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A Mechanistic Study of Enterprise Digital Intelligence Transformation, Innovation Resilience, and Firm Performance

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Abstract: Enterprise Digital Intelligence Transformation is based on the Digital Conversion of information and process service upgrading, further touching the enterprise's core business, with the goal of building a new business model of Digital Intelligence Transformation at a higher level. Based on dynamic capability theory, this paper conducts an in-depth study on the mechanism of enterprise Digital Intelligence Transformation and firm performance. This paper selects manufacturing companies listed in China's Shanghai and Shenzhen A-shares from 2013 to 2022 as the research sample, and analyzes and tests the sample data using empirical research methods in order to explore the actual impact of Digital Intelligence Transformation on firm performance, including the specific pathways of action and moderating effects. This study helps enterprises to positively face the megatrend of Digital Intelligence Transformation and upgrading and the challenges it brings, and to grasp the new opportunities in the digital era. This study finds that enterprises carry out digital empowerment transformation and development strategies, and implement information Digital Conversion, service upgrading, and Digital Intelligence Transformation to promote firm performance to different degrees. Enterprise innovation resilience has a mechanism effect between information digitalization conversion enterprise performance and process service upgrading enterprise performance. The higher the environmental uncertainty, the greater the positive contribution of information digitalization to firm performance. Digital Conversion is the base and service upgrading is the process. The current sample enterprises have limited years of data collection, and most of them have only carried out the strategic implementation of Digital Conversion or servitization, and have not reached the high-level stage of digital and intellectual transformation. Therefore, it is found that enterprise innovation resilience has not yet shown a significant role mechanism effect between digital–intelligent transformation and enterprise performance at present. And environmental uncertainty has not yet shown a significant moderating effect in the stage of Servitization Upgrading and digital–intelligent transformation. The marginal contributions of this paper are mainly reflected in the following: (1) This study introduces the dynamic capability theory to explore the role of Digital Intelligence Transformation (Digital Conversion + service upgrading) on enterprise performance. (2) This paper investigates the role of Digital Intelligence Transformation in influencing the performance of enterprises from the Digital Conversion and service upgrading phases, and enriches the relevant role and regulatory mechanisms. (3) This study provides new ideas and strategic suggestions on Digital Intelligence Transformation for enterprises with different factor intensities, at different stages of development, and in different regions.

Keywords: digital intelligence transformation; innovation resilience; firm performance; service-oriented upgrade

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1. Introduction

In recent years, the rapid advancement and application of new-generation digital intelligence technologies, such as big data, artificial intelligence, blockchain, and the Internet of

Things, have reshaped global industrial, supply, and value chains. These technologies are crucial in transforming enterprise business models and the methods of production and operation. Stemming from breakthroughs in the technological revolution, innovative resource allocation, and trends in industrial transformation and upgrading, a new level of productivity has emerged. This new productivity paradigm introduces a powerful mechanism for promoting high-quality development. Digital intelligence, characterized by the integration of "digitalization + intelligence", represents a novel strategic organizational form. It is distinguished by its high level of innovation, permeability, and extensive reach, making it a crucial driver of high-quality economic growth. The transformation and upgrading of digital intelligence are now inevitable trends in economic development. According to the 2022 China Internet Development Report by the Internet Society of China, there has been rapid development in the essential applications of digital intelligence. The market sizes for artificial intelligence, cloud computing, and the digital economy have increased by 25.7%, 40.9%, and 10.3%, respectively, year-on-year. These statistics underscore the role of digital intelligence as a new dynamic force in transforming the mode of economic growth, optimizing the structure of social governance, and promoting high-quality economic and social development.

From the perspective of enterprise operation, unlike the technical concept of "digitalization", "digital intelligence" pertains to the application of digital technology services. The enterprise digital empowerment transformation and development process can be divided into three stages:

Information Digitalization Conversion Stage: Information digitalization conversion involves transforming enterprise operational information into a digital format, representing the narrow sense of digitization, which is essentially the physical transformation of data. This is typically achieved through technologies such as computers, the internet, cloud computing, and big data. The process includes the collection, processing, storage, transmission, and analysis of information generated during enterprise operations and business activities, focusing primarily on the extent of information digitization [1]. In essence, Digital Conversion serves as the technical foundation for implementing an enterprise's digital strategy, laying the groundwork for the comprehensive planning and coordination of this strategy [2].

Process Service Upgrading Stage: Service upgrading pertains to the digital servicing of business processes, emphasizing the outcomes of digital technology applications and value realization. This belongs to the value-added process within enterprise business processes through the application of digital technology, specifically in the servicing of intelligent manufacturing processes. The main output here is the servicing gains from business processes [3]. Gebauer [4] also noted that with the advancement of a digital strategy, the internal management processes of enterprises undergo profound changes. These changes set new development blueprints, management strategies, and competitive boundaries for enterprises, ensuring the smooth implementation of data process Servitization Upgrading.

Business Digital Intelligence Transformation Stage: Business Digital Intelligence Transformation represents a high-level transformation that builds on the Digital Conversion of information and the upgrading of process servicing. This transformation deeply impacts the core business of the enterprise with the goal of reconstructing the business model [5]. Digital intelligence, as a new generation of enterprise technology, serves as a means to establish the enterprise's basic digital infrastructure, subsequently leading to comprehensive changes in technology, business, and business management. These changes can be described through three aspects: data, digitalization, and intelligence, thereby establishing a strong competitive advantage for the enterprise. From an operational perspective, digital intelligence is the innovative fusion of digitalization and servitization. It involves tightly integrating digital technology with business management activities to promote a multi-level and multi-dimensional digital empowerment change. This change focuses more on utilizing digital thinking to reshape business models and processes, thereby enhancing the customer experience and corporate profitability models.

In the context of the rapid transformation of the real economy to digital intelligence, an important question that urgently needs exploration is as follows: can the current stage of Digital Intelligence Transformation drive the sustained growth of the enterprise economy and form a new economic growth point? Therefore, this paper is dedicated to the study of how Digital Intelligence Transformation affects the economic efficiency of enterprises under the dynamic changes in internal and external resources and environment, which not only helps to reveal the mechanism of Digital Intelligence Transformation affecting the economic growth of enterprises theoretically, but also provides a scientific basis for the economic benefits brought by the Digital Intelligence Transformation of enterprises practically. At the same time, this paper also provides theoretical support and an empirical model for the integration and development of digital economy and real economy.

The marginal contributions of this paper are primarily reflected in three areas: (1) There is a relative lack of research in the existing literature on the relationship between digital–intelligent transformation and firm performance, which has not yet led to a unified and definitive conclusion. This paper employs dynamic capability theory to explore the relationship between Digital Intelligence Transformation (Digital Conversion + servicing upgrade) and enterprise performance, as well as the specific possible paths of action. (2) Digital–intelligent transformation represents a level of intelligence that builds upon information digitalization conversion and process Servitization Upgrading. This paper investigates the role paths of enterprise digitalization conversion and business process Servitization Upgrading on enterprise performance separately, enriching the research on the related role mechanisms and regulatory mechanisms. (3) It offers new ideas and strategic suggestions on Digital Intelligence Transformation for enterprises with varying factor intensities, at different stages of development, and in different regions. This addresses the oversight in the existing studies regarding the varied impacts on the economic development of enterprises at different levels during the Digital Intelligence Transformation process.

2. Theoretical Analysis and Research Hypotheses

2.1. Enterprise Digital Intelligence Transformation and Enterprise Performance

As a new form emerging from the new round of technological and industrial revolutions, the new business model of Digital Intelligence Reconstruction with the connotation of "Digital Conversion + service upgrading" has a high degree of innovation, strong permeability, and wide coverage, which is an important engine for realizing the high-quality development of enterprises. Teece et al. [6] define a firm's dynamic capabilities as the ability to construct, regulate, reconfigure, and integrate its internal and external resources. Dynamic capabilities can help enterprises achieve strategic upgrading and enable them to rapidly integrate and allocate resources to enhance sustainable competitive advantage in a dynamic environment [6]. This capability is pivotal for improving both the financial and innovation performance [7,8] of an organization. In the era of digital intelligence, enterprises are utilizing advanced digital technologies such as the internet, big data, and artificial intelligence to build capabilities that adapt to the rapid progress of digitization and technological changes in the industry. Concurrently, with the continuous innovation of digital technologies, enterprises are striving to build a more comprehensive dynamic capability system that integrates the capabilities of sensing, acquiring, and transforming. As a higher-order dynamic capability, digital intelligence addresses the boundary condition problems faced by enterprises in the rapidly changing market environment by utilizing big data to analyze, integrate, and reconfigure the resource structure. This leads to the value-addedness of digital technology service applications through the servitization of business processes, thereby adapting to the rapidly changing dynamic environment. Digital intelligence encompasses different dimensions such as digitization and servitization [3], and the hypothesis of the relationship between digital intelligence and its Digital Conversion and servitization phases and firm performance is discussed below.

2.1.1. The Relationship between Digital Intelligence Transformation and Firm Performance

Enterprises typically gain a sustainable competitive advantage by integrating productive resources and transforming their unique resources into the capabilities they need. Digital capabilities, when combined with intelligent capabilities, offer a viable solution to increasingly complex problems and help maintain diverse customer relationships [9]. This combination forms the essence of digital and intelligent capabilities. Based on the theory of dynamic capabilities, Digital Intelligent Capability optimizes and integrates enterprise resources by identifying and capturing value-creation opportunities in the market, thereby helping enterprises reduce costs and increase efficiency to improve performance.

Firstly, data elements, as new factor inputs to improve productivity in the course of an enterprise's economic activity, are able to enter the enterprise's production process and directly affect economic efficiency [10]. At the same time, data elements in the R&D sector can also contribute to long-term economic growth and improve the economic performance of enterprises through knowledge-based R&D [11]. Secondly, with the advancement in information digitalization, more intensive services are transformed into tradable, value-added products. These products are integrated into various aspects of production, transportation, and management, thus affecting the overall performance of the enterprise. The use of digital technology in business acts as an innovative mechanism for value creation by enhancing the customer experience, increasing customer perception of the firm, improving customer loyalty, and reducing purchase costs [12]. Eventually, the interaction between digitization and high servitization has a positive and significant impact on firm financial performance at higher levels of firm digitization [13]. Without this interaction, firms may face challenges such as the "digitization paradox" or the "servitization dilemma". Digital intelligence enhances operational and business outcomes and has a direct positive impact on a company's financial performance, including revenue, profit, and market value. Taken together, this paper concludes that digital intelligence can help reduce production and operational costs, enhance stakeholder communication and collaboration, improve service quality and customer experience, and, in turn, improve firm performance. Therefore, this paper proposes the following hypotheses:

H1. *Digital Intelligence Transformation positively affects firm performance.*

Digital–intelligent transformation is a high-level transformation of the business service intelligence established on the basis of the Digital Conversion of information and upgrading of process servitization, which further touches the core business of the enterprise with the purpose of reconstructing the business model. This paper focuses on the economic efficiency of enterprises, so enterprise performance focuses on the financial performance of enterprises.

2.1.2. The Relationship between Digital Conversion and Firm Performance

Digital technologies, such as big data, cloud computing, and artificial intelligence, collectively form the core infrastructure of an enterprise. The strategic integration of these technologies enhances the enterprise's value chain. As digital technologies evolve, traditional labor and capital are increasingly being supplanted by digitized knowledge and information, which transform into crucial external assets. These assets boost enterprises' core competitiveness during their transformation and upgrading processes, secure market advantages, and identify future opportunities. The main purpose of Digital Conversion is to automate processes through digital technology to reduce the cost of production and operation, as well as the use of the digital restructuring of business processes in order to enhance the customer experience and expand the market scale [14]. Enterprises leverage digital platforms and dynamic management capabilities to form business units adaptable to various contextual plans, thereby enhancing their perception of external environments. Digital technology enables enterprises to collect data and information about the competitive market, customers, and social trends, facilitating timely insights into potential customer needs, optimizing operational modes and profitability mechanisms, and achieving sustainable growth in performance. In the era of digital–intelligent transformation, Digital Conversion is deeply integrated into production to enhance output efficiency and economic value [15].

