity and applicability of our quantitative studies. With a large sample of Chinese manufacturing firms from 2016 to 2020, a fixed-effect model is employed to reveal that digital transformation practices have significant and positive impacts on all three aspects of firms' operational efficiency. It is further observed that industry competition weakens these positive associations. This study enriches the digitalization literature in operations management and expands the application of PBV by verifying the differentiated relationships between digital transformation practices and operational efficiency at different levels of competition. Furthermore, it provides significant practical implications for both managers and policy-makers to appropriately implement and popularize digital transformation practices under an external competitive context.

1. Introduction

Global manufacturing is currently undergoing unprecedented challenges associated with increasingly uncertain economic policy and intense competition. Concurrently, the advent of digitalization has also brought new opportunities in manufacturing sectors for responding to these challenges. An increasing number of manufacturing firms are embracing digitalization by adopting new digital technologies such as big data analytics, cloud computing, 5G, Internet of Things, and artificial intelligence (Khin and Ho, 2019). According to the previous forecast data released by IDC (2022), global spending on technologies and services to digital transformation in domains of business practices, products, and organization in 2022 would reach $1.8 trillion, presenting a 17.6 percent gain from the prior year. Furthermore, digital transformation spending will sustain this growth pace over the 2021–2025 forecast period with a five-year compound annual growth rate of 16.6 percent.

In the digital era, manufacturing firms expect to strengthen their competitiveness by resorting to the potential of digital transformation for new value-creation and revenue-generation opportunities (Kamalaldin et al., 2020). They integrate digital technologies into product design, production operations, and sales management, so as to improve product quality, optimize production efficiency, and expand market opportunities (Holmström et al., 2019). However, manufacturing firms are likely to encounter a disruptive reform and get into a digitalization paradox since several great challenges involving complex technology, high cost, and long period exist in the process of digital transformation. In other words, the increasing revenues induced by digital

* Corresponding author. School of Economics and Management, Hubei University of Technology, No. 28 Nanli Road, Wuhan, Hubei Province 430068, China.
E-mail addresses: mintyt0040@hbut.edu.cn (M. Tian), yangau0112@hbut.edu.cn (Y. Chen), stewart58586@gmail.com (G. Tian), huangwhbut@163.com (W. Huang), chuanhzuel@126.com (C. Hu).

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transformation fail to deliver greater profits because of these potential challenges (Sjödin et al., 2020). Everest Group (2019) reported that 78 percent of enterprises had experienced failure in their digital transformation initiatives, including unsustainable returns, lack of user adoption, or, even worse, abandoned projects.

Given the increasing importance of digital transformation in operations improvement in manufacturing firms, researchers have shown growing interest in the adoption and implementation of digital technologies, as well as the impact of digital transformation on firms' operational efficiency. Generally, digital technologies help firms build dynamic capabilities (Capurro et al., 2021), optimize business processes (Garzoni et al., 2020), facilitate higher productivity (Bergamaschi et al., 2021), improve product quality (Dalenogare et al., 2018), and ultimately enhance value creation (Tavoletti et al., 2021). Nevertheless, some other researchers hold diverse views on the effects of digital transformation on different performance metrics as many firms continue to fail. For instance, Sailer et al. (2019) found that the adoption of digital technology requires high investments and may result in a capital chain rupture, leading to a dilemma of digitalization paradox.

In recent years, many researchers in strategic management and operations management have attempted to further uncover the influence of digital transformation on firm performance. Most of them regard digital transformation as valuable, rare, imperfectly imitable, and non-substitutable (VRIN) resources or capabilities from the perspective of a resource-based view (RBV) (Lee and Falahat, 2019; Martinez et al., 2019; Elia et al., 2021). However, these studies overlook the importance of digitalization as an imitable and transferable practice in the operations of manufacturing firms. Particularly, managers frequently consider specific techniques at the initial stage of digitalization to develop digital strategies or generally applicable practices (Björkdahl, 2020). From a technology-centered perspective, digitalization integrating information technology and operational technology represents a new generation of digital management and analysis technology (Zheng et al., 2019). Thus, the potential explanation of firm performance variables should be deeply explored based on techniques and management practices.

A growing number of manufacturing firms adopt digital transformation practices in their operations with the enhancement of digital maturity. Practices are described as "a specified activity or set of activities that many firms might execute" (Bromiley and Rau, 2014). Practices can also be treated as a group of activities, routines, and material arrangements (Wang et al., 2018). In the domain of digitalization, digital technologies and tools have functioned as systems technology merging multiple base technologies (Khin and Ho, 2019). Meanwhile, the management and application of these technologies in operations play a critical role in firms' digital transformation since managerial practices are as essential as technological practices (Denicolai et al., 2021). Additionally, some informatization and Internet Plus actions are widely recognized during the transformation process from previous information technology applications to current digital practices (Pan et al., 2020). With the growing use of advanced technologies in operations, digital practices will also evolve toward a new intellectual operations phase, in which intellectual technologies and operational technologies are deeply integrated (Ghobakhloo, 2020). Given these crucial processes of digitalization, digital transformation practices are defined as sequential changes beginning with digital technologies and management and then transformed into expected organization performance outcomes through a set of digital actions composed of informatization, Internet Plus, and intellectual operations.

In line with the above observations and analysis, a practice-based view (PBV) as a theoretical foundation is proposed in this study for the potential impact of digital transformation on firm performance. Specifically, whether digital transformation practices can enhance manufacturing firms' efficiency in their operations is examined based on three crucial dimensions of human capital, physical assets, and working capital. Under the circumstance of increasing competition in the manufacturing industry, industry competition is taken as a vital factor to further examine its role in the above relationships.

The contribution of this study mainly consists of three aspects. First, it enriches the digitalization literature by demonstrating the relationship between digital transformation practices and operational efficiency in manufacturing firms from the theoretical perspective of PBV. Previous studies have converged on the notion that digital transformation is a powerful tool to build competitive advantage (Porter and Heppelmann, 2014; Bergamaschi et al., 2021). Nevertheless, they mainly emphasized the VRIN characteristics while neglecting the practical fact that numerous digital technologies and practices are a set of imitable and transferable practices. In this case, our study aims to explore the role of digital transformation practices in firms' operations improvement in virtue of PBV, so as to fill this gap.

Second, the role of industry competition in the relationship between digital transformation practices and firms' operational efficiency is investigated to further identify their potential influencing mechanisms in the background of fierce competition. Currently, digital transformation practices have become a crucial pivot for firms to tackle external competitive pressure. However, if firms implement radical digital reform without considering external environmental change, they probably enter into a digitalization trap that this high-risk, all-or-nothing digital decision-making probably limits the effectiveness of digital practices and even causes their failure in operations (Linde et al., 2020). Thus, the contingency effect of industry competition is also explored in our study.

Finally, this study provides a reference for filling in the existing methodological gap from a methodology perspective. The text analysis method is adopted to measure a firm's digital transformation practices, and its impacts on different dimensions of operational efficiency are examined through econometric methods, so as to compensate for previous studies mainly concentrating on interviews or surveys method (Cassetta et al., 2019; Seyedghorban et al., 2020). With the emerging text analysis method based on authoritative annual reports in recent literature (Nathan and Rosso, 2015), the objectivity and applicability of our study can be enhanced to some extent.

The rest of this paper is arranged as follows. In Section 2, the literature background and relevant theoretical basis are presented. Next, the hypotheses and research model are developed in Section 3. Afterward, the data and method framework established to investigate the empirical link is detailed in Section 4. In Section 5, the research results from the hypotheses testing are analyzed. Section 6 compares our study results with previous studies and provides academic and practical contributions and implications. Finally, conclusions, limitations, and future research directions are outlined in Section 7.

2. Literature review

The work regarding digital transformation toward operations improvement is first reviewed in this section. Besides, the theoretical basis of PBV related to the relationship between digital transformation practices and firms' operational efficiency is illustrated to propose the subsequent research hypotheses.

