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# The Impact of Digital Transformation on High-Quality Development of Manufacturing Enterprises: An Integrated Perspective on Efficiency and Social Responsibility

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**Abstract:** With the rise of a new wave of technological revolution and industrial transformation, digital technology has become a key force driving global economic and social development. Digital technology holds significant advantages in promoting industrial transformation and upgrading, as well as facilitating the high-quality development of manufacturing enterprises. This study selects 482 manufacturing enterprises in the Shanghai and Shenzhen A-share markets from 2010 to 2022 as samples and comprehensively measures the high-quality development level of enterprises from the two dimensions of production efficiency and social responsibility. Based on this, a two-way fixed effect model is used to test the impact of digital technology on the high-quality development of manufacturing enterprises. The results show that the digital transformation of manufacturing enterprises enhances their level of high-quality development by improving production efficiency and strengthening social responsibility. This conclusion remains robust after a series of robustness checks. The mechanism analysis reveals that digitalization influences the high-quality development of manufacturing enterprises by altering financing costs, innovation output, and human capital. The heterogeneity analysis indicates that this impact varies significantly across ownership types, industries, and regions. Therefore, further efforts should be made to promote the digital transformation of manufacturing enterprises, strengthen technological innovation, enhance talent cultivation, and promote industrial integration, thereby leveraging digital technology to significantly improve high-quality development levels.

**Keywords:** digital transformation; high-quality development; production efficiency; social responsibility

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## 1. Introduction

With the rapid development of information technology, the global economy is transitioning into the digital era, where digital knowledge and information serve as key production factors and digital technologies act as core driving forces. Supported by modern information networks, these technologies deeply integrate with the real economy. The widespread use of technologies such as artificial intelligence (AI), big data, cloud computing, and the Internet of Things (IoT) has brought new opportunities for enterprises.

However, these technologies also introduce challenges such as data silos, resource coordination, and social responsibility [1]. Studies show that the application of AI and big data has increased enterprise efficiency but also raised concerns around data privacy and security issues [2,3]. The digital economy plays a pivotal role in enhancing the digitalization, networking, and intelligence levels of the economy and society, while also reshaping economic development and governance models, forming a new economic paradigm. The added value of the digital economy has been increasing year by year, as shown in Figure 1. The proportion of the digital economy's added value in the GDP of China is approaching 50%, with billions of people benefiting from the "digital dividend". Looking ahead to 2024, the construction of Digital China will advance alongside the accelerated development of new productive forces, driving transformations in quality, efficiency, and innovation. For example, industrial digitalization and the integration of IoT into manufacturing sectors have significantly increased productivity [4], while digital governance is enabling smarter, data-driven policymaking. The digital economy comprises four main components: digital industrialization, industrial digitalization, digital governance, and data valorization, each playing a critical role in this transformation.

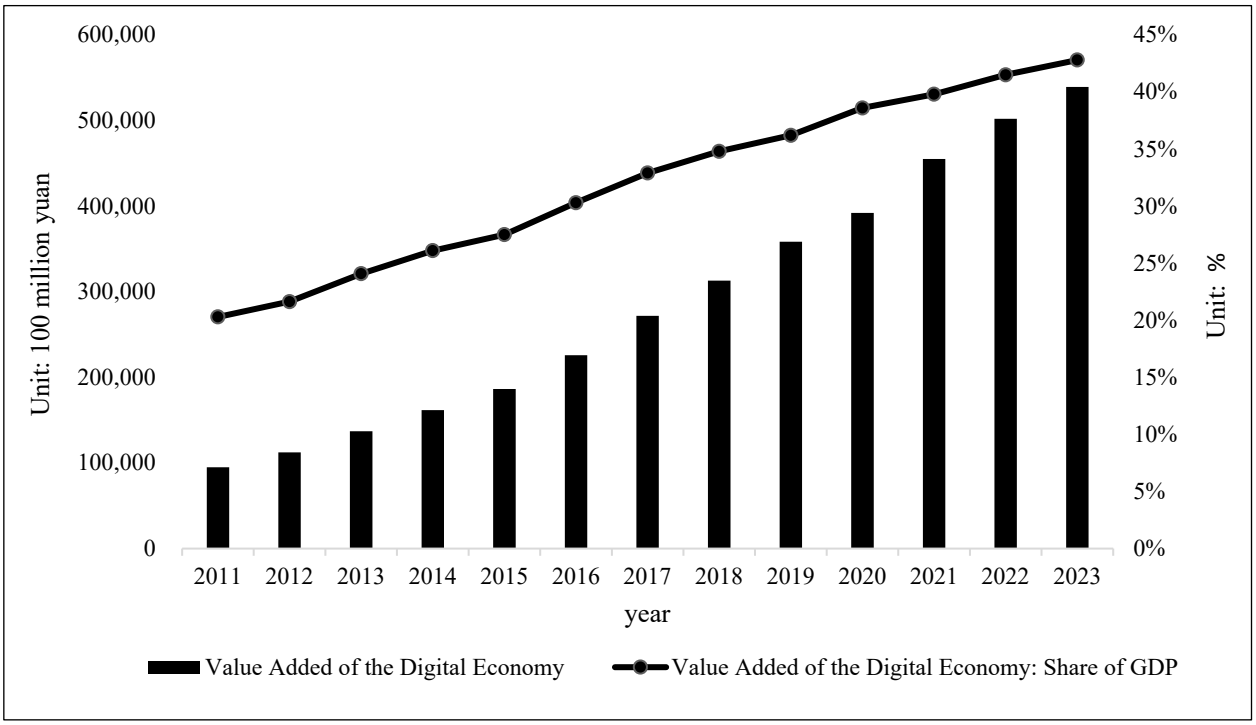



**Figure 1.** The scale of Value Added by China's Digital Economy and Its Share of GDP. Data Source: China Academy of Information and Communications Technology (CAICT).

Since the reform and opening up, China's manufacturing industry has rapidly risen to become the "world's factory" due to relatively low labor, land, and raw material costs. Since 2010, the value added by China's manufacturing sector has ranked first in the world, maintaining the highest output in over 40% of industrial product categories and establishing its status as a manufacturing powerhouse. However, the challenges facing China's manufacturing sector cannot be overlooked. Currently, China's manufacturing industry is at a critical juncture in its transition from "large but not strong" to "strong and excellent". Promoting high-quality development and enhancing the core competitiveness of the manufacturing sector are essential tasks for China's economic transformation and upgrading. Chinese manufacturing enterprises urgently need to master digital technologies and

strive for transformation and upgrading to regain competitive advantages in international competition [5].

Countries are implementing corresponding policies to promote the digital transformation of manufacturing. This trend indicates that digitalization in manufacturing has become a key strategy for major digital economies to enhance industrial competitiveness and drive economic transformation. The United States emphasizes leading the future of smart manufacturing through the National Advanced Manufacturing Strategy, promoting digitization and intelligent manufacturing while committing to the digital transformation of supply chains for seamless production connectivity across key sectors. Germany's "Manufacturing X" initiative aims to establish a universal infrastructure covering all areas of manufacturing and build an independent data ecosystem to enable collaborative use and sharing of data across industrial sectors [6]. South Korea's Industrial Digital Transformation Promotion Act creates a legal framework that includes regulations for the utilization and protection of industrial data, support systems, and promotion mechanisms, aiming to accelerate the digital transformation of industries and provide legal safeguards for policy formulation and implementation [7]. These policies illustrate that the digitalization of manufacturing has become a consensus and action direction among major global economies [8]. These global trends highlight the critical role of digitalization in the manufacturing sector in enhancing national competitiveness and driving economic transformation. At the same time, they indicate China's position and role in the global digital transformation, particularly in how it can further drive the transformation and upgrading of its manufacturing industry through mutual learning and experience sharing with other leading countries. Therefore, by focusing on China's digital transformation, this paper will incorporate studies of similar trends internationally, offering a broader global perspective to foster a more comprehensive understanding of China's role in the digital transformation of the global economy.

This study aims to explore how manufacturing enterprises can achieve high-quality development through digital transformation against the backdrop of rapid advancements in information technology and the rise of the digital economy. The existing literature often focuses on the macro effects and general descriptions of the digital economy, lacking in-depth studies of specific industries, particularly manufacturing. The digital economy has driven improvements in regional total factor productivity through innovation, increased efficiency, green development, and coordinated development [9,10], verifying its role in promoting high-quality regional economic development. The application of information technologies like the internet and artificial intelligence has become foundational for driving high-quality economic development [11]. The development of the digital economy has also fueled demand for digital governance, enhancing information transparency, improving institutional environments, and modernizing government governance capabilities. Digital finance promotes regional coordinated development by narrowing the income gap between urban and rural areas [12].

By analyzing the application of digital technologies in manufacturing and their impact on production efficiency, product quality, and enterprise competitiveness, this study provides practical paths and strategies for manufacturing enterprises during their digital transformation, aiding in the scientific planning of their digital transition and enhancing competitiveness in the global market. The study summarizes the successful experiences and practices of major economies in promoting the digital transformation of manufacturing, offering valuable references for the Chinese government in formulating and optimizing related policies. By learning from international best practices, this research provides policy recommendations to accelerate the digital transformation of manufacturing and drive high-quality economic development in China, helping the industry enter a new era of high-quality development. From a sustainable development (ESG) perspective, the study

emphasizes that manufacturing enterprises should not only pursue economic benefits during their digital transformation but also focus on environmental protection, social responsibility, and corporate governance to promote sustainable development. This research offers tools for a comprehensive assessment and optimization of business models, facilitating coordinated economic, social, and environmental development in the digital economy era. By examining the impact of the digital economy on high-quality development in manufacturing, it aims to enhance public awareness of digital transformation and high-quality development, fostering a consensus among all sectors of society and encouraging collective participation and support for the digital transformation and high-quality development of manufacturing.

Compared to the existing literature, the contributions of this research are as follows: First, it provides a novel exploration of the dual impact of digital transformation on total factor productivity (TFP) and sustainable development performance within a unified analytical framework, overcoming the limitations of existing studies that focus only on economic benefits. By demonstrating that digital transformation not only enhances economic efficiency but also promotes corporate social responsibility, this study highlights the win–win effect of digitalization, offering new perspectives and empirical evidence for balancing economic benefits with social responsibility during the digital transition. Second, through systematic mechanism analysis, the study confirms the positive impact of digital transformation on high-quality development and uncovers the underlying logic. By examining three key mechanisms—financing costs, innovation output, and human capital—it clarifies how digital transformation reduces financing costs, accelerates innovation, and optimizes human capital structure to support high-quality development. Furthermore, the study refines these effects by analyzing their variation across different types of enterprises. Third, the research introduces significant innovations in measuring digitalization by developing a new digital vocabulary dictionary and applying text analysis techniques to investigate the digital strategies and implementation outcomes of enterprises. This method enhances the accuracy of assessing the details and multidimensional impacts of digital transformation, and it establishes a new research paradigm for the field of digital studies, offering broad academic and practical value.

These contributions offer both theoretical insights and practical guidance for understanding and navigating the impacts of digital transformation, positioning this research as a key advancement in the field.

The primary objective of this study is to assess the impact of digitalization on the high-quality development of manufacturing enterprises listed on the Shanghai and Shenzhen A-shares from 2010 to 2022. Specifically, the study aims to accomplish the following: Evaluate the degree of digitalization within these enterprises and examine its effects on total factor productivity and sustainable development performance. Investigate the role of corporate executives' digital awareness as an instrumental variable to address potential endogeneity in the analysis, ensuring the validity of the research hypotheses. Explore the mechanisms through which financing costs, innovation output, and human capital impact the relationship between digitalization and high-quality development. Conduct heterogeneity analysis to assess how factors such as enterprise characteristics, regions, and industries influence the effects of digitalization on business performance.

The subsequent sections of this research are arranged as follows: The second section provides a literature review on digitalization research, high-quality development research, the relationship between digitalization and total factor productivity, and digitalization and ESG. The third section presents a theoretical analysis, proposing the internal mechanisms through which digital transformation may impact the high-quality development of manufacturing enterprises. The fourth section details the selection and processing of data. The

fifth section conducts empirical analysis, including baseline regression analysis, mechanism analysis, and heterogeneity analysis. The sixth section summarizes the empirical results and offers corresponding policy recommendations to provide practical references for the digital transformation and high-quality development of manufacturing enterprises.

## 2. Literature Review

### *2.1. Research on Digital Transformation*

In recent years, the trends of sustainable development and digitalization have been transforming economies and societies globally. Amid a new wave of technological revolution and industrial transformation, many countries have proposed digital economy development strategies such as "Industrial Internet" and "Industry 4.0", aiming to achieve economic and social upgrades through the digital transformation of manufacturing and to seize international competitive advantages [13]. Currently, the digital economy has become a new driving force for global economic development, with countries planning to rely on digital technologies to facilitate a new round of industrial transformation and achieve high-quality manufacturing development. Improving the technological level of manufacturing is crucial for transitioning to a new development model, and the enhancement of total factor productivity in manufacturing is a significant indicator of this technological advancement [14].

