Measurement Problem of Enterprise Digital Transformation: New Methods and Findings Based on Large Language Models

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Abstract: *Despite broad consensus on the importance of enterprise digital transformation, significant discrepancies persist regarding its actual effects. This divergence stems primarily from two key measurement challenges: (1) a lack of clear and consistent definitions of enterprise digital transformation, and (2) a lack of rigorous and accurate measurement methodologies. These shortcomings lead to research findings that are incomparable, difficult to replicate, and often conflicting. To effectively address the aforementioned challenges, this paper employs machine learning and large language models (LLMs) to construct a novel set of indicators for enterprise digital transformation. The work begins by manually annotating sentences from annual reports of listed companies in China from 2006 to 2020. These labeled sentences are then used to train and fine-tune several machine learning models, including LLMs. The ERNIE model, demonstrating the best classification performance among the models tested, is selected as the sentence classifier to predict sentence labels across the full text of the annual reports, ultimately constructing the enterprise digital transformation metrics. Both theoretical analysis and multiple data cross-validations demonstrate that the metrics developed in this paper are more accurate than existing approaches. Based on these metrics, the paper empirically examines the impact of enterprise digital transformation on financial performance. Our findings reveal three key points: (1) enterprise digital transformation significantly enhances financial performance, with big data, AI, mobile internet, cloud computing, and the Internet of Things (IoT) all playing a significant role; however, blockchain technology does not show a significant effect; (2) the significant positive effect of digital transformation on financial performance is primarily observed in firms with weaker initial financial performance; and (3) enterprise digital transformation improves financial performance mainly through enhancing efficiency and reducing costs. This research has practical implications for promoting enterprise digital transformation and fostering high-quality economic development.*

Keywords: *Enterprise digital transformation; digital economy; digital technology; AI; large language models (LLMs)*

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1. Introduction

Humanity is undergoing a shift from the industrial economy to the digital economy. In this context, the Report to the 20th National Congress of the Communist Party of China underscored the critical need to "accelerate the development of the digital economy and foster the deep integration of the digital economy with the real economy". For businesses, this integration represents a fundamental transformation toward digitalization. Digital transformation, in essence, involves harnessing digital technologies to fundamentally overhaul production systems, operational processes, management models, and core business strategies—ultimately driving disruptive innovation and reshaping industries (Siebel, 2019). As the digital economy continues to evolve, digital transformation has emerged as widely discussed issue for businesses worldwide. A 2020 report by the Boston Consulting Group (BCG) revealed that more than 80% of companies worldwide have been engaged in digital transformation initiatives[1]. For Chinese enterprises, the rapid expansion of the digital economy presents both significant opportunities and considerable challenges. In 2021, China's digital economy reached a staggering scale of \$7.1 trillion, second only to that of the United States, and accounted for 39.8% of the nation's GDP (China Academy of Information and Communications Technology, CAICT, 2022a).[2]

Practice serves as the foundation of theory. The latecomer advantages of China in the digital economy have spurred a burgeoning wave of research among Chinese scholars on the enterprise digital transformation. The number of papers on this topic indexed in CNKI (China National Knowledge Infrastructure) rose sharply from 110 in 2018 to 961 in 2022. Similarly, the number of related English-language papers indexed in the EconLit database grew from 48 in 2018 to 141 over the same period. Notably, the proportion of articles authored by Chinese scholars increased from 2% in 2018 to 25% in 2022.

While it is widely agreed in both industry and academia that enterprises should pursue digital transformation, there are sharply contrasting views on its success. A survey of 1,793 business executives by McKinsey, a prominent management consulting firm, suggests that over 80% of digital transformation initiatives fail[3]. This contrasts starkly with academic research, where numerous empirical studies of both Chinese and foreign firms generally find that digital transformation significantly improves financial performance (Zhao et al., 2021; Commander et al., 2011; Müller et al., 2018). Of course, even with some consensus on the overall positive effect, academics disagree on the specific impacts of digital transformation. For instance, DeStefano et al. (2018), using survey data from UK firms between 1999 and 2005, found that while digital transformation expanded firm size, it did not improve total factor productivity. Similarly, Liu et al. (2021), based on a five-year longitudinal survey of 1,950 Chinese firms, found a non-linear, inverted U-shaped relationship between digital transformation and efficiency.

This significant divergence between industry and academic perspectives on the success of enterprise digital transformation, we argue, stems primarily from problems in how digital transformation is measured. This is evident in two aspects: first, a lack of consistent and clear definitions of what constitutes digital transformation, leading to incomparable and even irreproducible results across studies; and second, a lack of rigorous and accurate measurement methodologies. Existing literature largely relies on the dictionary-based approach using listed companies' annual reports to measure the level of enterprise digital transformation (Wu et al., 2021; Fang et al., 2022). However, the dictionary-based approach has two significant flaws: (1) the dictionaries' coverage of digital technology keywords is incomplete, leading to some genuine digital transformation efforts being overlooked (Type I error: the

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[1] See: BCG: The Evolving State of Digital Transformation, September 25, 2020, https://www.bcg.com/publications/2020/the-evolving-state-of-digital-transformation.

[2] Both narrow and broad estimations of the digital economy by the United Nations in 2019 ranked the United States and China first and second worldwide, respectively (Chen, 2020). A detailed analysis of measuring the size of China's digital economy is provided by Cai and Niu (2021).

[3] See: "Unlocking success in digital transformations", October 2018, http://www.mcKinsey.com.

firm uses digital technology but it is not identified by the dictionary method); and (2) inaccurate semantic interpretation, incorrectly classifying some textual content as digital transformation when it does not reflect actual use of digital technology (Type II error: the text mentions keywords but digital technology is not actually implemented). Furthermore, different digital technologies can have varying effects on financial performance. For example, artificial intelligence (AI) might enhance financial returns, while blockchain might only increase production costs. In such cases, it is impossible to make a blanket judgment about the success or failure of digital transformation. Therefore, if theory is to inform practice, academia must reach a consensus on how to measure enterprise digital transformation and focus on mitigating the problem of inaccurate measurement methods. Only then can we clarify the confusion, reduce discrepancies, and provide theoretical insights into the widespread reluctance and hesitancy currently faced by Chinese enterprises in their digital transformation journeys.

Building upon a critical assessment of the strengths and weaknesses of existing literature, this paper employs cutting-edge machine learning methods and LLMs[4] to construct a set of digital transformation metrics for 4,181 listed Chinese companies, based on their annual reports from 2006 to 2020. This approach aims to comprehensively capture the actual usage of various digital technologies within enterprises. Specifically, the measurement of digital transformation proceeds in five steps:

(1) Data collection and preparation: Annual reports of listed companies, collected through web scraping and manual retrieval, were compiled. The "Management Discussion and Analysis" and "Directory, Interpretation, and Major Risk Warnings" sections of these reports were identified as the relevant text for analyzing enterprise digital transformation.

(2) Sentence segmentation: The relevant text was segmented into individual sentences using periods and semicolons, creating a sentences-for-prediction pool.

(3) Manual labeling: A sentences-to-label pool was created by randomly sampling sentences and also selecting sentences containing relevant keywords. This sentences-to-label pool was then manually annotated to determine whether the enterprise had undergone digital transformation.

(4) Model training: Supervised machine learning methods, including the large language model ERNIE[5], were employed to train sentence classification models based on the labeled dataset.

(5) Prediction and metric construction: The trained ERNIE model, selected for its superior classification performance, was used to predict the labels of each sentence in sentences-for-prediction pool, determining whether and which digital technologies were used by the listed companies. This process ultimately yielded a new set of enterprise digital transformation metrics.

To validate the effectiveness of these new metrics, we conducted six comparative analyses, benchmarking them against patent data, regional data, and findings from international literature. These comparisons consistently demonstrated a strong alignment between the metrics developed in this paper and real-world observations. Compared to the dictionary-based approach, the metrics constructed in this paper are more comprehensive in content and more accurate in semantic representation.

Building on the enterprise digital transformation metrics constructed using the new methodology, this paper empirically examines the relationship between enterprise digital transformation and financial performance, yielding three key findings: First, overall, enterprise digital transformation significantly enhances financial performance (ROA and ROE). However, not all digital technologies contribute equally to this positive effect. Specifically, big data, AI, mobile internet, cloud computing, and the Internet of Things all significantly improve both ROA and ROE, while blockchain does not demonstrate

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[4] LLMs refer to language models trained on massive amounts of text and containing an extremely large number of parameters. As a type of AI technology, they use deep learning algorithms to process natural language. They can use vast amounts of data to identify, summarize, translate, predict, and generate text and other content. ChatGPT, which became globally popular at the end of 2022, is a specific application of a large language model.

[5] The ERNIE model, developed by Baidu, is a large language model whose full name is Enhanced Representation through Knowledge Integration.

a significant positive impact on either. Second, the effect of digital transformation varies across firms with different levels of financial performance. For firms with weaker financial performance, digital transformation significantly improves ROA and ROE. Conversely, for firms with stronger, particularly very strong, financial performance, the effect of digital transformation on ROA and ROE is not significant. Third, enterprise digital transformation primarily improves financial performance through two channels: enhancing efficiency and reducing costs. The channel of increasing revenue was not empirically supported.

