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Can Enterprise Digitalization Promote Green Technological Innovation? Evidence from China's Manufacturing Sector

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Abstract: China's manufacturing industry is characterized by high energy consumption and high pollution, which urgently requires resolution through green technological innovation. This study focuses on China's A-share listed manufacturing enterprises to explore their development path for green technological innovation. The study primarily employs statistical regression analysis to uncover the causal link between digitalization and green technology innovation. The study's conclusion indicates that the digitalization of manufacturing enterprises has significantly promoted green technological innovation. This conclusion remains robust after a series of tests, including alternative variable measurements, instrumental variable (IV) estimation, and counterfactual analysis. Mechanism analysis reveals that digitalization can enhance green technological innovation by improving human capital and innovating business models. The results of the heterogeneity analysis show that the effect of digitalization on promoting green technological innovation is more pronounced in enterprises with higher green awareness among senior executives, high green credit, non-heavy pollution industries, a higher level of existing green technological innovation, and larger enterprise scale. The government should increase support for the digital transformation of enterprises and promote green technological innovation by enhancing the green awareness of enterprise senior executives, optimizing green credit policies, formulating transformation policies for heavily polluting enterprises, implementing differentiated policies based on enterprise scale, and promoting digital transformation.

Keywords: enterprise digitalization; green technological innovation; human capital; business models

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1. Introduction

Green technological innovation stands as a pivotal driving force in promoting the transformation of economic development patterns and attaining green and sustainable development goals [1,2]. It also constitutes a crucial foundation for China's pursuit of "carbon peak" and "carbon neutrality" objectives. To fulfill the "carbon peak" goal, the State Council of China explicitly stated in 2021 that green and low-carbon technological innovation is the primary means of achieving this objective, emphasizing the enhancement of enterprises' role as innovation subjects and encouraging them to undertake national green and low-carbon technology projects.

Amidst the global wave of digitalization, seizing digital opportunities is vital for bolstering China's core economic competitiveness and facilitating high-quality growth. The swift development of the digital economy has spurred enterprises to adopt emerging digital technologies to facilitate digital transformation and bolster their digital capabilities [3–5]. To this end, the Chinese government has introduced a series of policies, including the

"Special Action Plan for Digital Empowerment of Small and Medium-sized Enterprises" and the "Notice on Accelerating the Digital Transformation of State-owned Enterprises," to support enterprises in their digital transformation endeavors.

As a key means of achieving sustainable development, green technological innovation is garnering increasing attention in the context of digitalization. Traditional green technological innovation often encounters challenges such as incomplete data collection, inaccurate analysis, and low resource utilization efficiency. The innovative application of digital technologies is opening new avenues for green technological innovation. Big data analysis enables enterprises to more accurately grasp market dynamics and consumer needs, thereby developing products and services that align more closely with green concepts. Simultaneously, technologies like cloud computing and the Internet of Things have enhanced resource utilization efficiency and reduced the cost of green technological innovation [6–8].

Consequently, analyzing the impact of digitalization on green technological innovation holds immense value. Some scholars have commenced exploring the relationship between enterprise digitalization and green technological innovation. For instance, El-Kassar and Singh (2019) found that big data can enhance enterprises' competitive advantages [9,10]. Qureshi et al. (2023) investigated the effect of Industry 4.0 technologies on supply chain performance and discovered that disruptive technologies exert an influence on lean, agile, and green supply chains. These studies possess both theoretical and practical value in promoting the green transformation of enterprises and achieving sustainable development [11,12].

Nevertheless, existing research lacks clear standards for measuring the degree of enterprise digitalization and fails to conduct comprehensive empirical tests on the micro-processes that stimulate green technological innovation. This study contributes novel insights to the field of enterprise digitalization and green technological innovation. Specifically, it utilizes micro-level data to delve into how digitalization promotes green technological innovation in China's manufacturing industry, thereby broadening the micro-perspective of digitalization research. By employing innovative methods such as text mining technology, we have developed a set of detailed enterprise digitalization indicators, providing a more refined measurement framework for related research. Simultaneously, this study integrates digitalization elements into the theoretical framework of the green technological innovation driving system, offering a fresh perspective for examining the relationship between the two. This study aims to empirically test the role of digitalization in promoting green technological innovation and analyze whether digitalization facilitates this process by enhancing human capital and innovating business models, thereby comprehensively and deeply exploring the relationship between enterprise digitalization and green technological innovation at the micro level. Unlike similar studies, this research particularly emphasizes the heterogeneity of digitalization effects among enterprises with diverse characteristics. Through a series of heterogeneity analyses, it explores how factors such as senior executive green awareness, green credit, enterprise pollution levels, green technological innovation levels, and enterprise size influence the relationship between the two, providing valuable insights for enterprises and policymakers. This study is significant as it demonstrates how digital means can be harnessed to support green technological innovation, which is crucial for China's attainment of the "carbon peak" and "carbon neutrality" goals.