On the one hand, enterprises can improve operational performance by reducing business costs and increasing operational revenue through Digital Conversion. Among them, cost reduction includes reducing the cost of information flow and transaction costs. Digital technology can reduce the cost of searching on various business processes as well as the cost of cross-domain business transactions, and optimize internal and external communication and transactions [16,17]. On the other hand, rapid advancements in Digital Conversion have not only spawned innovative manufacturing models but also fostered new marketing strategies. The rise of e-commerce and smart manufacturing is driving a shift towards greater value addition in products and services [18]. By continuously innovating and applying digital technologies, enterprises have launched initiatives that transcend traditional boundaries, facilitating the construction of digital platforms and strengthening the capability to experiment with innovative business models. This enhances enterprises' access to internal and external resources and opportunities. The establishment of a digital platform enables the convergence of advantageous resources from each element in the value network, realizing value addition for all stakeholders in the system and thereby improving enterprise performance. Therefore, the following hypothesis is proposed:

H1a. *Digital Conversion positively affects firm performance.*

Digital Conversion is the digitization of information materials favoring the process of the technological transformation of business operation information into digital form.

2.1.3. The Relationship between Servitization Upgrading and Firm Performance

Since the 1960s, with the development of information technology and the deepening of the professional division of labor, the world's major developed countries have gradually shifted their economic center of gravity to the service industry, and the industrial boundaries between the manufacturing industry and the service industry have become increasingly blurred [19]. Servitization Upgrading involves continuously introducing high-value-added service offerings based on actual products, aimed at developing unique competitive advantages and sustained value creation. With the increasing complexity of product structures and production processes, the integration of service provision with product manufacturing has strengthened. This integration effectively addresses the traditional manufacturing industry's low position in the value chain [20]. Although possessing digital resources is crucial for gaining competitive advantages, these resources alone do not create value directly. They must be coordinated, deployed, and integrated through organizational capacity, which is key to unlocking resource potential. However, an enterprise's established operational mode may lead to path dependence, making strategic transformations difficult due to resource and practice rigidity. Especially in a complex and changing competitive environment, companies need to develop dynamic capabilities [21]. As a strategic orientation, servitization is a dynamic capability that enables enterprises to actively respond to market changes, reintegrate internal and external technological resources, and construct and reshape the core competitive advantages of the enterprise value chain. The upgrading of servitization, primarily based on digital development, enhances enterprise performance by improving differentiated competitiveness, increasing customer loyalty, and boosting multifaceted revenue streams.

First of all, when enterprises initially implement servitization, they will leverage digital technology, knowledge, and both internal and external resources [22] to launch service businesses that quickly attract market attention and expand the market share of the relevant service sectors. The personalized and interactive nature of these service businesses provides a more profound experience for downstream customers. Enterprises can rapidly adapt to the constant changes in market demand through a series of derivative services, and successfully attract new customer groups while maintaining the existing customer relationships, thus realizing a further expansion of the "siphon" effect in customer scale [23]. Since market demand is large at this time, it increases the number of service businesses, enhances customer loyalty, and improves the economic efficiency of the enterprise. Additionally, when other companies recognize such business opportunities, the relatively low imitation and entry barriers at the initial stage of servitization lead to an increasing number of companies choosing to implement Servitization Upgrading. This enhances the differentiated competitiveness of the company. This leads to the following hypothesis:

H1b. *Servitization Upgrading positively affects firm performance.*

Servitization Upgrading is a digital service of business processes, a servitization process of smart manufacturing processes, and the main form of output is the servitization of business process gains.

2.2. Mechanistic Effects of Firms' Innovation Resilience

From an evolutionary perspective, resilience is considered a dynamic process of continuous adjustment and adaptation, the ability of a system to respond and evolve in the face of external shocks [24]. Lv [25] believes that innovation resilience is the ability of an organization to integrate organizational resources in a stable, flexible, and effective way to cope with the risks of innovation activities. When an organization faces dynamic changes in the internal and external environment, it can maintain and enhance its innovation capability through innovation resilience. This maintains the stability of the organizational system, adapts to new changes, and even evolves into a higher level and functional state [26,27]. The development of enterprise innovation resilience is a dynamic process of evolution, adaptation, and adjustment. When faced with dynamic impacts from the internal and external environments, the innovation system within the enterprise can undergo structural adjustments, optimize resource allocation, and thus leap to a higher level of dynamic capabilities. Digital Intelligence Transformation reshapes the dynamic capabilities of the enterprise, which in turn are the foundation of Digital Intelligence Transformation [28]. The ability to enhance dynamic capabilities in transformation is critical for enterprises to gain a competitive edge. Leading companies in their industries have the strength to efficiently integrate and coordinate internal and external resources, and their innovative thinking is both rapid and highly flexible [6]. The transformation of companies through digital intelligence to leverage external digital resources to shape new competitive edges is a key strategic transition for companies' innovation resilience. The potential for growth within the industry provides the impetus for companies to innovate and evolve. The following discussion discusses how the different stages of digital intelligence may affect firm performance by enhancing firm innovation resilience.

2.2.1. Digital Intelligence Transformation, Innovation Resilience, and Corporate Performance

Egbetokun studied the drivers of the innovativeness of SMEs in developing countries based on Nigerian cable manufacturing firms and found that the interaction between firms and external customers and suppliers, as well as the upgrading of external resources and equipment, may be important drivers of innovation in firms [29]. In the process of Digital Intelligence Transformation, enterprises are able to systematically interpret internal and external data resources. They learn from, optimize, and utilize these data [30], leveraging the data-driven effect to eliminate barriers between organizational systems and achieve data flow interconnectivity. When a beneficial closed loop of data flow is established within an enterprise, digital technology can empower existing data resources to enhance enterprise value, direct the enhancement of enterprise innovation capabilities, and drive the development of economic efficiency. Through the transformation into digital intelligence, enterprises stimulate their data analysis capabilities to perceive new opportunities for the development of digital business. Furthermore, their capabilities for innovation and change help achieve the internalization of data resources, which promotes open sharing and knowledge innovation [31]. The development of digital intelligence, which is based on data, algorithms, and the ability to innovate and adapt, transforms enterprise business models and digital intelligence technology [32]. It also provides opportunities for new production factors to empower corporate innovation activities, thereby enhancing corporate performance.

The development of digital intelligence technology significantly enhances the dynamic ability of enterprises to acquire, integrate, reconfigure, and release resources. This enhancement is crucial for enterprises in continuously updating their technological capabilities, adjusting resource allocation, and creating unique and hard-to-imitate differentiated competitive advantages. This directly impacts the innovation resilience of the enterprises. On one hand, enterprises use digital intelligence technology to transcend traditional closed boundaries, enhancing information communication, technology exchange, and R&D cooperation among innovators through digital platforms [5]. This extensive use of digital intelligence technology enables the efficient collection of big data and timely access to cutting-edge information related to enterprise R&D and market-specific demands. It facilitates the management and analysis of this R&D information, subsequently yielding data that benefit enterprise R&D, improves the scientific nature of R&D decision making, and enhances the enterprise's innovation capability [33]. On the other hand, the transformation toward digitalization and intellectualization is challenging. In this transformative process, enterprises use digital technology to innovate their modes of operation, upgrade business processes, and harness more information technology across R&D, production, sales, and service innovation. This provides clearer direction and stronger motivation for enterprise innovation efforts, enhancing the core competitive advantage of enterprises and empowering performance improvements.

In the process of digital and intellectual transformation, enterprises continuously integrate internal and external resources. The new generation of information technology, combined with existing resources, reconstructs the modes of enterprise innovation and development and improves the resilience of innovation. This enhances the competitive advantage of enterprises and creates new profit growth points. The following hypothesis is proposed:

H2. *Digital–intelligent transformation positively affects firm performance by increasing firm innovation resilience.*

Innovation resilience is the ability of an innovation system to quickly prevent, resist, respond, and adapt to the impact of the external environment through self-learning and self-adaptation in the face of the impact and perturbation of the external environment, so as to recover to the initial state or transform to a higher functional state [34].

2.2.2. Digital Switchover, Innovation Resilience, and Firm Performance

The Digital Intelligence Transformation of information has led to a reduction in the cost of technology for enterprises, increasing the rate of substitution for other capital [35], and thus establishing a new competitive advantage for enterprises by leveraging both internal and external resources. Initially, digital technology enables companies to deliver high-level services, which, through innovative service offerings, facilitates the realization of economic benefits associated with advanced servitization. Digital switchover fundamentally represents technological progress at the higher levels of the value chain. This progress not only enhances product production in the mid-levels of the value chain but also injects new dynamics into service innovation at the lower tiers [36]. Furthermore, the Digital Intelligence Transformation process in enterprises is characterized by the application of advanced digital technologies and the empowerment of data elements. This not only provides robust technical support for information exchange and real-time sharing within the organization but also enhances the significance of multi-terminal access and sharing platforms for enterprise innovation knowledge under the impetus of digital technology. Such platforms reduce the costs associated with the exchange and transmission of knowledge, promote the flow and sharing of knowledge across the temporal and spatial boundaries within and outside the organization, and expand the coverage of enterprise knowledge. Additionally, enterprises are empowered by digital technology to delve deeper into innovative knowledge, further enhancing knowledge accumulation and improving innovation outcomes [37]. Ultimately, firms can create more value for their customers by innovating digital products, which in turn boosts organizational performance. This is evidenced by the ability to swiftly access information about consumer needs, reduce the costs of information gathering, and enhance market presence. Digital technology not only improves the efficiency of innovation and R&D and broadens opportunities for cross-disciplinary integration but also introduces new and effective value-creation methods [38]. These methods extend the range of actors and locations where value can be created, enabling companies to respond more flexibly [39] to environmental changes and thereby enhance firm performance [40]. Consequently, this paper posits that the Digital Intelligence Transformation of information can indirectly drive enterprise performance by enhancing enterprise innovation resilience. Therefore, the following hypothesis is proposed:

H2a. *Digital Conversion positively affects firm performance by increasing firm innovation resilience.*

2.2.3. Servitization Upgrading, Innovation Resilience, and Firm Performance

With the advancement of Digital Conversion strategies, the internal management processes of enterprises are undergoing profound changes, setting new development blueprints, management strategies, and competitive boundaries for enterprises, and ensuring the upgrade of process servitization for smooth data transmission [4]. Driven by digital technologies, servitization exhibits flexibility and versatility, enhancing the dynamic capability of enterprises to renew, integrate, and reconfigure internal and external resources. This capability is crucial for adapting to the ever-changing business environment. Thus, servitization not only boosts the innovation efficiency of enterprises but also supports their long-term survival and sustainable competitive advantages. In the process of upgrading servitization, the higher the frequency of dynamic interactions, the better the integration of knowledge and innovation capability within the enterprise. Innovation is considered a primary driver of sustained competitive advantage and enhanced corporate profitability [41]. Servitization provides firms with opportunities for continuous iteration and innovation. The dynamic capability to develop new services over time leads to the creation of new service businesses [42], which helps companies capture a larger market share [43], achieve industry leadership, secure a monopoly position, generate innovative “profits”, and further improve organizational performance.