This paper contributes to the literature in three main ways:

First, it provides a novel method for measuring enterprise digital transformation, thus laying a solid empirical foundation for digital transformation research. With the global rise of the digital economy, "digital economics" has emerged as a new field of study, and enterprise digital transformation is a key component of this field (Goldfarb and Tucker, 2019). In recent years, Chinese and international scholars have studied the impact of digital transformation on firm behavior and performance from various perspectives, including investment in digital technologies (Liu & Tian, 2019; Qi et al., 2020), the use of digital equipment (Acemoglu and Restrepo, 2020; Bloom et al., 2014; Brynjolfsson et al., 2021), and keyword extraction related to digital technologies (Fang et al., 2022; Wu et al., 2021; Yang and Liu, 2018; Yuan et al., 2021; Zhang et al., 2021; Zhao et al., 2021). However, due to inconsistencies and ambiguities in the measurement of digital transformation, as well as a lack of rigorous and accurate measurement methods, the results of different studies are often incomparable, difficult to replicate, and sometimes even contradictory. By leveraging machine learning and LLMs, this paper offers a set of digital transformation metrics characterized by clear definitions, comprehensive coverage, high accuracy, and replicability, providing a viable solution to mitigate these issues. Therefore, this paper contributes to advancing the in-depth study of enterprise digital transformation from a methodological perspective and provides empirical evidence from China to the broader digital economics literature. Given that China is both a rapidly developing nation and a dominant force in the global digital economy, we believe our approach - constructing enterprise digital transformation metrics from listed company texts and leveraging machine learning methods - provides valuable insights for both emerging and developed economies alike.

Second, this paper contributes to the literature on digital transformation by examining the distinct effects of various digital technologies on firm financial performance and identifying the specific channels through which these technologies influence outcomes. Existing literature analyzing the impact of digital transformation on firm performance often treats the adoption of any digital technology as synonymous with digital transformation itself (He & Liu, 2019; Zhao et al., 2021), or focuses on only one particular technology (Bloom et al., 2014). However, different digital technologies can, in fact, lead to varying transformation outcomes, and in practice, firms may adopt only a subset of available technologies. Drawing on government official statistical classifications and definitions from authoritative institutions, we classify digital technologies into six categories: big data, artificial intelligence, mobile internet, cloud computing, the Internet of Things (IoT), and blockchain. Our findings indicate that blockchain does not significantly impact firm financial performance, whereas the other five technologies have a notable positive effect. Furthermore, in terms of impact channels, we identify significant improvements through efficiency and cost channels but find no support for a revenue channel, corroborating with existing research. By offering a more granular classification of digital technologies and examining their distinct impact channels, this paper adds new insights to the literature on digital transformation and its effects on firm performance.

Third, this paper contributes to the growing body of literature on the application of large language models in economics. As AI and machine learning technologies continue to advance, scholars have increasingly turned to LLMs for microeconomic research. For instance, Xu and Tian, (2021) employed the BERT model to conduct sentiment analysis on financial news texts and predict the relationship between sentiment and stock market fluctuations. Liu and Xiao, (2023) used BERT[6] to develop a patent text classification model, which helped identify patents related to labor-saving technologies within a patent database. Similarly, Acikalin et al. (2022) trained the Longformer model (an advanced version of BERT) on 23,734 labeled patent texts to predict how a firm's patents might be impacted by specific U.S. legal precedents. Rajan et al. (2023) pre-trained a BERT model using 9,000 letters to shareholders from U.S. listed companies (spanning 1955-2020) and manually labeled approximately 2% of paragraphs to help the model identify company objectives, which they then analyzed for timing and reasons behind objective announcements.

Unlike these studies, which predominantly rely on BERT-based models, this paper leverages the ERNIE model (Sun et al., 2019), which is specifically designed to better accommodate the Chinese language context. By applying ERNIE to economic research, this study opens up new possibilities for utilizing large language models in the Chinese-language economic literature.

The remainder of this paper is organized as follows: Section 2 offers a thorough review of existing metrics for enterprise digital transformation; Section 3 outlines the methodology used to develop new digital transformation metrics leveraging machine learning and LLMs, and demonstrates their effectiveness through multiple validation approaches; Section 4 presents novel insights by analyzing the performance outcomes of enterprise digital transformation; and, finally, Section 5 concludes with key takeaways and policy implications.

2. Challenges in Measuring Digital Transformation: Literature Review

2.1 Three Methods for Measuring Enterprise Digital Transformation

Existing literature typically employs three main methods to assess the extent of enterprise digital transformation. The first method, the objective data approach, involves measuring various indicators related to digital technology adoption. This can include calculating the proportion of a firm's investments in digital technologies - such as software and hardware - relative to its total assets (Liu and Tian, 2019; Qi et al., 2020; Müller et al., 2018). Other examples include assessing the use of robots within enterprises through survey data (Acemoglu and Restrepo, 2020), analyzing the adoption of forecasting tools (Brynjolfsson et al., 2021), or measuring industry-level information technology (IT) intensity based on investments in computer software and hardware (Chun et al., 2008).

The second method is the event study approach, which evaluates enterprise digital transformation by examining how digital transformation policies influence a firm's group affiliation (region, industry). Commonly studied policies include the "Broadband China" initiative implemented by the State Council (Li et al., 2022), the "Integration of Informatization and Industrialization" policy introduced by the Ministry of Industry and Information Technology (MIIT) (Li et al., 2022), and the designation of National Information Consumption Pilot Cities (Fang et al., 2022). These policy events, or "policy shocks", serve as key instruments for analyzing the effects of digital transformation. They are also frequently employed to mitigate endogeneity concerns in research on how digital transformation impacts firm behavior and performance.

The third and most prevalent method is the dictionary-based approach. This involves first constructing a dictionary of keywords related to various digital technologies and then creating enterprise digital transformation metrics based on the frequency or proportion of these keywords appearing in the "Management Discussion and Analysis" section of listed companies' annual reports[7]. The underlying

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[6] BERT (Bidirectional Encoder Representations from Transformers) is a large language model developed by Google.

[7] This proportion represents the ratio of these keywords (or sentences containing these keywords) to the total number of words (or sentences) in the "Management Discussion and Analysis" section of the annual report. Some databases (CSMAR) or studies (Wu et al., 2021) only count the frequency of digital technology keywords when calculating enterprise digital transformation metrics, without calculating the proportion.

assumption of this method is that mentioning a keyword related to a digital technology indicates that the enterprise has undertaken digital transformation. Therefore, the higher the frequency or proportion of digital technology keywords mentioned in a listed company's annual report, the greater the extent of its digital transformation. This method is widely used in the literature, including studies by Yang and Liu (2018), Wu et al. (2021), Yuan et al. (2021), Zhao et al. (2021), Zhang et al. (2021), and Fang et al. (2022).

To be fair, the three methods outlined above provided a solid foundation for Chinese scholars to begin exploring the critical field of enterprise digital transformation. However, as the literature on this topic continues to grow, it is now essential for academia to critically assess the limitations of these approaches and work toward developing more comprehensive and refined measurement techniques to advance research in this area. The objective data approach, in particular, has two main drawbacks. First, its scope is relatively narrow, limiting its applicability to non-labor cost investments in specific digital technologies. For instance, when a company hires engineers to contribute to its digital transformation efforts, the wages paid to these professionals should be considered part of the transformation investment. However, this is often excluded from analyses that focus solely on investments in digital hardware or software. Second, the approach tends to be overly simplistic. For example, merely aggregating expenditures on digital hardware and software fails to capture the diverse applications of different types of digital technologies, such as big data and AI, each of which may have distinct implications for the enterprise's transformation.

The event study approach also has two main limitations. First, it assumes that all firms within a pilot region are affected to the same extent by a given digital technology policy, which is clearly not the case in reality. In fact, even within pilot regions, not all firms are impacted by the policy. For example, Jin et al. (2021) found that the "Broadband China" policy had a significant impact on the innovation and total factor productivity (TFP) of local private and growing firms but did not have a significant impact on state-owned enterprises (SOEs) or firms in decline. Second, firms in pilot regions are likely to be affected by other regional policies. Although parallel trend tests can rule out the interference of other policies within the sample period, they cannot exclude other policies implemented concurrently with the pilot policy. Furthermore, the simultaneous implementation of multiple related policies within a short period, coupled with policy lags, makes it difficult to distinguish the actual effects of different policies.

2.2 Limitations of the Dictionary-Based Method in Measuring Digital Transformation: Two Key Issues

Given that the dictionary-based approach is the predominant method used in domestic literature to measure digital transformation, we focus our analysis on its limitations. Many studies on enterprise digital transformation directly use the digital technology keyword frequency statistics provided by the CSMAR database as an indicator of the extent of enterprise digital transformation (Huang et al., 2023; Yao and Zhao, 2023). Therefore, we use the CSMAR keyword dictionary as the primary object of our analysis. The CSMAR dictionary contains a total of 62 digital technology keywords, such as "machine learning", "digital currency", "Internet of Things", and "data mining", and categorizes them into four types of technologies: AI (27 keywords), blockchain (8 keywords), cloud computing (17 keywords), and big data (10 keywords).