Digital transformation represents a deep integration of new-generation digital technologies with traditional business elements, providing new avenues for enhancing enterprise performance [15–18]. However, not all scholars recognize the impact of digital transformation on enterprise performance [19–21]. The reality of enterprise digital transformation confirms scholars' concerns, as many enterprises face challenges, such as reluctance, lack of knowledge, and inadequate implementation. For most enterprises, digital transformation often remains superficial, insufficiently penetrating business and system levels, making it difficult to complete the process. This indicates a significant deviation between the micro-level reality of digital transformation in enterprises and the macro trends of the digital economy. In practice, the actual effects of digital transformation often diverge from theoretical optimality, leading to increasing interest from governments, businesses, and academia in understanding its impact and mechanisms [22–24]. Digital transformation has become a critical trend in modern business development, with an increasing number of enterprises leveraging digital technologies to transform and optimize their business processes, enhance operational efficiency, expand market share, and create greater customer value [25]. The existing literature primarily focuses on the influencing factors and economic consequences of digital transformation, offering comprehensive analyses of its various stages from the perspectives of internal organizational innovation and external industrial revolution [26,27].

Digital technologies, represented by big data, cloud computing, and the Internet of Things, are essential for digital transformation. From the perspective of resource-based theory, digitalization in manufacturing enterprises is viewed as a strategic behavior based on the optimal allocation of enterprise resources. By achieving digitalization at various levels, enterprises can optimize resource allocation, enhance resource value, and create unique competitive advantages. From a management perspective, digital transformation is a process through which enterprises, in response to the challenges of the digital era, extensively apply digital technologies in critical growth areas, such as production and technology replacement, leading to comprehensive innovations in business and management. The success of this transformation relies on investments in intangible assets related to these digital technologies [28]. From this viewpoint, Vial [29] defines digital transformation as the process by which enterprises utilize digital technologies to adjust value-creation

activities in response to changing environments. The targeted organizational, procedural, and technological changes necessary for enterprises to achieve new business models constitute an essential part of digital transformation, reshaping the company's strategy, operations, and organizational patterns [30]. Some scholars have proposed the concept of the "digital dilemma," exploring the impact of digital transformation on enterprises. The digital paradox, similar to the productivity paradox, focuses on enterprises' inability to achieve expected revenue growth from digital investments, which may stem from the challenges encountered when altering business models [31]. Although most experts hold differing views, they agree that digital transformation can enhance enterprise capabilities by reducing expenses and improving operational efficiency [32].

### *2.2. Research on High-Quality Development of Enterprises*

Research on high-quality corporate development should take environmental factors into account, as corporate behavior is inevitably influenced by the effectiveness of urban environmental governance. Environmental governance is crucial for individual well-being and long-term societal progress, and it can significantly impact economic growth, especially in a large developing country like China. As a major manufacturing power, China has gained economic prosperity from the expansion of its manufacturing sector, but this has also led to significant environmental governance challenges. Digital transformation, as a vital factor influencing corporate operations, performance, and innovation, generates substantial data and technology for manufacturing enterprises and is closely related to total factor productivity. TFP measures the productivity of total output relative to total input, indicating the portion of output that cannot be explained by the growth of capital and labor [33]. High-quality development emphasizes creating both economic and social value. The growth of TFP aligns with the trends and requirements of China's economic development and high-quality growth. However, as previously analyzed, the impact of digital transformation on enterprises may vary. Resources such as funding, equipment, and relevant technologies are primary constraints on the influence of digital transformation [34].

Enterprises are affected by various aspects of urban environmental governance in terms of costs and human resources, making it necessary for them to assume this responsibility as they transition to high-quality development. On a macro level, research has primarily focused on optimizing urban economic growth models through policies supporting energy green transitions [35] and the roles of financial development and technological innovation in promoting economic and ecological sustainability [36]. High-quality corporate development is a comprehensive and inclusive concept involving core elements of "enterprise", "high-quality", and "development". The report of the 20th National Congress of the Communist Party of China emphasized that high-quality development is the foremost task in building a modern socialist country, urging efforts to promote it. From a high-quality perspective, three levels can be identified: the micro level (enterprises and products), the meso level (industries and cities), and the macro level (economy and public services) [37]. While the general meaning is easy to understand, precisely defining and scientifically grasping it is challenging due to its complexity and multidimensionality, often leading to cognitive discrepancies and a lack of consensus. High-quality corporate development aims at achieving high-level, high-efficiency economic and social value creation while shaping sustainable growth capabilities, distinguishing it from the extensive development model that relies solely on scale expansion. It represents a new paradigm of intensive, intrinsic, and sustainable development for enterprises. The core of high-quality corporate development includes product and service quality, resource utilization capability, management mechanisms, corporate performance, and social reputation [38].

Empirical research on factors influencing high-quality corporate development often focuses primarily on total factor productivity [39], with limited attention given to other potentially significant aspects. TFP reflects the efficiency and innovative capacity of enterprises in utilizing various resources during production. A high TFP indicates that enterprises expand production scale not only through increased input but also by improving production efficiency and product quality through technological advances, management optimization, and innovation, thus achieving sustainable, high-quality development. Enterprises need to drive financial management towards inclusivity, emphasizing green development, intangible assets, smart capital, and sustainable value, challenging finance personnel to integrate ESG concepts into financial decision making for sustainable growth. The top-level design of policies regarding ESG information disclosure is continuously being refined, with the government actively guiding enterprises to take on greater social responsibility while pursuing profitability, moving toward a green and low-carbon transition. According to recent data from Huazheng ESG, by 30 April 2024, more than 2110 A-share listed companies had released independent sustainable development reports, representing a 16% year-on-year increase. An increasing number of enterprises are incorporating ESG concepts into their strategic planning and development processes. Research has shown that digital transformation can positively promote improvements in corporate ESG performance [40], with mechanisms including fostering internal green technology innovation, increasing external legitimacy pressure, and alleviating information asymmetry [41].

### *2.3. Digitalization and Research on High-Quality Corporate Development*

#### 2.3.1. Digitalization and Corporate Efficiency

Total Factor Productivity was first proposed by Dutch economist Jan Tinbergen in 1942. He was the first to introduce a time variable into the Cobb–Douglas production function and studied the fluctuation characteristics and relationships between input factors and productivity. However, he only considered the impact of labor and capital on productivity, neglecting the influence of other intrinsic factors. Building on this foundation, American economist Hiam Davis revised and improved the concept of TFP, analyzing all input factors, including labor capital and raw materials. In 1956, Robert Solow addressed the issue of sustained economic growth by explaining the role of technological progress in his work "Contributions to the Theory of Economic Growth". In "Technical Change and the Aggregate Production Function", Solow further decomposed output growth into contributions from capital, labor, and technological advancement, proposing a method to calculate growth rates based on the weighted average of labor growth rates and technological progress minus their residual growth rates. Following this, a global wave of research on TFP emerged, with economists like Solow using TFP to measure broad technological progress [42] and analyze the sources of economic output growth. TFP has become an important indicator for assessing the quality of economic development in various countries [43].

TFP is influenced by internal factors, such as technological advancements and R&D investments, as well as external factors like the operating environment of enterprises [44]. Digital transformation plays a significant role in internal corporate activities, particularly in performance enhancement and innovation activities. On one hand, digital transformation facilitates the transition from low-end to high-end production, which is crucial for enhancing market competitiveness. When technologies such as artificial intelligence are appropriately applied to relevant business processes, digital transformation can promote high-quality corporate development by reducing information search costs, improving information processing capabilities, reducing internal capital misallocation, and enhancing R&D efficiency [45]. Furthermore, improvements in management efficiency and informa-

tion transmission provide reliable support for corporate decision making and can help businesses achieve upgrades by increasing investment demands and opportunities [46]. On the other hand, digital transformation has a positive impact on information exchange between enterprises and external agents. As digital transformation progresses and relevant business processes are appropriately applied, enterprises gradually establish dynamic capabilities that can flexibly meet the growing demands of customers and markets. This significantly enhances their economic efficiency and contributes to high-quality corporate development. Moreover, digital transformation and its related business model innovations fundamentally change consumer expectations and behaviors [47]. Rich and effective communication channels break down the fragmented relationships between enterprises and external entities in traditional environments, increasing information interaction among businesses, customers, suppliers, and competitors. Companies can also leverage this data to expand into other markets, pursuing new growth opportunities and ultimately achieving sustained improvements in efficiency over the long term.

#### 2.3.2. Digitalization and Corporate ESG

Digital transformation is not only a technological revolution for enterprises but also a powerful driver of innovation in management models, injecting strong momentum into corporate ESG (Environmental, Social, and Governance) performance. The ESG practices of enterprises exhibit multidimensional complexity, significantly influenced by a myriad of interwoven factors, including but not limited to financial performance drivers [48], considerations of market competitiveness [49], and the uniqueness of ownership structures [50]. The digital revolution is reshaping the landscape of corporate activities with unprecedented force [29], accelerating business process innovation while reinforcing the construction of a community-centered social order aimed at enhancing collective well-being and achieving comprehensive prosperity for all. This trend signifies that while pursuing economic benefits, enterprises must also actively assume environmental responsibilities, deepen social participation, and continuously optimize internal governance to respond to the profound calls for sustainable development in our times.

Digital transformation greatly improves the internal information environment of enterprises by introducing advanced information technology. The rapid flow and efficient processing of information enable companies to grasp the safety conditions of the workplace in real time, promptly warning of and addressing potential safety risks. Digital transformation optimizes internal communication mechanisms [51], enhancing the accuracy and timeliness of information processing, which is crucial for reducing safety incidents and ensuring employee safety. Additionally, digital transformation strengthens the internal supervision mechanisms of enterprises. By introducing digital management systems and smart monitoring devices, companies can achieve comprehensive, round-the-clock monitoring of the workplace, quickly identifying and rectifying potential safety hazards. Digital transformation significantly enhances the efficiency and effectiveness of internal supervision, effectively curbing illegal and irregular behaviors and maintaining a positive corporate image. By improving the internal information environment and strengthening internal oversight, digital transformation effectively enhances the quality of internal governance. This not only helps reduce the occurrence of safety incidents but also lays a solid foundation for improving corporate ESG performance. In the wake of the digital wave, enterprises should actively embrace digital transformation and promote the innovation and development of management models. The production capacity of digital technologies largely depends on local digital infrastructure and intelligence levels [35].

The manifestation of digital technologies in the real world has a significant impact on current production and lifestyles. Meanwhile, themes of green and sustainable develop-

ment, along with balanced growth, have emerged as key focuses of the new era. The value of corporate digital transformation is reflected not only in improved economic performance but also in non-economic performance areas such as environmental, social, governance, and cultural performance [52]. Particularly in the context of the digital economy, stakeholders have heightened expectations for enterprises' ability and performance in fulfilling social responsibilities, pressuring companies to innovate. Additionally, innovations in digital technology can enhance companies' capacity and performance in fulfilling social responsibilities. Post digital transformation, the support of digital technologies can help enterprises more efficiently improve and enhance their green image, customer reputation, and product quality, leading to increased orders and profits. Furthermore, digital transformation can bring about changes in organizational structure and internal management [53], reducing the expected costs associated with green transformation and activities, and even altering profit models, thereby creating more job opportunities for society while lowering corporate costs, which in turn promotes sustainable economic growth.

As an important country, China actively participates in global environmental governance and has released a series of policies, such as the "Coordinated Implementation Plan for Pollution Reduction and Carbon Reduction," supporting fundamental improvements to the ecological environment and focusing on the two main tasks of peak carbon emissions and carbon neutrality. This approach addresses pollution prevention at the source, emphasizes key areas, and aims to maximize environmental governance. Various industries are committed to improving clean production technology levels, and under legislative assistance and supervision, progress has been made in reducing pollutant emissions, laying the foundation for significant improvements in China's environmental quality. With the rise in living standards, the previously prevalent model of extensive, high-pollution economic growth can no longer meet people's demands for a natural environment. The public is increasingly yearning for and pursuing a cleaner, more comfortable, and environmentally friendly environment, making environmental governance increasingly important. As profit-seeking economic organizations, enterprises' production and operations are inextricably linked to the external environment [54]. Within this external environment, the harmonious coexistence of humans and nature has become a key aspect of social development, and achieving high-quality development is essential for realizing ecological protection and coordinated economic growth. The environmental governance system is also transitioning from a government-led approach to a joint governance model involving government, enterprises, and residents [55]. Manufacturing enterprises are both major sources of pollution emissions and key areas for environmental governance. This transition aims to enhance the effectiveness of environmental governance and improve environmental quality.