In the process of Servitization Upgrading, the service industry integrates digital resources with physical products, harnessing the collective impact of various knowledge types to advance technology. This integration is grounded in an understanding of the relationship between core product functions and user needs. Servitization amplifies the ability of enterprises to offer personalized services spurred by new product innovations. This capability not only helps enterprises mitigate business risks but also bolsters the stability of their economic returns. Moreover, servitization within an enterprise entails the incorporation of numerous innovative elements, such as talent, digital technology, and knowledge, throughout the entire business process. Optimizing the combination of production factors facilitates the deep integration of innovation elements with labor, technology, management, and other factors, thereby promoting the spillover effect of technology and enhancing the learning capabilities and profitability of enterprises. Servitization Upgrading not only provides enterprises with additional knowledge resources but also supports their transformation from a single innovation entity into a collaborative innovation model involving service providers, suppliers, and customers. This collaborative approach fosters co-innovation across all aspects of product design, R&D, manufacturing, sales, and after-sales services [44]. Furthermore, the integration of the manufacturing industry with the modern service industry introduces numerous professional and diversified innovation elements. This integration innovatively affects the original factor structure, innovation system, and organizational structure of enterprises. It not only increases the volume of enterprise innovations but also enhances their independent innovation capabilities and the quality of innovations [45]. Highly innovative firms are more attuned to market signals, creating more opportunities to optimize existing product designs or introduce innovative products [46]. Such enhancements in product offerings are instrumental in boosting customer loyalty, facilitating market expansion, and identifying new customer segments [47]. Therefore, this paper posits that Servitization Upgrading can indirectly drive value-added firm performance through the enhancement of firms' innovation capabilities. Consequently, the following hypothesis is proposed:

H2b. *Servitization Upgrading positively affects firm performance by increasing firm innovation resilience.*

2.3. Regulatory Mechanism Effects of Environmental Uncertainty

Dynamic capability theory integrates the dynamic changes in the environment and market into the study of corporate competitive advantage. For enterprises, environmental uncertainty is an essential organizational context for their survival and operation. The environmental uncertainties that enterprises face during the process of digital–intelligent transformation predominantly include market environment instability, technological environment instability, and intense market competition. Market uncertainty refers to the variability in customers' needs and preferences and the unpredictability of these changes. It also encompasses the adjustments in product quality and delivery made by suppliers and the associated uncertainties [48,49]. Technological uncertainty captures the rapid technological changes within the industry and the uncertainty regarding the direction of these technological developments [48]. Competitive intensity pertains to the firm's price competition, the imitation of products and services within its industry, and the depth of its promotional strategies [50]. In a highly competitive market, when rivals continuously introduce innovative products or marketing strategies, firms are compelled to make strategic decisions concerning their future survival and growth. Such decisions vary depending on the competitive environment of the industry [51]. As technological instability increases and the pace of technological innovation accelerates, it becomes challenging for firms to maintain their competitive advantage solely based on existing resources. Similarly, relying solely on well-crafted market strategies to achieve sustained profitability [52] becomes increasingly difficult. This situation necessitates that firms adapt their strategies promptly to respond to environmental changes [53]. As a higher-order dynamic capability, digital intelligence enables the analysis, recognition, integration, and redistribution of data resources both within and outside the organization to address drastic changes in the external environment [54]. The following are some examples of how digital intelligence can be utilized.

Uncertainty, as a manifestation of the organizational environment, plays a critical role in both the financial performance of the organization and in the formulation of management decisions [55]. The instability of the micro-environment faced by an enterprise directly reflects the unpredictable fluctuations in the industry and markets in which it operates. This volatility can be quantitatively assessed through operating income and other performance indicators [56]. In a highly uncertain market environment, consumer preferences diversify, and market demand continuously evolves. Increasing environmental uncertainty elevates the perceived risk to the enterprise, thereby enhancing the inclination toward information digitization. More critically, the advantages of Digital Intelligence Transformation become more pronounced in such an environment. Benefits such as improved operational efficiency, brought about by the adoption of digital technologies, may enhance organizational capabilities. This emphasizes the necessity to boost adaptability to environmental changes to mitigate the adverse impacts of uncertainty on organizational performance [57].

Environmental uncertainty increases the risk associated with service innovation [58] but also creates more profit potential for the firm. Specifically, a market environment characterized by high environmental uncertainty, rapid changes in customer demand, swift technological updates, and fierce market competition enables a firm to gather extensive data on customer demand, organizational processes, industry competition, and cutting-edge service models. This is facilitated through resource sharing and information communication with key external organizations such as customers and suppliers. Access to these external resources allows companies to better understand the market, increase the quantity and quality of internal resources, and enhance the firm's dynamic capabilities. Consequently, this improves the efficiency and effectiveness of Servitization Upgrading and further enhances company performance. Conversely, in environments with relatively low instability, fluctuations in demand and supply are minimal, leading to a stabilization of the industry as a whole. Although extensive information exchange, relationship alignment, and joint engagement between firms and their external stakeholders continue, it becomes challenging to sustainably acquire new and complementary resources necessary for servitization. This limitation impacts the efficiency and outcomes of innovative resource integration by firms. Additionally, when market resources are scarce and product homogeneity within the industry increases, the substitutability of products offered by different firms also rises, intensifying industry competition. Consequently, firms must consider how to differentiate their services with unique properties to achieve greater future profitability [59].

Based on the above analysis, the following hypotheses are proposed in this paper:

H3. *Environmental uncertainty positively moderates the relationship between Digital Intelligence Transformation and firm performance, i.e., the higher the environmental uncertainty, the greater the positive contribution of Numerical Intelligence Transformation to firm performance.*

H3a. *Environmental uncertainty positively moderates the relationship between Digital Conversion and firm performance, i.e., the higher the environmental uncertainty, the greater the positive contribution of Digital Conversion to firm performance.*

H3b. *Environmental uncertainty positively moderates the relationship between Servitization Upgrading and firm performance, i.e., the higher the environmental uncertainty, the greater the positive contribution of Servitization Upgrading to firm performance.*

Environmental uncertainty is the difficulty for an organization to make clear judgments due to the dynamic changes in the environment, which manifests itself as a continuous increase in business risk. Environmental uncertainty exacerbates principal–agent problems and makes management more difficult, ultimately increasing the volatility and unpredictability of corporate earnings [60].

Based on the above assumptions, the model diagram is shown in Figure 1.

This study takes the different stages of Digital Intelligence Transformation (Digital Conversion, Servitization Upgrading, and Digital Intelligence Transformation based on the first two stages) under the operation perspective as influencing factors, and argues that the dynamic capabilities grown by enterprises in this process will have a positive effect on enterprise performance (H1). In addition, this paper also suggests that the Digital Intelligence Transformation of enterprises will positively contribute to the improvement of enterprise innovation capability, which will enhance enterprise performance (H2). Finally, considering the contextual factor of environmental uncertainty, it is argued that the higher the environmental uncertainty, the greater the positive contribution of Digital Intelligence Transformation to firm performance (H3).

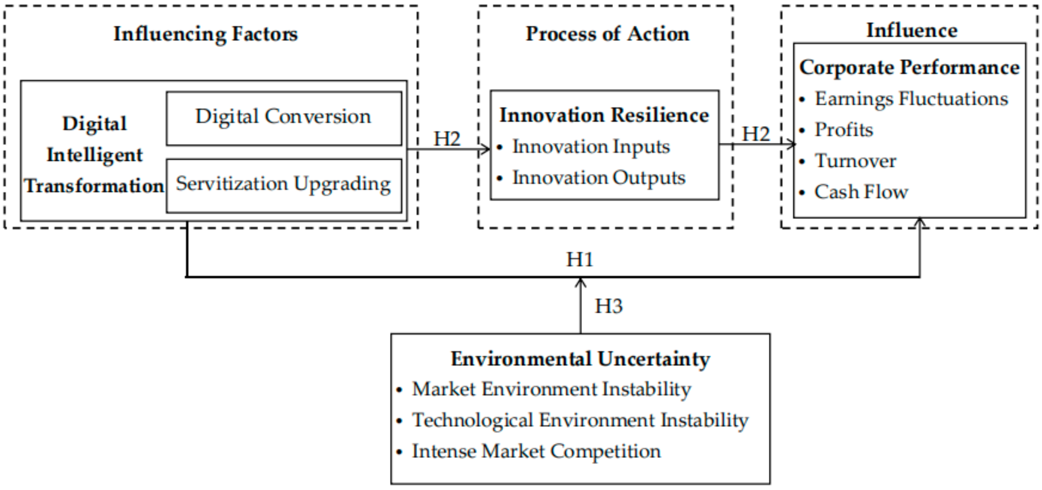

Figure 1. Model diagram.

3. Research Design

3.1. Sample Selection and Data Sources

In the face of the complexity and uncertainty of the global economic development environment, the manufacturing industry is facing many difficulties in transformation and upgrading as well as in finding new development momentum. Currently, manufacturing companies are in dire need of Digital Intelligence Transformation, and most of them are already in the process of implementing Digital Intelligence Transformation strategies. Consequently, Based on the availability of data and accuracy of financial data, this paper selects manufacturing corporations listed on China's Shanghai and Shenzhen A-shares as the initial research sample. According to the 2012 version of the industry classification guidelines of the Securities and Exchange Commission, companies with industry codes C13 to C43 were chosen for the period from 2013 to 2022. The empirical research objects were identified using data from these enterprises. The primary data sources are divided into two types: first, the CSMAR Cathay Pacific database, which provides relevant financial information; second, the WIND database, used to collect detailed data on the main business revenue of the sample enterprises. Data on servitization revenue in the appendix of the financial statements were corrected and supplemented through the Juchao Consulting Network and the annual reports of the enterprises. The initial research sample was screened as follows: (1) to ensure that the companies in the sample had at least two years of listing experience and maintained relative operational stability, the companies listed after 31 December 2020 and companies with a trading status of "special treatment" (ST, *ST, and PT companies) in the current year were excluded; (2) to ensure the continuity of the sample data, the companies that went bankrupt or collapsed between 2013 and 2022 were removed; (3) the companies with four consecutive years of missing data for the main research variables and those that did not engage in servitization were excluded; and (4) the observations with gearing ratios exceeding 100% were also excluded. The final sample comprised 6320 observations from 632 firms. In addition, to reduce the interference of extreme values on the results of the regression analysis, this paper performed 1% quantile shrinkage on the main continuous variables and employed linear interpolation for data supplementation. The statistical software used was Stata 16.0.

3.2. Variable Description and Measurement

Corporate performance: In this paper, in order to study the impact of Digital Intelligence Transformation on the economic efficiency of enterprises, Tobin's Q (*TQ*) is employed as an indicator of corporate financial performance [61]. This metric includes future expectations and risk adjustments for the enterprise, allowing for an assessment of the enterprise's potential to expand investment and sustain growth. Tobin's Q takes into account various factors such as profits, turnover, earnings fluctuations, and cash flow, thereby providing a comprehensive reflection of the financial performance of the enterprise. It is less susceptible to manipulation compared to other indicators, making it a more objective and reasonable measure of corporate performance.

Digital Intelligence Transformation: In the process of Digital Conversion, the enterprise makes full use of the multiple functional aspects of data collection, data analysis, and data decision making; carries out a comprehensive technological upgrade of the organizational structure and processes; and significantly improves the efficiency of resource organization and allocation [62]. The degree of information digitization (*Digi*) is assessed using the enterprise Digital Intelligence Transformation index. This index is derived from the enterprise Digital Intelligence Transformation database, which compiles data from annual reports, fund-raising announcements, qualification certifications, and other public disclosures of listed companies. The data source is both authoritative and reliable, presenting a complete and objective view of the enterprise Digital Intelligence Transformation. The specific calculation of the Digital Intelligence Transformation index is based on a weighted analysis of six indicators: strategic leadership, technology-driven, organizational empowerment, environmental support, digital achievements, and digital application.

Servitization Upgrading: Service-based upgrading is a process whereby manufacturing firms move from supplying goods alone to providing both goods and service packages, with services dominating the package as the main source of value added [63]. The business servitization level (*Ser_incom*) is used to represent the extent of the current Servitization Upgrading of a firm. This measure evaluates the proportion of service business income concerning the total main business income, reflecting the output servitization level of enterprises [64]. The variable construction primarily follows the methodology of Zhao [65] based on the National Economic Industry Classification standard (GB/T4754-2011) [66], which categorizes main business-related servitization activities into eight different types. Additionally, for the companies that may not detail the revenue of their main business in financial reports, this paper also examines the structure of servitization personnel in the robustness test to reflect the level of Servitization Upgrading.