The primary issue with the dictionary-based approach, as demonstrated by CSMAR, is the incomplete construction of its dictionary, which may overlook many key terms related to digital technologies. In our analysis of annual report texts, we identified several instances where companies discussed their use of digital technologies, yet the relevant technical terms were missing from the dictionary. For example: (1) "*Second, we focus on creating scenarios to address users' everyday needs, such as travel, healthcare, and education, and provide financial service capabilities through 'cloud +*

API' application programming interfaces to enhance customer retention and product penetration;*"* [8](2) "*Using optical character recognition (OCR) technology to streamline document identification, the recognition success rate exceeds 98%, improving business review efficiency*;*"*[9] (3) "*We have completed the research and development of techniques to enhance the usability of dialect and minority language recognition at a lower cost, significantly improving the recognition accuracy for dialects, Uyghur, and Tibetan*;*"*[10] (4) "*With advanced image recognition algorithms, we ensure an accuracy rate of over 95% in image recognition".*[11] In these examples, terms like "cloud + API", "OCR", "minority language recognition", and "image recognition" clearly indicate the company's use of relevant digital technologies, yet these key terms are absent from the CSMAR dictionary.

The omission of keywords arises because researchers manually select these terms based on a limited body of existing literature, making it challenging to apply consistent selection criteria across different individuals. Moreover, digital technologies evolve rapidly, with new terms emerging regularly. As a result, relying on a dictionary-based approach to measure digital transformation inherently leads to issues of incompleteness and delayed updates. In fact, keyword dictionaries used in other studies, in addition to the CSMAR dictionary, also face similar challenges of omission.

An ancillary issue arises from the subjective selection of keywords by researchers: differing individual standards and selection scopes lead to significant variations in the keywords chosen across different studies, making digital transformation metrics based on different dictionaries difficult to compare. For instance, several representative studies that disclose their keyword dictionaries illustrate this disparity. Wu et al. (2021) use a dictionary with 76 keywords, Li et al. (2022) include 95 keywords, Yang et al. (2022) also have 76 keywords, and Fang et al. (2022) lists 112 keywords. Among them, Fang et al. (2022) covers the widest scope, while the CSMAR dictionary contains the fewest, resulting in limited overlap between the dictionaries. Specifically, the CSMAR dictionary shares 62 keywords with both Wu et al. (2021) and Li et al. (2022), representing 63% of the total keywords in the CSMAR dictionary (i.e., an overlap rate). However, Wu et al. (2021) and Li et al. (2022) do not use exactly the same keywords, with the latter including 19 more than the former. Additionally, despite Fang et al. (2022) containing the largest number of keywords, it shares only 19 keywords with Li et al. (2022) - resulting in a mere 17% overlap rate between these two dictionaries.

The second major limitation of the dictionary-based approach is its propensity to misclassify textual content that does not genuinely reflect a firm's digital transformation activities. Using CSMAR as a case in point, we observe that even when a sentence within a listed company's annual report contains digital technology keywords, the surrounding context often reveals that the firm has *not* actually implemented such technologies. This misclassification arises in at least three distinct scenarios: first, the sentence employs negative phrasing, explicitly denying current adoption; second, the company expresses *future intentions* to engage in digital transformation rather than describing current practices; and third, the discussion focuses on broader *industry trends* rather than the firm's own digital initiatives. These scenarios inevitably lead to inaccuracies when using a purely keyword-based approach.

We provide the following illustrative examples for each scenario: (1) "To mitigate project uncertainties and R&D risks, the company has temporarily decelerated the development of its smart education robot research center project and, consequently, has not yet made substantial investments;[12]" (2) "Looking ahead, the company intends to capitalize on the rapid growth of the Internet of Things sector to

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[8] The 2018 Annual Report of the Listed Company (Stock Code: 600036).
[9] The 2020 Annual Report of the Listed Company (Stock Code: 000001).
[10] The 2017 Annual Report of the Listed Company (Stock Code: 002230).
[11] The 2017 Annual Report of the Listed Company (Stock Code: 002767).
[12] The 2019 Annual Report of the Listed Company (Stock Code: 300010).

expand its business operations and enhance profitability;"[13] (3) "In 2021, the company will pursue steady growth in its large-screen and professional display business, further diversifying its product portfolio and leveraging emerging opportunities in seven key areas: 3G base station construction, ultra-high-voltage power transmission, intercity rail transit, electric vehicle charging infrastructure, data centers, artificial intelligence, and the industrial Internet".[14] While the dictionary's incomplete keyword coverage might be considered a relatively minor oversight, the more critical flaw lies in the mechanical reliance on keyword presence to determine whether a firm has undergone digital transformation. The former issue constitutes a Type I error (false negative) - the firm has adopted digital technologies but is not identified as such by the dictionary-based method. The latter constitutes a Type II error (false positive) - keywords are present in the text, but the firm has not actually implemented the corresponding technologies. The novel measurement approach we propose aims to mitigate both of these types of errors.

3. A LLM-Based New Measurement Approach

3.1 The Large Language Model ERNIE

While the dictionary-based approach to text analysis is relatively straightforward to implement, it falls short in fully capturing the nuances and depth of the information within the text. This limitation often results in lower analytical accuracy and reduced metric validity. In contrast, recent advancements in natural language processing (NLP) have significantly enhanced text analysis. NLP, an interdisciplinary field that combines computer science, linguistics, and cognitive science, focuses on enabling machines to understand, interpret, and generate human language. Its primary applications include machine translation, sentiment analysis, automated summarization, opinion extraction, text classification, question answering, semantic comparison, speech recognition, and optical character recognition (OCR).

A typical NLP pipeline for machine learning tasks involves several key steps: data pre-processing, text representation, and model training for the target task. In recent years, the development of pre-training techniques has been a major driver of progress in NLP. Pre-training involves first training a model on a broad source task, then fine-tuning it on more specific downstream tasks (often referred to as target tasks) to enhance their accuracy (Che et al. (2021). This two-stage process plays a critical role in improving the quality of text representation and, by extension, the performance of models on specialized tasks. Pre-training has thus proven particularly valuable in refining text representations and boosting the overall effectiveness of downstream NLP applications.

The development of pre-training techniques can be divided into three stages: early static pre-training techniques, classic dynamic pre-training techniques, and recent novel pre-training techniques Li et al. (2020). The difference between static and dynamic lies in whether the representation of words changes with context. Dynamic pre-training techniques mainly include two categories of large language models: GPT and BERT. These models pioneered context-based text representation methods, resolving the problem of polysemy (one word having multiple meanings). However, in Chinese expression, knowledge mostly appears in units of words composed of individual characters (or short phrases acting as one unit), making it difficult for the BERT model to learn the complete semantic representation of these knowledge units. The ERNIE model, a novel pre-training technique based on improvements to the BERT model, introduces knowledge by masking words (knowledge units), further enhancing the model's semantic representation capabilities. Furthermore, regarding training data, BERT uses only encyclopedia-like corpora to train the model, while ERNIE uses encyclopedia-like, news information, and forum dialogue corpora. Experiments have demonstrated that the ERNIE pre-trained model exhibits comprehensive

[13] The 2019 Annual Report of the Listed Company (Stock Code: 603236).
[14] The 2020 Annual Report of the Listed Company (Stock Code: 000727).

performance surpassing BERT on five Chinese text classification tasks (Sun et al., 2019).[15] Based on these reasons, this paper chooses to primarily use the large language model ERNIE to complete the text classification task.

3.2 An ERNIE-Based Approach to Measuring Enterprise Digital Transformation

3.2.1 Step 1: Identifying the textual data for analysis

Given that digital transformation encompasses changes across multiple dimensions of a firm, including its organizational structure, internal management, and business processes, it is difficult to fully reflect in financial indicators. However, listed companies have a strong incentive to disclose information about their digital transformation efforts in annual reports to attract attention from the capital markets. As a result, text analysis of annual reports has become a common method in the literature for assessing the extent of digital transformation (Fang et al., 2022). In line with established practices, this paper also employs the annual reports of listed companies as the primary source of text for constructing metrics to measure enterprise digital transformation. We collected the annual reports of listed companies through two primary channels: web scraping and manual collection. The information sources included Wind, CNINFO, and the companies' official websites. Given that the new *Accounting Standards for Business Enterprises*, effective from January 1, 2007, introduced significant changes to corporate financial reporting requirements - and since the 2006 annual reports were actually disclosed in the first quarter of 2007 - we focused our analysis on the annual reports disclosed between 2006 and 2020. Within these annual reports, the "Management's Discussion and Analysis" (MD&A) section provides valuable insights into the company's operating performance during the reporting period, outlines future development strategies, and discloses the risks the company faces. As a result, the MD&A section is commonly used in existing literature to calculate the frequency or proportion of digital technology keywords (Yuan et al., 2021; Zhao et al., 2021). Additionally, some companies disclose potential risks in the "Contents, Definitions, and Significant Risk Warnings" section, which may also include information relevant to their digital transformation efforts. Therefore, this paper selects both the "Management's Discussion and Analysis" and the "Contents, Definitions, and Significant Risk Warnings" sections as the textual data sources. In total, we compiled 39,175 annual report texts from 4,181 companies spanning the years 2006 to 2020.

3.2.2 Step 2: Creating the prediction and labeling pool

We began by segmenting the entire text into sentences using periods and semicolons to create the sentences-for-prediction pool. Because most sentences in annual reports are unrelated to digital transformation, purely random sampling would result in an inefficient review process dominated by irrelevant labels. Therefore, to maximize efficiency and minimize contextual bias, we employed keyword extraction to identify representative sentences, which were then combined with randomly sampled sentences to form the sentences-to-label pool[16]. To facilitate this process, we first defined "digital technology" and constructed a corresponding dictionary to guide the keyword extraction.