In summary, this study addresses key research gaps by integrating the perspectives of total factor productivity and ESG criteria to offer a more comprehensive assessment of how digitalization impacts the high-quality development of the manufacturing industry. Traditional research has often treated economic benefits and sustainability as separate domains, overlooking the potential interplay between them in the context of digital transformation. This study bridges that gap by demonstrating how digitalization can simultaneously drive economic efficiency; optimize resource utilization; and foster improvements in environmental stewardship, social responsibility, and corporate governance. By evaluating both the economic and sustainability dimensions in tandem, the research offers a more nuanced and integrated view of how digitalization shapes industrial progress. The framework introduced in this study not only helps businesses enhance their production processes and economic performance, but it also emphasizes the importance of adopting more responsible practices to meet increasingly stringent sustainability standards. This dual focus empowers enterprises to achieve sustainable growth without sacrificing profitability, allowing them to

maintain a competitive edge in the market. Moreover, by aligning digital transformation with ESG principles, businesses can create long-term value that extends beyond financial returns, contributing positively to society and the environment. Ultimately, this approach paves the way for companies to make meaningful strides toward both economic growth and sustainable development, securing their place in a rapidly evolving global market.

## 3. Theory and Hypothesis

The digital economy is an extension and elaboration of the concept of the information economy, with the term "digital economy" first proposed by American expert Tapscott in 1996. The digital economy can be divided into narrow and broad definitions. The narrow definition refers to digital industrialization or the transformation of the foundational technologies of the digital economy into new industrial ecosystems. The broad definition refers to the digitalization of industries, which encompasses the integration of digital technology with traditional industries, thereby helping traditional industries improve quality and efficiency, including the construction of new models and business modes like the industrial internet and smart manufacturing.

(1) Technological Determinism and the Digital Economy. The theory of technological determinism suggests that technological developments are the primary drivers of societal change. In the context of the digital economy, technological innovations—such as AI, IoT, blockchain, and 3D printing—are transforming industries by reshaping business operations, organizational structures, and consumer behavior. This can form the basis for hypotheses exploring how specific digital technologies influence manufacturing firms' productivity, innovation, or organizational change.

(2) Resource-Based View. The RBV theory posits that competitive advantage is derived from unique resources and capabilities within the firm. In the digital economy, digital capabilities, such as data analytics, IT infrastructure, and skilled workforce, are critical resources that influence firm performance. The RBV can guide hypotheses focused on how digital resources enable firms to achieve a competitive edge, especially in traditional industries that are undergoing digital transformation.

(3) Innovation Diffusion Theory. Everett Rogers' Diffusion of Innovations theory can provide a framework for understanding how digital technologies spread within industries. This theory focuses on how innovations are adopted across organizations and what factors influence adoption rates. In the context of digital transformation, the adoption of new technologies such as the industrial internet and smart manufacturing systems can be studied through the lens of this theory, particularly in terms of perceived benefits, compatibility with existing processes, and organizational readiness.

With the rapid development of the digital economy, research has shifted from studying digital industrialization to exploring industrial digitalization. Currently, there is no unified standard for measuring the digital economy. In many countries, government agencies estimate the scale of the digital economy in specific regions using statistical methods or by comparing the development levels of digital economies across different areas based on multiple indicators [56]. Scholars are actively working to identify appropriate indicators for measuring the digital economy through various approaches. The digital economy emerged from the vast accumulation and use of machine-readable information in economic activities, evolving along the following trajectory: (1) Information digitalization, which involves converting mechanical and analog electronic technologies into digital formats, transforming various forms of information into processable digital data. (2) The rapid development of computing, communication, and information processing technologies, alongside the widespread adoption of the internet and mobile networks, has created abundant opportunities for applying digital technologies, such as the Internet of Things, artificial intelligence,

blockchain, and 3D printing. (3) The digitalization of economic activities and the rise of data-driven business models have significantly altered production organization, operational processes, and profit models within enterprises, as well as transforming consumer communication and consumption patterns, leading to the gradual emergence of digital economic characteristics within a nation's economy.

As a key production factor in the digital economy, data must be deeply integrated with other traditional production factors to realize its full potential. Unlike natural resources such as land, capital, and labor, data possess several unique characteristics that contribute to their complexity. First, data are inherently non-rivalrous, meaning they can be used simultaneously multiple times without diminishing their value. Second, while data flows have the potential to generate value, this value cannot be predicted at the moment the original data are created. Lastly, the value derived from data flows is influenced by the analytical techniques applied to the data. The continuous expansion of data flow volumes, coupled with advancements in digital technologies, often results in economies of scale. Consequently, the value creation of data is directly tied to the effective application of digital technologies in their analysis.

By deeply integrating digital technologies with traditional industries, the efficiency and quality of economic development can be enhanced. The better the construction of digital platforms, the more fully data can be developed and applied, and the more widespread internet technology becomes, the more robust the momentum for digital economy development [57]. Digital technologies can promote the digital transformation of traditional industries [58]. On this basis, key technologies of the digital economy can be upgraded and break through, thereby driving the development of the digital economy [59]. As the core of the digital economy, information technology has propelled improvements in production and management efficiency. Technologies such as big data, cloud computing, and the Internet of Things enable enterprises to better analyze market demand, optimize production processes, and manage supply chains, resulting in more efficient resource allocation and production. Digital platforms leverage network effects to rapidly expand their scale and influence, promoting economic growth. Knowledge and innovation-driven approaches are vital characteristics of the digital economy; through innovation, enterprises can develop new products, create new markets, and drive economic growth. Data, as a new production factor, are as important as traditional production factors such as land, labor, and capital. Enterprises can gain market insights, optimize business processes, and enhance competitiveness and market responsiveness through data analysis. The development of the digital economy allows production factors and production relationships to gradually evolve toward digitalization, reducing costs in economic activities and transforming the paradigm of economic and social development [60]. The essence of the digital economy is global; through digital technologies, enterprises can more easily enter international markets, expand market scale, and promote the process of global economic integration. Innovation empowerment through means such as technological innovation, business model innovation, and management innovation enhances the competitiveness and sustainable development capabilities of enterprises and industries. By researching and applying new technologies like smart manufacturing, industrial internet, and artificial intelligence, manufacturing enterprises can improve production efficiency, product quality, and flexibility. Digital technologies enable enterprises to explore new business models, such as on-demand customization, service-oriented manufacturing, and shared manufacturing, to meet consumers' personalized needs, optimize resource utilization, and reduce operational costs. Digital management tools and platforms help enterprises achieve refined management and decision support, improving overall operational efficiency and market competitiveness through decision systems driven by big data analysis. Innovation empowerment requires

the support of high-quality talent. Enterprises should focus on cultivating and attracting talent with digital skills and innovative thinking while fostering a corporate culture that encourages innovation. Innovation empowerment is not only the responsibility of individual enterprises but also requires collaboration across the entire industrial ecosystem, where governments, enterprises, research institutions, and intermediary organizations work together to build an open, shared, and cooperative innovation ecosystem; promote collaborative innovation along the upstream and downstream of the industrial chain; and form a virtuous cycle of innovation.

The degree of digitalization, which refers to the depth and breadth of a company's adoption of digital technologies in its business processes, management systems, and market operations, has a comprehensive impact on enterprises. Digital technologies, such as automated production lines, intelligent manufacturing systems, and industrial internet, can significantly enhance production efficiency by promoting the upgrade of lower-level production factors through internet technology. By accelerating the flow and transmission of information and knowledge, these technologies improve the transaction efficiency and quality for both enterprises and consumers, aligning with the demands of a well-functioning market supply and demand system [61]. Data-driven production management and real-time monitoring allow companies to reduce downtime, optimize production processes, lower production costs, and increase capacity utilization. By adopting digital detection and monitoring technologies, enterprises can monitor product quality in real-time, quickly identify and resolve production issues, and ensure high-quality standards for their products. Additionally, digital technologies can support customized production to meet personalized consumer demands, thereby enhancing product value. Companies with high levels of digitalization can significantly lower operational costs by optimizing resource allocation, reducing human errors, and improving decision-making efficiency. For example, big data analytics can optimize supply chain management, reducing inventory buildup and logistics costs, while intelligent systems can enhance energy management efficiency and lower energy consumption.

Firms with advanced digitalization exhibit greater innovative capabilities. Through digital platforms and tools, companies can conduct research and development (R&D) and innovation more efficiently, shortening product development cycles and enhancing the market conversion rates of innovative outcomes. Open innovation platforms can also facilitate collaboration with external innovation resources, promoting joint innovation. Moreover, digital technologies enable companies to better identify and manage risks. Data analysis can help enterprises anticipate market and operational risks, allowing them to formulate appropriate response strategies. Information security technologies can protect companies' digital assets and sensitive information, reducing the risks of information leaks and cyberattacks. The impact of digitalization on enterprises is profound and extensive. A high degree of digitalization not only enhances production efficiency, improves product quality, and lowers operational costs but also accelerates market response times, enhances customer experiences, and strengthens innovative capabilities and overall competitiveness. Furthermore, digital technologies aid in optimizing risk management. By comprehensively advancing digital transformation, enterprises can gain significant advantages in fierce market competition and achieve high-quality development.

### *3.1. Direct Impact of Digital Transformation on High-Quality Development*

As the global economy undergoes digital transformation, the application of digital technologies in business operations is becoming increasingly widespread, significantly altering traditional business models and production methods. Total Factor Productivity refers to the output growth achieved by enterprises through technological advancement

and management optimization under the same input conditions. Digital technologies, such as artificial intelligence, big data, the Internet of Things, and cloud computing, can significantly enhance a company's production efficiency and management level. For example, through data analysis and intelligent algorithms, companies can optimize production processes, reduce resource waste, and improve equipment utilization, achieving higher output without increasing inputs. Green and sustainable development, along with balanced growth, have become central themes in the new era. The value of digital transformation for enterprises is reflected not only in the improvement of economic performance but also in their non-economic performance, such as environmental, social, governance, and cultural performance [52]. Particularly in the context of the digital economy, stakeholders have higher expectations for companies to fulfill their social responsibilities, which pressures businesses to innovate. Moreover, innovations in digital technologies can enhance companies' capabilities and performance in fulfilling social responsibilities [62]. Additionally, digital technologies support enterprises in managing social responsibility, enhancing their sense of responsibility and public image, and improving their sustainable development performance. High-quality development requires not only improved economic benefits but also comprehensive enhancements in various aspects, including product quality, innovation capability, customer experience, and social responsibility. Companies with a high degree of digitalization continuously improve the quality of their products and services through technological innovation and management optimization, meeting diverse and personalized customer demands and enhancing market competitiveness.

Furthermore, digital platforms and tools facilitate continuous innovation within companies, enabling them to respond quickly to market changes and customer needs while maintaining sustained innovation capacity and market vitality. Digital technologies also support companies in their social responsibility practices, enhancing their social image and brand value, and promoting sustainable and high-quality development. Based on this, this study proposes Hypothesis 1:

**H1.** *A high level of digitalization will enhance a company's total factor productivity and sustainable development performance, contributing to the promotion of high-quality enterprise development.*

### *3.2. Impact Paths of Digital Transformation on High-Quality Development*

#### 3.2.1. Financing Costs Effect

The application of digital technology in business operations has significantly transformed traditional business and financial models. Digitalization enhances information transparency and credit assessment. Digital transformation helps companies demonstrate greater transparency, reliability, and profitability during the financing process, thereby reducing the perceived risk for financiers and lowering financing costs [26]. Big data analytics, blockchain, and artificial intelligence can significantly enhance a company's information transparency and credit assessment capabilities. Through big data analysis, financial institutions can access real-time operational data, financial status, and market performance of companies, allowing for more accurate credit assessments. Blockchain technology ensures the transparency and immutability of transaction records, enhancing the credibility of a company's creditworthiness. These technological advancements enable financial institutions to better assess credit risk, reduce information asymmetry, increase financing efficiency, and lower financing costs. The reduction in financing costs also alleviates the financial burden on companies, improving their profitability and financial stability, which lays a solid foundation for sustainable development. In terms of corporate financing, the digital economy can reduce financing constraints, helping companies secure better funding and promoting high-quality development [63]. By lowering financing costs

through digital means, companies can allocate resources more effectively and achieve high-quality development goals. Based on this, this study proposes Hypothesis 2:

**H2.** *A higher degree of digitalization will help promote high-quality development by lowering corporate financing costs.*

#### 3.2.2. Innovation Effect

The digital economy effectively addresses the supply–demand imbalance in regional innovation systems and entrepreneurial activities, breaking down spatial limitations on innovation efforts. Through digital platforms and technologies, innovation resources and entrepreneurial opportunities can flow rapidly and match efficiently on a global scale, facilitating broader and more efficient innovation and entrepreneurship activities [64]. In the era of the digital economy, the widespread application of digital technologies is profoundly changing the innovation models and development paths of enterprises. Digitalization enhances research and development efficiency and innovation capability. Technologies such as artificial intelligence, big data analytics, and cloud computing significantly boost enterprises' R&D efficiency and innovation capacity. AI and big data analytics can process vast amounts of data to identify potential market demands and technological trends, helping companies engage in proactive technology R&D and product development. Cloud computing provides robust computing power and data storage support, enabling companies to conduct large-scale experiments and data analyses quickly, thus accelerating the R&D process. The digital economy enhances the output and efficiency of enterprise innovation [65] and improves product and service quality by enhancing innovation capabilities, aligning with the requirements for green industrial development in China [66]. By increasing innovation output, companies can continuously launch high-quality, high-value-added products and services that meet the diverse needs of the market and customers, thereby enhancing market competitiveness and brand value. Moreover, ongoing technological innovation and product upgrades enable enterprises to maintain market vitality and technological leadership, achieving sustainable development. The increase in innovation output also leads to improved production efficiency and reduced costs, further enhancing enterprises' profitability and financial stability, providing strong support for high-quality development. Based on this, the following hypothesis is proposed:

**H3.** *A higher degree of digitalization will enhance the innovation output of enterprises, thereby contributing to the promotion of high-quality development.*

#### 3.2.3. Human Capital Structure Effect

The digital economy reduces the demand for low-skilled labor through the "substitution effect" while simultaneously increasing the skill requirements for existing employees through the "enhancement effect" [67]. These two effects work together to reshape the demand structure in the labor market, necessitating that policymakers and businesses focus on enhancing workforce skills and promoting reforms in education and training systems to help workers adapt to the changes brought about by the digital economy. With the rapid advancement of the digital economy, the demand for human capital in related industries has undergone a profound transformation. This change has not only led to a continuous increase in the employment share of highly educated talent in software development and high-tech manufacturing but has also triggered a significant shift in labor skill requirements [68]. Against this backdrop, manufacturing enterprises' hiring preferences have gradually shifted from a quantity-oriented approach to a quality-oriented one. Meanwhile, the deep integration of digital technologies and manufacturing has spurred the rise of

intelligent production, resulting in a trend where high-skilled personnel are increasingly substituting for low-skilled labor [13].