2. Theoretical Analysis

2.1. Enterprise Digitalization and Green Technological Innovation

There are numerous factors influencing the green technological innovation capabilities of enterprises, among which financial, human, technical, and knowledge resources stand out as pivotal elements [13–15]. Digital technologies, such as big data analytics and cloud computing, offer robust technical support to enterprises in managing and leveraging these resources. These technologies not only enhance the data processing capabilities of enterprises but also facilitate the integration and sharing of R and D information and resources within the enterprise innovation ecosystem, thereby improving the knowledge-sharing effect. Throughout the product R and D, design, production, and operation processes, digital technologies empower enterprises to achieve more precise and efficient green innovation. Big data analytics enables enterprises to optimize production plans and reduce resource waste, while cloud computing lowers the barrier to green technological innovation and provides flexible computing resources. Additionally, digitalization enhances the information transparency and financing capabilities of enterprises, offering financial and resource support for green technological innovation. Furthermore, research has demonstrated that the adoption of digital technology can significantly boost the innovation performance of green technologies within enterprises, with green human resource allocation acting as a mediating factor (Liu et al., 2024) [16–18]. Digitalization improves green innovation performance through three primary mechanisms: enhancing green technology, reducing costs, and optimizing green resource allocation (Zhao et al., 2024) [19,20]. In summary, enterprise digitalization has effectively facilitated the enhancement of green innovation levels by optimizing and innovating the management and application of technological resources.

2.2. Mechanisms of the Effect of Enterprise Digitalization on Green Technological Innovation

2.2.1. The Effect of Enterprise Digitalization on Improving Human Capital

Innovation diffusion theory, knowledge-based theory, and organizational learning theory posit that investments in digitalization empower enterprises to establish digital knowledge-sharing platforms and enhance their knowledge integration capabilities. This, in turn, promotes the accumulation and refinement of human resources.

On one hand, the adoption of digital, networked, and intelligent technologies replaces low-skilled, repetitive labor with advanced machinery and equipment, thereby increasing the demand for highly educated and skilled workers proficient in digital expertise. Consequently, the pool of human capital expands. On the other hand, digitalization facilitates knowledge sharing and flow within organizations, further elevating the quality of human capital. For instance, Sun et al. (2023) found that digitalization significantly boosts the accumulation of human capital in both urban and rural contexts [21–23].

Furthermore, Li et al. (2024) revealed that enterprises undergoing digital transformation exhibit a heightened demand for employees possessing advanced technical skills and higher education levels, while the demand for production workers diminishes. Digital transformation, therefore, gives rise to new workforce requirements for technical expertise and necessitates the retraining of existing manufacturing workers, enabling enterprises to harness greater value from the synergy between digitalization and workforce skills [24–26]. Grim et al. (2023) further emphasized that digital expertise is instrumental in retaining digital human capital [27–29].

The digital economy is driving structural shifts towards high-tech, high-skill-oriented manufacturing sectors, thereby elevating the level of human capital within enterprises. Enhanced human capital directly fosters technological innovation, indicating that human capital serves as a positive mediator in the relationship between enterprise digitalization and green technological innovation.

2.2.2. The Effect of Digitalization on Business Model Innovation in Enterprises

Enterprise digitalization signifies not merely a technological transition but also a digital revolution that redefines business models, operational frameworks, and process systems. Digital technologies empower enterprises to reevaluate and reshape value creation processes, facilitating data-driven decision-making, optimizing resource allocation, and enhancing operational efficiency.

Digitalization also opens new market channels and customer touchpoints, enabling enterprises to gain a better understanding of market demands, innovate product and service models, and cater to personalized customer needs. With the assistance of business model innovation, enterprises become increasingly competitive in the market, fostering sustainable development.