Enterprise innovation resilience: Innovation resilience is the ability of an organization to integrate its resources in a stable, flexible, and effective way in order to cope with the risks of innovation activities. This variable is assessed using the quantity and quality of enterprise innovation outputs. The current literature typically employs innovation inputs and outputs as proxies to measure enterprise innovation. However, innovation inputs alone do not fully capture the innovation quality and efficiency of enterprises [67]. This paper, therefore, opts to measure enterprise innovation resilience primarily through innovation outputs, which are assessed in two dimensions: the quantity and quality of innovation outputs. We adopt a generally recognized measurement method using the natural logarithm of the number of successful patent applications (including invention patents and utility model patents) by the sample company and its non-distant subsidiaries in the subsequent year plus one (*Pat_app*) to represent the quantity of innovation output. The quality of innovation output is represented by the natural logarithm of the number of citations a patent application receives plus one (*Cit_rec*). The frequency of citations often indicates the quality and influence of patents, thereby providing a robust measure of innovation quality. In addition, enterprise innovation input is selected as a proxy variable for the robustness test of the mediation effect, which will be discussed later in the analysis.

Environmental Uncertainty: Environmental uncertainty includes many uncertain factors such as macroeconomics, industrial structure, market demand, etc., which can more comprehensively reflect the degree of unpredictable changes faced by enterprises in various aspects. Drawing on existing research [57,60], environmental uncertainty is measured using the coefficient of variation of the firm's sales revenue. Fluctuations in a firm's core business activities, primarily caused by external environmental uncertainties, affect the firm's sales revenue [68]. To control for industry effects, the coefficient of variation is adjusted by the industry median, and an Ordinary Least Squares (OLS) regression is conducted on the operating income of each company over five consecutive years using annual data. The regression model is specified as follows:

$$\text{Sales} = \alpha_0 + \alpha_1 \text{Year} + \varepsilon$$

In this model, "Sales" represents the operating revenue of each sample firm. The year 2022 is designated as five, 2021 as four, decreasing incrementally to 2018, which is set as one. These values are substituted into the model for OLS analysis to derive the standard deviation of the residuals. This standard deviation is then adjusted by the industry median to determine the current year's degree of environmental uncertainty. A larger value indicates a higher environmental uncertainty.

Control variables: To enhance the accuracy of estimation, this paper includes several control variables based on related studies [36,69,70]. These variables include equity concentration, return on invested capital, gearing ratio, current ratio, working capital ratio, capital intensity, firm size, firm age, and current debt ratio. The definitions of these variables are detailed in Table 1.

Table 1. Definition of variables.

Variable Type	Variable Name	Variable Measurement	Notation	Variable Meaning
explanatory variable	Corporate Performance	Tobin's Q	*TQ*	(Price per share × number of shares outstanding + net assets per share × Number of non-circulating shares + liabilities)/total assets
explanatory variable	Digital Conversion	Digital Intelligence Transformation index	*Digi*	Reflects the degree of the Digital Conversion of the enterprise
	Service-oriented Upgrading	Percentage of serviced revenue	*Ser_income*	Revenue from servitization/revenue from main operations
intermediary variable	Innovative Resilience	Number of patent applications	*Pat_app*	The natural logarithm of the number of successful patent applications granted in the year plus 1
		Patent citations	*Cit_rec*	The natural logarithm of the number of citations plus one for successful patent applications
moderator variable	Environmental Uncertainty	Environmental uncertainty	*EU*	The coefficient of variation of company sales revenue
control variable		Shareholding concentration	*Co*	The sum of the shareholdings of the top ten shareholders
		Return on invested capital	*Roic*	EBITDA × (1 − income tax/total profit) × 2/(Capital invested at the beginning of the period + capital invested at the end of the period)
		Gearing	*Lev*	Total liabilities/total assets
		Current ratio	*Lip*	Current assets/current liabilities
		Working capital ratio	*Wcr*	Working capital/current assets
		Capital intensity	*Capital*	Total assets/operating income
		Enterprise size	*Size*	The natural logarithm of the total number of people in the enterprise
		Age of business	*Age*	Current year—the year of the establishment of the enterprise
		Current liabilities ratio	*Cdr*	Total current liabilities/total liabilities

3.3. Modeling

This paper uses the Hausman test to determine the appropriateness of either a fixed effect model or a random effect model for the regression analysis. The test results, showing a *p*-value less than 0.1 for all models, suggest the selection of the fixed effect model. Both year- and industry-fixed effects are incorporated into the regression model. The empirical model established for analysis is as follows.

3.3.1. Main Effects Baseline Regression Model

To test the direct effect of enterprise Digital Intelligence Transformation on performance (hypotheses 1, 1a, and 1b), the following multiple regression model is constructed:

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{2}$$

$$TQ_{i,t} = \alpha + \beta Ser\_income_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

$$TQ_{i,t} = \alpha + \beta Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{4}$$

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \beta Ser\_income_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{5}$$

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \beta Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \tag{6}$$

In this model, α is the intercept term, and β is the core coefficient reflecting the net effect of Digital Intelligence Transformation on firm performance, controlling for year (δ_t) and industry effects (θ_i). $Digi_{i,t}$ represents the degree of Digital Intelligence Transformation for firm i in period t. Subsequent models (2) to (4) incorporate additional firm-level control variables and explore the relationship between Servitization Upgrading and enterprise performance. Models (5) and (6) examine whether Digital Intelligence Transformation and servitization collectively influence enterprise performance, with both effects expected to be significantly positive.

3.3.2. Mechanism Effects Modeling

First, to explore whether the Digital Intelligence Transformation of corporate information can enhance corporate performance by improving innovation resilience, we introduce two metrics: the quantity of innovation output (*Pat_app*) and the quality of innovation output (*Cit_rec*). The development of the mediating mechanism model primarily draws on the related literature [71]. H2 is tested using models (15) through (18), while H2a and H2b are examined using models (7) through (10) and models (11) through (14), respectively.

$$Pat\_app_{i,t} = \alpha + \eta_1 Digi_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t} \tag{7}$$

$$TQ_{i,t} = \alpha + \eta_2 Digi_{i,t} + \xi_1 Pat\_app_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{8}$$

$$Cit\_rec_{i,t} = \alpha + \eta_3 Digi_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{9}$$

$$TQ_{i,t} = \alpha + \eta_4 Digi_{i,t} + \lambda_1 Cit\_rec_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{10}$$

$$Pat\_app_{i,t} = \alpha + \beta_1 Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \tag{11}$$

$$TQ_{i,t} = \alpha + \beta_2 Ser\_income_{i,t} + \xi_2 Pat\_app_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (12)$$

$$Cit\_rec_{i,t} = \alpha + \beta_3 Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (13)$$

$$TQ_{i,t} = \alpha + \beta_4 Ser\_income_{i,t} + \lambda_2 Cit\_rec_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (14)$$

$$Pat\_app_{i,t} = \alpha + \eta_5 Digi_{i,t} + \beta_5 Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (15)$$

$$TQ_{i,t} = \alpha + \eta_6 Digi_{i,t} + \beta_6 Ser\_income_{i,t} + \xi_3 Pat\_app_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (16)$$

$$Cit\_rec_{i,t} = \alpha + \eta_7 Digi_{i,t} + \beta_7 Ser\_income_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (17)$$

$$TQ_{i,t} = \alpha + \eta_8 Digi_{i,t} + \beta_8 Ser\_income_{i,t} + \lambda_3 Cit\_rec_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (18)$$

3.3.3. Models of the Effects of the Regulatory Mechanism

To verify the moderating effect of environmental uncertainty on the relationship between enterprises' Digital Intelligence Transformation, service-oriented upgrading, and enterprise performance, we introduce environmental uncertainty as a moderating variable in model (2), model (4), and model (6). We construct the following models to, respectively, verify H3:

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \varphi_1 EU_{i,t} + \phi_1 Digi_{i,t} \times EU_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (19)$$

$$TQ_{i,t} = \alpha + \beta Ser\_income_{i,t} + \varphi_2 EU_{i,t} + \phi_2 Ser\_income_{i,t} \times EU_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}, \quad (20)$$

$$TQ_{i,t} = \alpha + \eta Digi_{i,t} + \beta Ser\_income_{i,t} + \varphi_3 EU_{i,t} + \phi_3 Digi_{i,t} \times EU_{i,t} + \phi_4 Ser\_income_{i,t} \times EU_{i,t} + \gamma \sum Control_{i,t} + \theta_i + \delta_t + \varepsilon_{i,t}. \quad (21)$$

In model (19), $EU_{i,t}$ represents the environmental uncertainty faced by firm i in year t. This model introduces an interaction term, $Digi_{i,t} \times EU_{i,t}$, which represents the interaction between the firm's degree of digitization and environmental uncertainty, as a means to test the moderating effect of environmental uncertainty. Similarly, model (20) introduces the interaction term $Ser\_income_{i,t} \times EU_{i,t}$ to represent the interaction between servitization and environmental uncertainty. Finally, model (21) tests whether the relationship between Digital Intelligence Transformation and firm performance is moderated by environmental uncertainty, and it requires the observation of the coefficients η, β, ϕ_3, and ϕ_4.

4. Empirical Testing

4.1. Descriptive Statistics and Correlation Analysis

4.1.1. Descriptive Statistics

Using the Stata software, the variables were analyzed through descriptive statistics, and the results are displayed in Table 2. The statistical sample reveals that the degree of enterprise digitization (*Digi*) has a mean value of 39.85, a standard deviation of 11.13, an extreme deviation of 74.66, and a median value of 38.62, indicating that while most sample enterprises have implemented Digital Intelligence Transformation, the degree of digitization varies widely across them. The mean value of *Ser_income* is 0.0818, with a standard deviation of 0.122 and an extreme deviation of 0.586, suggesting that the overall level of servitization in the manufacturing industry is relatively low. Individual enterprise performance in implementing servitization varies, with most displaying a low level of servitization. The data on the number of patent applications (*Pat_app*) and the number of citations to enterprise patents (*Cit_rec*) indicate significant differences in innovation toughness among enterprises. The environmental uncertainty has an extreme variance of 234.58, while the mean value of 1.389 shows that the environmental uncertainty faced by the sample firms varies greatly.

Table 2. Descriptive statistics.

Variant	Average Value	Standard Deviation	Minimum Value	Upper Quartile	Maximum Values	Extremely Poor
TQ	2.284	1.347	0.879	1.859	8.649	7.769
Digi	39.85	11.13	20.00	38.62	94.66	74.66
Ser_income	0.0818	0.122	0.0002	0.0294	0.586	0.586
Pat_app	3.793	1.520	0	3.784	8.894	8.894
Cit_rec	3.352	1.706	−4.805	3.332	10.54	15.35
EU	1.389	1.735	0.013	1	234.59	234.58
Co	54.33	14.64	8.779	53.89	96.00	87.22
Roic	0.0568	0.0776	−1.209	0.0526	0.767	1.976
Size	8.067	1.171	4.220	7.978	13.25	9.034
Age	19.40	5.486	4.500	19.33	41.33	36.83
Lev	0.401	0.179	0.00797	0.400	0.975	0.967
Lip	2.559	3.799	0.265	1.757	144.0	143.7
Capital	2.083	1.339	0.283	1.783	21.85	21.56
Wcr	0.252	0.213	−0.493	0.250	0.862	1.355
Cdr	0.835	0.144	0.106	0.876	1.217	1.111

4.1.2. Relevance Analysis

Table 3 presents the correlation coefficient matrix between the relevant variables. The correlation coefficients of the degree of digitization (*Digi*) and the level of servitization (*Ser_income*) with the performance of the company (*TQ*) are 0.027 and 0.031, respectively, both significant at the 5% level. This preliminarily indicates a significant positive correlation between the degree of digitization, the level of servitization, and company performance; thus, digitization and servitization significantly promote the economic development of enterprises, providing preliminary support for hypotheses H1a and H1b. The correlation analysis reveals that the correlation coefficients between all variables are below the critical value of 0.7. In the variance inflation factor test, the VIF value of all variables is below 10, and the average variance inflation factor is 1.66, indicating that there is no multicollinearity between the variables, allowing us to proceed with the regression analysis of the model.