In today's digital economy, digital technologies not only alter the way businesses operate but also profoundly influence the structure and management of human capital. The development of digital technologies demands that employees possess higher technical qualifications and professional skills. Through digital training and online learning platforms, companies can continuously enhance their employees' skill levels and knowledge reserves. The application of technologies such as artificial intelligence, big data analysis, and cloud computing enables employees to master advanced tools and methods, improving work efficiency and innovation capability. Furthermore, digital training promotes self-learning and continuous development among employees, fostering a learning organizational culture that enhances the overall quality of human capital. An optimized human capital structure promotes technological innovation and product development capabilities within enterprises by enhancing employee qualifications and skill levels, thereby meeting the diverse demands of the market and customers. Additionally, efficient human resource management and flexible work models improve operational efficiency and adaptability, allowing businesses to respond quickly to market changes and customer needs while maintaining a competitive advantage. Moreover, an optimized human capital structure strengthens organizational vitality and innovation capability, providing a solid talent foundation and intellectual support for sustainable development. Based on this, the article proposes Hypothesis 4:

**H4.** *High levels of digitalization can promote high-quality development in enterprises by optimizing the structure of human capital.*

## 4. Methodology and Data

### *4.1. The Measurement of Key Variables*

This study employs total factor productivity, taking into account corporate social responsibility, to indicate the level of high-quality development of enterprises. Specifically, this paper first measures the total factor productivity of enterprises using the LP method then collects and organizes the ESG indices that characterize corporate social responsibility for individual enterprises. The total factor productivity and ESG indices are integrated into a corporate high-quality development index using the entropy method.

This paper adopts a two-way fixed effects model to test four hypotheses, aiming to comprehensively assess the impact of digitalization on various aspects of business development. First, Hypothesis 1 (H1) examines the effect of digitalization on total factor productivity and sustainability performance, exploring how digitalization can enhance production efficiency and drive improvements in corporate performance in terms of environmental, social responsibility, and governance, thereby promoting the long-term sustainable development of enterprises. Second, Hypothesis 2 (H2) analyzes how digitalization affects companies' financing channels and capital costs, particularly by improving capital acquisition efficiency and lowering financing costs, which in turn improves the financial condition and capital structure of firms. Hypothesis 3 (H3) focuses on the role of digitalization in promoting innovation output, measured by changes in the number of patent applications, to assess whether digitalization can enhance the firm's innovation capacity and drive technological advancement and market competitiveness. Finally, Hypothesis 4 (H4) tests the impact of digitalization on optimizing the human capital structure of firms, particularly by increasing the proportion of employees with a bachelor's degree or higher, to determine whether digitalization can improve the overall quality of human resources and talent structure, thereby driving high-quality development within the company. In testing each hypothesis, this paper controls for relevant variables such as company size, industry type, and regional

economic level, and employs regression analysis to ensure reliable empirical results. It also checks for statistical significance between the independent variable (digitalization level) and dependent variables (TFP, ESG, financing costs, innovation output, human capital structure) to ensure the robustness and interpretability of the findings.

4.1.1. Measurement of Enterprise Total Factor Productivity

The LP method is used to accurately estimate the total factor productivity at the enterprise level. This method employs intermediate inputs as instrumental variables to control for the endogeneity of input factors, enhancing the accuracy of the production function parameter estimates.

Initial Production Function. First, assume that the production function for firm $i$ at time $t$ takes the standard Cobb–Douglas form:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\beta} L_{i,t}^{\gamma} \tag{1}$$

where $Y_{i,t}$ is the output of firm $i$ at time $t$, $K_{i,t}$ and $L_{i,t}$ are capital and labor inputs, $A_{i,t}$ is Total Factor Productivity, and $\beta$ and $\gamma$ are the output elasticities of capital and labor.

Taking the natural logarithm of both sides of the production function:

$$\ln(Y_{i,t}) = \alpha + \beta \ln(K_{i,t}) + \gamma \ln\left(L_{i,t}\right) + u_{i,t} \tag{2}$$

where $u_{i,t}$ is the error term, which can be decomposed into two parts:

$$u_{i,t} = \omega_{i,t} + \varepsilon_{i,t} \tag{3}$$

$\omega_{i,t}$ is the observable productivity shock, and $\varepsilon_{i,t}$ is the unobservable residual.

Investment and Capital Accumulation Relationship. Assume that the capital accumulation follows the dynamic equation:

$$K_{i,t+1} = (1 - \delta) K_{i,t} + I_{i,t} \tag{4}$$

where $K_{i,t}$ and $K_{i,t+1}$ are the capital stocks in the current and next periods, respectively; $I_{i,t}$ is the total investment of the firm at time $t$; and $\delta$ is the depreciation rate of capital.

Investment Function and Optimal Investment. Assume that firms use investment to respond to productivity shocks. An investment function $I_{i,t} = I(K_{i,t}, \omega_{i,t})$ can be constructed. By solving for the inverse, we can express the productivity shock $\omega_{i,t}$ as:

$$\omega_{i,t} = I^{-1}(I_{i,t}, K_{i,t}) = h(I_{i,t}, K_{i,t}) \tag{5}$$

Modified Production Function. Substituting $\omega_{i,t}$ into the original production function, we obtain the modified production function:

$$Y_{i,t} = \alpha + \gamma \ln L_{i,t} + \Phi(I_{i,t}, K_{i,t}) + \varepsilon_{i,t} \tag{6}$$

where $\Phi(I_{i,t}, K_{i,t}) = \beta \ln K_{i,t} + h(I_{i,t}, K_{i,t}) = \beta \ln K_{i,t} + \omega_{i,t}$, so:

$$Y_{i,t} = \alpha + \gamma \ln L_{i,t} + \beta \ln K_{i,t} + \omega_{i,t} + \varepsilon_{i,t} \tag{7}$$

Assumptions and Further Derivation. Assume $\omega_{i,t}$ follows a first-order Markov process:

$$\omega_{i,t} = E(\omega_{i,t} | \Omega_{i,t-1}) + \xi_{i,t} = E(\omega_{i,t} | \omega_{i,t-1}) + \xi_{i,t} = g(\omega_{i,t-1}) + \xi_{i,t} \tag{8}$$

where $\xi_{i,t}$ is a white noise error term. To simplify, assume that $g(\omega_{i,t-1})$ represents the effect of past shocks on current output. The production function can now be rewritten as:

$$Y_{i,t} = \alpha + \hat{\gamma}\ln L_{i,t} + \beta\ln K_{i,t} + g(\hat{\omega}_{i,t-1}) + e_{i,t} \tag{9}$$

where $e_{i,t}$= $\xi_{i,t}$+ $\varepsilon_{i,t}$ is the new error term.

Using Linear Programming (LP) to Estimate Parameters. The goal of LP is to minimize the residuals $e_{i,t}$, and by controlling the relationship between investment and capital accumulation, we can address endogeneity. The following steps are involved:

Linearizing the Production Function, the production function is in linear form:

$$lnY_{i,t} = \alpha + \hat{\gamma}\ln L_{i,t} + \beta\ln K_{i,t} + \mathrm{g}(\hat{\omega}_{i,t-1}) + e_{i,t} \tag{10}$$

Choosing Instrumental Variables. In LP, suitable instrumental variables are selected to address endogeneity. Typically, investment $I_{i,t}$ and capital $K_{i,t}$ are chosen as instruments.

Minimizing the Residuals. The parameters of the production function, $\alpha$, $\hat{\gamma}$, and $\hat{\beta}$, are estimated by minimizing the difference between the predicted values and the observed values of the output, i.e., minimizing the residuals $e_{i,t}$.

Estimating TFP. Based on the estimated parameters $\hat{\gamma}$ and $\hat{\beta}$, the TFP log value for firm $i$ at time $t$ can be computed as:

$$TFP_{i,t} = e^{*}_{i,t} = Y_{i,t} - \alpha - \hat{\gamma}\ln L_{i,t} - \hat{\beta}(\ln K_{i,t} - \ln K_{i,t-1}) - \hat{\Phi}(I_{i,t-1}, K_{i,t-1}) \tag{11}$$

4.1.2. The Index of High-Quality Development

Enterprise development not only requires improving its own production efficiency but also increasing attention to enhancing social responsibility. Typically, most studies use the ESG index to characterize a company's commitment to social responsibility. Analyzing only the overall corporate social responsibility score may overlook the interaction between different dimensions of practices, making it difficult to accurately assess the actual impact of corporate social responsibility [69]. Characterizing corporate social responsibility from the three dimensions of environmental performance (E), social performance (S), and governance performance (G) provides a more comprehensive reflection of the practices and outcomes in each dimension [70]. Commonly referred to as ESG, it is an important indicator for assessing a company's performance in environmental protection, social responsibility, and corporate governance. As a comprehensive evaluation standard, ESG reflects not only a company's financial status but also its contributions and responsibilities towards sustainable development. The Huazheng ESG index is used to measure the sustainable development performance of manufacturing enterprises.

The entropy method is employed to measure the total factor productivity and sustainable development performance of enterprises, integrating these into a high-quality development indicator. This indicator comprehensively reflects the enterprise's overall strength in resource allocation, environmental protection, and other areas. Based on this, an in-depth analysis is conducted from a dual perspective to verify the impact of digitalization on high-quality development.

The entropy method is commonly used to determine the weights of indicators and measure uncertainty. In the entropy method, we calculate the information entropy for each indicator and use it to assess the influence of each indicator [71]. Suppose we have multiple indicators; the formula for calculating the weights in the entropy method is as follows:

The first step involves applying the critical value method to normalize the indicators.

$$x'_{ij} = \frac{x_j - \min(x_j)}{\max(x_j) - \min(x_j)} \text{ or } x'_{ij} = \frac{\max(x_j) - x_j}{\max(x_j) - \min(x_j)} \tag{12}$$

Since all the indicators in the comprehensive evaluation system are positive, the above formula is used to normalize the indicators, where $\max(x_j)$ and $\min(x_j)$ represent the maximum and minimum values of the $j$-th indicator in the sample interval, respectively.

$$P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{13}$$

$$\omega_j = \frac{1 - H_j}{\sum_{k=1}^{n}(1 - H_k)} \tag{14}$$

$\omega_j$ is the weight of the $j$-th indicator, and $H_j$ is the information entropy of the $j$-th indicator, calculated as follows:

$$H_j = -\sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \tag{15}$$

$p_{ij}$ is the normalized value of the $i$-th sample under the $j$-th indicator, m is the number of samples, and $n$ is the number of indicators.

Combine total factor productivity and sustainable development performance and then calculate the high-quality development indicator $HQD_i$ by determining the weights through the entropy method:

$$HQD_i = \omega_1 \cdot TFP_i + \omega_2 \cdot ESG_i \tag{16}$$

$\omega_1$ and $\omega_2$ are the weights for total factor productivity and sustainable development performance, calculated using the entropy method.

