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Research Article

Impact of the Digital Transformation of Small- and Medium-Sized Listed Companies on Performance: Based on a Cost-Benefit Analysis Framework

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The ultimate goals of digital transformation, which is the only means of realizing the sustainable development of current enterprises, are to achieve cost reduction, efficiency improvement, and innovation for enterprises. However, there are limited empirical quantitative studies on the investment costs and impact of organizational performance related to the digital transformation of small- and medium-sized listed companies. This study first uses Excel VBA to sort the digital transformation panel data of 319 small- and medium-sized listed companies in China's Shanghai and Shenzhen A-share markets from 2007 to 2020. Thereafter, Stata, a general-purpose statistical software package, is used to analyze the impact of digital transformation on the performance of small- and medium-sized listed companies. The results show that the digital transformation of small- and medium-sized listed companies has a positive correlation with operational performance, and an inverted U-shaped relationship with innovation performance; however, the U-shaped relationship with financial performance is not significant. For small- and medium-sized listed companies to promote digital transformation, first, it must help the organization to improve its internal operational efficiency; second, it can optimize and improve the organization's financial efficiency; and finally, through innovative efficiency, the organization can continue to develop steadily and improve its organizational resilience.

1. Introduction

With the acceleration of the digitalization process, a new round of scientific and technological revolution as well as industrial transformation and development led by 5G, big data, cloud computing, industrial Internet, artificial intelligence, and other digital technologies (DTs) advancing [1–3]. With the spread of coronavirus disease 2019 (COVID-19) and the support of government policies, DT has further integrated with the real economy. To optimize the efficiency of resource allocation and build a new type of competitive advantage for enterprises, digital transformation provides a new choice for small- and medium-sized listed companies to improve quality, increase efficiency, reduce costs, and minimize storage [4]. Digital transformation connotes the innovative and principled application of DTs by enterprises, and it is a strategic adjustment made by enterprises to improve their business models, industrial models, and processes, thereby finally breakings the old concept and establishing a new system [5]. According to the survey of the "Analysis Report on Digital Transformation of Small- and Medium-Sized Enterprises (2021 Edition)," 79% of small- and medium-sized enterprises (SMEs) are at the initial stage of digital transformation. Because digital transformation is a huge systematic project and SMEs often encounter problems such as inadequate professional capabilities and insufficient internal and external resources, the overall level of digital transformation is low [6]. Moreover, even if SMEs invest a lot of money in digital transformation, it does not seem to have an immediate effect. In addition, existing research has no clear conclusions on the impact of digital transformation on the performance of small- and medium-sized listed companies.

Digital technology is the foundation of digital transformation. There is a significant positive correlation between the adoption of DTs and firm performance [7]. Existing studies have found that the use of DT can help improve the performance of enterprises, including operational, financial [8–11], and innovation performance [12–14]. The role of DT in realizing enterprises' internal operations has attracted extensive attention [15]. The rapid development of DTs has penetrated all types of organizations, showing a strong development potential, not only supporting operations; but also bringing innovations in products, services, and models [16, 17]. From this perspective, digital transformation not only helps to optimize operations; but also facilitates business growth through value creation, which in turn improves profits [18]. Unlike before, digital transformation involves not only the technology; but also the rebuilding of vision, processes, capabilities, organizational structure, and culture [19, 20]. The benefits and costs of digital transformation differ from those of traditional information technology (IT) use, and the digital transformation of manufacturing has an impact on organizational performance [18]. Owing to a lack of resources and limited investment in digital transformation, SMEs are still uncertain about the impact of digital transformation on organizational performance.

The current status of the research on the relationship between enterprise digital transformation and performance is reflected in industry reports [5, 6]. For example, Accenture has cooperated with the National Industrial Information Security Development Research Center to conduct a research on the digital transformation index of Chinese enterprises. In 2020, the "2020 Chinese Enterprise Digital Transformation Index" was released. Notably, only 11% of Chinese enterprises have produced good results after digital transformation. Operational performance is better in terms of profitability, growth, and response to external shocks, while the digital transformation practices of most companies have not yet yielded substantial results [21]. However, these survey reports do not systematically study the theory, mechanism, and mode of digital transformation. Moreover, owing to the different indicators used and varying evaluation methods, the obtained results are inconsistent. Some papers have found that digital transformation investment in manufacturing has a significant impact on enterprise performance, but the effect has a lag, that is, the first-order lag term of digital transformation investment significantly improves enterprise performance [18, 22]. Other studies have focused on the impact of a particular technology on a firm's financial performance [23–27]. These studies find that organizational change derives from specific DTs. However, the current digital transformation process involves a variety of DTs to form a competitive advantage over the adoption of a single technology. Related research has been validated in the manufacturing industry [18]. The use of comprehensive assessments in the digital transformation of SMEs remains to be verified.

This paper analyzes the impact of digital transformation on the performance of small- and medium-sized listed companies from three dimensions: operational, financial, and innovation performance. From the perspective of cost and benefit theory, we explore the impact mechanism of digital transformation on operational, financial, and innovation performance. In terms of operational performance, digital transformation improves the efficiency of the main business by investing in DT [18, 22, 28]. Moreover, the greater the digital transformation, the stronger the "synergies" generated across digital businesses [29]. Therefore, our research proposes that digital transformation has a positive impact on the operational performance of enterprises. Digital transformation also has a positive impact on financial performance [28, 30–36]. However, the high investment cost of DT and rising management costs reduce the company's profit, and it takes a certain period of time for the marginal benefit to exceed the marginal cost to generate a positive net benefit [18]. Therefore, our research proposes a U-shaped relationship between digital transformation and the financial performance of firms. In terms of innovation performance, some studies have found that there is a positive correlation between the level of enterprise digitalization and enterprise innovation performance [12–14]. However, innovation performance depends on the size of research and development (R&D) expenditure. For SMEs with limited resources, if they cannot continuously invest in R&D, innovation performance will decline in the later stage. Therefore, our research proposes an inverted U-shaped relationship between digital transformation and firm innovation performance.