In defining digital technology, we initially referred to official policy definitions. The National Bureau of Statistics (NBS), in its *Statistical Classification of Digital Economy and Its Core Industries (2021)*, identifies representative technologies of industrial digitalization as digital technologies such as

[15] For example, BERT can infer that "Bei[x] is the capital of China", where [x] is "jing" , but it cannot learn about the knowledge unit "Beijing" as a whole. In contrast, ERNIE 1.0 can predict that "[xx] is the capital of China", where "[xx]" is "Beijing", thereby learning the relationship between Beijing and the capital of China.

[16] This approach of narrowing the scope of random review by constructing a keyword dictionary is widely adopted in similar studies. For instance, Chen et al. (2019) employed a supervised machine learning method to classify FinTech-related patent texts. Before conducting manual review, they used a self-constructed financial dictionary to filter relevant documents from the original text corpus, which were then extracted for labeling.

the Internet of Things (IoT), AI, big data, cloud computing, and mobile internet. The State Council, the Ministry of Industry and Information Technology (MIIT), and other departments have repeatedly issued policy documents proposing guidelines for promoting the development of digital technologies such as big data, AI, cloud computing, IoT, mobile internet, and blockchain. We then drew on the definitions from the business community. Pony Ma, Chairman of the Board of Tencent Computer Systems Co., Ltd., a leading Chinese digital technology company, pointed out in *The Chinese Digital Economy* that in recent years, digital technologies such as mobile Internet, cloud computing, big data, AI, the Internet of Things (IoT), and blockchain have continuously achieved breakthroughs and integrated development, promoting the rapid development of the digital economy (Ma et al., 2021). Synthesizing the above definitions, this paper categorizes digital technology into six types: big data, AI, mobile internet, cloud computing, IoT, and blockchain[17].

Based on policy texts, research reports, and existing literature, and through continuous supplementation after manual review, we compiled a dictionary containing 311 digital technology keywords[18]. We then extracted annual report texts containing 10 or more distinct keywords and extracted the sentences containing those keywords[19]. To improve the model's predictive ability for sentences without keywords, we also randomly extracted some annual reports and segmented them into sentences. Because the total number of listed companies increases year by year, directly performing random labeling on the above two sets of sentences would result in most of the labeled sentences being concentrated in recent years. To address this uneven distribution across years, we grouped these sentences by year, extracted the same number of sentences from each year, and then performed random sampling without replacement from this evenly distributed set of sentences to obtain the sentences-to-label pool for this study. Ultimately, the sentences-to-label pool for this study contains 38,994 sentences.

3.2.3 Step 3: Manually labeling the sentences in the sentences-to-label pool

The rationale behind manual labeling is to initially identify the specific digital technologies a company has implemented, and then assess whether those technologies indicate that the company has undergone digital transformation. This process is essential for constructing accurate training, testing, and validation datasets, which will serve as the foundation for subsequent machine learning models.

We divided 24 researchers into 12 pairs, with each pair rotating periodically. To ensure consistent labeling standards, we conducted multiple sessions explaining the details of the labeling task before formal labeling began, with a focus on clarifying and demonstrating easily confused labels. After establishing clear standards, we conducted thorough labeling training and regularly discussed difficulties and ambiguities encountered during the annotation process. During formal labeling, each sentence in the sentences-to-label pool was labeled by two research team members. If both members' labels agreed, the sentence's label was recorded. For sentences with conflicting labels, the entire team discussed and determined the final label. Sentences for which a definitive label could not be determined were excluded from the training set. Finally, all sentences in the labeling sentence corpus, except those with indeterminable labels, were classified into eight categories: six novel digital technologies, non-novel digital technologies[20], and non-digital technologies.

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[17] Due to space constraints, the specific definition of digital technology and examples are not shown in the main text and are available upon request.

[18] Due to space constraints, the detailed list of digital technology keywords is not shown in the main text and are available upon request.

[19] The threshold of 10 or more keywords is an empirical value; lowering this threshold would capture a larger number of annual reports but could reduce the efficiency of manual review. Additionally, we do not directly search for sentences containing keywords within the prediction sentence corpus, as this approach complicates tracking their source. By first extracting the relevant annual reports and then selecting sentences, we not only ensure randomness but also maintain the traceability of each sentence's origin, which facilitates both labeling and error checking.

[20] "Non-novel" digital technologies refer to traditional digital technologies or generic terms for digital technology. Examples include terms like "the Internet", "platform economy", "digitalization", "digital technology", and "intelligentization".

3.2.4 Step 4: Employing supervised machine learning for model training

A key step in measuring digital transformation is using machine learning models to determine whether digital technology keywords in text accurately reflect a company's actual digital transformation. This helps address the challenge of keywords being mentioned without the actual implementation of the corresponding technologies. To achieve this, we relied on classification models. We used the PaddleHub framework, an open-source platform from Baidu that integrates ERNIE, for training the model. The framework's built-in tokenizer quickly converts sentences into the format required for ERNIE. We split the labeled sentences into training, testing, and validation sets in an 8:1:1 ratio. For model comparison, we also trained BERT_base_Chinese using PaddleHub and tested seven other common models based on the sklearn framework: Support Vector Machine (SVM), Neural Networks, a Voting algorithm combining SVM and Neural Networks[21], K-Nearest Neighbors (KNN), and Gaussian Naive Bayes (GaussianNB).

The primary objective of the machine learning model is to identify whether and which digital technologies are reflected in the text. For classification tasks like this, model performance is typically evaluated using metrics such as Precision, Recall, and Accuracy. Given the imbalanced distribution of labels across different classes in the training set, the F-score is also commonly used to assess overall classification performance[22].

Among these metrics, Precision refers to the proportion of correctly predicted positive samples out of all samples predicted as positive. A model with high Precision accurately identifies truly positive samples, reducing the risk of false positives. In this paper, Precision measures the proportion of sentences classified as related to digital technology that are indeed labeled as such. Recall measures the proportion of correctly predicted positive samples out of all actual positive samples. A model with high Recall can identify as many actual positives as possible, minimizing false negatives. Given that multiple sentences in annual reports may indicate a company's use of digital technologies, correctly classifying these sentences is particularly important. Therefore, we also calculate the F0.8-score, which places greater emphasis on Precision.

Upon comparing the performance of different models on the same training set, we found that ERNIE achieved Precision, Recall, Accuracy, F1-score, and F0.8-score values of 81%, 70%, 93%, 75%, and 76%, respectively. While ERNIE lags behind BERT in Recall (which impacts the F1-score), its higher Precision results in the highest F0.8-score among all the models. Based on these findings, we select ERNIE as the final sentence classification model.

Panel A of Figure 1 compares the performance of the models, showing that ERNIE and BERT outperform other common classification models in terms of overall classification ability (F1 and F0.8)[23].

3.2.5 Step 5: Constructing enterprise digital transformation metrics via the ERNIE model

Leveraging the ERNIE large language model, we performed prediction on each sentence within the 2006-2020 sentences-for-prediction pool to ascertain both the presence and type of digital technologies

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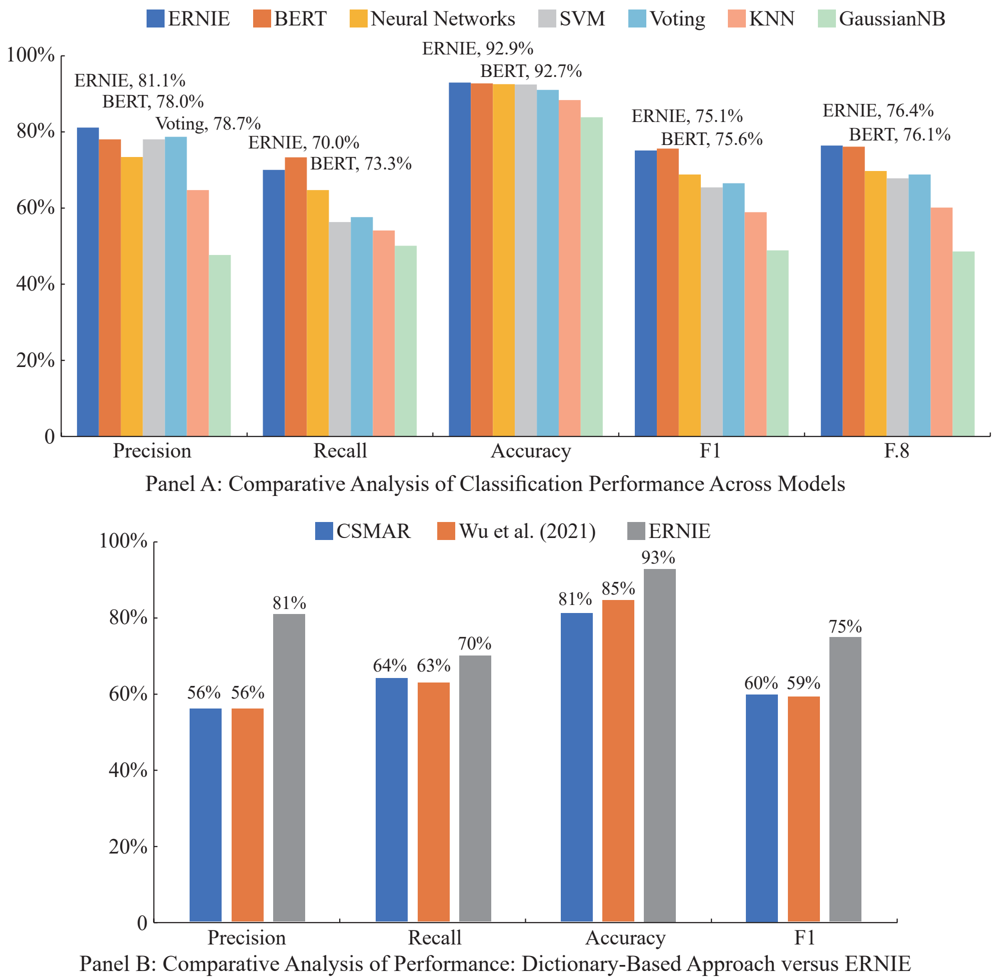
[21] The classification performance of SVM and NN is strongest among the selected traditional algorithms; therefore, we construct a Voting model by combining these two algorithms.