#### 4.1.3. The Index of Digitalization

The level of enterprise digitalization (DCG) is used as the independent variable. Following the method of Wu et al. (2021) [72], the digitalization level of enterprises is measured through an analysis of annual report texts. Keywords and phrases related to enterprise digitalization, such as "digital transformation", "blockchain", "big data", "cloud computing", and "artificial intelligence", are extracted. Python 3.11 is employed to count the frequency of these digitalization keywords in the annual reports, and the frequency data are processed by adding one and taking the natural logarithm to obtain the digitalization level indicator DCG. This indicator accurately reflects the extent to which enterprises emphasize and implement digitalization in their annual reports, providing a solid data foundation for analyzing the impact of digitalization on high-quality development.

The calculation results of the enterprise digitalization level are shown in Table 1 and Figure 2, demonstrating a growth trend from 2010 to 2022, although the growth rates vary. The growth of cloud computing technology and digitalization is particularly significant, while artificial intelligence and big data technologies also show rapid growth trends. The growth of blockchain technology is relatively slow but is gradually increasing. Blockchain involves complex concepts and implementations, requiring manufacturing enterprises time to understand and master these new technologies. Most manufacturing enterprises have limited knowledge of blockchain and lack strong motivation to adopt and implement it. The year 2015 marks a significant turning point, with almost all technology indices showing noticeable growth that year, coinciding with the release of the "Internet Plus"

initiative, which promoted digital transformation across various industries. This growth can be attributed to the maturation and wider application of technology, increased market demand and competitive pressure, enhanced policy support and capital investment, the formulation and implementation of enterprise digital transformation strategies, as well as the promotion of technology popularization and talent cultivation, all contributing to the noticeable increase in technology indices during that year.

**Table 1.** Digitalization Index and Sub-Indices of Manufacturing Enterprises from 2010 to 2022.

| Year | Artificial Intelligence Technology | Blockchain Technology | Cloud Computing Technology | Big Data Technology | Digital Technology Application | Digitalization |
|---|---|---|---|---|---|---|
| 2010 | 0.0176 | 0.0014 | 0.0952 | 0.0070 | 0.2276 | 0.2890 |
| 2011 | 0.0186 | 0.0028 | 0.1529 | 0.0098 | 0.2614 | 0.3618 |
| 2012 | 0.0188 | 0.0014 | 0.1853 | 0.0228 | 0.3166 | 0.4174 |
| 2013 | 0.0366 | 0.0014 | 0.2130 | 0.0722 | 0.3804 | 0.4965 |
| 2014 | 0.0374 | 0.0014 | 0.2860 | 0.1504 | 0.4763 | 0.6152 |
| 2015 | 0.0917 | 0.0042 | 0.3609 | 0.2899 | 0.5774 | 0.7556 |
| 2016 | 0.1606 | 0.0028 | 0.4065 | 0.3368 | 0.5874 | 0.8042 |
| 2017 | 0.2972 | 0.0028 | 0.4667 | 0.4076 | 0.6351 | 0.8890 |
| 2018 | 0.3690 | 0.0112 | 0.4926 | 0.4260 | 0.6600 | 0.9277 |
| 2019 | 0.4200 | 0.0149 | 0.5148 | 0.4203 | 0.6847 | 0.9514 |
| 2020 | 0.4441 | 0.0304 | 0.5240 | 0.4524 | 0.7286 | 0.9888 |
| 2021 | 0.4428 | 0.0209 | 0.5258 | 0.4446 | 0.7444 | 0.9923 |
| 2022 | 0.4616 | 0.0216 | 0.5273 | 0.4504 | 0.7631 | 1.0251 |

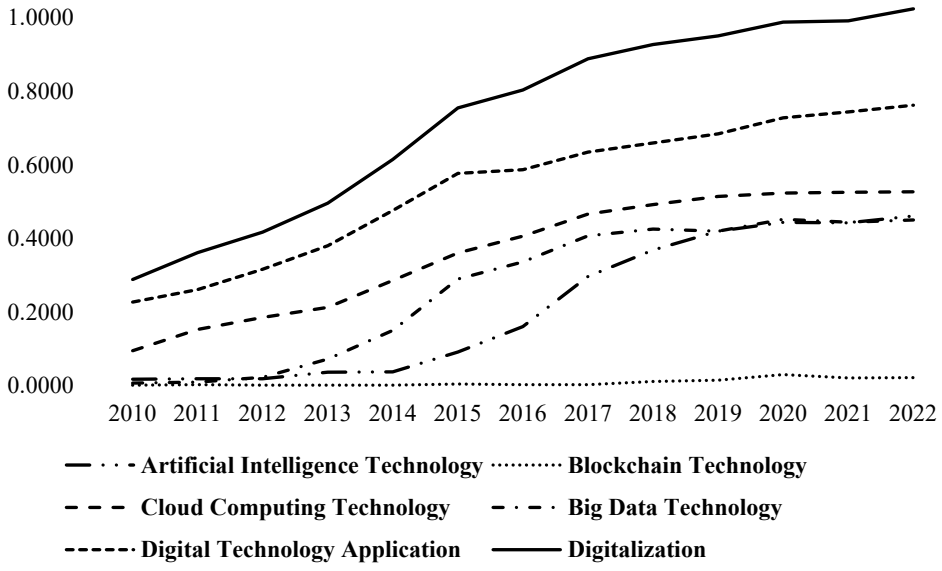



**Figure 2.** Trends of Digitalization Index and Sub-Indices of Manufacturing Enterprises from 2010 to 2022.

### *4.2. Benchmark Regression Model*

The bidirectional fixed effects model constructed is as follows:

$$HQD_{it} = \gamma_0 + \gamma_1 DCG_{it} + \sum \gamma_c Control_{it} + \mu_t + \eta_i + \varepsilon_{it} \quad (17)$$

In this model, the dependent variable $HQD_{it}$ represents the high-quality development level of the $i$-th manufacturing enterprise in the $t$-th year, primarily reflected through the dimensions of total factor productivity $TFP_{it}$ and sustainable development $ESG_{it}$. The

independent variable is the degree of digitalization $DCG_{it}$, $Control_{it}$ represents the control variables, $\mu_t$ is the time fixed effect, $\eta_i$ is the individual fixed effect for enterprises, and $\varepsilon_{it}$ is the residual term.

In this study, we selected several control variables to ensure a comprehensive analysis of high-quality development. Return on Total Assets (Tao) measures how efficiently a company utilizes its total assets to generate profits, reflecting profitability. It is calculated as earnings before interest and taxes divided by average total assets. Return on Assets (Roa) assesses the company's profitability and asset management capabilities, calculated as net profit divided by total assets. Firm Age (Age) refers to the duration of a firm's existence from the establishment to the end of the study period, indicating its maturity and experience accumulation, which may influence digitalization and high-quality development. Equity Concentration (Shrcr) indicates the degree of dispersion in the company's equity structure, typically represented by the shareholding ratio of the top ten shareholders, affecting decision-making efficiency and governance levels. Fixed Asset Ratio (Fassetr) refers to the proportion of fixed assets in total assets, reflecting capital structure and asset allocation, which can influence production capacity and operational efficiency. Debt-to-Asset Ratio (Assert) measures financial leverage, indicating the ratio of total liabilities to total assets and reflecting solvency and financial risk. The Proportion of Independent Directors (Outdir) indicates the share of independent directors on the board, reflecting corporate governance levels; a higher proportion enhances board independence and supervisory function.

These control variables comprehensively consider profitability, maturity, governance structure, capital structure, and financial condition, helping to control for other factors that may affect high-quality development. This ensures a more accurate and reliable assessment of the impact of digitalization on enterprises.

### *4.3. Data Sources and Descriptive Statistics*

This study selects listed manufacturing companies on the Shanghai and Shenzhen Stock Exchanges in A-shares from 2010 to 2022 as the research sample. ST companies, which typically face financial distress or other operational issues, were excluded to prevent bias in the research results. Samples with missing data were also removed from the dataset, as missing data could affect the completeness and accuracy of the analysis. Companies that underwent an initial public offering (IPO) during the study period were excluded from the sample, as their operating conditions before and after the IPO may experience significant changes that could interfere with the research findings. Through these data processing steps, we ensured the quality and consistency of the sample data, providing a reliable foundation for subsequent analysis. These measures help eliminate the interference of outlier data on the research results, enhancing the credibility and accuracy of the conclusions. The data primarily come from the China Economic Information Network, Wind Database, and relevant companies' annual reports. Descriptive statistics are presented in Table 2.

Based on the descriptive statistics, the mean value of the variable TFP is 8.431, indicating that, overall, the total factor productivity of the enterprises is at a relatively high level. The standard deviation is 1.003, suggesting that there is some variability in productivity among the enterprises, although the differences are not excessively large, with observations ranging from 5.212 to 11.805. This indicates that the productivity levels of enterprises are quite broad but are concentrated in the medium to high range. The mean value of DCG is 1.148, with a standard deviation of 1.254 and observations ranging from 0.000 to 5.587. The mean value of ESG is 3.995, suggesting that enterprises perform slightly above average in terms of ESG. The standard deviation is 1.102, indicating significant variability in ESG performance among enterprises, with a minimum value of 1 and a maximum value of 7. This shows that some enterprises perform poorly in ESG, while others perform exception-

ally well. These variables highlight the performance and variability of enterprises across different dimensions.

**Table 2.** Descriptive Statistics of Main Variables.

| Variable | Observations | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| TFP | 6318 | 8.431 | 1.003 | 5.212 | 11.805 |
| DCG | 6318 | 1.148 | 1.254 | 0.000 | 5.587 |
| ESG | 6318 | 3.995 | 1.102 | 1.000 | 7.000 |
| Tao | 6318 | 0.049 | 0.167 | −2.095 | 11.006 |
| Roa | 6318 | 0.033 | 0.159 | −2.071 | 10.401 |
| Fassetr | 6318 | 0.230 | 0.141 | 0.002 | 0.825 |
| Age | 6318 | 2.953 | 0.328 | 1.099 | 3.807 |
| Shrcr | 6318 | 51.945 | 14.072 | 10.364 | 94.670 |
| Assetr | 6318 | 0.473 | 0.341 | 0.016 | 13.711 |
| Outdir | 6318 | 0.370 | 0.054 | 0.182 | 0.667 |
| HQD | 6318 | 7.737 | 0.919 | 4.710 | 10.577 |

## 5. Empirical Results

### *5.1. Benchmark Regression*

The results of the benchmark regression are shown in the Table 3, where HQD is the composite index calculated using the entropy method, incorporating both Total Factor Productivity and Environmental, Social, and Governance factors. In our study on the high-quality development of enterprises, we conducted a regression analysis on the degree of digitalization and obtained the following results. Columns 1, 3, and 5 include only the degree of digitalization in the regression model. When the dependent variable is high-quality development (HQD), the regression coefficient for digitalization is positive at a 1% significance level. When the dependent variables are Total Factor Productivity and Digital Governance Capability, the regression coefficients are positive at a 5% significance level. Columns 2, 4, and 6 show the regression results after incorporating control variables, where the regression coefficients for digitalization remain positive at a 5% significance level.

**Table 3.** The Impact of Digitalization on the High-Quality Development of Manufacturing Enterprises.

| Variable | HQD | | TFP | | ESG | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| DCG | 0.049 *** | 0.041 ** | 0.049 ** | 0.040 ** | 0.052 ** | 0.051 ** |
| | (3.54) | (3.01) | (3.20) | (2.72) | (2.29) | (2.24) |
| Tao | | 1.193 | | 2.518 ** | | −5.979 *** |
| | | (1.31) | | (2.46) | | (−4.54) |
| Roa | | −0.956 | | −2.312 ** | | 6.384 *** |
| | | (−1.04) | | (−2.25) | | (4.55) |
| Age | | 0.727 *** | | 0.885 *** | | −0.135 |
| | | (3.77) | | (4.08) | | (−0.43) |
| Shrcr | | 0.006 ** | | 0.007 ** | | 0.002 |
| | | (3.36) | | (3.41) | | (1.00) |
| Fassetr | | −1.326 *** | | −1.472 *** | | −0.542 ** |
| | | (−7.48) | | (−7.54) | | (−2.31) |
| Assetr | | 0.050 | | 0.055 | | 0.030 |
| | | (1.18) | | (0.89) | | (0.33) |
| Outdir | | −0.201 | | −0.363 * | | 0.643 * |
| | | (−1.00) | | (−1.73) | | (1.67) |
| Constant | 7.381 *** | 5.516 *** | 8.058 *** | 5.808 *** | 3.727 *** | 3.941 *** |
| | (345.49) | (10.00) | (340.04) | (9.34) | (103.91) | (4.65) |
| year/code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 6318 | 6318 | 6318 | 6318 | 6318 | 6318 |
| R-squared | 0.242 | 0.322 | 0.262 | 0.352 | 0.025 | 0.041 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

We find that the degree of digitalization has a multidimensional and profound impact on the high-quality development of enterprises, primarily manifested in two core areas:

enhanced economic efficiency and significant improvements in social benefits. Digital transformation not only dispels the inefficiencies of traditional economic models but also significantly accelerates the speed of economic operations, boosting total factor productivity and elevating enterprise productivity and profitability to new heights. This transformative enhancement not only solidifies the competitive position of enterprises in the market but also lays a solid economic foundation for their high-quality development. Meanwhile, the wave of digital transformation also brings broader and more profound social and environmental benefits, perfectly aligning with the demands of the era for high-quality development. On the environmental front, enterprises leverage digital tools to achieve refined management of production processes and efficient resource utilization, effectively reducing energy consumption and pollution emissions, thus contributing significantly to sustainable development. On the social front, digital transformation promotes deep integration between enterprises and society. Through technological and model innovations, enterprises not only meet the increasingly diverse demands of consumers but also actively engage in public welfare, fulfill social responsibilities, and promote social harmony and progress.