Based on the text analysis of the annual reports of small- and medium-sized listed companies, this paper first quantitatively measures the intensity of the digital transformation of small- and medium-sized listed companies. The panel data from 2007 to 2020 of the digital transformation of 319 small- and medium-sized listed companies in China's Shanghai and Shenzhen A-share markets provide strong support for this article. Small- and medium-sized enterprises are the main force in the development of the digital economy and the main battlefield of digital transformation. The Chinese government has issued relevant policies to support the digital transformation of SMEs, providing us with a good empirical research environment. Our research enriches the literature on the impact of digital transformation on organizational performance and helps organizations set digital transformation goals by exploring the differential impact of digital transformation on operational, financial, and innovation performance. The inverted U-shaped relationship between digital transformation and innovation performance resolves the theoretical and practical debates on the innovative value of digital transformation. Through empirical research, it is found that for small- and medium-sized listed companies, the impact of digital transformation on operational and innovation performance is more evident than financial performance.

2. Theory and Hypotheses

2.1. Digital Transformation and Organizational Performance. By perusing the domestic and foreign literature, it is found that academic and industrial circles have paid great attention to digital-transformation-related issues. This has great research potential from both theoretical and applied perspectives. However, we are still at an exploratory stage in this field. The essence of digital transformation is to fully utilize DT and data resources to solve complex and uncertain problems, which not only improves efficiency; but also enhances capabilities, thereby engendering a new type of competitive advantage for enterprises [37]. There are also studies that believe that digital transformation is a change based on DT that leads to unique changes in enterprise operations, business processes, and value creation [3]. A digital transformation strategy supports companies in managing the changes resulting from the integration of DTs and supports transformed operations [38]. Academia generally believes that digital transformation should reflect two notable characteristics of the application of DT and the profound transformation of the organization. For enterprises, promoting the wide application of the new generation of IT, and integrating intelligent manufacturing into all aspects of business activities, such as enterprise design, production, management, and service, can bring about a doubled increase in operating efficiency [39]. However, there are merely a few studies on the impact of the digital transformation of small- and medium-sized listed companies on the operational performance of enterprises.

Under Moore's Law, with the development of DT, digital transformation is further integrated with the real economy, the purpose of which is the survival and profit growth of enterprises. Some scholars believe that digital transformation refers to profound changes in society and industry through the use of DTs [40, 41]. As a reform, it emphasizes the process of improving entities by triggering significant changes in their attributes through the combination of information, computing, communication, and connectivity technologies; as an inductive framework, digital transformation can be described as an organization's process of responding to changes that occur in the environment, altering their value creation through the use of DTs [42]. Some studies explain the relationship between digital transformation and enterprise performance from different perspectives [12, 18, 22, 28, 32]. However, there are few positive conclusions about the relationship between digital transformation and the financial performance of small- and medium-sized listed companies. Industry research reports focus more on financial performance than academic research. According to McKinsey's global survey, the success rate of enterprise digital transformation is only 20% [18].

Digital transformation involves changes in business processes, organizational structures, and strategic models [43]. Through the application of DTs, digital transformation seeks fundamental changes in an organization's infrastructure, products and services, business processes, business models and strategies, interorganizational relationships, and even organizational networks [44]. According to the IDC's survey of 1,340 SMEs in 14 major economies in the Asia-Pacific region: 38% of enterprises believe that digitalization can make them more flexible when launching new products and services, that is, through IT to achieve office collaboration, the efficiency of product development, sales service, production, and transportation has been improved [45]. Digital transformation has significantly improved the willingness to innovate and the innovation intensity of manufacturing companies. Digital transformation plays a greater role than independent innovation in promoting collaborative and imitative innovation in manufacturing companies. Digital transformation has greatly improved the innovation of large and medium-sized enterprises, enterprises without financing constraints, and export enterprises. The promotion effect is greater than that of small- and micro enterprises, enterprises with financing constraints, and non-export enterprises [46]. However, merely a few empirical quantitative studies exist on the digital transformation and innovation performance of small- and medium-sized listed companies.

The impact of the digital transformation of SMEs on operational, financial, and innovation performance is very important, but merely a few relevant empirical quantitative studies are presently available. First, because the financial reports of SMEs do not need to be disclosed, the impact of digital transformation on the performance of SMEs can only be studied from a case perspective [47, 48]. Second, digital transformation metrics are difficult to identify. Some studies use five indicators: operational efficiency, employee engagement and productivity, customer retention, innovation speed, and scale [49]. There are also 26 refined indicators in 7 aspects, including digital infrastructure, digital R&D, digital investment, organizational structure, digital talents, business digital management, production digital management, and financial digital management, to build an enterprise digital transformation capability evaluation system [50]. It can be seen that the above indicators are still difficult to quantify. Third, some studies focus on the economic effects of specific DTs, for instance, Industry 4.0 technologies can improve profitability and sales [24] or the positive impact of technology mix on operational and financial performance [18]. Little research has been conducted on how the combined use of DTs in digital transformation impacts operational, financial, and innovation performance.

The potential benefits of digital transformation have been mentioned in the relevant literature and industry reports [5, 12, 18, 22, 32, 35]. However, enterprises undergoing digital transformation also face high organizational change costs. In February 2021, PTC Corporation of the United States released "The State of Industrial Digital Transformation." The survey reveals that 77% of digital transformation projects require more than US$ 1 million per year, while 30% of them consume over US$ 5 million per year [51]. This is undoubtedly a huge investment for SMEs. Referring to the performance measures of digital transformation [18, 46, 49, 50], this study classifies organizational performance into operational, financial, and innovation performance. Operational performance measures cost reduction or efficiency improvement in a company's operations [52]. In this article, we focus on business processes in the digital transformation of SMEs. According to Accenture's survey report, 80% of the surveyed companies deployed remote office tools during the epidemic, 63% of the surveyed companies strengthened the layout of online channels, and 11% of the companies' digital investment was transformed into operational performance [21]. Financial performance reflects the ultimate need for business operations to be profitable [18, 22, 32]. Innovation performance refers to exponential growth through product/service innovation, which is measured by the patent results formed after R&D investment [12–14].