2.1. Digital transformation toward operations improvement

In the era of the digital economy, the difficulty for manufacturing firms to maintain their continuous competitive advantage is reinforced by the rapidly changing external environment. Firms have to dynamically adjust their manufacturing operations model (Malik and Kotabe, 2009). In this circumstance, digitalization offers new and disruptive opportunities for firms seeking intelligent production equipment, networked operation process, and advanced manufacturing technology (Ghobakhloo, 2018). As a result, higher attention is paid to the potential of digitalization across manufacturing firms, especially for those in an essential stage of upgrading and transformation.

On a micro level, digital transformation can be deemed as a process of reengineering business models and manufacturing operations with big data analytics, cloud computing, 5G, Internet of Things, and artificial intelligence (Yang et al., 2021). From the perspective of RBV, the key elements of digital transformation are digital resources, majorly consisting of data itself such as traditional production data and equipment data, as well as digital infrastructures such as cloud platforms and hardware and software platforms (Coreynen et al., 2020). The massive data streams, as an imperative data asset, can facilitate the refinement of the production and thus generate new asset value (Jin et al., 2019). Digital technologies and infrastructures empower firms with stronger capabilities in information acquisition and resource integration and thus generate new opportunities to create value (Nambisan et al., 2017). Additionally, the importance of other related resources such as digital strategy and human resources is stressed in some research since they contribute to firms' rapid self-adjustment and rematch with the external environment (Bharadwaj et al., 2013).

The role of digital transformation in enabling firms' competitive advantage has recently become an emerging research agenda in the field of strategic management. Researchers have considered the influences of digital transformation on firm performance concerning productivity, organizational restructuring, profitability, environmental innovation, and supply chain performance (Bergamaschi et al., 2021; Coreynen et al., 2017; Dalenogare et al., 2018; Ghobakhloo et al., 2021; Yang et al., 2021). Many of them have highlighted the positive consequences of digital transformation. For instance, Huang et al. (2017) suggested that the adoption of digital technologies is conducive to optimizing firms' production process, accelerating the integration of research and development, production, sales, and service, and thus reshaping the value chain. Kristoffersen et al. (2021) argued that firms utilizing digitalization can identify potential opportunities and threats effectively and transform their business processes accordingly since some previously unavailable insights and options can be captured through digitalization to expand the current locus of decision-making.

Research on digital transformation has also demonstrated the potential of digital technologies and solutions in operational fields (Chauhan et al., 2021). Compared with traditional information systems (IS) or information technology (IT) applications, the transition to digitalization has been the most recent enabler of continuous operational improvement in manufacturing firms. Various digital technologies and practices such as big data analysis, Internet plus actions, and Internet of Things (IoT) technologies emerge from operations management. Big data analysis reveals that firms have great potential to maximize their production and minimize material waste (Guha and Kumar, 2018). Internet plus actions can improve communication and collaboration between different business units. IoT technologies contribute to operational visibility as they allow the operational process decomposition so that each step can be conducted in a distributed way (Agrifoglio et al., 2017). The Industry 4.0 concept, accompanied by a collection of enabling technologies and methods involving intelligent products and production processes, has also rapidly grown in recent years to highlight the revolutionary potential of digital transformation in manufacturing industries (Pagliosa et al., 2021). With an empirical analysis based on a representative sample of manufacturing industry units, Büchi et al. (2020) discovered that the breadth and depth of Industry 4.0 help firms have obtained greater opportunities. From the perspective of operational performance, the technologies supporting Industry 4.0 have positive influences on firms' cost, quality, delivery, and flexibility performance (Szász et al., 2020).

In contrast to these positive perspectives, some other studies suggest that utilizing digital transformation to pursue better economic performance may not be straightforward (Calvino et al., 2018). The impacts of digital transformation on different performance metrics are mixed since many firms keep falling into the so-called digitalization paradox, which is originally raised as Solow Productivity Paradox (Yang et al., 2021). The Solow Productivity Paradox, which describes the paradoxical relationship between high-speed information technology investment and slow-growing productivity, has been widely discussed in the domain of digitalization (Wen et al., 2021). Considering that digitalization is a rather complex and multifaceted phenomenon, its adoption and implementation are more likely to be intervened by other factors such as firm characteristics and resource heterogeneity. Hajli et al. (2015) unveiled that digitalization boosts the operational level of firms more dependent on digital technology such as the information communication industry while exerting no significant effect on the traditional manufacturing industry. Li and Jia (2018) argued that the operational benefits of digitalization can be largely achieved through resource-focused actions concerning internal and external resources.

2.2. Theoretical development-the practice-based view

To explain how digitalization influences firms' performance, many researchers in strategic management and operations management draw on RBV as a theoretical underpinning to develop their theoretical framework (Lee and Falahat, 2019; Martinez et al., 2019; Elia et al., 2021). However, RBV works on certain premises that the managers in a firm are strictly rational and pursue profit maximization (Alexy et al., 2018). As an aggregation of various resources, firms can provide differentiated products and services through these unique resources to improve performance and obtain excess profits (Wernerfelt, 1984). RBV emphasizes that these resources meet the VRIN criteria. In other words, firms have to acquire and develop valuable, rare, inimitable, and non-substitutable resources if they pursue a continuous competitive advantage (Helfat and Peteraf, 2003).

Whilst importance is attached to the heterogeneous resources owned by firms, special concern is raised on the static characteristics of resources (Barney, 1991). In connecting RBV to the increasingly dynamic market environments more deeply, Teece et al. (1997) discussed the notion of "dynamic capabilities" and defined it as a firm's capabilities to integrate, build and reconfigure internal and external resources to handle changing environments. Nonetheless, either RBV or dynamic capability relies on the core argument that the heterogeneous resources and capabilities are specific and arise within the firm through a path-dependent process (Rockart and Dutt, 2015). Notably, some readily available practices in current operations without requiring hard-to-transfer resources or capabilities lead to performance differences across firms (Bloom et al., 2012). This practical fact facilitates the discussion on another alternative theoretical perspective, namely the practice-based view.

PBV, as a supplementary theoretical foundation for RBV and dynamic capability, has attracted a lot of attention since it was proposed by Bromiley and Rau (2014). PBV aims to explain variation in firm performance under those broadly available practices that are in no way inimitable or rare (Bromiley and Rau, 2014). Firms do not know or do not use all the practices that may benefit them due to the managers' bounded rationality. They are more inclined to execute those publicly known, imitable, and transferable practices. In extant studies of operations management, some practices and techniques such as just-in-time principles, kanban, six sigma, balanced scorecard, statistical process control, and open innovation practices have been widely concerned and variously labeled as best practices (da Silveira and Sousa, 2010; Bellisario et al., 2015; Kazemargi et al., 2022). Best practice, manufacturing competition, and manufacturing strategy choices constitute three alternative paradigms for operations strategy (Kalchschmidt, 2012). With the fast growth of lean practices and the popularity of advanced technologies, best practice is increasingly prominent among the three paradigms.

In operations management research, various researchers have embraced and extended the best practice concept from different perspectives. From a universal perspective, the best practices are universally effective regardless of which firms are considered and in which contexts they are operating (Kalchschmidt, 2012). This perspective reflects a strong relationship between the adoption of best practices and operation improvement. However, being in parallel to the growth in best practice research has enriched the critical literature. A major criticism is no absolute "best" practice (Voss, 2005). Some practices verified to be effective previously may not be appropriate in the current operational context. Thus, the contextual conditions, which constitute the core points of a contingency perspective, need to be considered when identifying the contribution of practices to operations (Davies and Kochhar, 2002; Beaumont, 2005). The subsequent research stream on operations strategy has also focused on adopting and implementing the appropriate practices in operations management (Vogl et al., 2019). Under this circumstance, the emergence of PBV may be a better choice for operations management scholars to illuminate the performance variation induced by practices as PBV grapples with the influence of those imitable and transferable practices rather than simply best practices.