The positive effects of digital transformation on promoting the high-quality development of enterprises are indisputable. It has achieved significant improvements in total factor productivity in the economic realm and has had a positive impact across multiple dimensions, including environmental, social, and governance factors. This finding not only points the way for the future development of enterprises but also emphasizes the indispensable role of digital transformation in the comprehensive development of enterprises. Therefore, enterprises should actively embrace digital transformation, and deepen technological applications and innovations, to achieve higher quality and more sustainable development goals. Hypothesis H1 is validated.

### *5.2. Robustness Checks*

#### 5.2.1. Endogenous Treatment

In this study, there may be endogeneity issues, especially regarding the potential bidirectional relationship between the degree of digitalization and high-quality development of enterprises (including total factor productivity, TFP, and ESG performance). Enterprises that have already achieved higher levels of development generally have more capacity and motivation to invest more in digitalization, which could lead to reverse causality between digitalization and high-quality development. This reverse causality can cause endogeneity problems and affect our research results. To address this issue, we selected the digital awareness of company executives as an instrumental variable for the degree of digitalization. Specifically, we measure the frequency with which digital-related terms are mentioned in the "Management Discussion and Analysis" section of the company's annual report to gauge executives' awareness of digitalization. The level of importance that executives place on digitalization often directly influences the company's investments and practices in digitalization, making this proxy variable strongly correlated with digitalization. It is also important to note that executives' digital awareness is primarily influenced by personal preferences and cognition, and does not directly determine the company's economic performance (e.g., TFP) or social impact (e.g., ESG). Therefore, we consider executives' digital awareness to be an exogenous factor, which can effectively serve as an instrumental variable for digitalization, thus addressing the potential endogeneity problem.

When conducting instrumental variable regression analysis, we assessed the validity and strength of the instrumental variables. This study reports two key statistics, refer to Table 4. The Cragg–Donald Wald F statistic exceeds the commonly used rule of thumb value of 10, indicating that the instrumental variables we used are very strong and nearly

eliminate the influence of weak instruments. The Kleibergen–Paap rk LM statistic is 197.23, with a corresponding *p*-value of 0.000, suggesting that the test results are significant and there are no identification issues. Even after considering endogeneity issues, the positive promotional effect of digitalization on the high-quality development of manufacturing enterprises remains verified. The role of digitalization in driving manufacturing enterprises toward high-quality development is increasingly evident. Through rigorous instrumental variable regression analysis and various statistical tests, we can be confident that digital transformation fundamentally reshapes the competitive landscape of enterprises. It not only strengthens their market adaptability but also achieves significant improvements in brand value, social responsibility, and sustainable development, thereby comprehensively promoting the steady advancement of manufacturing enterprises toward the high-quality development stage.

**Table 4.** Endogeneity Test: Instrumental Variables.

| Variable | DCG | TFP | DCG | ESG |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| DCG | | 0.178 *** | | 0.170 *** |
| | | (5.85) | | (5.66) |
| IV | 0.973 *** | | 0.973 *** | |
| | (71.10) | | (70.74) | |
| Tao | 1.442 * | −1.333 | 1.556 * | −9.835 ** |
| | (1.73) | (−0.69) | (1.86) | (−4.74) |
| Roa | −1.557 * | 2.194 | −1.680 * | 11.037 *** |
| | (−1.78) | (1.01) | (−1.90) | (5.06) |
| Age | −0.055 | 0.488 *** | −0.047 | −0.125 |
| | (−1.21) | (3.62) | (−1.01) | (−0.99) |
| Shrcr | 0.001 | 0.018*** | 0.001 | 0.008 ** |
| | (0.98) | (7.77) | (1.26) | (3.38) |
| Fassetr | −0.590 *** | −1.133 *** | −0.598 *** | 0.410 |
| | (−5.58) | (−4.63) | (−5.60) | (1.58) |
| Assetr | 0.017 | 0.494 | 0.017 | −0.037 |
| | (0.36) | (1.33) | (0.35) | (−0.32) |
| Outdir | 0.130 | 0.110 | 0.117 | 0.563 |
| | (0.62) | (0.20) | (0.56) | (1.11) |
| Wald F | | 17,874.62 | | |
| Kleibergen–Paap rk LM | | 197.23 *** | | |
| N | 6318 | 6318 | 6318 | 6318 |
| R-squared | | 0.196 | | 0.066 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.2.2. Replacement of Dependent Variables

To verify the robustness of the research findings, we conducted a replacement indicator test. We conducted robustness checks by replacing key variables with alternative indicators to test whether the results are significantly affected by the choice of variables. This ensures that our findings are not dependent on specific indicators but are generalizable. TFP_OLS: we calculated total factor productivity using the ordinary least squares (OLS) method. TFP_FE: we measured total factor productivity using the fixed effects method. ESGM: we used the summary of the ESG performance advantage scores for listed companies provided by the CESG database as an alternative indicator. As shown in the results of Table 5, the regression coefficients remained significantly positive at the 5% level. Through the robustness test with replacement indicators, our research results remained robust. This result strongly supports our conclusion that digitalization plays a significant and robust role in promoting the high-quality development of manufacturing enterprises, providing a solid theoretical basis for policymakers and business decision-makers. This indicates that digitalization has a significant impact on driving the high-quality development of manufacturing enterprises, further validating the reliability of the conclusions.

**Table 5.** Robustness Test: Replacement Indicator Test.

| Variable | TFP_OLS | TFP_FE | ESGM | TFP | ESG |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| DCG | 0.051 ** | 0.055 ** | 0.045 ** | 0.040 ** | 0.051 ** |
| | (2.92) | (3.00) | (2.04) | (2.72) | (2.24) |
| Tao | 1.765 | 1.579 | −5.546 *** | 2.518 ** | −5.979 *** |
| | (1.61) | (1.40) | (−4.45) | (2.46) | (−4.54) |
| Roa | −1.488 | −1.287 | 5.921 *** | −2.312 ** | 6.384 *** |
| | (−1.33) | (−1.11) | (4.47) | (−2.25) | (4.55) |
| Age | 1.184 *** | 1.275 *** | −0.150 | 0.885 *** | −0.135 |
| | (4.44) | (4.47) | (−0.50) | (4.08) | (−0.43) |
| Shrcr | 0.009 *** | 0.009 *** | 0.002 | 0.007 ** | 0.002 |
| | (3.80) | (3.84) | (0.83) | (3.41) | (1.00) |
| Fassetr | −0.633 ** | −0.493 *** | −0.454 ** | −1.472 *** | −0.542 ** |
| | (−2.85) | (−2.13) | (−2.00) | (−7.54) | (−2.31) |
| Assetr | 0.124 | 0.142 | 0.019 | 0.055 | 0.030 |
| | (1.54) | (1.61) | (0.21) | (0.89) | (0.33) |
| Outdir | −0.461 * | −0.490 * | 0.599 | −0.363 * | 0.643 * |
| | (−1.87) | (−1.88) | (1.61) | (−1.73) | (1.67) |
| Constant | 7.076 *** | 7.443 *** | 4.044 *** | 5.808 *** | 3.941 *** |
| | (9.31) | (9.18) | (4.94) | (9.34) | (4.65) |
| year/code FE | Yes | Yes | Yes | Yes | Yes |
| N | 6318 | 6318 | 6318 | 6318 | 6318 |
| R-squared | 0.363 | 0.362 | 0.036 | 0.352 | 0.041 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.2.3. Exclusion of 2015 Sample

To ensure the robustness of the research results, we conducted a robustness test by excluding sample data from 2015 due to the impact of the Chinese stock market crash and the COVID-19 pandemic in 2020 on the development of the digital economy. Considering that the 2015 Chinese stock market crash and the 2020 COVID-19 pandemic may have had significant impacts on the development of the digital economy, we performed a sample data exclusion robustness check by excluding data from these two periods. We then observed whether the research results were significantly altered. This helps verify whether our conclusions are influenced by these exceptional time events. Firstly, considering that the 2015 Chinese stock market crash might interfere with the research results, we excluded the sample data from that year and re-conducted the regression analysis. Given the potential impact of the COVID-19 pandemic in 2020 on the development of the digital economy, we further excluded sample data from both 2015 and 2020, followed by another round of regression analysis.

To eliminate the influence of companies that had not undergone digital transformation on the research results, we also excluded all samples of companies that had not digitized and re-performed the regression analysis, the results are shown in Table 6. We found that regardless of whether we excluded the 2015 sample data, the samples from both 2015 and 2020, or the samples of companies that had not undergone digitization, the positive impact of digitalization on total factor productivity and ESG performance remained significant. This further confirms the substantial role of digitalization in promoting high-quality development in manufacturing enterprises, and the conclusions remain valid.

**Table 6.** Robustness Test: Sample Deletion.

| Variable | Deleting Non-Digital Samples | | Deleting Samples to Remove Stock Market Crash Impact | | Deleting Samples to Remove Stock Market Crash and Pandemic Impact | |
|---|---|---|---|---|---|---|
| | TFP | ESG | TFP | ESG | TFP | ESG |
| DCG | 0.043 ** | 0.041 * | 0.043 ** | 0.051 ** | 0.040 ** | 0.051 ** |
| | (2.82) | (1.82) | (2.88) | (2.15) | (2.71) | (2.16) |
| Tao | 2.522 ** | −6.096 *** | 2.268 ** | −6.292 *** | 2.129 ** | −6.953 *** |
| | (2.28) | (−4.28) | (2.14) | (−4.91) | (2.01) | (-4.94) |

**Table 6.** *Cont.*

| Variable | Deleting Non-Digital Samples | | Deleting Samples to Remove Stock Market Crash Impact | | Deleting Samples to Remove Stock Market Crash and Pandemic Impact | |
|---|---|---|---|---|---|---|
| | **TFP** | **ESG** | **TFP** | **ESG** | **TFP** | **ESG** |
| Roa | −2.341 ** | 6.518 *** | −2.057 * | 6.696 *** | −1.944 * | 7.391 *** |
| | (−2.10) | (4.29) | (−1.93) | (4.89) | (−1.79) | (4.91) |
| Age | 0.908 *** | −0.005 | 0.887 *** | −0.143 | 0.881 *** | −0.099 |
| | (3.82) | (−0.02) | (4.08) | (−0.46) | (4.16) | (−0.32) |
| Shrcr | 0.007 ** | 0.002 | 0.007 ** | 0.002 | 0.007** | 0.002 |
| | (3.26) | (1.01) | (3.43) | (1.02) | (3.46) | (1.12) |
| Fassetr | −1.620 *** | −0.448 * | −1.464 ** | −0.541 ** | −1.528 *** | −0.499 ** |
| | (−7.84) | (−1.74) | (−7.05) | (−2.27) | (−7.79) | (−2.17) |
| Assetr | 0.051 | 0.034 | 0.063 | 0.046 | 0.064 | 0.064 |
| | (0.86) | (0.37) | (1.05) | (0.53) | (1.04) | (0.80) |
| Outdir | −0.410 * | 0.412 | −0.376 * | −0.721 * | −0.275 | 0.879 ** |
| | (−1.95) | (1.05) | (−1.73) | (1.82) | (−1.24) | (2.15) |
| Constant | 5.821 *** | 3.637 *** | 5.797 *** | 3.922 *** | 5.801 *** | 3.734 *** |
| | (8.56) | (3.97) | (9.30) | (4.59) | (9.54) | (4.41) |
| year/code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 5720 | 5720 | 5832 | 5832 | 5346 | 5346 |
| R-squared | 0.353 | 0.042 | 0.356 | 0.043 | 0.366 | 0.047 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.2.4. Adding Control Variables

To further validate the robustness of our research findings, we conducted a supplementary test for omitted variables, selecting the following three variables: GDP Growth Rate of the City (GGDP): The economic growth rate of the city where the enterprise is located may significantly impact its operating environment and development. Rapidly growing urban economies may provide more opportunities and resources for enterprises. Capital. It should be noted that CI = ln(Net Fixed Assets/Total Employees + 1). To further confirm the robustness of our results, we conducted a check for omitted variables. We have examined whether there were any variables that had been overlooked and could potentially affect the results, ensuring that these omitted variables do not alter the main conclusions of our study.