2.2. Digital Transformation and Organizational Operational Performance. Industry 4.0 technologies, such as big data, cyber-physical systems, and interoperability, have a significantly positive impact on improving the business performance of SMEs [34]. In contrast to enterprise informatization triggered by traditional IT technology, the digital transformation of enterprises triggered by DT extends beyond technology and affects all aspects of the entire organization. According to a survey by the IT research firm, Gartner, digital transformation initiatives should first focus on improving current operational efficiency, a "cost-first" approach adopted by 62% of companies given the current economic conditions caused by the COVID-19 pandemic [51].

The digital transformation of SMEs improves operational efficiency by reducing costs [40, 53]. First, DT has the characteristics of connection, sharing, and openness, which optimize the transaction process and reduce external transaction costs. Second, DT can improve the resource allocation efficiency of human, financial, and material resources; reduce resource waste; improve resource utilization; and reduce internal management costs [30]. Third, for small- and medium-sized manufacturing enterprises, the Internet of Things technology is used to perceive production factors such as people, machines, materials, methods, and environments, as well as to carry out dynamic optimization and allocation of all factors to reduce the production cost of unit products. Finally, with the continuous development of artificial intelligence technology, for some labor-intensive SMEs, the use of intelligent robots can reduce labor costs.

There are two main methods toward realizing digital transformation in SMEs. Some recruit troops to do it themselves, and some use "borrowing resources." However, regardless of the approach adopted, the capital and human investment that need to be invested are substantial. First, there is a lot of initial investment in various software and hardware. For example, a data center, which is an important foundation for enterprises to achieve digital transformation, is worth tens of millions. However, subsequent maintenance and upgrading are also expensive. Second, digital professionals are currently scarce, which also means that the cost of introducing digital labor is high [54]. Third, the cost of using "outsourced" services, including traditional IT services, and the cost of new cloud platforms and other data intelligence services [55]. This method is divorced from industry and business, and there will be situations wherein digital investment is ineffective.

Some studies have reported that the digital transformation of enterprises can help improve operational performance [18]. The combination of DT and other resources of the enterprise can form an efficient organic system, such as OA and ERP. Through the integration of human, financial, and sales department information, structural barriers that prevent employees from obtaining information, opportunities, and resources can be eliminated. Communication problems derive from information asymmetry [33]. Digital technology can also accelerate the response process between resources, thereby boosting the overall operational efficiency of enterprises through a specialized division of labor and collaborative operations [56]. Online offices during the epidemic (such as DingTalk), through the online digitization of people, finance, materials, affairs, office mobility, and business intelligence, improve the operational efficiency of enterprise organizations in an all-round way, and significantly reduce the cost of enterprise organization digitization.

Therefore, despite the operational costs, we believe that digital transformation can reduce costs and increase efficiency. Based on this, this paper proposes the following assumption.

Hypothesis 1 (H1). Digital transformation is positively correlated with operational performance.

2.3. Digital Transformation and Organizational Financial Performance. Financial performance entails whether a business strategy and its implementation and execution contribute to the ultimate business performance. Financial performance can fully express the composition of the return on shareholders' equity, as well as the effects of cost control, asset utilization and management, and capital allocation. Financial performance is broader and more complex than operational performance. Enterprises carry out digital transformation to not only reduce costs; but also create incremental values [57]. The digital transformation of SMEs requires building an open business system driven by user needs and empowered by digital capabilities; accelerating the cultivation of new technologies, products, models, and business formats; acquiring incremental value; and opening up new value space. The first is the extension and value-added of products and services. On the one hand, relying on intelligent products/services, it provides operation and maintenance services for the entire life cycle of products/services and supply chains/industrial chains, and it transforms one-time product delivery to obtain value from long-term service transactions. On the other hand, we expand product service scenarios and enhance product market competitiveness and value space [57]. The second is to connect and empower partners to create incremental value. On the one hand, it transforms stakeholders, such as users, suppliers, and distributors, into value creators; strengthens user stickiness; and satisfies users' needs with the "long tail effect." Fragmented, personalized, and scenario-based needs will further create incremental value. On the other hand, relying on "value network externalities," it rapidly expands the value space boundary, continues to expand market capacity, and achieves sustainable value growth [18]. The third is a new digital business. Through digital transformation, enterprises can modularize and convert digital resources, digital knowledge, and digital capabilities into services, realize the development and asset operation of internal and external data value, and form data-driven information production. The new format of information service can not only fully revitalize the stock value; but also bring sustainable incremental value to enterprises [57].

In addition to operating costs, the digital transformation costs include integration [16, 18] and hidden costs [58, 59]. In the process of enterprises' digital transformation, change needs to eliminate organizational inertia [20], that is, resistance to change. This incurs communication, coordination, and integration costs [18]. First, businesses must regularly replace digital platforms and infrastructure to avoid investing in two overlapping and incompatible digital platforms. In practice, the integration of DTs creates many costs, both old and new [57]. Second, digital transformation means that companies need to create entirely new capabilities and integrate them into an organization with a strong traditional culture and operating model or form a new digital culture [60]. The usual practice is to bring in a chief digital officer from outside at a high price [61]. Finally, there are some other external transaction costs that are generally considered as administrative or nonoperating expenses [18].

Considering integration costs and "synergies," we assume a curvilinear relationship between digital transformation and the financial performance of SMEs because when enterprises are digitally transformed, integration costs rise sharply, resulting in a substantial increase in administrative or nonoperating expenses [20]. Digital transformation is a long-term and complex system engineering, and its benefits do not appear quickly; therefore, integration costs and contributions may offset business growth and operations [62]. When the intensity of digital transformation of an enterprise is relatively low, the marginal cost will exceed the marginal benefit of business growth and operation. The intensity of digital transformation has a negative impact on financial performance. When the intensity of digital transformation reaches a certain threshold, data will be connected and flow, forming a collaborative effect, and then optimizing operations [18]. At this point, the marginal benefits of digital transformation in business growth and operations cover the cost of integration, and digital transformation has a positive impact on financial performance.

Because of the large investment in digital transformation in the early stages, the financial performance of the company declines, but after the critical point, as the intensity of digital transformation increases, the financial performance of the company increases accordingly. Based on this, this paper proposes the following assumption.