Table 3. Correlation analysis.

	TQ	***Digi***	***Ser_income***	***Pat_app***	***Cit_rec***	***EU***	***Co***
TQ	1						
Digi	0.027 **	1					
Ser_income	0.031 **	0.144 ***	1				
Pat_app	−0.187 ***	0.386 ***	0.053 ***	1			
Cit_rec	−0.100 ***	0.269 ***	0.073 ***	0.650 ***	1		
EU	0.057 ***	−0.077 ***	0.018	−0.115 ***	−0.091 ***	1	
Co	−0.003	−0.109 ***	−0.083 ***	0.056 ***	0.038 ***	0.042 ***	1
Roic	0.205 ***	−0.111 ***	−0.102 ***	0.079 ***	0.042 ***	−0.062 ***	0.176 ***
Size	−0.308 ***	0.095 ***	−0.015	0.597 ***	0.440 ***	−0.153 ***	0.190 ***
Age	−0.094 ***	0.023 *	0.006	0.108 ***	−0.059 ***	−0.081 ***	−0.188 ***
Lev	−0.350 ***	0.066 ***	0.008	0.358 ***	0.248 ***	0.005	−0.010

Table 3. *Cont.*

	TQ	***Digi***	***Ser_income***	***Pat_app***	***Cit_rec***	***EU***	***Co***
Lip	0.157 ***	0.015	−0.013	−0.181 ***	−0.138 ***	0.028 **	0.038 ***
Capital	0.060 ***	0.061 ***	0.123 ***	−0.155 ***	−0.097 ***	0.123 ***	−0.095 ***
Wcr	0.308 ***	0.106 ***	−0.001	−0.208 ***	−0.141 ***	0.006	0.055 ***
Cdr	0.068 ***	0.066 ***	−0.057 ***	−0.038 ***	−0.024 *	−0.019	0.094 ***
	Roic	Size	Age	Lev	Lip	Capital	Wcr
Roic	1						
Size	0.192 ***	1					
Age	0.006	0.128 ***	1				
Lev	−0.163 ***	0.489 ***	0.119 ***	1			
Lip	0.016	−0.301 ***	−0.091 ***	−0.461 ***	1		
Capital	−0.271 ***	−0.352 ***	−0.097 ***	−0.213 ***	0.319 ***	1	
Wcr	0.143 ***	−0.429 ***	−0.101 ***	−0.738 ***	0.488 ***	0.150 ***	1
Cdr	0.057 ***	−0.095 ***	−0.034 ***	−0.131 ***	−0.078 ***	−0.270 ***	0.125 ***
	Cdr						
Cdr	1						

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.2. Main Effects Benchmark Regression Results

To examine the relationship between corporate Digital Intelligence Transformation and corporate performance, this paper incorporates year- and industry-fixed effects into the regression analysis, as detailed in Table 4.

Table 4. Main effects benchmark regression results.

Variant	***TQ***					
	Digital Conversion		**Service-Oriented Upgrading**		**Digital Intelligence Transformation**	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Digi	−0.002	0.010 ***			−0.003	0.009 ***
	(0.002)	(0.002)			(0.002)	(0.002)
Ser_income			0.287 *	0.584 ***	0.315 *	0.505 ***
			(0.125)	(0.114)	(0.126)	(0.114)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	2.366 ***	5.346 ***	2.292 ***	5.440 ***	2.382 ***	5.350 ***
	(0.151)	(0.225)	(0.140)	(0.225)	(0.151)	(0.225)
Sample Size	6320	6318	6319	6317	6319	6317
R^2	0.232	0.380	0.233	0.380	0.233	0.382
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

Model (1) introduces the relevant control variables to the framework of model (2). The regression results indicate a significantly positive coefficient of 0.010 for the degree of digitization at the 1% level, thus confirming hypothesis H1a. Similarly, models (3) and (4) assess the impact of the level of enterprise servitization on enterprise performance. The regression outcomes demonstrate that after the inclusion of the control variables, the core explanatory variables are significantly positive at the 1% level, enhancing the robustness and fit of the models, thus confirming hypothesis H1b. In model (6), both digitization and servitization are considered simultaneously. The results reveal that the coefficients for both are significant at the 1% level after the inclusion of the control variables, supporting the notion that a higher-order integration of Digital Intelligence Transformation and servitization process upgrading positively influences enterprise performance, thus confirming hypothesis H1. Additionally, among the control variables, the regression coefficients of enterprise size (*Size*) and capital intensity (*Capital*) relative to enterprise performance (*TQ*) are significantly negative, suggesting that these factors may inhibit the enhancement of enterprise performance. This finding indicates the presence of heterogeneity in how enterprise Digital Intelligence Transformation impacts performance, providing a valuable reference for the subsequent analyses of heterogeneity within the article.

4.3. Testing for Mechanism Effects

Building on the theoretical mechanisms discussed earlier, this section verifies the mediating role of enterprise innovation capability and explores whether Digital Intelligence Transformation, service-based upgrading, and digital–intelligent transformation can enhance the economic development of enterprises by improving both the quantity and quality of enterprise innovations.

4.3.1. Digital Switchover, Innovation Resilience, and Firm Performance

The regression results concerning the mediating effect of Digital Intelligence Transformation on enterprise performance are presented in Table 5. The coefficient of 0.026 for the enterprise digitization degree on the number of innovations in model (7) is significantly positive at the 1% level, preliminarily confirming that an increase in the degree of enterprise digitization significantly boosts the number of innovative outputs. However, the coefficient of 0.023 for the number of innovations in model (8) is not significant. This outcome may be attributed to the generally low level of digitization in current manufacturing enterprises and the incomplete mastery of digital technologies, which could make the extensive application of digitization in licensed patents challenging. Thus, the significant impact of digitization level on the number of innovations still requires further practical validation. Conversely, model (9) confirms that Digital Intelligence Transformation can positively influence the economic efficiency of enterprises by enhancing the quality of innovations. Although the effect of Digital Intelligence Transformation on the number of innovations was not confirmed in this analysis due to developmental stage limitations, the improvement in innovation quality through Digital Intelligence Transformation has been validated. Overall, the degree of Digital Intelligence Transformation is likely to stimulate enterprise innovation vitality, thereby creating new avenues for profit growth.

Table 5. Regression results from the mechanism of action of Digital Conversion, innovation resilience, and firm performance.

Variant	Model (7)	Model (8)	Model (9)	Model (10)
	Pat_app	***TQ***	***Cit_rec***	***TQ***
Digi	0.026 ***	0.009 ***	0.028 ***	0.008 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Pat_app		0.023		
		(0.013)		
Cit_rec				0.039 ***
				(0.010)
Controls	Yes	Yes	Yes	Yes
_cons	−4.952 ***	5.457 ***	−4.314 ***	6.081 ***
	(0.215)	(0.235)	(0.233)	(0.244)
Sample size	6318	6318	6309	6309
R^2	0.555	0.381	0.589	0.276
Year-fixed	Yes	Yes	Yes	Yes
Industry-fixed	Yes	Yes	Yes	Yes

Note: *** indicates significance at the 1% levels.

4.3.2. Servitization Upgrading, Innovation Resilience, and Firm Performance

The results of model (12) in Table 6 show that the regression coefficient of 0.566 for the level of servitization with the inclusion of the number of innovations also shows significance at the 1% level. And under this model, the regression coefficient of 0.032 for the number of innovations shows a significant positive correlation at the 10% level. This indicates that the improvement of the level of enterprise servitization can stimulate the enthusiasm for enterprise innovation and increase the number of innovation outputs, which positively affects the level of enterprise performance, and the enterprise innovation ability plays a part in the mediation role. Model (13) and model (14) are used to test the mediating effect of the quality of corporate innovation output (*Cit_rec*). The regression coefficient of 0.692 for the level of servitization on the quality of innovation in model (13) is significantly positive at the 1% level, indicating that the implementation of the servitization strategy by enterprises and the improvement of the level of enterprise servitization are conducive to the improvement of the quality of enterprise innovation. Model (14) shows that the coefficient of servitization level 0.568 and the coefficient of innovation quality 0.039 are both significantly positive at the 1% level. This confirms the mediating role of innovation quality in the path of "upgrading of servitization—enterprise performance". Consequently, this result confirms H2b.

Table 6. Regression results from the role mechanism of Servitization Upgrading, innovation resilience, and firm performance.

Variant	**Model (11)**	**Model (12)**	**Model (13)**	**Model (14)**
	Pat_app	***TQ***	***Cit_rec***	***TQ***
Ser_income	0.556 ***	0.566 ***	0.692 ***	0.568 ***
	(0.110)	(0.114)	(0.119)	(0.127)
Pat_app		0.032 *		
		(0.013)		
Cit_rec				0.039 ***
				(0.010)
Controls	Yes	Yes	Yes	Yes
_cons	−4.686 ***	5.589 ***	−4.028 ***	5.147 ***
	(0.218)	(0.233)	(0.236)	(0.204)
Sample Size	6317	6317	6308	6308
R^2	0.540	0.380	0.576	0.200
Year-Fixed	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

4.3.3. Digital Intelligence Transformation, Innovation Resilience, and Firm Performance

The results of the regression analysis on Digital Intelligence Transformation, corporate innovation capacity, and corporate performance are displayed in Table 7. Following the baseline regression model (6), the mediation test is conducted. Initially, the regression coefficients for the degree of enterprise digitization and the level of servitization on the quantity and quality of innovation in models (15) and (17) are significantly positive at various levels. This finding preliminarily confirms that the implementation of digital–intelligent transformation substantially enhances an enterprise's innovation capabilities. However, the coefficients of 0.020 and 0.010 for the quantity and quality of innovation in models (16) and (18), respectively, are not significant, indicating that there is no significant mediating effect of enterprise innovation capability between Digital Intelligence Transformation and enterprise performance. This result shows that H2 is not significant. This may be attributed to the fact that the current level of enterprise Digital Intelligence Transformation is not sufficiently advanced to stimulate improvements in enterprise performance through enhanced innovation capabilities.

Table 7. Regression results from the mechanism of action of Digital Intelligence Transformation, innovation resilience, and firm performance.

Variant	Model (15)	Model (16)	Model (17)	Model (18)
	Pat_app	***TQ***	***Cit_rec***	***TQ***
Digi	0.026 ***	0.008 ***	0.027 ***	0.009 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Ser_income	0.333 **	0.499 ***	0.457 ***	0.503 ***
	(0.109)	(0.114)	(0.118)	(0.115)
Pat_app		0.020		
		(0.013)		
Cit_rec				0.010
				(0.012)
Controls	Yes	Yes	Yes	Yes
_cons	−4.942 ***	5.451 ***	−4.298 ***	5.395 ***
	(0.215)	(0.234)	(0.232)	(0.232)
Sample Size	6.317	6.317	6.308	6.308
R^2	0.556	0.382	0.590	0.382
Year-Fixed	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

4.4. Tests of the Effects of Regulatory Mechanisms

In Table 8, environmental uncertainty (*EU*) is added to the baseline regression results of model (2), model (4), and model (6), respectively, to verify the moderating effect of environmental uncertainty. First, according to the regression results of model (19), the regression coefficient of the digitization degree (*Digi*) of 0.011 and the regression coefficient of the environmental uncertainty (*EU*) of 0.033 are consistently positive in sign and are significant at the 1% and 10% levels, respectively. And the regression coefficient of the interaction term of digitization and environmental uncertainty (*Digi* × *EU*) reaches 0.048, which successfully passes the significance test at the 10% level. This result indicates that when enterprises face a high degree of environmental uncertainty, they face greater survival pressure and risk challenges, and resource and capacity constraints are more prominent, and at this time, the higher the degree of digitization of the enterprise, the more pronounced the positive impact on the economic performance of the enterprise, i.e., H3a is established. Second, the coefficient of environmental uncertainty (*EU*) and the coefficient of the interaction term (*Ser_income* × *EU*) in model (20) are not significant, indicating that H3b does not hold. Finally, Digital Conversion, servitization, environmental uncertainty, and the interaction term (*Ser_income* × *EU*) are significant in model (21), but the interaction term (*Digi* × *EU*) is not significant, which indicates that environmental uncertainty is not yet significant for the relationship between digital–intelligent transformation and enterprise performance, i.e., H3 does not hold. The reason may be that most enterprises in China are not mature enough for the development of Digital Intelligence Transformation, and the level of environmental uncertainty has no significant moderating effect on the relationship between Digital Intelligence Transformation and enterprise performance. Moreover, the overall domestic enterprises are in the development stage of low level of servitization, and the level of environmental uncertainty does not have a more significant impact on the results of the benefits of servitization.