[22] Precision measures the proportion of sentences predicted as positive (i.e., "Yes") that are actually positive. Recall assesses the model's ability to identify all the positive sentences in a report. Accuracy measures the overall correctness of the model's classifications, including both positive and negative classes (i.e., "No"). F1-score is the harmonic mean of Precision and Recall. For example, assume a text contains 100 sentences, and 10 sentences are manually judged to be related to digital technology. The model predicts that 12 sentences are related to digital technology, and upon comparison, it is found that 8 of the 12 predicted sentences match the manual judgment. In this case, the Precision is 8/12 = 0.75, and the Recall is 8/10 = 0.8. The main difference between these two metrics lies in the denominator. Additionally, this result indicates that the model made 4 errors in predicting 90 negative sentences and 2 errors in predicting the 10 positive sentences. Therefore, the Accuracy is calculated as [(10 - 2) + (90 - 4)] / 100 = 0.94.

F-score = $(1 + \beta^2) \times$ Precision $\times$ Recall / ($\beta^2 \times$ Precision + Recall).

F1-score = $(1+1^2) \times$ Precision $\times$ Recall / ($1^2 \times$ Precision + Recall) = 0.774. For F.8-score, $\beta = 0.8$.

[23] Due to space limitations, the specific performance of different models across all metrics is not shown in the main text and are available upon request.



Panel A: Comparative Analysis of Classification Performance Across Models

Panel B: Comparative Analysis of Performance: Dictionary-Based Approach versus ERNIE

Figure 1: Comparison of Classification Performance of Different Methods

a firm utilized. We then constructed an enterprise digital transformation dummy variable, assigning it a value of 1 if a firm employs any of the following technologies in a given year - big data, artificial intelligence, mobile internet, cloud computing, blockchain, or the Internet of Things - and 0 otherwise.[24]

3.3 Validation of the Enterprise Digital Transformation Metrics

While we have demonstrated the theoretical rationale for using the large language model ERNIE to develop enterprise digital transformation metrics, a crucial question remains: Do the metrics generated through this novel approach offer greater accuracy and a more realistic reflection of the transformation process? To address this, we thoroughly evaluate the validity of our new method from six key perspectives: classification performance, patent data, time trends, regional variations, industry differences, and international comparisons.

[24] We opted not to construct a continuous variable of enterprise digital transformation based on the quantity or proportion of digital technology-related sentences. The rationale for this decision is that while repeated mentions of digital technology keywords within a firm's annual report - assuming truthful representation - demonstrate engagement in digital transformation, they do not provide a reliable metric for quantifying the degree of transformation.

3.3.1 Classification performance

We first compared our method with the dictionary-based approach, which is widely used in the existing literature. To do this, we classified sentences from a test set, which had been manually reviewed, based on two keyword sets: 62 digital technology keywords from CSMAR and 76 keywords from Wu et al. (2021). If a keyword appeared in a sentence, we classified it as indicating the company's use of the corresponding digital technology. After obtaining the classification results, we evaluated four performance metrics: Precision, Recall, Accuracy, and F1-Score. As shown in Panel B of Figure 1, the ERNIE model outperforms the dictionary-based approach across all metrics, while the performance of the CSMAR and Wu et al. (2021) keyword sets is similar and not significantly different. This indicates that machine learning approaches, like ours, are more effective in accurately identifying whether a sentence truly reflects a company's digital transformation, thus enhancing the reliability of the conveyed meaning.

Specifically, our method shows notable improvements in error handling compared to the dictionary-based approach. For Type II errors (i.e., sentences that mention a technology but do not actually use it), our model improves Precision by nearly 25 percentage points. For Type I errors (i.e., sentences that indicate the use of digital technology but are missed by the model or keyword set), our model improves Recall by 6-7 percentage points. These results demonstrate that our method performs better than the dictionary-based approach in addressing both types of errors.

3.3.2 Patent data

The principal criterion for determining a firm's digital transformation is its utilization of specific digital technologies. The most robust indicator of such utilization is the firm's patenting activity related to those technologies. It is theoretically posited that a firm's application for a patent in a given digital technology domain implies its engagement with that technology, though the inverse relationship does not necessarily hold. Consequently, we compare the firms identified as utilizing digital technologies by both the dictionary-based approach and the ERNIE model with those firms that have demonstrably filed patent applications for digital technologies. The method exhibiting the greatest concordance with patent application data is deemed to possess the highest accuracy.

We first matched the patent database and the listed company database. Specifically, the first step was to use the InnoJoy patent search platform (from Daway) to identify the patent application records of listed companies. The second step was to determine the patent classification codes for the three digital technologies, including big data, AI, and cloud computing, according to the *World Intellectual Property Report 2022: Innovation Trends* published by the World Intellectual Property Organization (WIPO), in order to filter the patent applications of listed companies for these three technologies[25]. Finally, we obtained lists of companies identified as using these three digital technologies by Wu et al. (2021), the dictionary-based approach using CSMAR keywords, and our ERNIE-based approach, and compared the overlap of these lists with the listed companies that had actually applied for patents in these three digital technology categories[26]. The statistical results show that the overlap between the companies identified by the ERNIE model as using digital technologies and the companies that actually applied for digital technology patents is the highest. This indicates that, based on patent data, the ERNIE model used in this paper has the highest accuracy in determining enterprise digital transformation.

[25] The focus on these three digital technologies - AI, big data, and cloud computing - stems from the fact that, despite WIPO's classification codes encompassing a broad range of technologies, including AI, big data, cloud computing, and the Internet of Things (IoT), only artificial intelligence, big data, and cloud computing are consistently present across both the WIPO classifications and the technology sets identified by Wu et al. (2021) and CSMAR.

[26] Due to space limitations, for the results of the overlap comparison are not shown in the main text and are available upon request.

3.3.3 Temporal trend

We calculated the adoption rates of specific digital technologies, as well as digital technologies in general, across different years (Figure 2). This was done by summing the dummy variables that indicate whether a listed company used a particular technology in a given year and then calculating the average adoption rate. For instance, in 2020, 42% of A-share listed companies adopted big data technology. From a time-trend perspective, the adoption rates of various digital technologies clearly increased over time, especially between 2011 and 2017. This trend aligns with expectations and is consistent with the global diffusion of technology.

Take AI as an example. As shown in Figure 2, AI adoption exceeded 18% after 2011 and grew rapidly between 2012 and 2018. This period corresponds to key global developments in AI: in 2013, Facebook established its AI lab; Google acquired DNNResearch, a company specializing in voice and image recognition; and Baidu founded its Institute of Deep Learning. In 2015, Google open-sourced TensorFlow, marking a breakthrough year for machine learning. Additionally, Google's AI program, AlphaGo, defeated world champions Lee Sedol and Ke Jie in 2016 and 2017, respectively, sparking significant public interest in AI technology.

When considering the overall adoption rates of different digital technologies, we find that IoT and AI lead, with adoption rates of around 60%, followed by big data and mobile internet at approximately 40%, and cloud computing at around 20%. Blockchain has the lowest adoption rate, at just 7%. We also examined the adoption rate of big data technology in Guizhou Province and found a strong correlation with key policy milestones[27]. Similarly, we calculated the growth rate of mobile internet adoption from 2007 to 2020, revealing that growth peaked around the issuance of 3G, 4G, and 5G licenses by the Chinese Ministry of Industry and Information Technology (MIIT)[28]. These trends and findings provide strong evidence supporting the reliability of the adoption metrics presented in this paper.

	Big data	AI	Mobile internet	Cloud computing	IoT	Blockchain	Any item
2006	2%	4%	3%	1%	12%	0%	15%
2007	3%	6%	4%	1%	16%	1%	20%
2008	3%	7%	5%	1%	19%	0%	23%
2009	6%	9%	6%	2%	22%	1%	28%
2010	7%	12%	7%	4%	25%	1%	31%
2011	10%	16%	10%	6%	29%	1%	37%
2012	11%	18%	13%	8%	33%	2%	42%
2013	16%	21%	19%	10%	38%	2%	50%
2014	22%	29%	25%	12%	42%	3%	57%
2015	32%	39%	32%	17%	49%	4%	65%
2016	32%	41%	32%	18%	48%	4%	66%
2017	35%	48%	34%	18%	54%	5%	70%
2018	39%	53%	36%	20%	59%	7%	73%
2019	40%	54%	39%	21%	59%	7%	75%
2020	42%	58%	41%	22%	62%	7%	78%
Mean value	25%	34%	25%	13%	43%	4%	

Figure 2: Adoption Rate of Digital Technologies

Explanation: The table shows the changes in the adoption rate of different digital technologies from 2006 to 2020. "Any" in the table refers to the proportion of listed companies that used any one of the digital technologies in that year out of all listed companies in that year. Because the adoption rates of different digital technologies vary significantly, the length of the bars in the table is standardized based on the maximum adoption rate of each type of digital technology. This is done to help readers see the changing trends in the adoption rate of each digital technology, and therefore, the bars for different digital technologies are not comparable to each other.