Capital intensity reflects the level of capital equipment investment in a company. A higher capital intensity usually indicates greater investment in fixed assets, which may influence the enterprise's production efficiency and overall performance. The Ratio of Local Fiscal Expenditure to Revenue (GOV): This ratio is an important indicator of the financial condition of local governments. High fiscal expenditure may signify significant investment by local governments in public services and infrastructure, which can impact the enterprise's operational environment and resource acquisition.

The results of these robustness tests for the supplementary omitted variables further confirm the reliability of our research conclusions, the results are shown in Table 7. Even after accounting for the impacts of the macroeconomic environment, internal resource allocation of the enterprise, and the financial situation of local governments, the degree of digitalization still significantly promotes the high-quality development of enterprises. It continues to enhance both total factor productivity and ESG performance, indicating that digital transformation has a lasting positive impact on improving economic efficiency and social benefits, thereby comprehensively promoting high-quality development in enterprises.

**Table 7.** Robustness Test: Supplementary Omitted Variables.

| Variable | TFP | ESG |
|---|---|---|
| | (1) | (2) |
| DCG | 0.041 ** | 0.053 ** |
| | (2.78) | (2.33) |
| GGDP | 0.144 | −0.164 |
| | (1.17) | (−0.66) |
| GOV | −0.014 | 0.021 |
| | (−0.36) | (0.45) |
| CI | 0.064 ** | 0.063 |
| | (2.06) | (1.47) |
| Controls | Yes | Yes |
| Constant | 5.121 *** | 3.252 ** |
| | (7.34) | (3.47) |
| year/code FE | Yes | Yes |
| N | 6318 | 6318 |
| R-squared | 0.356 | 0.043 |

Note: The coefficients with *** and ** are significant at the 1% and 5% confidence levels.

### *5.3. Mechanism Analysis*

#### 5.3.1. Financing Cost Mechanism

In the examination of the financing cost mechanism, the SA index was selected for measurement. The SA index considers only the size and age of the enterprise, which are relatively exogenous variables [73].

$$SA = 0.043 \times Size^2 - 0.737 \times Size - 0.04Age \quad (18)$$

where Size refers to the enterprise size, with total assets taken in logarithmic form. The size and age of the enterprise reflect its development stage and market position, rather than being influenced by other endogenous factors in the short term. Therefore, using size and age as indicators effectively avoids endogeneity issues and enhances the reliability of the measurement results. The results in columns (1) and (2) of Table 8 show that digitization significantly reduces the financing cost of enterprises, at the level of 1%. After advancing the digitalization process, enterprises can more effectively acquire and manage funds, thus reducing financing costs. Digitalization enables enterprises to transparently showcase their financial status and operational data, reducing information asymmetry and increasing investor and creditor confidence. Digitalization also enhances the operational efficiency and profitability of enterprises, strengthening their debt repayment capacity and credit ratings, and leading to lower financing costs. The issue of "expensive financing" not only increases operational costs and financial pressure on enterprises, limiting their investment and innovation capabilities, but also decreases the overall economic resource allocation efficiency and growth potential. Addressing the issue of expensive financing is crucial for improving economic operational efficiency and promoting high-quality development of micro-enterprises. Therefore, Hypothesis 2 is validated: a higher degree of digitalization contributes to promoting high-quality enterprise development by lowering financing costs.

**Table 8.** Mechanism Test Results.

| Variable | SA | | Patent | | HC | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| DCG | 0.090 *** | 0.087 *** | 0.090 *** | 0.090 *** | 0.005 ** | 0.005 ** |
| | (4.37) | (4.31) | (3.66) | (3.63) | (2.01) | (2.03) |
| Tao | | −3.035 ** | | −3.103 ** | | −0.256 ** |
| | | (−3.04) | | (−2.37) | | (−2.24) |
| Roa | | 3.428 ** | | 3.345 ** | | 0.281 ** |
| | | (3.12) | | (2.39) | | (2.33) |

**Table 8.** *Cont.*

| Variable | SA | | Patent | | HC | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Age | | 1.547 *** | | 0.151 | | −0.053 * |
| | | (4.85) | | (0.46) | | (−1.78) |
| Shrcr | | 0.013 *** | | 0.007 ** | | 0.001 * |
| | | (4.47) | | (2.40) | | (1.73) |
| Fassetr | | −0.479 * | | −0.143 | | −0.051 * |
| | | (−1.94) | | (−0.51) | | (−1.82) |
| Assetr | | 0.298 ** | | 0.197 ** | | 0.008 ** |
| | | (2.40) | | (2.03) | | (2.18) |
| Outdir | | −0.418 | | 0.088 | | 0.001 |
| | | (−1.43) | | (0.24) | | (0.01) |
| Constant | 3.720 *** | −0.841 | 1.601 *** | 0.758 | 0.191 *** | 0.313 *** |
| | (113.54) | (−0.92) | (37.92) | (0.84) | (41.74) | (3.70) |
| year/code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 6318 | 6318 | 6318 | 6318 | 6292 | 6292 |
| R-squared | 0.340 | 0.340 | 0.240 | 0.247 | 0.206 | 0.216 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.3.2. Innovation Capability Mechanism

In the examination of the innovation capability mechanism, the number of patent applications was selected for measurement, with the logarithm of the application quantity taken. The test results are shown in columns (3) and (4) of Table 8, indicating that digitalization significantly enhances enterprise innovation capability at the 1% significance level. The application of digital technology not only improves internal R&D efficiency and collaboration levels but also expands the ability of enterprises to access external innovation resources. The advancement of digitalization brings more innovation opportunities to enterprises, significantly promoting their innovation capabilities. The digital economy provides new technologies and models that enable manufacturing enterprises to innovate more quickly and efficiently. Through big data analysis, artificial intelligence, and IoT technologies, enterprises can optimize production processes, improve product quality, and reduce costs, thereby enhancing market competitiveness. By seizing opportunities arising from the development of the digital economy, stimulating the innovative vitality of manufacturing enterprises, improving human capital quality, and driving industrial upgrading, Chinese manufacturing can achieve high-quality development, transitioning from a manufacturing giant to a manufacturing powerhouse. Thus, Hypothesis 3 is validated: a higher degree of digitalization promotes high-quality enterprise development through increased innovation output.

#### 5.3.3. Human Capital Mechanism

In the examination of the human capital mechanism, the proportion of employees with at least a bachelor's degree was selected for measurement. The test results are shown in columns (5) and (6) of Table 8, indicating that digitalization significantly enhances human capital at the 5% level. In the era of the digital economy, high-quality human capital not only directly drives invention, innovation, and competitiveness in manufacturing but also significantly promotes high-quality development of the manufacturing sector through the effective application of digital technologies. The digital economy provides more educational and training opportunities, enabling more individuals to receive high-quality education and enhance their skills and knowledge levels. With the improvement of human capital, manufacturing enterprises can more easily find talent with new knowledge and skills, which can drive innovation and enhance production efficiency, thereby promoting high-quality development in the manufacturing sector. The development of the digital economy not only expands human capital accumulation by improving the quality of education and training, allowing manufacturing to acquire more high-quality talent, but also stimulates

entrepreneurial vitality by providing more entrepreneurial opportunities and resources, bringing about new business models and technological innovations, driving high-quality development in manufacturing. Therefore, Hypothesis 4 is validated: a higher degree of digitalization optimizes human capital structure, contributing to promoting high-quality enterprise development.

### *5.4. Heterogeneity Analysis*

#### 5.4.1. Considering the Ownership Structure of Enterprises

The examination of the ownership structure of enterprises in the heterogeneity analysis is presented in Table 9. The specific results indicate that state-owned enterprises (SOEs) show a significant positive relationship with total factor productivity and environmental, social, and governance performance at the 5% level, while non-state-owned enterprises do not demonstrate significant performance in these areas. This finding suggests that the nature of ownership has a crucial impact on the high-quality development of enterprises. The management structure and decision-making processes of SOEs may be more robust and systematic, which helps maintain strategic consistency and implementation efficiency during the complex process of digital transformation, thereby enhancing TFP. Additionally, SOEs often bear greater social responsibilities and national missions, and the government may impose higher requirements on them regarding environmental protection, social responsibility, and corporate governance. This may prompt SOEs to place more emphasis on their ESG performance and achieve significant results in these areas. SOEs possess unique advantages in terms of institutional support, funding, and scale, which provide them with great potential for digital transformation. While leveraging these advantages, SOEs must actively respond to challenges by enhancing their flexibility and innovation capabilities. By continuously optimizing management mechanisms, improving market adaptability, and promoting technological innovation, SOEs can play a leading role in digital transformation and achieve high-quality development.

**Table 9.** Heterogeneity Analysis: Nature of Enterprises.

| Variable | State-Owned Enterprises | | Non-State-Owned Enterprises | |
|---|---|---|---|---|
| | TFP | ESG | TFP | ESG |
| DCG | 0.038 ** | 0.079 ** | 0.027 | 0.054 |
| | (2.17) | (2.92) | (1.46) | (1.60) |
| Tao | 4.149 ** | −5.367 ** | 0.370 | −5.909 ** |
| | (2.28) | (−3.33) | (0.35) | (−2.94) |
| Roa | −2.921 | 5.263 ** | −0.155 | 6.291 ** |
| | (−1.55) | (3.12) | (−0.14) | (2.94) |
| Age | 0.943 ** | 0.623 * | 0.697 ** | −0.197 |
| | (2.95) | (1.68) | (2.43) | (−0.46) |
| Shrcr | 0.009 ** | −0.001 | 0.005 ** | 0.002 |
| | (3.51) | (−0.41) | (2.03) | (0.54) |
| Fassetr | −1.275 *** | −0.381 | −1.788 *** | −0.682 * |
| | (−4.99) | (−1.41) | (−7.22) | (−1.74) |
| Assetr | 0.734 *** | −0.230 | 0.078 ** | 0.074 |
| | (4.33) | (−1.03) | (2.05) | (1.17) |
| Outdir | −0.454 * | 1.349 ** | 0.002 | −0.229 |
| | (−1.79) | (2.88) | (0.01) | (−0.38) |
| Constant | 5.305 *** | 2.036 * | 6.123 *** | 4.326 *** |
| | (6.11) | (1.97) | (7.52) | (3.74) |
| year/code FE | Yes | Yes | Yes | Yes |
| N | 3357 | 3357 | 2961 | 2961 |
| R-squared | 0.382 | 0.088 | 0.379 | 0.046 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.4.2. Considering the External Environment of Enterprises

The "digital divide" refers to the gap between different groups in accessing, using, and benefiting from information technology and the internet [74]. Inequalities in technology access and usage affect the development of individuals, enterprises, and society. Bridging

the digital divide requires not only investments in technology and infrastructure but also comprehensive efforts in education, policy, and social services. Through multi-party collaboration, the adverse effects of the digital divide on individuals and society can be reduced, promoting fair and inclusive digital development.

In the context of the digital economy, the importance and urgency of the digital transformation of the manufacturing industry are clear. Provinces have included this strategy in their 14th Five-Year Plan, reflecting the national emphasis and clear support for the digitalization of manufacturing. Through policy guidance and resource investment, the digitalization of manufacturing will become an important engine driving high-quality economic development, helping provinces achieve economic catch-up and coordinated regional development. Regional differences may produce a "digital divide" effect, and this study divides regions into three categories: Eastern, Central, and Western.

The results of the regional heterogeneity analysis are shown in the Table 10. It can be seen that there are significant differences in the performance of digitalization and high-quality development of manufacturing enterprises across different regions. The Eastern region performs well in both TFP and ESG, with manufacturing enterprises able to significantly enhance TFP at the 5% level through digitalization, and ESG at the 10% level. In contrast, the Central region does not show significant improvements in either aspect. The Western region, while not significant in TFP, shows remarkable performance in ESG, with a regression coefficient significant at the 5% level. The baseline regression coefficient is 0.051, while the regression coefficient in the Western region analysis is 0.133. The Eastern region is the most economically developed area in China, with good infrastructure, abundant resources, and a high level of talent reserves, providing a solid foundation for enterprises' digital transformation. The economic development level of the Central region is intermediate between the East and the West, and it may have certain deficiencies in infrastructure, resources, and talent, affecting enterprises' TFP and ESG performance. Compared to the Eastern region, the Central region may lack sufficient policy support and preferential measures, resulting in insufficient motivation for enterprises in digital transformation and environmental governance. The Western region, with a lower economic development level and relatively scarce infrastructure and resources, affects the enhancement of enterprises' TFP. Due to its relatively fragile ecological environment, the Western region may receive more policy bias and support for environmental protection, encouraging enterprises to make significant progress in ESG. This regional disparity reflects the multi-layered impact of digitalization on the high-quality development of manufacturing enterprises.