4.5. Robustness Tests

To ensure the accuracy and reliability of the empirical results, and to exclude the interference of other policies, changes in time trends, and other factors, this paper tests the robustness of the empirical model. The robustness is evaluated by replacing explanatory variables and mediating variables and addressing the potential endogeneity of the model using the system GMM method.

Table 8. Tests of the effects of the regulating mechanisms.

Variant	TQ		
	Model (19)	**Model (20)**	**Model (21)**
Digi	0.011 ***		0.010 ***
	(0.002)		−0.002
Ser_income		0.583 ***	0.504 ***
		(0.115)	−0.116
EU	0.033 *	0.018	0.032 *
	(0.014)	(0.014)	−0.014
Digi × *EU*	0.048 *		−0.000
	(0.024)		−0.023
Ser_income × *EU*		0.002	0.049 *
		(0.023)	−0.024
Controls	Yes	Yes	Yes
_cons	5.229 ***	5.402 ***	5.234 ***
	(0.230)	(0.227)	−0.23
Sample Size	6318	6317	6.317
R^2	0.381	0.380	0.383
Year-Fixed	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

4.5.1. Replacement of Explanatory Variables

Enterprise sales revenue (*GOI*) is introduced as a new measure in the robustness tests. As shown in Tables 9–11, the benchmark regressions and mechanism effects of Digital Conversion, service upgrading, and digital–intelligent transformation on enterprise performance are robustly tested. The results affirm that enterprise Digital Intelligence Transformation continues to have a significant positive impact on enterprise annual sales revenue, and the mediating effect of enterprise innovation capability remains significant. The findings in Tables 10 and 11 are broadly consistent with the previous regression results. The results again validate H1, H1a, H1b, H2a, and H2b.

Table 9. Robustness test with replacement of explanatory variables (Digital Conversion of information and firms' sales revenues).

Variant	(1)	(2)	(3)	(4)	(5)
	GOI	***Pat_app***	***GOI***	***Cit_rec***	***GOI***
Digi	0.020 ***	0.026 ***	0.013 *	0.028 ***	0.011
	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
Pat_app			0.251 ***		
			(0.042)		
Cit_rec					0.315 ***
					(0.039)
Controls	Yes	Yes	Yes	Yes	Yes
_cons	−12.661 ***	−4.952 ***	−11.416 ***	−4.314 ***	−11.336 ***
	(0.714)	(0.215)	(0.741)	(0.233)	(0.731)
Sample Size	6318	6318	6318	6309	6309
R^2	0.262	0.555	0.267	0.589	0.270
Year-Fixed	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

Table 10. Robustness test with replacement of explanatory variables (servicing upgrades and firms' sales revenues).

Variant	(6)	(7)	(8)	(9)	(10)
	GOI	*Pat_app*	*GOI*	*Cit_rec*	*GOI*
Ser_income	0.976 **	0.556 ***	0.829 *	0.692 ***	0.737 *
	(0.360)	(0.110)	(0.359)	(0.119)	(0.359)
Pat_app			0.264 ***		
			(0.041)		
Cit_rec					0.323 ***
					(0.038)
Controls	Yes	Yes	Yes	Yes	Yes
_cons	−12.467 ***	−4.686 ***	−11.231 ***	−4.028 ***	−11.196 ***
	(0.712)	(0.218)	(0.735)	(0.236)	(0.726)
Sample Size	6317	6317	6317	6308	6308
R^2	0.262	0.540	0.267	0.576	0.270
Year-Fixed	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Robustness test with replacement of explanatory variables (digitization transformation and firm sales revenues).

Variant	(11)	(12)	(13)	(14)	(15)
	GOI	*Pat_app*	*GOI*	*Cit_rec*	*GOI*
Digi	0.018 **	0.026 ***	0.000	0.027 ***	0.010
	(0.006)	(0.002)	(0.005)	(0.002)	(0.006)
Ser_income	0.819 *	0.333 **	0.586	0.457 ***	0.661
	(0.363)	(0.109)	(0.364)	(0.118)	(0.362)
Pat_app			0.252 ***		
			(0.040)		
Cit_rec2					0.311 ***
					(0.039)
Controls	Yes	Yes	Yes	Yes	Yes
_cons	−12.648 ***	−4.942 ***	−11.884 ***	−4.298 ***	−11.341 ***
	(0.714)	(0.215)	(0.607)	(0.232)	(0.731)
Sample Size	6.317	6.317	6.317	6.308	6.308
R^2	0.263	0.556	0.223	0.590	0.270
Year-Fixed	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.5.2. Substitution of Explanatory Variables

(i) Replacement of measurements for Digital Conversion: Based on the study by Wang et al. [72], the proportion of the intangible assets of enterprises (*Int_assets*) is employed as a new proxy variable for Digital Conversion, substituting the Digital Intelligence Transformation index for robustness testing. The results presented in Table 12 reaffirm the findings previously discussed. The results again verify H1a, H2a, and H3a.

(ii) Replace the measurements for the business process Servitization Upgrading: To enhance the reliability of the empirical results, the measurement of servitization is revised. Drawing from Zhao's methodology [65], the level of servitization is now assessed using the servitization personnel structure (*Ser_ratio*). The specific test outcomes, as shown in Table 13, are consistent with the earlier regression results. The results of verifying H1b, H2b, and H3b here are consistent with the above.

Table 12. Robustness test for replacing digitization levels.

Variant	(16)	(17)	(18)	(19)	(20)	(21)
	TQ	*Pat_app*	*TQ*	*Cit_rec*	*TQ*	*TQ*
Int_assets	4.761 ***	2.324 ***	4.696 ***	1.189 *	4.748 ***	4.841 ***
	(0.489)	(0.477)	(0.490)	(0.516)	(0.528)	(0.490)
Pat_app			0.028 *			
			(0.013)			
Cit_rec					0.040 ***	
					(0.010)	
EU						0.013 ***
						(0.014)
Int_assets × *EU*						0.056 **
						(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	4.874 ***	−4.967 ***	5.014 ***	−4.175 ***	5.594 ***	4.853 ***
	(0.231)	(0.226)	(0.240)	(0.244)	(0.250)	(0.233)
Sample Size	6318	6318	6318	6309	6309	6318
R^2	0.386	0.540	0.387	0.574	0.283	0.387
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 13. Robustness tests for replacement of servitization levels.

Variant	(22)	(23)	(24)	(25)	(26)	(27)
	TQ	*Pat_app*	*TQ*	*Cit_rec*	*TQ*	*TQ*
Ser_ratio	0.624 ***	1.401 ***	0.604 ***	1.598 ***	0.910 ***	0.941 ***
	(0.084)	(0.080)	(0.086)	(0.086)	(0.084)	(0.079)
Pat_app			0.014			
			(0.014)			
Cit_rec					0.022 *	
					(0.010)	
EU						0.027
						(0.015)
Ser_ratio × *EU*						0.004
						(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	5.163 ***	−5.428 ***	5.240 ***	−4.872 ***	4.822 ***	4.048 ***
	(0.234)	(0.222)	(0.245)	(0.240)	(0.212)	(0.201)
Sample Size	6093	6093	6093	6084	6084	6093
R^2	0.380	0.560	0.380	0.596	0.211	0.313
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

4.5.3. Endogeneity Test

The endogeneity problem is a challenge for all empirical studies, and in order to address the endogeneity problem posed by dynamic panels, generalized moment estimation is chosen here for the endogeneity test. The lagged first order of firm performance, digitization degree, and service level as well as the industry average digitization degree and service level are chosen for the test to control for time-fixed effects. In addition, a two-step systematic GMM test is conducted to prevent underestimating the standard errors of the regression coefficients. The results show that firstly, the lagged first-order coefficients of the dependent variable are significant and the regression results of digitization and servitization are consistent with the previous section, i.e., the regression results of digitization and servitization are both significantly positively correlated for enterprise performance; secondly, the AR autocorrelation test shows that the AR (1) first-order autocorrelation is significant, and the p-value of AR (2) second-order autocorrelation is >0.1, i.e., the original hypothesis is rejected. Finally, according to the Sargan test p-value greater than 0.1, the results are not significant indicating that the original hypothesis is not rejected, i.e., indicating that the instrumental variables are valid.

4.6. Heterogeneity Analysis

During the digital–intelligent transformation of enterprises, variations in the effects of this transformation are observed due to factors such as the nature of the enterprise, its developmental history, and the economic development level of the region where it is located. To explore the heterogeneity of the factors affecting firm performance during Digital Intelligence Transformation, this paper examines the impact of the different stages of Digital Intelligence Transformation on firm performance in terms of factor intensity and the developmental stage of the enterprise, as well as sub-regional heterogeneity.

4.6.1. Group Regression Based on Different Factor Intensities

The heterogeneity in factor input structure is a significant aspect of enterprises during the digital–intelligent transformation process. Drawing on the perspectives of the relevant research [72,73], enterprises in the sample are categorized into labor-intensive, capital-intensive, and technology-intensive groups based on their factor input structures and industry subdivisions. Following the methodology of Zhang and Li's fuzzy C-mean clustering classification [74], the two-digit industry classification of C13-C43 in the manufacturing sector is divided into three main categories: labor-intensive, capital-intensive, and technology-intensive.

From Table 14, it is evident that Digital Conversion, service upgrading, and digital–intelligent transformation significantly enhance the performance of capital- and technology-intensive manufacturing enterprises. Conversely, for labor-intensive enterprises, these effects are not significant and may even exert a slight inhibitory influence. This disparity could be attributed to the relative deficiency in high technology and human capital in labor-intensive firms compared to their capital-intensive and technology-intensive counterparts. As intelligent machinery and equipment increasingly replace low-skilled labor in the course of digital–intelligent transformation, the lack of high-level labor accumulation may obscure technological spillovers, thus impeding the expansion of related service businesses. Additionally, while the effects are significant in both capital-intensive and technology-intensive enterprise subgroups, they are most pronounced in technology-intensive enterprises. This suggests that the positive impact of Digital Intelligence Transformation on economic performance is most apparent in technology-intensive manufacturing enterprises, likely because these enterprises have invested more heavily in technology and related capital, thereby enhancing service quality and digitization levels, and providing innovative solutions that significantly boost economic performance.

Table 14. Heterogeneity analysis (by factor intensity).