[27] Due to space constraints, the trend of big data technology adoption in Guizhou Province is not shown in the main text and are available upon request.
[28] Due to space constraints, the growth rate of mobile internet technology adoption is not shown in the main text and are available upon request.

3.3.4 Regional comparison

This paper statistically analyzes the distribution of digital technology adoption among listed companies across different provinces[29]. The results reveal that regions such as Beijing, Fujian, Shanghai, Zhejiang, and Jiangsu have the highest proportion of companies utilizing digital technologies. In contrast, provinces like Ningxia, Tibet, Qinghai, and Inner Mongolia exhibit the lowest adoption rates. This disparity suggests that companies in the economically developed southeastern coastal areas are more advanced in their digital transformation, while those in the less economically developed central and western regions lag behind. Supporting this observation, CAICT (2022b) reported that by the end of March 2022, there were over 200 industrial parks in China dedicated to the "digital economy". Of these, 41% were located in the eastern region, 28% in the central region, 25% in the western region, and just 6% in the northeastern region. These figures align closely with our findings, further validating the regional digital divide in China's industrial landscape.

3.3.5 Sectoral comparison

This paper analyzes the proportion of listed companies adopting digital technologies across various industries, based on the National Industrial Classification of Economic Activities[30]. The findings reveal that industries such as information transmission, software, and information technology services, along with the financial sector and scientific research and technology services, exhibit the highest levels of digitalization. In contrast, sectors such as agriculture, forestry, animal husbandry, and fisheries, mining, and public utilities show lower levels of digital adoption. When broken down into the three main industry sectors - primary, secondary, and tertiary - the service sector leads in digitalization, with approximately 35% of companies employing digital technologies. The industrial sector follows at around 20%, while the agricultural sector lags behind at just 9%. According to CAICT, the estimated digital economy penetration rates for China in 2020 were 40.7% for the service sector, 21% for the industrial sector, and 8.9% for the agricultural sector. These findings underscore the validity of our measurement approach, aligning closely with CAICT's estimates.

3.3.6 International comparison

Finally, we conducted an international comparison. Zolas et al. (2020)conducted by the Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES surveyed the use of advanced technologies by 850,000 U.S. firms, including the use of AI. The results showed that larger firms have a higher proportion of AI adoption. The proportion of AI adoption reached as high as 60% among the largest firms, while for those with fewer than 50 employees, the proportion did not exceed 10%. Taking 2020 as an example, we described the relationship between firm size and AI adoption by grouping firms according to the number of employees[31]. We found that our AI metrics are highly consistent with the U.S. statistics in terms of size characteristics, that is, larger firms have a higher proportion of AI adoption.

4. Enterprise Digital Transformation and Financial Performance: New Findings

4.1 Regression Model and Variable Definitions

A robust indicator is defined by both its accuracy and applicability. In this context, applicability

[29] Due to space constraints, the proportion of listed companies using digital technologies in different provinces are not shown in the main text and are available upon request.

[30] Due to space constraints, the proportion of listed companies using digital technologies in different industries are not shown in the main text and are available upon request.

[31] Due to space limitations, for details on artificial intelligence technology use by enterprises of different sizes are not shown in the main text and are available upon request.

refers to the ability of the indicator to yield results that align with established economic theory when subjected to empirical analysis. To further validate the enterprise digital transformation metrics developed through our novel methodology, and to address the ongoing debate surrounding the outcomes of digital transformation as outlined in the introduction, we proceed with an analysis of the impact of digital transformation on enterprise financial performance. The decision to use financial performance as the dependent variable is based on its objective nature, ease of measurement, and the inherent comparability it offers across different enterprises.

Existing literature typically examines either the broad impact of enterprise digital transformation on financial performance - such as the studies by Yang & Liu (2018), He & Liu (2019), and Zhao et al. (2021) - or the specific effects of individual digital technologies on financial outcomes, including big data (Müller et al., 2018), cloud computing (Alali & Yeh, 2012), blockchain (Lin & Wu, 2021), ICT (Commander et al., 2011; De Stefano et al., 2018), and mobile internet (Yang et al., 2018), among others. However, there is a lack of comparative analysis on how different digital technologies impact enterprise financial performance in distinct ways. To address the question of the success or failure of digital transformation, as introduced earlier, it is essential to not only assess the overall effects of digital transformation but also to differentiate the financial returns associated with specific digital technologies. Additionally, understanding the channels through which digital transformation influences financial performance is crucial.

To investigate the impact of enterprise digital transformation on financial performance, we propose the following baseline model:

$$Y_{i,t}=\alpha+\beta\cdot DT_{i,t}+\sum_n \chi_n\cdot Controls_{i,t}+\lambda_t+\mu_i+\varepsilon_{i,t} \tag{1}$$

In equation (1), dependent variable, $Y_{i,t}$, represents the financial performance of firm i in year t, measured by Return on Assets (ROA) and Return on Equity (ROE). The key explanatory variable, DT, is a set of dummy variables capturing enterprise digital transformation. These include whether the firm has undergone digital transformation (denoted as *DigiTech*, i.e., whether the firm has adopted any form of digital technology), and whether it has utilized one of six specific digital technologies: big data, AI, mobile internet, cloud computing, the Internet of Things (IoT), and blockchain. The variable *Controls* represents a series of control variables. Consistent with established literature (Yang & Liu, 2018; Zhao et al., 2021; DeStefano et al., 2018), we control for firm age, firm size, growth rate (measured by year-over-year revenue growth), market-to-book ratio, the shareholding ratio of the largest shareholder, whether the chairman also serves as the general manager, and cash flow in the regression model. Additionally, λ_t captures time fixed effects, μ_i accounts for firm fixed effects, and $\varepsilon_{i,t}$ represents the random error term. Firm-level clustered standard errors are employed.

Regarding data sources, in addition to the enterprise digital transformation metrics, the other variables used in this study are drawn from the Wind and CSMAR databases. Given the impact of the global financial crisis in 2008 and the COVID-19 pandemic outbreak in 2020, the sample period for this analysis spans from 2010 to 2019. We have excluded ST and ST* companies, removed samples from the financial industry, and omitted observations with missing key variables. Continuous variables are winsorized at the 1% level at both the upper and lower tails to mitigate the influence of extreme outliers. This process results in a final sample of 25,107 observations.

Table 1 provides the variable definitions and descriptive statistics. It shows that 60.6% of the firms in the sample have undergone digital transformation, defined as the adoption of at least one of the six new digital technologies. Among these technologies, the Internet of Things (IoT) and AI exhibit the highest adoption rates. Regarding financial performance, the average Return on Assets (ROA) for listed companies is 6%, while the average revenue growth rate exceeds 14%.

Table 1: Variable Definitions and Descriptive Statistics

Variable Name	Variable Definition	Observations	Mean	Standard Deviation	Min.	Max.
Column A: Dependent Variable						
ROA	Net profit / Total assets	25107	6.043	6.459	-19.819	25.415
ROE	Net profit / Equity	25107	6.872	12.661	-63.093	36.335
Column B: Explanatory Variable						
DigiTech	Digital Transformation (Yes/No)	25107	0.606	0.489	0	1
BD	Big Data Adoption (Yes/No)	25107	0.269	0.443	0	1
AI	AI Adoption (Yes/No)	25107	0.369	0.483	0	1
MI	Mobile Internet Adoption (Yes/No)	25107	0.269	0.444	0	1
CC	Cloud Computing Adoption (Yes/No)	25107	0.143	0.350	0	1
Iot	IoT Adoption (Yes/No)	25107	0.476	0.499	0	1
BC	Blockchain Adoption (Yes/No)	25107	0.0332	0.179	0	1
lnAge	Log(Firm Age + 1)	25107	2.879	0.306	2.079	3.555
lnAsset	Log(Total Assets + 1) (in 10,000 Yuan)	25107	12.881	1.278	10.566	16.808
Growth	Revenue Growth Rate (YoY) (%)	25107	14.270	30.283	-49.863	157.13
MB	Market Value to Book Value Ratio	25107	0.585	0.230	0.114	1.081
Top1	Largest Shareholder Ownership (%)	25107	34.836	14.845	8.800	74.660
Dual	Chairman-CEO Duality (1 = Yes)	25107	0.272	0.445	0	1
Cashflow	Cash Flow/Total Assets	25107	0.0433	0.0697	-0.166	0.234
Column C: Channel Variables						
TFP1	Sales-based *TFP* using the ACF method	21934	1.588	1.133	-1.322	4.623
TFP2	EVA-based *TFP* using the ACF method	18743	2.575	3.127	-7.424	11.820
lnIncome	Log(Total revenue + 1)	25107	12.185	1.439	9.013	16.168
lnCost	Log(Total expenditure + 1)	25107	12.116	1.445	9.100	16.132
Cost2Income	Expenditure-to-revenue ratio	25107	0.947	0.182	0.560	1.971

4.2 Baseline Regression

Table 2 presents the results of the baseline regression, where the primary explanatory variable is the enterprise digital transformation dummy variable (*DigiTech*). As shown, regardless of whether the dependent variable is Return on Assets (*ROA*) or Return on Equity (*ROE*), the coefficient of DigiTech is significantly positive at the 1% level. This suggests that, when using the newly constructed metrics based on the ERNIE model, digital transformation has a substantial positive impact on enterprise financial performance.