In this study, our interests in PBV stem from the fact that a firm's digital transformation involves a series of transferable techniques and practices (Bag et al., 2021). Particularly, firms are more likely to introduce those common techniques that have been proven efficient at the initial stage of digitalization to lower the potential risks of investing in digitalization. Nevertheless, these practices may or may not necessarily be "best" in their operations (Bromiley and Rau, 2016a). Moreover, PBV focuses on performance outcome and allows for a wide variety of intermediate and final dependent variables like cost per unit or overall profitability, different from RBV and dynamic capability that consider sustained competitive advantage as the primary outcome or dependent variable (Bromiley and Rau, 2016b). Intuitively, firms, especially those in the manufacturing industry, always expect to obtain direct operational benefits in a short time. Thus, PBV has a good degree of fit with the target of our research. Additionally, PBV offers some flexibility in that firms' practices can exert positive, negative, or neutral impacts on performance directly and indirectly (Bromiley and Rau, 2016b). Meanwhile, the impacts may differ with various circumstances such as institutional or industrial factors.

Given the above observations, PBV is utilized as a theoretical lens to examine the role of digital transformation practices in the operations improvement in manufacturing firms. From one perspective, this study can add practical insights for businesses in the field of digital transformation and provide specific guidelines for managers to achieve operational benefits based on PBV. From another perspective, this study supports the compatible views of operations management researchers targeting RBV and PBV and further illuminates the operations management discipline.

3. Hypotheses and research model

Drawing on PBV, whether digital transformation practices can facilitate manufacturing firms' operational efficiency is investigated in this study. The operating framework outlined in Fig. 1 is a practice-based framework developed from firms' digital transformation practices covering a set of activities in that firms might perform digital techniques, digital management, informatization, Internet Plus actions, and intellectual operations. The operational efficiency indicators including workforce productivity, physical asset efficiency, and working capital efficiency are taken from related operations management studies and are adopted to examine the impact of digitalization's transferable practices on operational efficiency. Furthermore, the contingency role of industry competition is examined to demonstrate the potential influencing mechanism. Fig. 1 illustrates a visual representation of the theoretical framework used in our study. Then, the logic of this framework and corresponding hypotheses are developed.

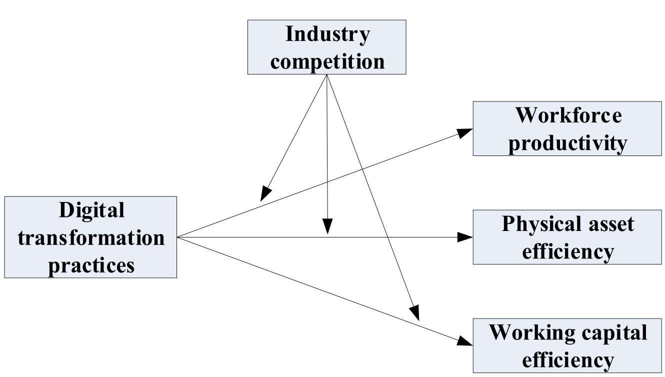

Fig. 1. Research model.

3.1. *Digital transformation practices and firms' operational efficiency*

Digital transformation, as a modern hot term in the business and technological domain, has been deemed a critical cornerstone for manufacturing firms. From the perspective of PBV, digital transformation practices centered on data resources and digital technologies might be crucial forces for increasing operational efficiency in manufacturing firms. First, the data element, combined with other elements such as technology and labor, can be characterized as key production factors to generate the production function (i.e., higher production output) (Jin et al., 2019). Second, advanced digital technologies can help curtail communication costs and information asymmetry across different departments in a firm, alleviating the difficulty of inefficient resource allocation (Aben et al., 2021). Simultaneously, some complex production plans and operation complications can be tackled with the increasing computing power induced by digital algorithms (Louridas and Ebert, 2016).

With the acceleration of the digital process, research on manufacturing firms has emphasized the influence of digital transformation practices on their operation efficiency (Zhu et al., 2019). In operations management, human capital, physical assets, and working capital are three crucial aspects reflecting the extent to which firms allocate resources efficiently (Riley et al., 2017). Thus, the impacts of digital transformation practices on these aspects should be further examined. First, human capital, as the most active element in various resource combinations, plays a significant role in firms' strategic decisions and operating activities (Chadwick and Dabu, 2009). With the advent of the digital age, the value creation capability of human capital in a firm would be largely influenced by the degree of its digitalization. Firms' adoption of a series of digital techniques, which is a potential substitute for a low-skilled workforce and a complement to a highly-skilled workforce, may optimize their human capital structure (Acemoglu and Restrepo, 2018). Furthermore, digitalization enables employees to conduct more creative thinking and work, so as to generate more high-quality intellectual capital and strengthen their output efficiency (Björkdahl, 2020). Thus, the following hypothesis is proposed.

H1. Digital transformation practices have a significantly positive effect on a firm's workforce productivity.

PBV offers some flexibility in that the introduction of physical assets can be a source of operating performance improvement (Bromiley and Rau, 2016b). Traditionally, physical assets refer to those machines, equipment, and tools used for producing products or providing services (Ghobakhloo, 2018). In the digital economy, those assets are upgraded in a more intelligent and flexible way. Meanwhile, the adoption of digital techniques improves asset deployment and utilization efficiency, especially in the processes of production and operations management (Ye et al., 2021). For instance, the introduction of an advanced intelligent network allows for interconnection across different business processes, beneficial to real-time data collection, synchronous analysis, and decision-making (Bharadwaj et al., 2013). In this sense, the processing time required for various procedures such as process switching, accidental shutdown, or machine maintenance can be considerably lessened, and the asset efficiency is accordingly enhanced. Thus, the following hypothesis is proposed.

H2. Digital transformation practices have a significantly positive effect on a firm's physical asset efficiency.

Working capital indicates a firm's investment in short-term assets with the purpose of maintaining its normal production and operation, involving receivables, inventory, payables, and using cash efficiently for day-to-day operations (Lyngstadaas and Berg, 2016). Efficient management of working capital is necessary for firms to foster their growth (Aktas et al., 2015). In a digital environment, firms can employ digital technologies to alleviate information asymmetry and reduce agent costs, so as to optimize the capital structure. Moreover, digitalization can help employees in the finance department, dynamically manage and control the expenditure in production and operation and thus improve the working capital efficiency (Agostini et al., 2019). From the perspective of capital source, whether a firm can obtain sufficient funds to maintain development relies largely on its own financing ability. Hence, the adoption of digital fintech can enhance firms' capabilities to gather information, contributing to broadening their financing channels and mitigating financing constraints (Lu et al., 2021). Thus, the following hypothesis is proposed.

H3. Digital transformation practices have a significantly positive effect on a firm's working capital efficiency.

3.2. The contingency role of industry competition

At present, many firms in the manufacturing industry are subjected to a rapidly changing dynamic environment. The competition among them is also increasingly fierce, characterized by numerous price wars and increasing advertisement and promotion activities (Martin and Javalgi, 2016). Under this circumstance, industry competition (Porter, 1980) has received constant attention from researchers in current business and operations strategy research. According to the viewpoints of Porter (1980), five forces, composed of the competitive ability of the existing competitors, the entry ability of potential competitors, the substitution ability of substitutes, the bargaining power of suppliers, and the bargaining power of buyers, will exert broad influences over firms' competitive strategy decisions.

As an important contingency factor, industry competition plays an increasing role in firms' digital transformation. Facing a highly competitive environment with intensive rivalry, firms must compete for limited market resources to profit and survive (Brisley et al., 2011). The resource allocation regarding risky activities and relatively robust activities will be also reshaped. In a short time, more resources will flow to those advertisement or promotion activities used to limit competitive rivalry in a rapid manner (Cao et al., 2020), hindering firms from obtaining operating benefits and even generating a transformation failure when adopting new digital practices and business process management mode because of the massive divestment for resources and cost invested in these practices. Additionally, in industries with higher competition, the counterparts, especially those under great competitive pressures, will strive to catch up with the technological frontiers of the industry by imitating and learning from this firm's behaviors, though a focal firm endeavor to pursue operations improvement through digital technologies and practices (Jia, 2020). This would weaken the advantage of digitalization in the focal firm to a large extent. Finally, a highly competitive environment makes it difficult for firms to maintain their bargaining power but more likely to act as price takers (Tang and Chen, 2020). In this case, the high-cost firms induced by the investment into digital transformation practices could suffer a relative loss in their operational benefits based on given human, physical, and capital resources.