Hypothesis 2 (H2). A U-shaped relationship exists between digital transformation and financial performance.

2.4. Digital Transformation and Organizational Innovation Performance. Some scholars conducted a questionnaire survey on 938 Portuguese companies from different industries by telephone and found that digital transformation could improve the innovation ability and performance of enterprises [63]. Some studies have also found that the level of enterprise digitization is positively correlated with enterprise innovation performance; and that the promotion effect of enterprises that have set up a digital resource information-sharing platform is more significant [12].

The impact of digital transformation on enterprise innovation performance is mainly realized through the following three paths. First, the extensive use of DT is gradually improving the structural [64] and operational [65] efficiencies of enterprise organizational models. By improving the organizational management model, the application of advanced and efficient management tools brings organizational innovation [56]. Second, the improvement in the level of digitalization gives the information flow between participating enterprises and between enterprises more scale, efficiency, and integration, which has a profound impact on the innovation value of enterprises [66]. Technological process innovation can be achieved by improving the production and processing of a certain link in the industrial chain [56]. Third, DT is an effective part of enterprise innovation value creation [67]. Product innovation is achieved by embedding DT into actual products and enhancing product functions and features, such as upgrading to intelligent interconnected products [56, 68, 69]. By expanding its own market through more channels of marketing, sales means, and more diversified services to achieve market expansion and innovation [56], the digital transformation of SMEs can enable employees to integrate and consolidate existing R&D business processes and products and also improve R&D exploration capabilities through continuous self-breakthrough and innovation [13, 14].

Enterprise innovation performance refers to the improvement in enterprise performance due to the adoption of new operating systems, technologies, and other innovative means. Generally, it can be evaluated from the perspectives of the innovation resource investment and enterprise market-value improvement [70]. Generally, the inputs of innovation resources are the R&D expenses, including personnel and labor expenses, direct input expenses, depreciation and long-term deferred expenses, amortization of intangible assets, design experiments, and other related expenses [71]. This is a huge expense for SMEs. In terms of improving the market value of enterprises, listed companies are generally measured by the number of patent applications [22, 72]. Intellectual property rights, represented by patents, are an indispensable part of information disclosure as an important manifestation of the innovation level of listed companies, and patent applications also incur costs.

Considering R&D expenses and innovation diffusion effects, we assume a curvilinear relationship between digital transformation and the innovation performance of SMEs. Technological innovation diffusion refers to the process of technological innovation dissemination and adoption among potential users through certain channels [70]. Some scholars have found that the impact of digitalization level on enterprise and innovation performance is an inverted "U" shape because there is a boundary for enterprises to improve their digitalization level. The marginal benefit of the digitalization level on innovation performance improvement is equal to the marginal cost of the digitalization level, which is the boundary of enterprise digitalization level improvement [72, 73]. To support the digital transformation of SMEs, an essential instrument is the subsidy policy for R&D investment, which can be supported according to a certain proportion of sales revenue, and special deductions for R&D can be made [45]. This reduces R&D costs to a certain extent. Therefore, owing to the policy subsidy for the R&D funds of digital transformation, the marginal benefit will cover the marginal cost in the early stage. At this point, digital transformation has a positive impact on innovation performance. However, the government subsidy policy is limited in time or amount; coupled with the diffusion effect of technological innovation, the success rate of patent conversion is not high; and small- and medium-sized enterprises are inherently short of resources, and over time, the marginal benefit will be less than the marginal cost. At this point, the impact of digital transformation on innovation performance will slowly diminish.

The government's subsidy policy to support SMEs in their digital transformation will help improve their innovation performance in the early stages. However, the policy support will not last long. If SMEs cannot convert blood transfusion into hematopoiesis, innovation performance will decline in the later stage. Therefore, this study proposes the following assumption.

Hypothesis 3 (H3). An inverted U-shaped relationship exists between digital transformation and innovation performance.

3. Materials and Methods

3.1. Sample and Data Collection. Wind data shows that there are 4,803 listed companies in China's Shanghai and Shenzhen A-share markets. According to the relevant literature suggestions and combined with the research needs of this paper, the screening conditions are set as follows: (1) We exclude large group listed companies, leaving a total of 1895. (2) We delete ST-type companies, leaving a total of 1760. (3) We exclude samples with companies that have been in existence for less than 5 years, leaving a total of 1494. (4) We delete companies with missing key data, leaving a total of 341. (5) We delete companies with abnormal indicators, leaving a total of 319. Finally, this study selects 319 small- and medium-sized nonfinancial listed companies in Shanghai and Shenzhen A-share markets from 2007 to 2020. The data of listed companies in this study are obtained from the China Stock Market & Accounting Research (CSMAR) database, which is currently the largest economic and financial research database with the most accurate information and the most comprehensive data in China [74]. Some incomplete data are confirmed by comparison through financial reports, and individual data need to be calculated manually by the author. Some empirical variables need to be collected through the Wind database, cninfo websites, official websites of listed companies, Shenzhen Stock Exchange, Shanghai Stock Exchange, and other channels.

Owing to the huge complexity of data, Visual Basic for Applications (VBA) technology is used for data cleaning. Notably, VBA is a new generation of standard macro language shared by applications developed by Microsoft. The emergence of macros broadened the application scope of Excel, and later this application promoted the comprehensive development of the VBA language in Excel [75]. From stock, option, and finally bond calculations, VBA is widely used in various calculations in the financial field [76]. Because the data to be processed in this article are Excel format data exported from the CSMAR, by comparing the ease of learning, development time, and convenience of Excel operation, VBA is finally chosen.

After the above-described screening, this study selects the relevant data of 319 Shanghai and Shenzhen A-share small- and medium-sized listed companies from 2007 to 2020. The sample companies are distributed in 17 industries. Table 1 lists the top 5 industries with the largest number of companies. The number of companies in these industries accounted for more than 94.68% of the complete sample. Panel data refer to the indicator data of different objects at different times. When panel data are used to study the relationship between regression and influence, it is referred to as a panel model. Data analysis was performed using the Stata software for panel regression analysis.