Variant	*TQ*								
	Digital Conversion			Service-Oriented Upgrading			Digital Intelligence Transformation		
	Labor-Intensive	Capital-Intensive	Technologically Intensive	Labor-Intensive	Capital-Intensive	Technologically Intensive	Labor-Intensive	Capital-Intensive	Technologically Intensive
Digi	0.005	0.012 **	0.011 ***				0.004	0.012 *	0.010 ***
	(0.005)	(0.005)	(0.002)				(0.005)	(0.005)	(0.002)
Ser_income				0.274	0.521 *	0.786 ***	0.243	0.415	0.683 ***
				(0.320)	(0.250)	(0.140)	(0.321)	(0.232)	(0.142)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	3.054 ***	4.671 ***	5.407 ***	3.066 ***	5.587 ***	5.555 ***	3.023 ***	4.767 ***	5.438 ***
	(0.475)	(0.478)	(0.411)	(0.475)	(0.508)	(0.410)	(0.477)	(0.480)	(0.410)
Sample Size	1290	940	4088	1289	940	4088	1.289	940	4.088
R^2	0.430	0.418	0.371	0.430	0.311	0.372	0.430	0.420	0.375
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.6.2. Regressions Based on Groups of Enterprises at Different Stages of Development

Drawing from the existing research, it is observed that the impact of Digital Intelligence Transformation and upgrading varies across different stages of an enterprise's life cycle [45]. Enterprises are categorized based on whether their years of establishment exceed the average within the sample, and group regressions are conducted for those in the growth and maturity stages. As indicated in Table 15, there is a marked difference between the outcomes for enterprises at the growth stage versus those at the maturity stage. Enterprises in the growth stage derive more substantial benefits from the transformation process. Due to their exposure to greater market risks, these firms are more inclined to integrate resources comprehensively and undergo strategic transformations to enhance the differentiation of their products and services. Moreover, growing enterprises tend to be more adaptable in their strategies, enabling them to upgrade their products and technologies in response to evolving customer needs, thereby increasing their competitive edge in the market.

Table 15. Heterogeneity analysis (by stage of enterprise development).

Variant	*TQ*					
	Digital Conversion		**Service-Oriented Upgrading**		**Digital Intelligence Transformation**	
	Growing Company	**Mature Companies**	**Growing Company**	**Mature Companies**	**Growing Company**	**Mature Companies**
Digi	0.022 ***	−0.003			0.021 ***	−0.004
	(0.002)	(0.003)			(0.003)	(0.003)
Ser_income			0.870 ***	0.250	0.663 ***	0.278
			(0.166)	(0.155)	(0.166)	(0.156)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	5.360 ***	4.980 ***	5.648 ***	4.929 ***	5.415 ***	4.960 ***
	(0.322)	(0.347)	(0.324)	(0.347)	(0.321)	(0.347)
Sample Size	3158	3159	3158	3159	3.158	3.159
R^2	0.409	0.386	0.399	0.386	0.412	0.386
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** indicates significance at the 1% level.

4.6.3. Regressions Based on Subgroups of Enterprises from Different Regions

According to the research by Shen et al. [75], the sample enterprises are segmented into eastern, central, and western regions for group regression analysis. As shown in Table 16, the impact of Digital Intelligence Transformation on enterprise performance is significant for enterprises in the eastern region but not for those in the central and western regions. This discrepancy may stem from the fact that enterprises in the central and western regions lag behind those in the eastern region in several respects, including asset investment, the scale of assets, core technology, human capital investment, attractiveness to investors, supply chain completeness, and efficient resource restructuring. These factors likely hinder the rapid realization of economic benefits from digital intelligence in these regions.

Table 16. Heterogeneity analysis (by region).

Variant	*TQ*								
	Digital Conversion			**Service-Oriented Upgrading**			**Digital Intelligence Transformation**		
	The East	**Central Section**	**Western Part**	**The East**	**Central Section**	**Western Part**	**The East**	**Central Section**	**Western Part**
Digi	0.012 ***	0.010 *	−0.002				0.011 ***	0.010 *	−0.001
	(0.002)	(0.005)	(0.006)				(0.002)	(0.005)	(0.006)

Table 16. *Cont.*

Variant	TQ								
	Digital Conversion			**Service-Oriented Upgrading**			**Digital Intelligence Transformation**		
	The East	**Central Section**	**Western Part**	**The East**	**Central Section**	**Western Part**	**The East**	**Central Section**	**Western Part**
Ser_income				0.812 ***	0.632	−0.419	0.716 ***	0.539	−0.415
				(0.153)	(0.397)	(0.236)	(0.154)	(0.396)	(0.237)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	5.405 ***	7.159 ***	2.961 ***	5.596 ***	7.186 ***	3.002 ***	5.461 ***	7.134 ***	3.033 ***
	(0.305)	(0.659)	(0.628)	(0.300)	(0.667)	(0.666)	(0.306)	(0.661)	(0.636)
Sample Size	4342	1111	865	4342	1110	865	4.342	1.110	865
R^2	0.366	0.485	0.513	0.366	0.484	0.514	0.370	0.486	0.514
Year-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

5. Conclusions and Implications

This paper analyzes data from A-share manufacturing enterprises listed in Shanghai and Shenzhen from 2013 to 2022, exploring the influence of enterprise Digital Intelligence Transformation on performance. The research examines the direct effects, indirect transmission mechanisms, regulatory mechanisms, and heterogeneity tests of Digital Conversion strategies on economic outcomes through empirical analysis. The main conclusions are as follows: (1) In the era of digital empowerment, enterprises can enhance their performance by digitally converting information, upgrading business process servitization, and integrating digital–intelligent transformation strategies, thus confirming hypothesis H1, H1a, and H1b. (2) Enterprise innovation resilience acts as a mediating mechanism between information digitalization conversion and enterprise performance (H2a holds), as well as between process service upgrading and enterprise performance (H2b holds). However, it does not yet mediate between Digital Intelligence Transformation and enterprise performance, indicating that enterprise Digital Intelligence Transformations have not yet reached the advanced stage necessary to stimulate innovation resilience and enhance performance. Additionally, Digital Conversion is the base and Servitization Upgrading is the process. The current sample enterprises have limited years of data collection, and most of them have only carried out the strategic implementation of Digital Conversion or servitization, and have not reached the high-level stage of digital–intelligent transformation. (3) Enterprises in highly uncertain environments are more compelled to adopt digital strategies, which more clearly demonstrate the benefits of Digital Conversion (H3a holds). Currently, the overall low level of servitization and Digital Intelligence Transformation in enterprises means that environmental uncertainty does not significantly impact the relationship between these factors and enterprise performance. (4) The positive impact of Digital Intelligence Transformation on enterprise performance is most pronounced in technology-intensive enterprises and less significant in labor-intensive ones. Enterprises in the growth stage derive greater benefits from digital intelligence development compared to those in the mature stages.

Based on these conclusions, the following practical insights are offered:

Firstly, enterprises should prioritize the core concept of "digital technology" and adopt a "long-term" perspective to stabilize their technological foundations, promoting innovation in products, management, and processes through digital technology. In manufacturing, there is a need to accelerate the application of digital technologies, such as intelligent factories, manufacturing robots, and high-end CNC machine tools throughout the production process to reduce costs and increase efficiency. In expanding enterprise value-added services, enterprises should utilize big data to monitor dynamic market demand changes and expand their service business areas, thereby creating new opportunities for profit growth. Additionally, enterprises should actively build a digital industrial internet, forming a unique core competitiveness of "digital + manufacturing + services" to promote sustainable development. Relevant government departments should also work towards creating a digitally driven innovation environment by improving related laws and policies to standardize the business environment, thus fostering an atmosphere conducive to continuous enterprise innovation.

Secondly, enterprises should recognize the significant driving force of the servitization strategy for overall transformation and upgrading. Realizing the positive benefits of servitization transformation depends on accurately matching service capabilities with market demand. The essence of servitization profitability lies in enhancing efficiency, creating value growth, and securing competitive advantages in the market. Enterprises should dynamically adjust their product, process, manufacturing, and market-oriented servitization transformation strategies based on internal resource changes and external environmental shifts. Additionally, different factor-intensive manufacturing enterprises should tailor their servitization strategies to industry characteristics, selecting service businesses that leverage industry-specific advantages and enterprise heterogeneity.

Thirdly, enterprises must continually monitor the development direction of the market, technology, and industry environment to seize resources and development opportunities effectively. They should promote the upgrading of their digital intelligence strategies in response to different phases of industry changes and innovate additional value-added service businesses to increase market share and enhance customer loyalty. Enterprises need to recognize the impact of complex and dynamic factors such as the market environment, the intensity of industry competition, and the development of digital technology on the demand for resources and the relative costs of Digital Intelligence Transformation. Accordingly, they should adjust the implementation of their strategies to adapt their digital strategies to real-time environmental changes.

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Abbreviations

The following abbreviations are used in this manuscript:

R&D	Research & Development
CSMAR	China Stock Market & Accounting Research
OLS	Ordinary Least Squares
VIF	Variance inflation factor
CNC	Computerized Numerical Control
GMM	Generalized Method of Moment

References

1. Jiang, Y.; Zhao, X.; Zhai, L. Digital empowerment to improve the operational profitability in e-commerce supply chain. *Electron. Commer. Res. Appl.* **2023**, *58*, 101253. [CrossRef]
2. Warner, K.S.R.; Waeger, M. Building dynamic capabilities for Digital Intelligence Transformation: An ongoing process of strategic renewal. *Long Range Plan.* **2019**, *52*, 326–349. [CrossRef]
3. Baines, T.W.; Lightfoot, H. Servitization of the manufacturing firm: Exploring the operations practices and technologies that deliver advanced services. *Int. J. Oper. Prod. Man.* **2013**, *3*, 2–35. [CrossRef]
4. Gebauer, H.; Arzt, A.; Kohtamaki, M.; Lamprecht, C.; Parida, V.; Witell, L.; Wortmann, F. How to convert digital offerings into revenue enhancement-Conceptualizing business model dynamics through explorative case studies. *Ind. Mark. Manag.* **2020**, *91*, 429–441. [CrossRef]
5. Urbinati, A.; Chiaroni, D.; Chiesa, V.; Frattini, F. The role of digital technologies in open innovation processes: An exploratory multiple case study analysis. *R&D Manag.* **2020**, *50*, 136–160.
6. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic capabilities and strategic management. *Strategy Manag. J.* **1997**, *18*, 509–533. [CrossRef]
7. Zott, C. Dynamic capabilities and the emergence of intraindustry differential firm performance: Insights from a simulation study. *Strategy Manag. J.* **2003**, *24*, 97–125. [CrossRef]
8. Helfat, C.E. Know-how and asset complementarity and dynamic capability accumulation: The case of R&D. *Strategy Manag. J.* **1997**, *18*, 339–360.
9. Parida, V.; Sjoedin, D.; Lenka, S.; Wincent, J. Developing global service innovation capabilities: How global manufacturers address the challenges of market heterogeneity. *Res. Technol. Manag.* **2015**, *58*, 35–44. [CrossRef]
10. Bergemann, D.; Bonatti, A. Markets for information: An introduction. *Annu. Rev. Econ.* **2019**, *11*, 85–107. [CrossRef]
11. Veldkamp, L.; Chung, C. Data and the aggregate economy. *J. Econ. Lit.* **2019**. Available online: https://business.columbia.edu/faculty/research/data-and-aggregate-economy (accessed on 22 May 2024). [CrossRef]
12. Weinman, J. The economics and strategy of manufacturing and the cloud. *IEEE Cloud Comput.* **2016**, *3*, 6–11. [CrossRef]
13. Sjödin, D.; Parida, V.; Kohtamäki, M.; Wincent, J. An agile co-creation process for digital servitization: A micro-service innovation approach. *J. Bus. Res.* **2020**, *112*, 478–491. [CrossRef]
14. Verhoef, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Dong, J.Q.; Fabian, N.; Haenlein, M. Digital Intelligence Transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [CrossRef]
15. Li, P.; Liu, J.; Lu, X.; Xie, Y.; Wang, Z. Digitalization as a Factor of Production in China and the Impact on Total Factor Productivity (TFP). *Systems* **2024**, *12*, 164. [CrossRef]
16. Sanders, N.R.; Autry, C.W.; Gligor, D.M. The impact of buyer firm information connectivity enablers on supplier firm performance: A relational view. *Int. J. Logist. Manag.* **2011**, *22*, 179–201. [CrossRef]
17. Mithas, S.; Ramasubbu, N.; Sambamurthy, V. How information management capability influences firm performance. *MIS Q.* **2011**, *1*, 237–256. [CrossRef]
18. Niedergassel, B.; Curran, C.S.; Lessing, M.; Leker, J. What drives partners in industry-academia cooperation? A special consideration of reducing uncertainty through computational chemistry. *Int. J. Technol. Intell. Plan.* **2007**, *3*, 331–342. [CrossRef]
19. Fontagné, L.; Harrison, A. *The Factory-Free Economy: Outsourcing, Servitization, and the Future of Industry*; Oxford University Press: Oxford, UK, 2017.
20. Huang, H.; Miao, Z.; Yuan, Y.; Li, S. A study on global value chain of producer service industry and the level of China's participation. *Manag. World.* **2020**, *36*, 82–97.
21. Sirmon, D.G.; Hitt, M.A.; Arregle, J.L.; Campbell, J.T. The dynamic interplay of capability strengths and weaknesses: Investigating the bases of temporary competitive advantage. *Soc. Sci. Electron. Publ.* **2010**, *31*, 1386–1409. [CrossRef]
22. Feng, C.; Jiang, L.; Ma, R.; Bai, C. Servitization strategy, manufacturing organizations and firm performance: A theoretical framework. *J. Bus. Ind. Mark.* **2021**, *36*, 1909–1928. [CrossRef]
23. Justyna, K. Servitization of manufacturing: Survey in the Polish machinery sector. *Eng. Manag. Prod. Serv.* **2020**, *12*, 20–33.
24. Walker, B.; Hollin, C.S.; Carpenter, S.R.; Kinzig, A.P. Resilience, adaptability and transformability in social-ecological systems. *Ecol. Soc.* **2004**, *9*, 5. [CrossRef]
25. Lv, W.D.; Tian, D.; Wei, Y.; Xi, R.X. Innovation resilience: A new approach for managing uncertainties concerned with sustainable innovation. *Sustainability* **2018**, *10*, 3641. [CrossRef]