On the contrary, the external market leaves more room for firms' performance growth in a relatively low competitive environment (Chang and Rhee, 2011). Following the global digitalization trend, firms are more motivated to proactively pursue new growth points for performance through digital techniques and practices and thus allocate more available resources to support digital implementation (Cenamor et al., 2019). Meanwhile, they possess sufficient resources and markets to release the potential of digitalization. Besides, a relatively low level of competition leaves more room for managers to take discretionary decisions regarding innovative activities or risky activities rather than simply performing opportunistic actions like imitation (Bimo et al., 2022). Thus, managers will allocate more attention and put effort into the implementation of digital transformation practices to contribute to improving operations management. Furthermore, the near-monopoly market structure increases firms' monopoly rents in a less competitive industry where industrial concentration is particularly high (Agarwal et al., 2020). This could provide support for their innovation investments and fund digital practice projects to address difficulties they may encounter. The strong resources and fund support facilitate the output effects of digital transformation practices. To this end, the following hypotheses are proposed.

H4. Industry competition weakens the positive relationship between digital transformation practices and workforce productivity.

H5. Industry competition weakens the positive relationship between digital transformation practices and physical asset efficiency.

H6. Industry competition weakens the positive relationship between digital transformation practices and working capital efficiency.

4. Methodology design

4.1. Sample selection

Given the significant roles of digital transformation practices in Chinese manufacturing firms in recent years, Chinese A-share manufacturing firms listed in Shanghai Stock Exchange and Shenzhen Stock Exchange are taken as samples in this study. After initial sample selection, the samples are further screened following several procedures: (1) Firms with "ST" or "*ST" (special treatment, implying that firms have undergone at least two consecutive annual losses) are removed. (2) Firms with B-share, H-share, and N-share[1] are excluded since they are registered in different Stock Exchanges and differ from A-share in terms of stock valuation methods. (3) Firms with highly incomplete data for major variables are eliminated. Finally, 2574 firms are confirmed as final samples in this study, and 10,115 firm-year observations from 2016 to 2020 are yielded.

4.2. Measurement of variables

With the purpose of examining the impact of digital transformation practices on firms' operational efficiency, operational efficiency is first divided into workforce productivity, physical asset efficiency, and working capital efficiency (reflecting the contributions to firms' performance from the perspectives of human, physical, and capital resources, respectively) (Riley et al., 2017). From the perspective of resources' output efficiency, these three aspects can be measured by the ratio of operating income obtained from firms' main production and operation activities to the number of employees, fixed assets, and working capital, respectively. In this study, the data for them are acquired from the Chinese Stock Market and Accounting Research (CSMAR) Database, which has been widely used in the relevant literature (Du and Boateng, 2015).

Regarding the independent variable, indicators for digital trans-

[1] A-share firms and B-share firms are mainly listed on both Shanghai Stock Exchange and Shenzhen Stock Exchange. However, the former is traded in renminbi and the latter is traded in other currencies. H-share and N-share firms are listed on Hong Kong Stock Exchange and New York Stock Exchange, respectively.

formation practices are established through text analysis to supplement the existing questionnaire survey method in terms of sample objectivity and comprehensiveness (Guerreiro et al., 2016; Cassetta et al., 2019). Given that some critical information concerning firms' adoption of the cutting-edge technologies and practices would be disclosed in the section of major business analysis in their annual reports, it is appropriate to identify the application degree of digital transformation practices in their operations using the text analysis. In this study, several procedures are employed to conduct the text analysis. First, some important policy documents and announcements issued by Chinese governments are collected, such as "Outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development and Vision 2035 of the People's Republic of China" and "Circular on accelerating the digital transformation of State-Owned enterprises". Then, a series of keywords concerning digital transformation is identified based on these documents. Second, 90 representative samples that have been deemed as implementing digital transformation successfully are selected according to the data released by China Business Industry Research Institute. Afterward, the keywords involving a digital transformation in their annual reports are gathered as a supplement to the previous procedure. With these two procedures, a set of keywords related to digital transformation are obtained as the seed words, as listed in Table 1. The seed words are mainly ascribed to five aspects: digital technologies, digital management, informatization, Internet Plus actions, and intellectual operations. They not only correspond to the aforementioned definition of digital transformation practices in this study but also largely extend the preceding research finding that the five most frequent words associated with digital business practices across information economy firms are 'technology', 'software', 'online', 'Internet', and 'management' (Nathan and Rosso, 2015). Third, 10,115 annual reports of all sample firms are collected, and the texts of a section of major business analysis in each annual report are intercepted. Subsequently, word segmentation for these texts is further conducted using the Python package Jieba, which has a module function for keyword extraction (Zhao et al., 2020). Finally, the preceding seed word sets and these words obtained from the texts are matched, and then the number of their occurrences is counted. As the indicator for digital transformation practices involves multiple seed words and different weights, it is necessary to objectively judge the weight coefficient of each seed word to the overall indicator for digital transformation practices. Thus, the entropy method, as a widely accepted and objective weight method (Han et al., 2015; Mete and Belgin, 2021), is used to calculate the weight of each seed word, with the weighted average being used as the proxy variable for digital transformation practices. The steps given below are applied to calculate the entropy weights.

Table 1
The seed words used for identifying digital transformation practices.[21]

Categories	Seed words
Digital technologies	5G, artificial intelligence (AI), big data, big data platform, big data analytics, digital platform, blockchain, Internet of Things (IoT), augmented reality (AR), virtual reality (VR), machine learning, deep learning, automatic speech recognition, natural language processing (NLP), machine vision, robot, image identification, image processing, cloud computing, and cloud platform.
Digital management	data acquisition, data transmission, data processing, data analysis, data management, data-driven, digitalization, digitization, data-enabled, digital construction, digital marketing, digital manufacturing, digital transformation, digital practices, and digital operation.
Informatization	information analysis, information sharing, information management, information system, informatization, information construction, information platform, software system, and information transformation.
Internet Plus actions	Internet, Internet Plus (Internet +), Internet techniques, Internet platform, Industrial Internet, mobile Internet, e-commerce, e-commerce platform, online, online and offline (O2O), Business to Business (B2B), and Business to Customer (B2C).
Intellectual operations	intellectual analysis, intellectual plant, intellectual management, intellectual control, intelligent production, intelligent marketing, intelligent operation, intelligent manufacturing, intellectualization, Industry 4.0, automobile monitoring, automobile check, automobile control, automobile production, automation, and integration system.

Step 1 Standardization of data: We standardize the data matrix composed of m samples and n seed words. Standardization is done using the following equation:

$$Z_{ij} = \left\{X_{ij} - min\ X_{ij}\right\} \Big/ \left\{maxX_{ij} - min\ X_{ij}\right\} \tag{1}$$

where Z_{ij} is the standardized value, and X_{ij} is the values of the samples.

Step 2 Calculation of the entropy values: Entropy values E_j are calculated using Eq. (2):

$$E_j = -c\sum_{i=1}^{m}\left(Z_{ij} \Big/ \sum_{i=1}^{m} Z_{ij}\right)\ln\left(Z_{ij} \Big/ \sum_{i=1}^{m} Z_{ij}\right), 1 \le j \le n \tag{2}$$

where c is the entropy constant equal to lnm^{-1} assuring $0 \le E_j \le 1$.

Step 3 Calculation of the entropy weights: Finally, the weight of j is calculated as in Eq. (3):

$$W_j = \frac{(1 - E_j)}{\sum_{j=1}^{n}(1 - E_j)} \tag{3}$$

Industry competition is considered a moderating variable influencing the relationship between digital transformation practices and firms' operational efficiency in this study. Consistent with previous studies (Wang and Zhang, 2015; Tang and Chen, 2020), industry competition is generally proxied by Hirschman-Herfindahl Index (HHI) HHI, expressed as:

$$HHI = \sum_{i=1}^{N} {S_i}^2 \tag{4}$$

where N denotes the number of firms in an industry, and ${S_i}^2$ represents the market share of a firm i in its industry, which is calculated by the ratio of a firm's revenue to total revenues in its industry. Eq. (4) illustrates that the higher the HHI, the higher the industry concentration. In this circumstance, monopolistic firms may exist in this industry. In other words, a relatively lower HHI implies that the industry is more diversified and the industry competition is more intense.