However, the baseline regression may suffer from reverse causality - firms with better financial performance may have more available resources and, therefore, a higher likelihood of adopting digital technologies. To address this concern, columns (3) and (4) of Table 2 present a modified analysis where all dependent variables are lagged by one period. The results indicate that the coefficients of enterprise digital transformation remain significantly positive, providing preliminary evidence that digital transformation generally enhances financial performance. This suggests that the positive relationship is not merely due to reverse causality and that digital transformation efforts are typically successful.

These findings align with both economic theory and the results of prior research (He & Liu, 2019; Zhao & Liu, 2018; Zhao et al., 2021)[32]. To further validate the robustness of our results, we excluded

[32] Replicating the results of related literature shows that when the dependent variable is *ROA*, the enterprise digital transformation dummy variable constructed based on CSMAR and Fang et al. (2022) is significantly positive, the results of Wu et al. (2021) are not significant, and the results of Yang et al. (2022) are significantly negative. When the dependent variable is lagged by one period, only the results of Fang et al. (2022) are significant. Due to space constraints, these results are not shown in the main text but are not shown in the main text and are available upon request.

firms from the information transmission, software, and information technology services sectors, as these industries are typically more digitally advanced and may adopt digital technologies at different rates compared to firms in other sectors. The re-estimated regression results, after excluding this industry, remain consistent with those from the baseline regression, reinforcing the robustness of our conclusions.[33]

Table 2: Baseline Regression Results of Enterprise Digital Transformation and Financial Performance[34]

	(1)	(2)	(3)	(4)
Independent Variable	*ROA*	*ROE*	*F.ROA*	*F.ROE*
DigiTech	0.398***	0.740***	0.183*	0.435**
	(0.0896)	(0.208)	(0.0968)	(0.218)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	25107	25107	22552	22552
R^2	0.204	0.152	0.109	0.0777

Note: The numbers in parentheses are clustered standard errors at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The same applies to the tables below.

4.3 Endogeneity Problems

To address potential endogeneity concerns, we account for both reverse causality and omitted variable bias. To mitigate this issue, we construct an instrumental variable (IV) for digital transformation. A key challenge for companies that undergo digital transformation is the supply of technology talent. Previous literature has employed various IVs to address this. For instance, Babina et al. (2024) use the connection between firms and top AI universities as an IV for AI adoption, hypothesizing that firms hiring more employees from prestigious AI institutions - measured by AI-related publications - are more likely to adopt AI technology, which in turn affects firm growth. Similarly, Zhang et al. (2021) used “Project Qomolangma” (named after the highest peak in the world, also known as Everest) as an IV for the adoption of big data technology to investigate its impact on firm value, as measured by Tobin’s Q. Following this precedent, our study employs the “Project Qomolangma” as an IV for digital transformation, providing a robust means of isolating the causal effect of digital transformation on firm outcomes.

The “Project Qomolangma”, short for the “Pilot Program for Training Top Students in Basic Disciplines”, is a talent development initiative launched by the Chinese government in response to the “Dr. Qian Xuesen’s Question”. Its primary aim is to create national talent development hubs in key basic scientific disciplines at top-tier research universities and institutes. The program focuses on fostering high-level training mechanisms for exceptional talent and attracting the brightest students to engage in fundamental scientific research. The first phase of the project involved 17 universities, selecting science and engineering majors such as mathematics, physics, chemistry, biology, and computer science at prestigious institutions like Tsinghua University and Peking University for pilot programs. This initiative significantly increased the likelihood that university graduates would pursue careers in science and technology, thereby enhancing the overall supply of skilled professionals in these fields (Song & Lu, 2020).

We hypothesize that the farther a listed company’s office is from the 17 “Project Qomolangma” pilot

[33] Due to space constraints, the regression results excluding the information transmission, software, and information technology service industries are not shown in the main text and are available upon request.

[34] Due to space constraints, the regression results of the control variables are not shown in the main text and are available upon request.

universities, the less likely it is to recruit science and technology talent, and consequently, the less likely it is to undergo digital transformation. Additionally, in regions with a higher concentration of listed companies, the individual impact of this program on any single company diminishes, making digital transformation less probable. Thus, both the physical distance from the pilot universities and the number of listed companies in a region are negatively correlated with the likelihood of a company's digital transformation. This relationship aligns with the relevance assumption of the instrumental variable (IV). The defined IV is as follows:

$$IV_{i,t} = mSumdis_i * mN_{i,t} * Post_t$$

In the above equation, i represents a listed company, t denotes the year, *mSumdis* refers to the sum of the straight-line distances (divided by 10,000 km) from the registered office address of company i to the main campuses of the 17 pilot schools, and *mN* represents the total number of listed companies (divided by 1,000) in city c where company i is located during year t. Since the first cohort of students benefiting from the "Project Qomolangma" were primarily undergraduates who enrolled in 2010, their graduation years were 2014 and beyond, we introduce a time dummy variable *Post*, which takes the value of 0 for years prior to 2014 and 1 for 2014 and later[35].

Table 3 presents the results of the instrumental variable (IV) regression. Column (1) shows the first-stage regression results, where the IV coefficient is significantly negative, and the F-statistic exceeds 10, which is consistent with the expected relevance of the instrument. Moreover, we argue that the "Project Qomolangma" itself does not have a direct effect on the digital transformation of individual companies, thereby satisfying the exclusive hypothesis. The results in columns (2) and (3) indicate that, after applying the IV, the coefficient for the key explanatory variable - enterprise digital transformation - is significantly positive at the 5% level. This finding supports the robustness of our conclusions.

Table 3: Instrumental Variable Regression Results

	(1)	(2)	(3)
	DigiTech	*ROA*	*ROE*
IV	-0.102***		
	(0.0300)		
DigiTech		9.455**	21.628**
		(4.599)	(10.053)
Cragg-Donald Wald F statistic	21.487		
Kleibergen-Paap Wald rk F statistic	11.456		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	25107	25107	25107
R^2		-0.232	-0.346

4.4 Impacts of Different Digital Technologies

To examine the effect of firms utilizing specific digital technologies (such as big data, AI, mobile internet, cloud computing, the Internet of Things (IoT), and blockchain) on financial performance, we redefined the treatment and control groups in this analysis. Firms not employing any of these digital technologies were categorized as the control group and assigned a value of 0. Firms using any of the

[35] In consideration of the possibility that some students may elect to pursue postgraduate education, thereby deferring their graduation year, we iteratively modified the graduation year from 2014 to 2015, 2016, 2017, and 2018, observing consistent robustness in the results. Due to space limitations, these findings are not presented herein but are available upon request.

individual technologies - big data (BD), AI, mobile internet (MI), cloud computing (CC), the Internet of Things (IoT), or blockchain (BC) - were each assigned a value of 1.

Table 4 presents the relationship between the use of specific digital technologies and return on assets (*ROA*). Columns (1)-(5) show that the use of any digital technology, except blockchain, is associated with a significant improvement in ROA. These findings align with existing literature. Notably, column (6) indicates that the regression coefficient for blockchain technology is not statistically significant. This result may be explained by the fact that while blockchain enhances the security of corporate information (Sharma et al., 2023), its effect on stock prices tends to be short-lived and it can increase a firm's earnings volatility (Jain & Jain, 2019)[36]. Similar conclusions were drawn when return on equity (ROE) was used as the dependent variable[37].

Table 4: Impact of Different Digital Technologies on ROA

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	*ROA*	*ROA*	*ROA*	*ROA*	*ROA*
BD	0.533***					
	(0.151)					
AI		0.544***				
		(0.125)				
MI			0.344**			
			(0.150)			
CC				0.686***		
				(0.217)		
IoT					0.447***	
					(0.102)	
BC						-0.108
						(0.370)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16627	19150	16643	13476	21821	10714
R^2	0.193	0.198	0.198	0.189	0.202	0.187

4.5 Quantile Regression

The above analysis shows that enterprise digital transformation can significantly improve enterprise financial performance. However, for firms with different financial performance levels, the impact of firms using digital technologies may vary. At the same time, the sum of squared residuals in ordinary least squares (OLS) models is susceptible to extreme values, which can lead to biased regression results. To further investigate the impact of digital transformation on financial performance for firms with different financial performance levels, we use the quantile regression method. This paper selects five representative quantiles - 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles - for quantile regression.

Using *ROA* as the dependent variable, the regression results are shown in Table 5. The regression results in columns (1)-(3) show that digital transformation has a significant positive impact on firm *ROA*. The results in columns (4) and (5) show that as the quantile increases, at the high quantiles of 75% and

[36] Our interviews revealed that the deployment of blockchain technology remains nascent, with a preponderance of applications utilizing private or consortium blockchain architectures; genuinely decentralized public blockchains are exceedingly rare.

[37] Due to space limitations, for details on the impact of different digital technologies on *ROE* are not shown in the main text and are available upon request.

90%, the impact of digital transformation on firm *ROA* is not significant. One possible explanation is that digital technologies (such as cloud computing) empower emerging small and medium-sized enterprises (SMEs), mitigating their relative disadvantages in large capital expenditures and scale through asset-light operations (Jin & McElheran, 2017). Therefore, digital transformation can provide "leapfrogging" opportunities for firms with poorer performance. Similar results were obtained when we used ROE as the dependent variable[38].