3.2. Measure

3.2.1. Dependent Variable. This study divides the performance of small- and medium-sized listed companies into operational, financial, and innovation performance. Operational performance (*Y1*), which represents the efficiency of business processes, is usually expressed as costs and expenses [52]. Here, we focus on the operational performance of the main business processes of small- and medium-sized listed companies. The calculation formula is as follows: operating performance = 1−(operating cost + sales expenses)/operating income, and financial performance (*Y2*), which is measured by the overall profitability of small- and medium-sized listed companies. Profitability-based financial metrics are a common choice for measuring financial performance and are often used to study the impact of DTs on business performance [18, 52]. Industry reports believe that the contribution rate to profits is one of the main indicators for enterprises to evaluate digital transformation [5, 21]. This study uses return on assets (ROA) as a proxy variable for financial performance using the following formula: financial performance = return on assets (ROA) = net profit/total assets ×100%. The ROA is one of the most widely used indicators in the industry to measure bank profitability. The higher the indicator, the better the utilization of corporate assets. Regarding innovation performance (*Y3*), the existing research mainly considers two dimensions of input and output (patents) for the level of enterprise innovation. Our database includes both R&D investment and number of patents. Considering that the patent index is a yardstick for measuring enterprise innovation; thus the number of patent applications is chosen to represent the innovation efforts of

Table 1: Top 5 industries by number of sample companies.

Industry code	Industry name	Number of firms
C-39	Communication equipment, computer, and other electronic equipment manufacturing	176
I-65	Software and information technology services	68
I-64	Internet and related services	43
I-63	Telecommunications, radio and television, and satellite transmission services	10
C-38	Electrical machinery and equipment manufacturing	9

SMEs. This paper uses the total number of patent applications as a proxy variable for innovation performance. The patents include three invention patents, utility model patents, and design patents. The calculation formula is: innovation performance = total number of patent applications = number of invention patents + number of utility model patents + number of design patents.

3.2.2. Independent Variable. The intensity of digital transformation is the independent variable in our study and represents the use of DTs by companies to improve customer relationships, operational processes, or business models [77]. The intensity of digital transformation reflects the aggressiveness of a company's digital business practices [18]. As the research on digital transformation is currently in the ascendant stage, it is difficult to measure it with quantitative indicators. Therefore, this study measures the intensity of digital transformation through the text analysis of the annual reports of small- and medium-sized listed companies [18, 33].

A company's annual report is an official document that discloses the company's financial position and operating performance for a fiscal year. It not only includes financial indicators, but also reveals some important events, such as: the digital transformation of a company being an important strategic choice in the digital economy era [78]. Given the publicity and importance of the annual report, the company will be very careful in its wording. Existing research has constructed a dictionary of enterprise digital word segmentation that can determine the basic way of expressing digital-related information in annual reports [79]. Based on this, it is reasonable and feasible to mine the information of the company's digital transformation from the annual report.

In annual reports, the frequency of a term indicates its relative importance [80]. The word frequency method is the best choice for measurement based on big data [81]. Therefore, the keyword frequency method can be used to quantify the intensity of a company's annual digital transformation [18]. However, the digital development of enterprises is closely related to the market environment full of competition and uncertainty, so the absolute number of disclosure times is not sufficiently convincing. Therefore, we refer to Qi et al.'s method and use the weight of the keyword word frequency in each enterprise's annual report to the total keyword word frequency in all sample annual reports of the same industry in that year as a metric index [58].

As the focus of small- and medium-sized listed companies in digitalization is more refined than that of large enterprises, large companies concentrate on the formulation of systems and strategies, while small- and medium-sized listed companies pay more attention to the use of specific tools, such as office software, live broadcast, and e-commerce [33]. Therefore, the dictionary constructed by the existing research needs to be further supplemented or modified. After comparing with the thesaurus of the CSMAR database, a word segmentation dictionary suitable for small- and medium-sized listed companies is finally formed. Table 2 lists the keywords extracted from the annual reports of 319 sample companies. All the keywords are divided into three categories: paradigm characteristics, scope of influence, and infrastructure. We use the natural logarithmic measure of the frequency of occurrence of subdivision indicators in the CSMAR database of small- and medium-sized listed companies' DT applications (that is, indicators included in the scope of influence). And the frequency of each subdivision index of artificial intelligence technology, big data technology, cloud computing technology, and block-chain technology appearing in the report [74]. The application of DT emphasizes the combination of DT and other fields. The subdivision indicators of other DTs, such as data mining, appear relatively infrequently in the report, and the frequency of subdivision indicators of DT application accounts for more proportions, more than the sum of the frequencies of the subdivision indicators of artificial intelligence technology, big data technology, cloud computing technology, and block-chain technology appearing in the report. In this paper, the natural logarithm of the frequency of occurrence of the five subdivision indicators discussed above in the report will be used as the estimation result of the proxy variable of digital transformation.

As there is an event lag in the impact of digital transformation on company performance, a time window was chosen as the lag phase. Some studies have found that within two to three years after companies introduce IT, it usually has a significant impact on organizational performance [8]. We consider the hierarchical impact of digital transformation on business, financial, and innovation performance [18]; however, for the convenience of analysis, we uniformly set the sample period of independent variables to be 2007–2020. Considering the emergence of the COVID-19 epidemic in 2020, it has also dealt with it accordingly and conducted a robustness test.

3.2.3. Control Variable. The performance of small- and medium-sized listed companies is affected by several factors. Some commonly used control variables are usually employed in the analysis, including company size, company

Table 2: Keywords on digital transformation in the annual reports.

Category	Keywords
Paradigm characteristics	Automation, digitalization, informatization, intellectualization
Influencing scope	Internet finance, Internet healthcare, digital finance, digital marketing, smart marketing, smart healthcare, smart energy, smart grid, smart environmental protection, smart home, smart transportation, smart cultural tourism, smart agriculture
Infrastructure	Artificial intelligence, block-chain, cloud computing, big data

age, company attributes, industry sensitivity, and the shareholding ratio of the largest shareholder reflecting the corporate governance structure. This paper adopts four control variables on a case-by-case basis: company size, asset turnover, year, and digital maturity. The size of a company affects its operations and decision-making and has been used as a control variable in research [52]. A company's size is measured by the natural logarithm of its total assets in its fiscal year [18]. In this study, *SIZE* is used to represent the natural logarithm of total assets. The asset turnover ratio reflects the efficiency of using the company's total assets and is measured by dividing the operating income by the average of the total assets at the beginning and end of the period. In this study, AT is used to represent the asset turnover rate.