Additionally, several control variables are also introduced to exclude the potentially confounding influences. Firm size (SIZE) and firm age (AGE) are controlled to reduce the impacts of basic corporate characteristics, as stated by Tan and Peng (2003). Leverage (LEV), operating cash flow (OPCA), operating cost ratio (OPCO), and proportion of fixed assets (FIXPR) (Lee and Wu, 2016) are also chosen as control variables to control for potential effects of firm-level economic factors on firms' operational efficiency. Some factors related to corporate governance, such as ownership concentration (OWC), ownership types (OWT), the shareholding ratio of the first shareholder (FIRSH), and independent director ratio (INDIR) are also controlled (Li et al., 2015). Finally, industry and year are included as dummy variables to eliminate the unobserved heterogeneity. The specific variable definitions are presented in Table 2.

4.3. Models

The following baseline model is estimated to investigate the influence of digital transformation practices on firms' operational efficiency

Table 2
Variables definition.

Variables	Definition	Supporting references
Workforce productivity (WOPRI)	The log of the ratio of operating income to the number of employees in a firm	Datta et al. (2005); Lo et al. (2014)
Physical asset efficiency (PHASS)	Fixed asset turnover ratio, the ratio of operating income to average fixed assets of a firm	Jiang et al. (2006); Treacy et al. (2019)
Working capital efficiency (WOCA)	Working capital turnover ratio, the ratio of operating income to average working capital of a firm	Aktas et al. (2015)
Digital transformation practices (DITR)	The indicators established through the text analysis method	Nathan and Rosso (2015)
Industry competition (INCO)	Hirschman-Herfindahl Index	Wang and Zhang (2015); Tang and Chen (2020)
Firm size (SIZE)	The log of the year-end total assets of a firm	Tan and Peng (2003); Lee and Wu (2016); Li et al. (2015)
Firm age (AGE)	The time between the initial creation of a firm and the present time (in years)	
Leverage (LEV)	The ratio of total debts to total assets of a firm	
Ownership concentration (OWC)	The log of the shareholding ratio of the top ten shareholders in a firm	
Ownership types (OWT)	If a firm is state-owned, OWT = 1, otherwise 0	
Operating cash flow (OPCA)	The log of the annual net operating cash flow of a firm	
Operating cost ratio (OPCO)	The ratio of operating cost to operating income of a firm	
Proportion of fixed assets (FIXPR)	The ratio of net fixed assets to total assets of a firm	
Shareholding ratio of the first shareholder (FIRSH)	The ratio of number of shares held by the first shareholder to total shares of a firm	
Independent director ratio (INDIR)	The ratio of the number of independent directors to the total number of directors in a firm	

(Hypothesis 1 through 3).

$$WOPRI \Big/ PHASS \Big/ WOCA = \alpha_0 + \alpha_1 DITR + \sum_{i=1}^{n} \beta_i CONTROL_i + \varepsilon \tag{5}$$

Then, the subsequent regression equation is utilized to examine the moderating role of industry competition in the above relationship (Hypothesis 4 through 6):

$$WOPRI / PHASS/WOCA = \alpha_0 + \alpha_1 DITR + \alpha_2 INCO + \alpha_3 DITR \times INCO$$

$$+ \sum_{i=1}^{n} \beta_i CONTROL_i + \varepsilon \tag{6}$$

5. Results and analysis

5.1. Descriptive statistics and correlation analysis

The descriptive statistics of variables are summarized in Table 3. According to Table 3, the values of digital transformation practices vary from 0.01 to 1.03, and the mean value is only 0.15, suggesting that the degree of firms' digital transformation in China is probably not high.

[2] Due to the differences across languages, the seed words shown here may be translated into more than one Chinese word. These Chinese words are adequately and precisely considered. The abbreviations in English are also shown here as they are also widely used in the Chinese context.

Table 3
Descriptive statistics.

Variables	Obs.	Mean	Sd	Min	Max
WOPRI	10,115	13.72	0.77	5.80	20.61
PHASS	10,115	7.31	17.66	0.00	140.50
WOCA	10,115	2.97	5.98	0.00	43.64
DITR	10,115	0.15	0.19	0.01	1.03
INCO	10,115	0.16	0.18	0.01	0.94
SIZE	10,115	3.20	0.46	2.21	4.54
AGE	10,115	16.92	4.99	7.00	30.00
LEV	10,115	0.36	0.18	0.06	0.82
OWC	10,115	56.54	14.82	22.55	90.63
OWT	10,115	0.02	0.15	0.00	1.00
OPCA	10,115	15.69	7.20	0.00	22.55
OPCO	10,115	0.66	0.19	0.00	3.34
FIXPR	10,115	0.18	0.13	0.00	0.58
FIRSH	10,115	33.26	14.39	8.57	73.35
INDIR	10,115	0.38	0.06	0.27	0.60

Similar results appear in the statistics of dependent variables including workforce productivity, physical asset efficiency, and working capital efficiency. Regarding the industry competition, the mean HHI is 0.16, revealing that most of the industries are diversified and widespread competition exists.

Table 4 presents the Pearson correlation results of all variables. Most of the correlation coefficients are below 0.5, demonstrating that significant multicollinearity among the variables is not an issue for this study. Besides, the results of the variance inflation factors are calculated to further verify the preceding judgment of the non-existence of multicollinearity because all the variance inflation factors are below the reference value of 5.

5.2. Main effects analysis

With a panel dataset of 2574 firms and 10,115 firm-year observations spanning from 2016 to 2020, the model is estimated using a panel data approach. The Hausman test is performed to determine whether we should adopt fixed-effect or random-effect panel regression models. The Hausman test results demonstrate that both models are appropriate for examining the association between digital transformation practices and working capital efficiency ($\chi^2 = 4.02$, $p = 0.403$), while the fixed-effect model should be employed to verify the impacts of digital transformation practices on workforce productivity ($\chi^2 = 67.63$, $p = 0.000$) and physical asset efficiency ($\chi^2 = 14.83$, $p = 0.005$). Thus, a fixed-effect panel regression model is adopted. Stata 15.1 is utilized for conducting the statistical analysis.

Table 5 reports the results of the fixed-effect model with workforce productivity, physical asset efficiency, and working capital efficiency as the dependent variables. Models 1–3 illustrate moderate goodness of fit ($R^2 = 0.397, 0.281, 0.187$, respectively). Model 1 suggests that digital transformation practices have a positive influence on workforce productivity at a 5% level of significance ($\beta = 0.077$, $p < 0.05$), supporting H1. Model 2 supports H2 in that the coefficient estimation of digital transformation practices is positive and significant ($\beta = 1.783$, $p < 0.1$). Likewise, Model 3 confirms H3 in that the coefficient estimation is also positive and significant ($\beta = 0.845$, $p < 0.05$).