Building on the previous subsection, we can draw three key conclusions. First, the impact of digital transformation varies depending on the specific digital technologies adopted by firms. Current evidence suggests that blockchain technology, in particular, does not lead to improved financial performance for firms. Second, there is significant heterogeneity in the effects of digital transformation; namely, the benefits are more evident for firms with weaker financial performance, while the effects are negligible for firms already performing well, or exceptionally well, financially. Third, different approaches to constructing metrics for digital transformation can yield varying regression results. This highlights the ongoing debate about the success or failure of digital transformation, as discussed in the introduction. The discrepancies in findings arise from the diverse digital technologies employed, the differing financial conditions of firms, and the varying methodologies used by researchers. Therefore, it is crucial for future research to differentiate between types of digital technologies and financial performance levels, while also developing standardized and comparable metrics for assessing digital transformation across firms.

Table 5: Quantile Regression of Enterprise Digital Transformation on ROA

	(1)	(2)	(3)	(4)	(5)
	QR_10	QR_25	QR_50	QR_75	QR_90
DigiTech	0.341*	0.154*	0.346***	0.147	0.158
	(0.198)	(0.0803)	(0.107)	(0.112)	(0.192)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	25107	25107	25107	25107	25107

4.6 Channel Analysis

Next, we examine the channels through which digital transformation enhances enterprise financial performance. Existing literature identifies three primary channels: efficiency, revenue, and cost. The first channel is efficiency. Studies such as those by Liu (2020) and Zhao et al. (2021) show that digital transformation significantly boosts productivity, and this increase in efficiency directly contributes to improved financial performance (Bao & Liang, 2022). The second channel is revenue. Research by Yadav (2014) highlights how digital transformation facilitates greater participation in international trade, expanding market opportunities. Additionally, the accumulation and analysis of consumer data enable firms to build stronger product loyalty, which, as Hänninen et al. (2017) demonstrate, drives repeat consumption. These factors collectively contribute to increased operating revenue, further enhancing financial performance. The third channel is cost. Shivajee et al. (2019) found that digital transformation helps firms reduce manufacturing costs, minimize scrap, and decrease raw material waste. Similarly, He & Liu (2019) also confirm the cost-reduction benefits of digital transformation.

In light of this, the present study aims to verify the validity of the efficiency, revenue, and cost

[38] Due to space constraints, the quantile regression results with ROE as the dependent variable are not shown in the main text and are available upon request.

channels as mechanisms through which digital transformation influences financial performance.

To test the efficiency channel, this paper uses firms' *TFP* (Total Factor Productivity) as the dependent variable. A core issue in measuring firm *TFP* is addressing the endogeneity problem in production function estimation. The ACF method can effectively solve the multicollinearity problem that may arise when the OP and LP methods estimate the elasticity of labor input, and therefore it is widely accepted (Loecker & Warzynski, 2012). In columns (1) and (2) of Table 6, we use the ACF method to calculate *TFP1* and *TFP2* based on sales and economic value added, respectively.

To test the revenue channel, in column (3) of Table 6, this paper uses the logarithm of total revenue (*lnIncome*) as the dependent variable. To test the cost channel, in column (4) of Table 6, the logarithm of total cost (*lnCost*) is used as the dependent variable. Considering both cost and revenue dimensions, we included the cost-to-income ratio (*cost2income* = total cost / total revenue) as the dependent variable in column (5). Table 6 shows that after firms underwent digital transformation, their TFP significantly increased, while total cost significantly decreased, which confirms the efficiency and cost channels[39]. However, at the same time, their total revenue did not increase significantly, indicating that the revenue channel is not supported. Meanwhile, column (5) of Table 6 shows that the cost required per unit of revenue decreased, which indicates a decrease in the cost-to-income ratio. Therefore, overall, the use of digital technology improves firms' financial performance.

Table 6: Channel Analysis

	(1)	(2)	(3)	(4)	(5)
	TFP1	*TFP2*	*lnIncome*	*lnCost*	*Cost2income*
DigiTech	0.0121**	0.0214*	-0.00184	-0.0187***	-0.0164***
	(0.00516)	(0.0121)	(0.00682)	(0.00720)	(0.00268)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	21934	18743	25107	25107	25107
R^2	0.422	0.0989	0.727	0.718	0.145

5. Concluding Remarks and Policy Implications

China, as the world's largest developing economy, has rapidly emerged as a dominant force in the digital economy, achieving significant progress. Within this dynamic digital landscape, the digital transformation of enterprises serves as a critical micro-foundation. While the digital transformation efforts of Chinese enterprises have attracted considerable attention, academic research in this field is also expanding. However, current scholarly work on measuring enterprise digital transformation indicators faces key challenges, including a lack of a clear framework for defining the key components of digital transformation, as well as unscientific or inaccurate measurement methods. These shortcomings have led to significant disagreements regarding the current state and effects of digital transformation among enterprises.

To address these challenges and foster deeper research into enterprise digital transformation, particularly in the context of China, this paper introduces a novel set of indicators for measuring digital transformation, leveraging cutting-edge technologies such as machine learning and LLMs. The approach

[39] According to Jiang (2022), when analyzing mediating variables (channels) in the economics literature, the primary focus is on verifying the impact of the explanatory variable on the mediating channel. This is because the channel's influence on the dependent variable is typically self-evident. Consequently, we exclude the regression analysis of the channel's effect on firm financial performance.

is built upon a comprehensive analysis of the annual reports of Chinese listed companies, collected between 2006 and 2020. We developed a dictionary comprising 311 digital technology keywords, categorizing these technologies into six key types: big data, AI, mobile internet, cloud computing, the Internet of Things (IoT), and blockchain.

Next, the paper employed manual annotation of these annual reports to create a training dataset, which was then used in a supervised machine learning model. By leveraging Baidu's ERNIE large language model, our study predicted whether and which digital technologies each enterprise was adopting based on its annual report text. This process resulted in a refined set of digital transformation indicators for Chinese listed companies.

Cross-validation tests indicated that the new indicators proposed in this study outperformed traditional dictionary-based methods, offering a more accurate and practical reflection of digital transformation practices in Chinese enterprises. In the latter part of the paper, these indicators were used to demonstrate that digital transformation significantly enhanced the financial performance of Chinese listed companies. Moreover, the impact was particularly evident in companies with relatively poor financial performance, suggesting that digital transformation plays a pivotal role in leveling the playing field. The paper also identified that the primary mechanisms through which digital transformation drives financial improvements are increased operational efficiency and cost reduction.

In summary, this study provides a robust, data-driven framework for measuring the digital transformation of enterprises in China, offering valuable insights into how these transformations influence business performance.

This paper offers valuable policy insights for advancing enterprise digital transformation and fostering high-quality economic development in China.

First, it emphasizes the need for close collaboration among the government, businesses, and academia to establish a solid foundation for digital transformation through data collection and basic research. A key challenge currently faced by enterprises is the absence of standardized digital transformation metrics and authoritative analysis of transformation outcomes. This gap prevents relevant authorities from effectively tracking, assessing, and learning from the successes and setbacks of digital transformation initiatives. To develop a comprehensive, unified, and accurate digital transformation index and database, it is essential to capture detailed data on various aspects of enterprise investments, including digital technologies, human resources, capital, and more. While existing academic research predominantly relies on text analysis, the digital transformation indicators proposed in this paper - based on advanced LLMs - offer a promising starting point and a practical roadmap. However, further validation with real-world data is needed to ensure robustness and reliability. Ultimately, achieving a holistic understanding of the digital transformation "baseline" for Chinese enterprises requires the active participation of all stakeholders: government bodies, businesses, and academic institutions. Only through this multi-party collaboration can we accurately assess the current state of digital transformation, providing the necessary theoretical frameworks and policy support to guide enterprises in their digital transformation journeys.

Second, enterprises must commit to accelerating their digital transformation efforts. The findings of this paper demonstrate that digital transformation significantly enhances financial performance by improving efficiency and reducing costs. Therefore, Chinese enterprises must break free from the mindset of being "unwilling" or "hesitant" to transform and instead fully embrace digitalization as a vital pathway to sustainable growth and competitiveness. In the rapidly evolving digital economy, Chinese enterprises can leverage the "late-mover advantage" to compete more equitably with established global players, even as they face the entrenched advantages of multinational corporations in scale, brand recognition, and capital.

Third, the government should adopt differentiated policies to promote digital transformation, tailored to the specific circumstances of different enterprises. This study finds that digital transformation has a more significant impact on firms with poor or average financial performance, while it has little effect on firms with strong financial performance. Therefore, in encouraging enterprise digital transformation, the government should abandon the one-size-for all approach, offering more targeted support to struggling firms and minimizing unnecessary assistance to well-performing firms, thereby avoiding the waste of fiscal resources. Such a strategy would facilitate a deeper integration of digital technologies with the real economy, driving high-quality economic development.

Fourth, enterprises in the central and western regions should be encouraged to accelerate their digital transformation. Due to their lower levels of economic development, these regions exhibit a slower pace of digital transformation and must place greater emphasis on adopting digital technologies. Considering the late-mover advantage offered by digital technologies, the government could introduce preferential policies to support these regions. For instance, increasing investment in digital infrastructure and facilitating technical and talent support from enterprises in the more developed eastern regions could help accelerate transformation in the central and western areas. This would prevent a "digital divide" from emerging between regions, promoting more equitable development and contributing to the achievement of common prosperity.

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