**Table 10.** Heterogeneity Analysis: Geographic Region.

| Variable | Eastern Region | | Central Region | | Western Region | |
|---|---|---|---|---|---|---|
| | TFP | ESG | TFP | ESG | TFP | ESG |
| DCG | 0.058 ** | 0.049 * | 0.0001 | 0.009 | 0.033 | 0.133 ** |
| | (2.87) | (1.70) | (0.01) | (0.22) | (1.06) | (2.77) |
| Tao | 1.571 | −6.918 *** | 3.441 | −4.454 | 6.146 ** | −2.179 |
| | (1.32) | (−4.30) | (1.62) | (−1.39) | (3.11) | (−0.63) |
| Roa | −1.409 | 7.362 *** | −1.688 | 4.423 | −5.646 ** | 2.085 |
| | (−1.14) | (4.26) | (−0.73) | (1.27) | (−2.93) | (0.57) |
| Age | 0.837 ** | −0.426 | 0.906 ** | 0.487 | 1.055 ** | 1.544 |
| | (3.09) | (−1.15) | (2.42) | (0.81) | (2.05) | (1.58) |
| Shrcr | 0.005 * | 0.001 | 0.011 *** | 0.003 | 0.004 | 0.003 |
| | (1.89) | (0.41) | (3.75) | (0.70) | (0.85) | (0.68) |
| Fassetr | −1.410 *** | −0.727 ** | −1.818 *** | −0.741 * | −1.110 ** | 0.070 |
| | (−5.27) | (−2.23) | (−5.97) | (−1.73) | (−2.48) | (0.15) |
| Assetr | 0.069 | 0.087 | 0.228 | −0.310 | 0.122 | −0.565 |
| | (1.13) | (1.31) | (0.78) | (−0.90) | (0.43) | (−1.48) |

**Table 10.** *Cont.*

| Variable | Eastern Region | | Central Region | | Western Region | |
|---|---|---|---|---|---|---|
| | TFP | ESG | TFP | ESG | TFP | ESG |
| Outdir | −0.256 | −0.043 | −0.368 | 2.613 ** | −0.691 | 0.183 * |
| | (−0.88) | (−0.08) | (−1.00) | (3.02) | (−1.58) | (0.25) |
| Constant | 6.022 *** | 5.073 *** | 5.434 *** | 1.712 | 5.233 *** | −0.469 |
| | (7.44) | (5.00) | (5.17) | (1.02) | (4.08) | (−0.19) |
| year/code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3909 | 3909 | 1397 | 1397 | 1012 | 1012 |
| R-squared | 0.331 | 0.046 | 0.498 | 0.072 | 0.367 | 0.066 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

#### 5.4.3. Consideration of Industry Classification

Different industries in manufacturing exhibit varying paths and effects of digital transformation due to differences in factor intensity and the level of digitization. The factor intensity in manufacturing refers to the proportion of inputs, such as labor, capital, technology, and natural resources, required in the production process. There are significant differences in factor intensity among different manufacturing industries. This study classifies industries into technology-intensive, labor-intensive, and capital-intensive categories based on the 2017 National Economic Industry Classification Standard for heterogeneity analysis, with the test results presented in the Table 11.

**Table 11.** Heterogeneity Analysis: Industry Classification.

| Variable | Technology-Intensive | | Labor-Intensive | | Capital-Intensive | |
|---|---|---|---|---|---|---|
| | TFP | ESG | TFP | ESG | TFP | ESG |
| DCG | 0.036 ** | 0.063 ** | 0.027 | 0.221 * | 0.058 * | −0.039 |
| | (2.10) | (2.52) | (0.75) | (1.91) | (1.90) | (−0.76) |
| Tao | 1.016 | −6.576 *** | 6.314 ** | 1.094 | 3.559 | −7.342 ** |
| | (0.84) | (−3.90) | (2.96) | (0.24) | (1.64) | (−3.28) |
| Roa | −0.795 | 6.993 *** | −4.397 * | −0.816 | −2.852 | 7.630 ** |
| | (−0.64) | (3.87) | (−1.93) | (−0.17) | (−1.28) | (3.11) |
| Age | 0.742 ** | −0.187 | −0.001 | 0.721 | 1.461 *** | 0.088 |
| | (2.91) | (−0.51) | (−0.00) | (0.31) | (5.03) | (0.15) |
| Shrcr | 0.006 ** | 0.002 | 0.003 | 0.008 | 0.011 *** | 0.007 |
| | (2.44) | (0.09) | (0.57) | (0.84) | (3.69) | (1.44) |
| Fassetr | −1.907 *** | −0.375 | −0.693 | −1.263 | −0.930 *** | −0.522 |
| | (−6.41) | (−1.12) | (−1.69) | (−1.61) | (−4.88) | (−1.55) |
| Assetr | 0.075 | 0.068 | 0.464 ** | −0.779 | 0.433 ** | −0.205 |
| | (1.52) | (0.93) | (2.25) | (−0.99) | (2.37) | (−0.62) |
| Outdir | −0.594 ** | 0.280 | 0.203 | 0.161 | 0.473 | 2.085 ** |
| | (−2.31) | (0.66) | (0.39) | (0.13) | (1.32) | (2.21) |
| Constant | 6.356 *** | 4.184 *** | 7.509 ** | 2.090 | 3.549 *** | 2.939 * |
| | (8.58) | (4.25) | (2.40) | (0.33) | (4.68) | (1.86) |
| year/code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 4693 | 4693 | 429 | 429 | 1196 | 1196 |
| R-squared | 0.360 | 0.044 | 0.533 | 0.126 | 0.367 | 0.069 |

Note: The coefficients with ***, **, and * are significant at the 1%, 5%, and 10% confidence levels.

In the regression results for technology-intensive industries, manufacturing enterprises can significantly improve TFP and ESG at the 5% level through digitization. Technology-intensive industries rely on high levels of technology and innovation, and these industries typically achieve rapid improvements in production efficiency and technical standards during digital transformation, thereby significantly enhancing TFP. This may be because these industries recognized the importance of sustainable development and social responsibility earlier and have better resources and capabilities to implement relevant ESG measures. Labor-intensive industries show no significant improvement in TFP, but a positive significant effect at the 10% level in ESG, with a regression coefficient of 0.221 (compared to a benchmark regression coefficient of 0.051). This may be because these industries primarily depend on a large workforce, and the impact of digital transformation on productivity improvement is not as significant as in technology-intensive and capital-intensive indus-

tries. However, the notable performance in ESG indicates that labor-intensive industries have made more apparent improvements in environmental issues, social responsibility, and governance. The higher ESG regression coefficient likely reflects the efforts made by these industries to improve labor conditions, environmental protection, and social responsibility, which positively impact long-term enterprise development.

For capital-intensive industries, there is no significant effect on ESG, while TFP shows a positive significant effect at the 10% level, with a regression coefficient of 0.058 (compared to a benchmark regression coefficient of 0.049). This may be due to these industries focusing more on production and technological upgrades, with relatively less emphasis on environmental, social responsibility, and governance issues, or because their improvement measures have not yet fully shown effects. The results indicate that digital transformation positively affects the production efficiency of capital-intensive industries. Although these industries already have a high foundation in equipment and technology, the room for further improvement is relatively limited; nonetheless, digital transformation still brings significant efficiency gains.

## 6. Conclusions and Policy Implications

### *6.1. Research Conclusions*

This study focuses on 482 manufacturing enterprises listed on the Shanghai and Shenzhen A-shares from 2010 to 2022. By employing various methods to calculate their Total Factor Productivity and sustainable development performance, it explores the impact of digital transformation on the high-quality development of manufacturing enterprises. Robustness tests, including the substitution of explanatory variables, the use of instrumental variables, and sample adjustments, indicate that increased levels of digitalization have a significant positive impact on enterprises' TFP and ESG performance, thereby contributing to high-quality development.

In Mechanism Analysis, the digitalization promotes high-quality development through the following three mechanisms. (1) Reducing Financing Costs: Enterprises with high levels of digitalization can more effectively lower financing costs and enhance capital utilization efficiency, promoting high-quality development. Digital tools and platforms provide more transparent and efficient financing channels, making it easier for enterprises to access financial resources and reducing information asymmetry and transaction costs during the financing process. (2) Enhancing Innovation Output: Digitalization can improve enterprises' innovation capabilities and outcomes, thereby maintaining competitive advantages in the market and promoting high-quality development. Digital technologies such as big data analysis, artificial intelligence, and the Internet of Things not only accelerate the R&D process but also increase the market conversion rate of innovation results, enabling enterprises to respond swiftly to changes in market demand. (3) Optimizing Human Capital Structure: Digitalization helps improve employees' skill levels and work efficiency, optimizing human resource allocation and enhancing overall productivity and sustainable development capabilities. Through digital training and skill enhancement programs, employees can master the latest technologies and tools, improving work efficiency and consequently strengthening the enterprise's competitiveness and innovation capacity.

In the heterogeneity analysis, the study further examines the effects of ownership structure, regional differences, and industry variations on the relationship between digitalization and high-quality development. State-owned enterprises show significant positive impacts on both TFP and ESG performance, indicating that digitalization plays a more pronounced role in their high-quality development. Due to resource availability and policy support, state-owned enterprises are more likely to undertake large-scale digital transformation, yielding significant results.

While the results of this study provide valuable insights, there are several limitations that need to be acknowledged: (1) Sample Size and Scope: The research is based on a specific set of enterprises, which may limit the generalizability of the findings. Future studies could expand the sample size and include enterprises from different industries, regions, and sizes to validate the robustness of the results. (2) Measurement of Digitalization: The study uses the degree of digitalization as a composite measure, but digitalization is a broad and multifaceted concept. A more granular analysis of different aspects of digitalization, such as digital infrastructure, digital skills, and digital culture, could provide deeper insights into how these factors influence high-quality development.

To build upon the findings of this study, several potential research directions can be explored: (1) Sector-Specific Analysis: investigating the impact of digitalization on high-quality development within specific industries (e.g., manufacturing, services, or technology) could reveal industry-specific dynamics and provide more tailored recommendations for digital transformation strategies. (2) Longitudinal Studies: Longitudinal studies could examine the evolution of digitalization over time and its long-term impact on high-quality development. This would help understand how digitalization affects enterprises across different stages of their digital transformation journey. (3) Comparative International Studies: Cross-country or cross-regional comparisons could be conducted to understand how digitalization affects enterprises in different cultural, economic, and regulatory environments. This would help identify the contextual factors that influence the effectiveness of digital transformation.

### *6.2. Recommendations*

Based on the empirical conclusions, mechanism analysis, and heterogeneity analysis, the following targeted recommendations are proposed to further promote high-quality development in manufacturing enterprises. These suggestions aim to provide comprehensive support and guidance for manufacturing firms through various measures, including optimizing the policy environment, enhancing digital infrastructure, alleviating financing constraints, accelerating technological innovation, and optimizing human capital structure.

Recommendations for Policymakers: The government should increase investment in digital infrastructure, especially in remote and underdeveloped areas, to reduce the digital divide. This includes expanding high-speed internet coverage, promoting the widespread use of cloud computing services, and supporting the application and development of technologies such as big data and artificial intelligence. For manufacturing companies undergoing digital transformation, the government can offer financial support through tax reductions, fiscal subsidies, or low-interest loans. In addition, specific policies should be developed for small and medium-sized enterprises (SMEs) to assist them in reducing transformation costs and improving their digital capabilities. The government should encourage collaboration between enterprises and research institutions in the research and application of digital technologies. This will help share technological resources and research results, accelerating technological innovation and industrial upgrading. The government should strengthen the cultivation and attraction of digital talent, particularly in fields like big data, artificial intelligence, and the Internet of Things. Collaborations with higher education institutions and vocational training organizations should be encouraged to offer digital skills training programs, enhancing the overall digital skill level in the labor market.

Recommendations for Enterprises: Enterprises should develop personalized digital transformation strategies based on their size, industry characteristics, and regional environment. In particular, SMEs should progressively implement digital projects in line with their resources, avoiding blind following of trends. Enterprises should increase investment in digital technologies, especially in cutting-edge fields like big data, artificial

intelligence, and cloud computing. They should also focus on employee digital skills training to improve work efficiency and innovation capabilities, ensuring that the company can fully leverage digital technologies to enhance its competitiveness. Enterprises should use digital technologies to accelerate their research and development processes, enhancing innovation capabilities and market responsiveness. They can consider establishing digital innovation platforms or accelerators to integrate internal and external resources, boosting the efficiency and output of innovation. As digital transformation deepens, enterprises should place greater emphasis on attracting and managing digital talent. Through digital training and the establishment of talent pipelines, companies can improve employee skill levels, ensuring sustained high efficiency and innovation throughout the transformation process. Enterprises should strengthen the management of risks that may arise during the digital transformation process, such as data security risks and technological failure risks. A sound risk prevention mechanism and emergency response system should be established to ensure that no major operational or safety issues arise during the transformation process.

By vigorously developing the digital economy, advancing the construction of new digital infrastructure, alleviating financing constraints for enterprises, accelerating technological innovation, and optimizing human capital structures, targeted support measures for different types of enterprises can effectively enhance the Total Factor Productivity of manufacturing firms, thereby facilitating high-quality development. These measures not only help improve enterprise competitiveness but also lay a solid foundation for the sustainable development of China's economy.

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