5.3. Robustness check

In this study, several important aspects reflecting a firm's operating efficiency are considered, which represent a robustness check for the dependent variable. Additionally, some additional analyses are performed to check the robustness of the results. First, the word frequency data related to digitalization are utilized as a substitute indicator for the independent variable without considering the calculation process of the entropy method, and then regression analysis is conducted again. The results (Model 1 through 3 in Table 6) are consistent with the above-

Table 4
Pearson correlation coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) WOPRI	1														
(2) PHASS	0.308***	1													
(3) WOCA	0.160***	0.116***	1												
(4) DITR	−0.061***	0.144***	0.000	1											
(5) INCO	0.123***	0.039***	0.063***	−0.079***	1										
(6) SIZE	−0.182***	−0.066***	0.224***	0.111***	0.118***	1									
(7) AGE	−0.007	−0.007	0.012	−0.016	−0.069***	0.000	1								
(8) LEV	0.208***	0.109***	0.285***	0.014	0.080***	0.356***	−0.003	1							
(9) OWC	−0.004	−0.058***	−0.054***	−0.114***	0.071***	0.069***	−0.060***	−0.088***	1						
(10) OWT	0.028***	−0.007	0.008	0.017*	0.012	0.039***	−0.005	0.018*	0.015	1					
(11) OPCA	−0.014	−0.087***	0.025**	−0.044***	0.032***	0.209***	0.039***	−0.112***	0.110***	0.000	1				
(12) OPCO	0.262***	0.051***	0.196***	−0.110***	0.145***	0.134***	0.024**	0.413***	−0.074***	0.014	−0.146***	1			
(13) FIXPR	−0.101***	−0.357***	0.148***	−0.282***	0.093***	0.176***	0.017*	0.065***	0.096***	0.012	0.181***	0.183***	1		
(14) FIRSH	−0.005	−0.059***	−0.021**	−0.104***	0.069***	0.116***	−0.043***	−0.026***	0.726***	0.034***	0.103***	−0.002	0.130***	1	
(15) INDIR	−0.038***	0.013	−0.009	−0.017*	−0.014	−0.051***	−0.013	−0.027***	0.048***	−0.046***	−0.01	−0.031***	−0.019*	0.049***	1

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Two-tailed.

mentioned regression analysis in Table 5. Second, whether the results are sensitive to the measure of digital transformation practices is examined. The log of new investment in digital software is adopted to represent its digital practices level. The data can be acquired from firms' annual financial statement annotations. The results of Models 4–6 in Table 6 suggest that digital transformation practices have positive influences on workforce productivity and physical asset efficiency at 1% and 5% levels of significance, respectively. Meanwhile, the coefficient of digital transformation practices on working capital efficiency is positive but not significant. In other words, other diversified practices like the five aspects mentioned in our study should be considered since firms may adopt a different set of practices according to their actual operations, though the investment in digital software can reflect a firm's digital practices to some extent. Finally, the dataset spanning from 2016 to 2019 is taken to examine the robustness of the results in different samples. The results are again substantively the same (Models 7 through 9 in Table 6). In summary, there is no substantive difference with the above-mentioned results.

5.4. Moderating effects

The moderating effect of industry competition on the relationship between digital transformation practices and firms' operational efficiency is tested, as presented in Table 7. Correspondingly, the interaction effects are also plotted in Figs. 2–4. As illustrated in Table 7, Models 1–3 exhibit adequate goodness of fit ($R^2 = 0.407, 0.282, 0.189$, respectively). The results reveal that the interaction between digital transformation practices and industry competition is significantly positive. In other words, the moderating roles of industry competition in the three models are significant. Specifically, industry competition (contrary to the HHI index) weakens these main effects. Moreover, the relationships between digital transformation practices and all three aspects of operational efficiency including workforce productivity, physical asset efficiency, and working capital efficiency are positive at low levels of industry competition; these focal relationships become negative at high levels of competition (Figs. 2–4). It can be concluded that industry competition weakens the positive relationship between digital transformation practices and operational efficiency. H4, 5, and 6 are thus supported.

The total samples are split into two subsamples with a low level of competition and a high level of competition following the median HHI index to further verify the difference of main effects in different levels of industry competition. Compared with the test method of interaction coefficient, the intergroup comparison is conducive to observing the differentiation in different subgroups. Although the results in subgroups cannot be directly compared with the aforementioned results of interaction terms analysis, we can still observe the difference from the perspective of comparative analysis to some extent. As illustrated in Table 8, Models 1, 3, and 5 suggest that digital transformation practices in a relatively low competitive environment have positive impacts on three aspects of operational efficiency with at least a 5% level of significance. However, their focal relationships are no longer significant and even become negative regarding the association between digital transformation practices and physical asset efficiency in a highly competitive environment. The underlying explanation for the seemingly differentiated results in Table 8 and Figs. 2–4 is that the grouping regression is conducted based on two samples with smaller scales, which may limit the representation of each subsample. In essence, these two methods are different in their emphasis. However, in general, the results based on the intergroup comparison are also consistent with the logic of the hypotheses that the positive relationship between digital transformation practices and operational efficiency is weakened in industries with a higher level of competition.

Table 5
Main effects.

Variables	WOPRI		PHASS		WOCA	
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.
DITR	0.077**	0.038	1.783*	0.951	0.845**	0.343
SIZE	−0.550***	0.017	−2.331***	0.413	1.352***	0.149
AGE	−0.005***	0.001	0.040	0.032	−0.001	0.012
LEV	0.894***	0.042	9.819***	1.058	6.997***	0.381
OWC	0.004***	0.001	−0.006	0.017	−0.014**	0.006
OWT	0.147***	0.042	−1.078	1.057	0.116	0.381
OPCA	0.011***	0.001	0.030	0.023	0.019**	0.008
OPCO	0.866***	0.043	6.948***	1.073	1.954***	0.387
FIXPR	−1.402***	0.059	−45.313***	1.483	4.534***	0.534
FIRSH	0.001	0.001	−0.005	0.016	−0.008	0.006
INDIR	−0.369***	0.097	2.773	2.419	1.052	0.871
Constant	14.160***	0.128	9.830***	3.198	−6.802***	1.152
Year dummies	YES		YES		YES	
Industry dummies	YES		YES		YES	
F-stat	45.6550***		27.0431***		15.9551***	
R-squared	0.397		0.281		0.187	
Observations	10,115		10,115		10,115	

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Two-tailed.

Table 6
Robustness check.

Variables	Method 1			Method 2			Method 3		
	WOPRI	PHASS	WOCA	WOPRI	PHASS	WOCA	WOPRI	PHASS	WOCA
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
DITR	34.756***	780.563***	206.712**	0.004***	0.062**	0.008	0.117***	2.637**	0.684*
	(11.521)	(288.061)	(103.773)	(0.001)	(0.026)	(0.009)	(0.044)	(1.113)	(0.408)
SIZE	−0.552***	−2.372***	1.369***	−0.557***	−2.393***	1.392***	−0.498***	−2.390***	1.327***
	(0.016)	(0.412)	(0.148)	(0.017)	(0.415)	(0.150)	(0.019)	(0.484)	(0.178)
AGE	−0.005***	0.040	−0.001	−0.005***	0.041	−0.001	−0.005***	0.033	0.007
	(0.001)	(0.032)	(0.012)	(0.001)	(0.032)	(0.012)	(0.001)	(0.038)	(0.014)
LEV	0.891***	9.758***	6.978***	0.884***	9.656***	6.971***	0.942***	9.483***	7.696***
	(0.042)	(1.058)	(0.381)	(0.042)	(1.060)	(0.382)	(0.050)	(1.255)	(0.460)
OWC	0.004***	−0.006	−0.014**	0.004***	−0.007	−0.014**	0.004***	−0.016	−0.020***
	(0.001)	(0.017)	(0.006)	(0.001)	(0.017)	(0.006)	(0.001)	(0.019)	(0.007)
OWT	0.148***	−1.051	0.123	0.143***	−1.130	0.108	0.123**	−1.588	−0.283
	(0.042)	(1.056)	(0.381)	(0.042)	(1.057)	(0.381)	(0.049)	(1.226)	(0.449)
OPCA	0.011***	0.031	0.019**	0.011***	0.028	0.019**	0.007***	0.007	0.020**
	(0.001)	(0.023)	(0.008)	(0.001)	(0.023)	(0.008)	(0.001)	(0.026)	(0.010)
OPCO	0.866***	6.945***	1.931***	0.872***	7.004***	1.925***	1.070***	8.611***	2.541***
	(0.043)	(1.072)	(0.386)	(0.043)	(1.074)	(0.387)	(0.051)	(1.292)	(0.474)
FIXPR	−1.391***	−45.087***	4.515***	−1.402***	−45.436***	4.387***	−1.311***	−45.065***	4.515***
	(0.059)	(1.486)	(0.535)	(0.059)	(1.473)	(0.531)	(0.068)	(1.715)	(0.628)
FIRSH	0.001	−0.005	−0.008	0.001	−0.005	−0.008	0.001	−0.006	−0.006
	(0.001)	(0.016)	(0.006)	(0.001)	(0.016)	(0.006)	(0.001)	(0.018)	(0.007)
INDIR	−0.370***	2.734	1.006	−0.370***	2.697	0.983	−0.255**	4.394	2.087**
	(0.097)	(2.418)	(0.871)	(0.097)	(2.418)	(0.871)	(0.112)	(2.829)	(1.037)
Constant	14.156***	9.744***	−6.830***	14.164***	9.887***	−6.805***	13.943***	8.761**	−7.599***
	(0.128)	(3.198)	(1.152)	(0.128)	(3.198)	(1.152)	(0.145)	(3.656)	(1.340)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-stat	45.7127***	27.0801***	15.9370***	45.7832***	27.0628***	15.9086***	35.2795***	21.5785***	12.9818***
R-squared	0.398	0.281	0.187	0.398	0.281	0.187	0.397	0.287	0.195
Observations	10,115	10,115	10,115	10,115	10,115	10,115	7520	7520	7520

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Two-tailed.