In addition, to control the impact of the year and industry of small- and medium-sized listed companies on performance, this paper also introduces *year*, and *ind* representing the year and industry dummy variables, respectively. Firm age affects its operations and decision-making and has been used as a control variable in research [52]. Because the digital foundation of each industry varies significantly [82,83], the digital maturity of the industry is used as a control variable, and it is expressed by the average value of the digital transformation intensity of all companies in the industry [18]. This study uses DT to represent digital maturity.

3.2.4. Model Construction. By analyzing the data of 319 small- and medium-sized listed companies from 2007 to 2020, this study conducts a correlation test of panel data. The first step entails processing the data accordingly (finishing the unbalanced data) and performing descriptive statistics to understand the basic situation of the variable data of the study. Thereafter, we use Stata to perform correlation analysis, not only to initially establish the correlation between the variables on the right-hand side of the model and the affected variables but also to study whether there is a high degree of correlation between the explanatory variables. To understand whether the data may have a high degree of multicollinearity and to further determine the existence of collinearity through the variance inflation factor test, a multivariate regression estimation of the model is developed to obtain the final influencing factors, and a robustness test is carried out to obtain the research results of this study.

By setting the explained variables, explanatory variables, and control variables, three models are constructed as follows:

$$\begin{aligned}
Y_{1\,it} &= \beta_0 + \beta_1 X_{it} + \beta_2 DT_{it} + \beta_3 \mathrm{SIZE}_{it} + \beta_4 AT_{it} \\
&\quad + \sum \mathrm{year} + \sum \mathrm{ind} + \varepsilon_{it}, \\
Y_{2\,it} &= \beta_0 + \beta_1 X_{it} + \beta_2 X^2{}_{it} + \beta_3 DT_{it} + \beta_4 \mathrm{SIZE}_{it} \\
&\quad + \beta_5 AT_{it} + \sum \mathrm{year} + \sum \mathrm{ind} + \varepsilon_{it}, \\
Y_{3\,it} &= \beta_0 + \beta_1 X_{it} + \beta_2 X^2{}_{it} + \beta_3 DT_{it} + \beta_4 \mathrm{SIZE}_{it} \\
&\quad + \beta_5 AT_{it} + \sum \mathrm{year} + \sum \mathrm{ind} + \varepsilon_{it}.
\end{aligned} \tag{1}$$

In the three models presented above, i represents the ith enterprise, t represents the year t ($t = 2007, 2008, \ldots, 2020$), and ε_{it} represents other random influencing factors that have not been considered, indicating a random error term. To prevent the data and variable data from the adverse effects caused by the large difference between the two, natural logarithm processing is performed on the absolute value, that is, the data with relatively large data, and logarithmic processing is not performed on the relative value, that is, the ratio or percentage data; where Y_1 is the operating performance, Y_2 is the financial performance, Y_3 is the natural logarithm of the number of patent applications +1, X is the total word frequency/total word frequency in the same industry, SIZE is the natural logarithm of the total assets, AT is the asset turnover rate, DT is the digital maturity, and year and ind are the year and industry dummy variables, respectively. Among them, X and Y_1 are used to study the linear relationship, X and Y_2, Y_3 are used to study the nonlinear relationship.

4. Results

4.1. Descriptive Statistics. The descriptive statistics of the sample data for each variable can be used to understand the basic situation of the research data in this study. The descriptive statistics are shown in Table 3.

It can be seen from the observations (*obs*) of 2022 that the number of samples of each variable is 2022, the standard deviation of the SIZE data is less than the mean, there is no significantly large fluctuation, and for the standards of Y_1, Y_2, Y_3, X, ST, and AT, the difference is large, indicating that the differences in Y_1, Y_2, Y_3, X, ST, and AT of each enterprise are large. Next, to prevent the influence of outliers, we will shrink the outliers.

4.2. Descriptive Statistics after Abbreviated. Owing to a large number of enterprises and the relatively large data sample size, there will inevitably be some outliers that may cause deviations in the results. The upper and lower 1% tailing

Table 3: Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
Y_1	2022	0.2570	0.3014	−6.8530	0.9846
Y_2	2022	0.3997	16.8734	−3.5008	758.7382
Y_3	2022	1.6731	1.4514	−2.0794	6.3244
X	2022	1.1586	2.3897	0.0147	47.3333
DT	2022	6.8356	8.7926	0.2000	72.2000
SIZE	2022	21.1269	0.8271	14.1581	24.3746
AT	2022	0.4193	0.4360	0.0001	10.4509

Table 4: Descriptive statistics after abbreviated.

Variable	Obs	Mean	Std. dev.	Min	Max
Y_1	2022	0.2687	0.1724	−0.2843	0.7793
Y_2	2022	0.0289	0.0936	−0.4782	0.2217
Y_3	2022	1.6710	1.4383	0.0000	5.2832
X	2022	1.0601	1.4816	0.0238	8.6471
DT	2022	6.7494	8.3476	0.2000	44.0000
SIZE	2022	21.1302	0.7963	19.4628	23.3742
AT	2022	0.4040	0.2523	0.0056	1.3059

Table 5: Correlation analysis.

Variables	Y_1	Y_2	Y_3	X	DT	SIZE	AT
Y_1	1						
Y_2	0.4414***	1					
Y_3	0.016	0.1336***	1				
X	0.0461**	−0.0397*	0.0259	1			
DT	0.0109	−0.1098***	0.0444**	0.7575***	1		
SIZE	−0.0697***	−0.0820***	0.0590***	0.0887***	0.1891***	1	
AT	−0.2254***	0.1341***	0.0973***	−0.0585***	−0.0555**	−0.0973***	1

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

processing is adopted, that is, the values less than the 1st quantile and the values higher than the 99th quantile are shortened to the 1st quantile and the 99th quantile, respectively. This makes the data fall within a more reasonable range, thereby reducing the impact of too small- or too large values. The descriptive statistics after the abbreviated processing are shown in Table 4.