26. Fey, S.; Kock, A. Meeting challenges with resilience–How innovation projects deal with adversity. *Int. J. Proj. Manag.* **2022**, *40*, 941–950. [CrossRef]
27. Martin, R.; Sunley, P.; Gardiner, B.; Tyler, B. How regions react to recessions: Resilience and the role of economic structure. *Reg. Stud.* **2016**, *50*, 561–585. [CrossRef]
28. Lin, C.; Kunnathur, A. Strategic orientations, developmental culture, and big data capability. *Bus. Res.* **2019**, *105*, 49–60. [CrossRef]
29. Egbetokun, A.A.; Siyanbola, W.O.; Adeniyi, A.A. Assessment of Innovation Capability in the Cable and Wire Manufacturing Industry in Nigeria: A case study approach. In *Micro Evidence on Innovation in Developing Economies [MEIDE]*; UNU-MERIT: Maastricht, The Netherlands, 2007; pp. 1–25.
30. Kaplan, A.M.; Haenlein, M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
31. Eller, R.; Alford, P.; Kallmünzer, A.; Peters, M. Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *J. Bus. Res.* **2020**, *112*, 119–127. [CrossRef]
32. Erevelles, S.; Fukawa, N.; Swayne, L. Big data consumer analytics and the transformation of marketing. *J. Bus. Res.* **2016**, *69*, 897–904. [CrossRef]
33. Wang, L.; Kwoh, Y. Digital intelligence and innovation quality of manufacturing firms—Evidence from Chinese listed companies. *Ind. Technol. Econ.* **2023**, *42*, 13–23.
34. Wang, S.; Liu, Q.; Wang, H. Evaluation of regional innovation resilience, spatio-temporal differentiation and dynamic evolution. *Stat. Decis. Mak.* **2024**, *40*, 63–67.
35. Colecchia, A.; Schreyer, P. ICT Investment and Economic Growth in the 1990s: Is the United States a Unique Case? A Comparative Study of Nine OECD Countries. *Rev. Econ. Dyn.* **2002**, *5*, 408–442. [CrossRef]
36. Kastalli, I.V.; Van Looy, B. Servitization: Disentangling the impact of service business model innovation on manufacturing firm performance. *J. Oper. Manag.* **2013**, *31*, 169–180. [CrossRef]
37. Ettlie, J.E. R&D and global manufacturing performance. *Manag. Sci.* **1998**, *44*, 1–11.
38. Yoo, Y.; Boland, R.J.; Lyytinen, K.; Majchrzak, A. Organizing for innovation in the digitized world. *Organ. Sci.* **2012**, *23*, 1398–1408. [CrossRef]
39. Barrett, M.; Davidson, E.; Prabhu, J.C.; Vargo, S.L. Service innovation in the digital age: Key contributions and future directions. *MIS Q.* **2015**, *39*, 135–154. [CrossRef]
40. Teece, D.J. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Pol.* **2018**, *47*, 1367–1387. [CrossRef]
41. Eisenhardt, K.M.; Martin, J.A. Dynamic capabilities: What are they? *Strategy Manag. J.* **2000**, *21*, 1105–1121. [CrossRef]
42. Kevill, A.; Trehan, K.; Harrington, S.; Kars-Unluoglu, S. Dynamic managerial capabilities in micro-enterprises: Stability, vulnerability and the role of managerial time allocation. *Int. Small Bus. J.* **2020**, *39*, 507–531. [CrossRef]
43. Ehie, I.C.; Olibe, K. The effect of R&D investment on firm value: An examination of US manufacturing and service industries. *Int. J. Prod. Econ.* **2010**, *128*, 127–135.
44. Ramani, G.; Kumar, V. Interaction orientation and firm performance. *J. Mark.* **2008**, *72*, 27–45. [CrossRef]
45. Visnjic, I.; Wiengarten, F.; Neely, A. Only the brave: Product innovation, service business model innovation, and their impact on performance. *Prod. Innov. Manag.* **2016**, *33*, 36–52. [CrossRef]
46. Subramaniam, M.; Youndt, M.A. The influence of intellectual capital on the types of innovative capabilities. *Acad. Manag. J.* **2005**, *48*, 450–463. [CrossRef]
47. McWilliams, A.; Siegel, D.S.; Wright, P.M. Corporate social responsibility: Strategic implications. *J. Manag. Stud.* **2006**, *43*, 1–18. [CrossRef]
48. Kohli, A.K.; Jaworski, B. Market orientation: Antecedents and consequences. *J. Mark.* **1993**, *57*, 53–70.
49. Li, S.; Lin, B. Accessing information sharing and information quality in supply chain management. *Decis. Support Syst.* **2006**, *23*, 1641–1656. [CrossRef]
50. Zhang, J.; Duan, Y. An empirical study of the effect of market-oriented equilibrium on product innovation performance of manufacturing firms. *Manag. World.* **2010**, *12*, 119–130.
51. Rodrigo-Alarcón, J.; García-Villaverde, P.M.; Parra-Requena, G.; Ruiz-Ortega, M.J. Innovativeness in the context of technological and market dynamism: The conflicting effects of network density. *Organ. Chang. Manag.* **2017**, *30*, 548–568. [CrossRef]
52. Zhang, J.; Baden-Fuller, C. The influence of technological knowledge base and organizational structure on technology collaboration. *Manag. Stud.* **2010**, *47*, 679–704. [CrossRef]
53. Zhang, Y.; Rajagopalan, N. Once an outsider, always an outsider? CEO origin, strategic change and firm performance. *Strategy Manag. J.* **2010**, *31*, 334–346. [CrossRef]
54. Gnizy, I. Big data and its strategic path to value in international firms. *Int. Mark. Rev.* **2019**, *36*, 318–341. [CrossRef]
55. Burkert, M.; Lueg, R. Differences in the sophistication of Value-based Management–The role of top executives. *Manag. Account. Res.* **2013**, *24*, 3–22. [CrossRef]
56. Shen, H.; Yu, P.; Wu, L. State ownership, environment uncertainty and investment efficiency. *Econ. Res.* **2012**, *47*, 113–126.
57. Lv, W.; Zhao, Y.; Wei, Y. On resilient risk management—An organizational management technique for responding to uncertainty. *Manag. World.* **2019**, *35*, 116–132.

58. Koufteros, X.A.; Rawski, G.E.; Rupak, R. Organizational integration for product development: The effects on glitches, on-time execution of engineering change orders, and market success. *Decis. Sci.* **2010**, *57*, 47–60. [CrossRef]
59. Coreynen, W.; Matthyssens, P.; Vanderstraeten, J.; van Witteloostuijn, A. Unravelling the internal and external drivers of digital servitization: A dynamic capabilities and contingency perspective on firm strategy. *Ind. Mark. Manag.* **2020**, *89*, 265–277. [CrossRef]
60. Ghosh, D.; Olsen, L. Environmental Uncertainty and managers' use of discretionary accruals. *Account. Org. Soc.* **2009**, *34*, 188–205. [CrossRef]
61. Singh, S.; Tabassum, N.; Darwish, T.K.; Batsakis, G. Corporate governance and Tobin's Q as a measure of organizational performance. *Br. J. Manag.* **2018**, *29*, 171–190. [CrossRef]
62. Chanias, S.; Myers, M.D.; Hess, T. Digital Intelligence Transformation strategy making in pre-digital organizations: The case of a financial services provider. *J. Strateg. Inf. Syst.* **2019**, *28*, 17–33. [CrossRef]
63. Vandermerwe, S.; Rada, J. Servitization of business: Adding value by adding services. *Eur. Manag. J.* **1988**, *6*, 314–324. [CrossRef]
64. Chen, X.; Shen, H. How Manufacturing Servitization Affects Firm Performance and Factor Structure—An Empirical Analysis of PSM-DID Based on Listed Company Data. *Econ. Perspect.* **2017**, *5*, 64–77.
65. Zhao, C. Digital Development and service oriented transformation—Empirical evidence from listed manufacturing companies. *Nankai Bus. Rev.* **2021**, *24*, 149–163.
66. *GB/T4754-2011*; Classification of National Economic Industries. National Bureau of Statistics of China: Beijing, China, 2011.
67. Chang, X.; Fu, K.; Low, A.; Zhang, W. Non-executive employee stock options and corporate innovation. *J. Financ. Econ.* **2015**, *115*, 168–188. [CrossRef]
68. Bergh, D.D.; Lawless, M.W. Portfolio restructuring and limits to hierarchical governance: The effects of Environmental Uncertainty and diversification strategy. *Org. Sci.* **1998**, *9*, 87–102. [CrossRef]
69. Kohtamki, M.; Einola, S.; Rabetino, R. Exploring servitization through the paradox lens: Coping practices in servitization. *Int. J. Prod. Econ.* **2020**, *226*, 107619. [CrossRef]
70. Hu, Y.; Han, Q. A study on the impact of customer participation on innovation performance of product-service systems—A moderation analysis based on product-service portfolios. *Manag. Rev.* **2018**, *30*, 76–88.
71. Wen, Z.; Zhang, L.; Hou, J.; Liu, H. Testing and application of the mediating effects. *J. Psychol.* **2004**, *36*, 614–620.
72. Wang, F.; Zhong, J.; Liu, S. The impact of Digital Intelligence Transformation on servitization in manufacturing: Theoretical exploration and empirical identification. *Inq. Econ. Issues* **2023**, *7*, 121–141.
73. Hu, Z.; Xia, Q.; Sun, G. Manufacturing servitization, technological innovation and industrial structure transformation and upgrading—An empirical study based on WIOD cross-country panel data. *Int. Econ. Trade Explor.* **2017**, *33*, 4–21.
74. Zhang, Q.; Li, L. Manufacturing transformation and upgrading and regional economic growth. *Econ. Manag. Res.* **2017**, *38*, 97–111.
75. Shen, X.; Chen, Y.; Lin, B. Impact of technological progress and industrial structure distortion on China's energy intensity. *Econ. Res.* **2021**, *56*, 157–173.