6. Discussions and implications

First, our findings indicate that digital transformation practices have a significantly positive effect on a firm's operational efficiency. Hence, the introduction and implementation of digital practices can improve a firm's operations. The digitalization-performance link has been a controversial topic with ambiguous results. This controversy largely originated from the digitalization paradox that the payoff of digitalization investment is minimal or even negative (Yang et al., 2021). Although many manufacturers are struggling with capturing value from digitalization but not every firm could achieve the expected value, they still need to endeavor to seek transformation step by step. Previous research also argued that although the trend of digital transformation is inevitable, the association between digitalization and performance in economic and operational terms remains mixed. For instance, Gul and Ellahi (2021) revealed that the impacts of digital transformation on some critical profitability indicators such as return on assets, return on equity, or net interest income may appear negative, demonstrating the "profitability paradox". In a similar vein, the adoption and implementation of a series of digital technologies and practices in operations management are inevitably accompanied by huge investments of resources and cost, leading to a negative impact on operational output in a

Table 7
Moderating effects.

Variables	WOPRI		PHASS		WOCA	
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.
DITR	−0.016	0.012	−0.009	0.008	−0.009	0.010
INCO	−0.003	0.027	0.001	0.019	−0.033	0.022
DITR*INCO	0.238***	0.058	0.179***	0.041	0.235***	0.047
SIZE	−0.146***	0.004	−0.017***	0.003	0.030***	0.003
AGE	−0.001***	0.000	0.000	0.000	0.000	0.000
LEV	0.247***	0.011	0.070***	0.008	0.161***	0.009
OWC	0.001***	0.000	−0.000	0.000	−0.000**	0.000
OWT	0.041***	0.011	−0.008	0.008	0.003	0.009
OPCA	0.003***	0.000	0.000	0.000	0.000**	0.000
OPCO	0.219***	0.011	0.048***	0.008	0.044***	0.009
FIXPR	−0.382***	0.015	−0.321***	0.011	0.106***	0.012
FIRSH	0.000	0.000	−0.000	0.000	−0.000	0.000
INDIR	−0.116***	0.024	0.019	0.017	0.024	0.020
Constant	0.525***	0.034	0.068***	0.024	−0.144***	0.028
Year dummies	YES		YES		YES	
Industry dummies	YES		YES		YES	
F-stat	46.7956***		26.8651***		15.9445***	
R-squared	0.407		0.282		0.189	
Observations	10,115		10,115		10,115	

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Two-tailed.

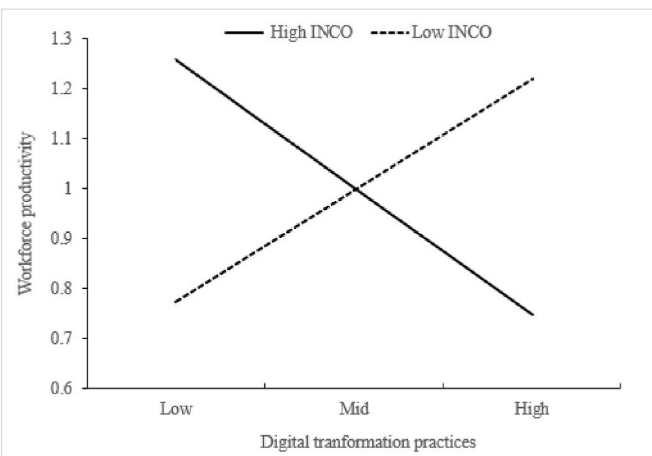

Fig. 2. Relation between digital transformation practices and workforce productivity influenced by industry competition.

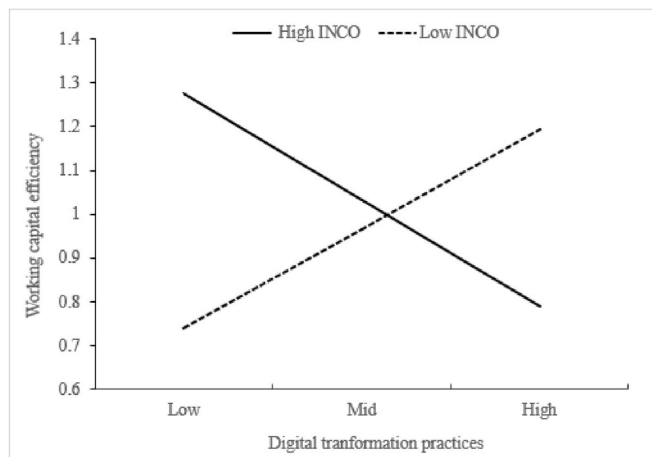

Fig. 4. Relation between digital transformation practices and working capital efficiency influenced by industry competition.

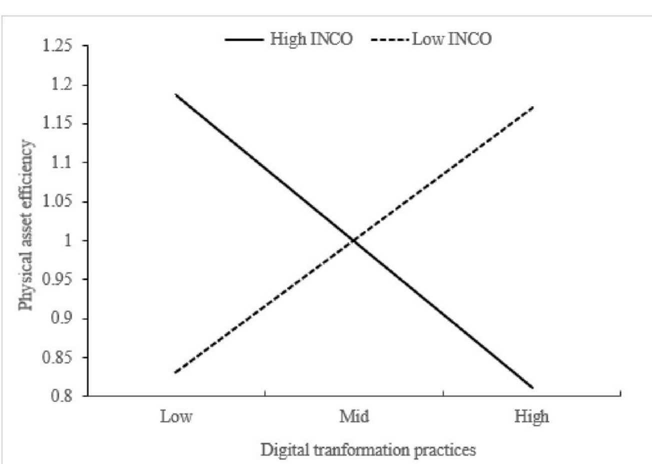

Fig. 3. Relation between digital transformation practices and physical asset efficiency influenced by industry competition.

short time (De Luca et al., 2020). However, firms' operational efficiency closely related to PBV is more likely to largely benefit from their digital transformation practices, different from these profitability indicators derived from RBV and dynamic capability (Wang et al., 2018). With the PBV as a strong theoretical lens in this study, the empirical results regarding the positive and significant association between digital transformation practices and firms' operational efficiency enlighten the explanation of the inconsistent findings in the literature (Hajli et al., 2015; Huang et al., 2017).

Besides, industry competition plays a moderating role in the relationship between digital transformation practices and all three aspects of firms' operational efficiency. Moreover, the influence of digital transformation practices on firms' operational efficiency is positive in a relatively low competitive environment, while insignificant and even partially negative impacts arise in a highly competitive environment. This result is in good agreement with one of the basic tenets of PBV from a contingency perspective, revealing that the efficacy of practices depends on specific contingency variables (Kalchschmidt, 2012). Sufficient resources support, more management attention, and even near-monopoly market structure release a positive signal to the implementation of digital transformation practices in operations management

Table 8
Regression results of two subsamples divided by industry competition.