After the descriptive statistics are abbreviated, the sample size is still the same as that before the abbreviation; however, regardless of the minimum or maximum value, there is a certain change, and the subsequent analysis is continued with the data after the abbreviation processing.

4.3. Correlation Analysis. Subsequently, correlation analysis is performed on the data, where the absolute value of the correlation coefficient represents the magnitude of the correlation, and the positive and negative values indicate the direction of the correlation. If the influencing variable on the right-hand side of the equation has a significant correlation with the affected variable, the correlation between the variables can be initially understood, but it does not represent the final regression result. The variables on the right-hand side of the equation are expected to not have a high degree of correlation, otherwise there may be multicollinearity that will have a bad impact on the model results. The details of the correlation analysis are shown in Table 5.

The correlation coefficient between explanatory variables X and Y_1 is 0.4414, which is significant at the 0.01 significance level; that is to say, the correlation between X and business performance is initially positive. As shown in Table 6, the correlation coefficient between explanatory variable X and corporate financial performance Y_2 is negative, and the linear relationship between explanatory variable X and Y_3 is not significant. However, as this has no influence from other control variables nor controls the influence of year and industry effects, it cannot be used as the final regression result. The correlation coefficients between the selected control variables and the explained variables are all significant, indicating that the selected control variables are relatively reasonable, the correlation coefficient between the explanatory variables, and the control variables is less than 0.8, and there is no strong correlation, that is, there is no high degree of multicollinearity.

4.4. Regression Analysis. Next, a regression analysis was performed, using a fixed effects model that controlled for year and industry to obtain the relationship between the study variable and the affected variable. The results are given in Table 6.

Table 6: Regression results of the effects of digital transformation on organizational performance.

Variables	Model 1 Y_1	Model 2 Y_2	Model 3 Y_3
X	0.0112**	0.0013	0.1782*
	(1.9642)	(0.1780)	(1.6686)
X_2		0.0003	−0.0203**
		(0.4624)	(−2.0545)
DT	−0.0021**	−0.0011	0.0183*
	(−2.1601)	(−1.6010)	(1.8480)
SIZE	−0.0158***	−0.0009	0.1182***
	(−3.2229)	(−0.3383)	(3.0485)
AT	−0.1452***	0.0479***	0.4625***
	(−9.8238)	(5.8519)	(3.9548)
Constant	0.4515***	0.1287	−3.1689***
	(2.9126)	(1.4992)	(−2.5839)
Year	Control	Control	Control
Ind	Control	Control	Control
Observations	2,022	2,022	2,022
R-squared	0.1014	0.0669	0.1928
r2_a	0.0906	0.0552	0.1827
F	9.3856***	5.7198***	19.0701***

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The regression analysis results of Model 1 show that the adjusted R-square value of the model is 0.0906. Owing to the difference in panel data, the goodness of fit of the panel data is generally lower than that of the time-series data. The F-test value is 9.3856 and the p-value is <0.01. In other words, there are more than 99% probability explanatory variables, and the combined influence coefficient of control variables on Y_1 is not 0, that is, the entire model has passed the significance test, and the test of the single variable coefficient can be continued. The probability value corresponding to X is less than 0.05, implying that there is a significant impact, while the influence coefficient is 0.0112, indicating that, there is a significant positive impact, that is, every increase of 1 unit in X will cause an average increase of 0.0112 units in Y. Control variables ST, SIZE, and AT all have significant, and there is a significant negative impact.

The regression analysis results of Model 2 show that the adjusted R-square of the model is 0.0552, the F-test value is 5.7198, and the p-value is <0.01, that is, there are more than 99% probability explanatory variables and the combined influence coefficient of control variables on Y_2 is not 0, that is, the entire model has passed the significance test and the test of the coefficient of a single variable can be continued. Both X and the square term of X are insignificant, that is, there is no nonlinear relationship. The control variable AT has a significant effect, and there is a significant positive effect.

Similarly, the goodness of fit of Model 3 is 18.27%, and the F-test value is 19.0701, indicating that the significance of the overall model has passed the test, and the influence coefficient of X is 0.1782, which is significant at the 0.1 significance level, and the square of X, the influence coefficient of the item is −0.0203, which is significant at the 0.05 significance level, that is, there is an inverted U-shaped curve relationship, thereby implying that, with the increase of X, the number of innovative patents of the enterprise increases, and with the increase of X to a certain extent, the number of innovative patents of enterprises is reduced, and the control variables ST, SIZE, and AT all have significant positive effects.

Table 7: Robustness check.

Variables	(1) Y_1	(2) Y_2	(3) Y_3
X	0.0093*	0.0036	0.2195*
	(1.6585)	(0.4750)	(1.8929)
X_2		0.0000	−0.0247**
		(0.0394)	(-2.2330)
DT	−0.0017*	−0.0011	0.0151
	(−1.7766)	(−1.5564)	(1.4255)
SIZE	−0.0253***	−0.0034	0.1014**
	(−4.8929)	(−1.2098)	(2.3935)
AT	−0.1591***	0.0396***	0.4136***
	(−10.2251)	(4.7411)	(3.2383)
Constant	0.6497***	0.1839**	-2.8047**
	(4.1658)	(2.1958)	(−2.1907)
Year	Control	Control	Control
Ind	Control	Control	Control
Observations	1,738	1,738	1,738
R-squared	0.1226	0.0644	0.1884
r2_a	0.1114	0.0519	0.1775
F	10.8959***	5.1313***	17.3015***

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

4.5. Robustness Check. To examine the robustness of the results obtained in this study, a robustness test can generally be carried out in the form of changing variables, changing estimation methods or changing samples. To prevent the impact of the COVID-19 epidemic, this study removes the sample data in 2020 for analysis. If the explanatory variables, the direction of influence, and the significance of the influence on the affected variables remain unchanged, the robustness test has been passed. See Table 7 for details.