Variables	WOPRI				PHASS				WOCA			
	Low INCO		High INCO		Low INCO		High INCO		Low INCO		High INCO	
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.	Model 5	S.E.	Model 6	S.E.
DITR	0.034**	0.017	0.002	0.012	0.036***	0.012	−0.001	0.007	0.045***	0.014	0.003	0.009
SIZE	−0.130***	0.006	−0.165***	0.006	−0.016***	0.005	−0.019***	0.004	0.029***	0.005	0.032***	0.004
AGE	−0.001**	0.001	−0.001***	0.000	0.001*	0.000	0.000	0.000	0.000	0.000	−0.000	0.000
LEV	0.278***	0.017	0.217***	0.014	0.088***	0.012	0.053***	0.009	0.179***	0.014	0.143***	0.010
OWC	0.001***	0.000	0.001***	0.000	0.000	0.000	−0.000	0.000	−0.001**	0.000	−0.000	0.000
OWT	0.052***	0.017	0.028**	0.014	−0.019	0.013	0.003	0.009	0.009	0.014	−0.002	0.010
OPCA	0.003***	0.000	0.003***	0.000	0.000	0.000	0.000	0.000	0.001*	0.000	0.000	0.000
OPCO	0.255***	0.017	0.189***	0.013	0.060***	0.013	0.038***	0.009	0.082***	0.015	0.013	0.010
FIXPR	−0.409***	0.022	−0.346***	0.021	−0.355***	0.016	−0.281***	0.013	0.088***	0.019	0.125***	0.015
FIRSH	0.000	0.000	0.000	0.000	−0.000	0.000	0.000	0.000	−0.000	0.000	−0.000	0.000
INDIR	−0.127***	0.038	−0.102***	0.031	0.019	0.029	0.022	0.020	0.015	0.033	0.035	0.023
Constant	0.441***	0.040	0.655***	0.031	0.055*	0.030	0.103***	0.020	−0.175***	0.034	−0.131***	0.023
Year dummies	YES		YES		YES		YES		YES		YES	
Industry dummies	YES		YES		YES		YES		YES		YES	
F-stat	27.7071***		70.0080***		17.1444***		33.3331***		9.7001***		22.2631***	
R-squared	0.428		0.352		0.316		0.206		0.208		0.148	
Observations	5059		5056		5059		5056		5059		5056	

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Two-tailed.

for firms operating in a relatively low competitive environment. This is favorable for firms to acquire positive operational output. However, firms cannot allocate sufficient resources and attention to digital transformation practices when they are confronted with intense competition in an industry. Additionally, the possible emergence of opportunistic behaviors (such as blind imitation) and firms' high-cost commitment will further weaken and even eliminate the positive impact of digital transformation practices on operations improvement. The results generate extended knowledge on the moderating factor (i.e., industry competition) influencing the output efficiency of digital transformation practices.

6.1. Theoretical contributions

In this study, several research contributions can be summarized. First, a theoretical framework of digital transformation practices-operational efficiency is established based on PBV; the impacts of digital transformation practices on different aspects of operational efficiency are analyzed from the perspectives of human, physical, and capital resources; new research ideas and directions are provided in the field of digitalization. The previous studies on strategic and operations management mainly focused on the impacts of digitalization on a firm's financial performance (Hajli et al., 2015), operational performance (Szász et al., 2020), and enterprise innovation (Blichfeldt and Faullant, 2021), while yielding ambiguous and inconsistent findings. Simultaneously, most of the studies on RBV and dynamic capability highlight the VRIN characteristics of resources, neglecting the practical fact that a firm's digitalization is often accompanied by a series of transferable and imitable techniques and practices. Starting from the theoretical background of PBV, therefore, this study fills the gap and extends the understanding of how digital transformation practices are associated with firms' operational efficiency.

Second, the complex influences of digital transformation practices on operational efficiency in different levels of industry competition are further explored from a contingency perspective. The relationship between digitalization and firm performance was simply explored in previous studies (Bergamaschi et al., 2021; Dalenogare et al., 2018), which drew mixed conclusions. Although various researchers have highlighted the potential influences of competition in a firm's operations management (Han et al., 2012; Jeong et al., 2017), there is little research on the influence mechanism in the digital context based on PBV. In a transition economy, an increasing number of firms are faced with growing competition and uncertainty. It is indispensable for them to develop new practices to adapt to this external contingency. Thus, industry competition is employed as a crucial contextual factor to conduct further research in the Chinese institutional background. Our research results uncover the moderating effects of industry competition. This enriches previous studies on both the essential role of competition and the differentiated digitalization-performance relationship.

Finally, regarding the empirical methodology, digital transformation practices are measured quantitatively in this study using text analysis targeting authoritative annual reports to enhance the objectivity and applicability of empirical analysis, different from the interviews or surveys used widely in previous research. Previous studies have employed interviews or surveys method to investigate the role of digitalization in strategic and operations management (Cassetta et al., 2019; Seyedghorban et al., 2020). These methods extend researchers' interviews with managers or employees in charge of digital projects through the multiple validation process. However, the data reliability, response rate, objectivity of evaluation, and explanatory power of questions are difficult to be guaranteed (Davies and Kochhar, 2002). Thus, our study fills this methodological gap to some extent. The text analysis through authoritative annual reports in this study echoes the emerging empirical method in recent literature (Nathan and Rosso, 2015).

6.2. Managerial implications

From a managerial viewpoint, this study also has relevance for managers involved in digital transformation practices and policymakers involved in fostering firms' digitalization. Given the positive association between digital transformation practices and operational efficiency in manufacturing firms, firms should first recognize the great value of digitalization and then regard digital transformation as an important strategic and operational orientation. Firms should be aware that the improvement of the operations induced by digitalization is very likely to prevail over the upfront investments, though firms may be confronted with several difficulties like substantial resources and cost investment, painful operational structure adjustment, and shortage of digital professionals in their transformation processes. Under this circumstance, firms can start by introducing some digital techniques or practices that are imitable and transferable to foster their successful embedding in production and operations in a short time.

However, our results suggest that industry competition weakens the positive relationship between digital transformation practices and firms' operational efficiency. In such cases, firms should properly adjust their digital transformation practices following external environmental changes. In a relatively low competitive environment, firms can allocate more attention and resources to the adoption and implementation of digital techniques and practices, so as to benefit their production and operations. If firms are facing a fiercely competitive environment, radical digitalization may exert an adverse outcome on their operations. Hence, they should take careful consideration and reevaluate their resources and economic conditions in the case that inadequate preparation for digital transformation leads to failure.

Some implications also apply to public policies. The significantly positive relationship between digital transformation practices and firms' operational efficiency provides a reference for policymakers to allocate their attention to fostering firms' digitalization. Policymakers could offer some direct and indirect support such as providing financial subsidies or introducing technical assistance to encourage firms' investment in digitalization. Concurrently, policymakers need to recognize the complexity and uncertainty that firms may face in the digital transformation process and boost support as complementation for the firms in a highly competitive industry.

7. Conclusions, limitations, and future research directions

With the advancement and growth of information technology, digital technologies are being embedded in firms' production and operations at an unprecedented speed. Based on the actual observation of industrial digital transformation, the influences of digital transformation practices on firms' operational efficiency are investigated in this study from the perspectives of workforce productivity, physical asset efficiency, and working capital efficiency. Then, the role of industry competition in their relationships is explored. Using a massive sample of manufacturing firms in the period from 2016 to 2020, further empirical analysis is conducted with a fixed-effect model. The results demonstrate that digital transformation practices have significant and positive influences on all three aspects of firms' operational efficiency. Additionally, these positive associations are weakened as industry competition increases.

Similar to most studies, this paper also has limitations. First, firms' operational efficiency is the result of multiple factors such as information transparency, absorptive capacity, or knowledge coupling. This study only focuses on digital transformation practices, industry competition, and other related factors from the perspective of PBV. More related factors could be considered in future studies. Second, digital transformation practices are measured using the text analysis method given the data availability and sample objectivity. However, the questionnaire survey, as a crucial source of collecting first-hand data, is also another method widely used in existing studies. In future research, multi-source data could be collected for the comparison of the results. Finally, how firms affiliated with other developed countries implement digital transformation and the subsequent influence on operational efficiency should be investigated in future research to extend the applicability of our findings, though China could share similarities with other developing countries.

Data availability

Data will be made available on request.

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