The results show that the influence coefficient of X on Y_1 is 0.0093, which is significant at the 0.1 significance level, that is, there is a significant positive influence, indicating the same directional changes, and the nonlinear relationship between X and Y_2 is also insignificant. There is still an inverted U-shaped relationship between X and Y_3, that is, a relationship between positive and negative, which is also significant. These results are consistent with the previous findings. Therefore, the results of this study are more credible and feasible for further research.

5. Discussion

Digital transformation is a complex system engineering technique, and there are high uncertainties in terms of technical routes, performance results, and social evaluation [84]. This paper analyzes the costs and benefits of digital transformation of small- and medium-sized listed companies from the perspectives of operational, financial, and innovation performance, and then discusses the impact of digital transformation on organizational performance. This study tested three hypotheses. The U-shaped relationship between digital transformation and financial performance is not significant. However, for small- and medium-sized listed companies, digital transformation can reduce costs and increase efficiency through process optimization, affecting the business performance of the organization [18]. Moreover, R&D investment can help improve innovation performance, but the situation is more complicated. This paper verifies that the implementation of digital transformation by enterprises will significantly promote enterprise innovation [46], and it further finds that the two have a curvilinear relationship, that is, digital transformation and innovation performance have an inverted U-shaped relationship.

The existing research on digital transformation and organizational performance is still in the exploratory stage, and the results obtained are mixed with different samples and data [18]. "Performance" is a very important concept in management research, and it is also the most commonly used dependent variable in research. Several industry reports have investigated the impact of digital transformation on business, financial, nonfinancial, market, innovation, and long-term performances [6, 21]. The results of such studies are not sufficiently rigorous and lack a theoretical basis, and there are also academic studies focusing on the impact of specific technologies on organizational performance [23–27]. However, DT is an integration of many technologies. In practice, few companies use only a single technology [69, 72]. At present, the basic principles of performance evaluation include the cost-benefit, capital preservation, principal agent principles, business performance assessment, and strategic planning control [85]. Starting from the cost-benefit principle, we study the potential benefits and advance costs of digital transformation at the microlevel. Only when the value of products and services realized by the enterprise through the exchange is equal to or greater than the cost advanced, the enterprise has the value of existence. To continue to grow and develop, enterprises must do everything possible to expand revenue and reduce costs. We examine the impact of digital transformation on three levels of performance from a cost-benefit perspective, going further than previous research.

We found that digital transformation can improve business performance through DT investments [22, 72]. Digital technology is only a means, and when it needs to be integrated with business and management, corresponding costs are incurred. Our research object is small- and medium-sized listed companies with limited resources. Therefore, in the short term, the benefits of digital transformation cannot cover the advance costs, thereby affecting financial performance. Some studies have found that the intensity of digital transformation reaches a certain threshold (0.284 in the research sample) to have a positive impact on financial performance [18]. Our research found that innovation performance can be improved through R&D investment; however, R&D investment is very expensive. If there is no policy support, there is a certain window period and low success rate for the transformation of patents into products or services, and later, innovation performance will decrease.

6. Conclusion

6.1. Research Implications. The implementation of digital transformation by SMEs is an important strategic choice for their sustainable operation and growth in the rapidly developing digital economy era [33]. The performance of digital transformation is also a core focus, but related research is still in the exploratory stage [18]. Based on a cost-benefit analysis framework, this paper explores the relationship between digital transformation and operational, financial, and innovation performances. The hypothesis is verified based on the second-hand data of 319 small- and medium-sized listed companies in Shanghai and Shenzhen A-share markets in China, and panel regression analysis is performed. The results show that digital transformation can enhance business performance based on process and business improvement. The U-shaped relationship between digital transformation and financial performance is not significant. There is an inverted U-shaped relationship between digital transformation and innovation performance. Summarily, it is easier for SMEs to improve their operational performance through digital transformation investment, but the impact on financial and innovation performance is more complex.

6.2. Management Implications. The results of this study have important practical implications. First, the digital transformation of small- and medium-sized listed companies requires higher costs [51, 57], but it helps to improve operational performance and organizational resilience. This will increase the confidence of managers and decision-makers of SMEs in their pursuit of digital transformation. The inverted U-shaped relationship between digital transformation and innovation performance means that R&D investment contributes to the improvement of innovation performance, but it will decline in the later stage. The U-shaped relationship between digital transformation and financial performance is not significant. Unlike previous transformations that mostly focused on a certain level or a certain business, digital transformation should be more strategic, systematic, and long-term [16, 21]. This also means that digital investment is slow and the cycle is long, and SMEs with limited resources are often eager to see results. In this case, enterprises will feel that digital deployment is "failed" in the short term, and digital value is often affected by management. Questions from employees and weak sustainability of digital investment create a vicious circle [5, 6, 21]. For SMEs, it is more suitable to adopt the strategy of "overall planning and local first" [86]. Starting from sales and procurement, it can reduce costs and quickly increase efficiency, thereby building confidence, and promoting it to the entire enterprise.

6.3. Limitations and Further Research. Although we take a rigorous attitude, some limitations are inevitably entailed in the whole study. First, the sample of this study comprises 319 small- and medium-sized listed companies in China's Shanghai and Shenzhen A-share markets. The regional and limited sample size means that the research results must be further verified. Future studies may consider using larger samples on a larger scale to improve the generalizability of the conclusions. Another limitation of this study is that only three performance indicators are used to measure the digital transformation effect. Future research should consider the performance indicator system, and its setting should comprehensively consider various internal and external environmental and conditional factors that affect corporate performance to establish more comprehensive conclusions. Finally, digital transformation is a long-term systematic project [16, 21]. The current digital transformation of SMEs is uneven, and future research can support a targeted performance evaluation system based on the actual situation and deployment plan of each enterprise. It may be more feasible to progressively stage and evaluate the process and value of digital transformation.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Conceptualization was performed by X. T. and Z. W.; methodology was performed by X. T. and F. Y.; software was provided by X. T.; validation was performed by X. T. and F. Y.; formal analysis was performed by X. T.; resources were provided by X. T.; data curation was performed by X. T. and Z. W.; original draft preparation was performed by X. T.; review and editing was performed by X. T. and Z. W.; visualization was performed by X. T.; supervision was performed by Z. W. All authors have read and agreed to the published version of the manuscript.

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