Li et al. (2023) identified five configurations of business model formation: executive-led improvement, digital leadership improvement, adaptive, expansion, and complex, highlighting their intrinsic connections to digitalization and servitization. It was demonstrated that enterprise performance is positively correlated with the executive-led, digital leadership-improved, and adaptive models [30–32]. Similarly, Yang et al. (2023) found that digital technologies drive business model transformation, enhance knowledge management capabilities, and sustain high levels of enterprise performance [33–35].

Moreover, Li et al. (2020) argued that digital twin platform networks provide enterprises with comprehensive information about products, manufacturing, supply chains, customer experiences, and profitability. These platforms facilitate the creation of sustainable business models by integrating product lifecycles and forming networks that drive overall upgrades [36,37].

As digital technologies become increasingly integrated into business operations, traditional business models are disrupted, giving rise to new value propositions, creation processes, and delivery paths. Through enterprise model innovation, this change ushers in a new era of innovation.

Hypothesis1 (H1): *Enterprise digitalization can promote green technological innovation.*

Hypothesis2 (H2): *Enterprise digitalization can promote green technological innovation by improving human capital.*

Hypothesis3 (H3): *Enterprise digitalization can promote green technological innovation through innovating business models.*

3. Research Design

3.1. Materials and Methods

The data for this study were sourced from the China Securities Market and Accounting Research Database (CSMAR) and the China Research Data Service (CNRDS) databases, covering annual data spanning from 2017 to 2022. China's A-share listed manufacturing enterprises are used as samples in this study, which is to analyze the effect of digitalization on green technological innovation. Choosing manufacturing enterprises for research is of great significance and unique value. First, the manufacturing industry has complex production processes, and digitalization can accurately reduce consumption. Studying them will help explore efficient energy-saving models and provide examples for other industries. Secondly, the manufacturing industry consumes a lot of resources. Studying their digital resource utilization can achieve green and efficient results. Finally, the manufacturing industry has a fast product replacement. Studying them can grasp digitalization to promote green product innovation, meet market demand, and promote the green development of the industry.

In the process of data cleaning, we took the following steps: First, according to the exclusion criteria, we eliminated samples classified as "ST" during the study period, samples that had an initial public offering (IPO) during the sample period, samples that were delisted during the sample period, and samples with missing key variables. Second, in order to maintain the integrity of the data set, the adjacent value interpolation method was used to partially fill in the missing values. Lastly, to lessen the effect of extreme outliers on the empirical results, continuous variables were winsorized at the 1% and 99% levels on both sides.

Statistical regression analysis methods: fixed effect regression model, instrumental variable method, double difference method, threshold effect model, quantile regression method, and subsample regression.

Statistical analysis software: Stata18.

3.2. Regression Model

A fixed-effects regression model is employed to examine the impact of enterprise digitalization on green technological innovation. The model is specified as follows:

$$envpat_{it} = \beta 0 + \beta 1 Dig_{it} + \rho X + \delta t + \theta i + \varepsilon_{it}\ . \tag{1}$$

Here, i and t represent listed enterprises and years, respectively. The dependent variable, *envpatit*, signifies the level of green technological innovation within an enterprise. Specifically, it encompasses three measurement indicators: $envpat\_total_{it}$, $envpat\_inv_{it}$, *and* $envpat\_uti_{it}$. The independent variable, Dig_{it}, indicates the extent of enterprise digitalization, which is quantified using a text analysis approach. The effect of enterprise digitalization on green technological innovation is captured by the coefficient β1. ρX represents a set of control variables. The variable δt denotes year-specific fixed effects, while θi denotes enterprise-specific fixed effects. The term εit represents the random error term.

3.3. Variable Definitions

3.3.1. Green Technological Innovation

The "green patent list," published by the World Intellectual Property Organization (WIPO), employs IPC codes to classify green technological innovations. This category of patents comprises three subcategories: industrial design patents, utility model patents, and invention patents. This paper focuses on invention patents and utility model patents, as industrial design patents do not utilize IPC classification. Invention patents are characterized by higher levels of innovation and technological content, whereas utility model patents primarily protect the degree of innovation and basically safeguard the shape and structure of products. Based on these two types of patents, this study constructs three variables to gauge the level of enterprise green technological innovation: (1) ln(number of independently applied-for green inventions in the current year + number of independently applied-for green utility models in the current year + 1) (envpat_total); (2) ln(number of independently applied-for green inventions in the current year + 1) (envpat_inv); (3) ln(number of independently applied-for green utility models in the current year + 1) (envpat_uti).

3.3.2. Enterprise Digitalization (Dig)

Numerous studies have adopted the frequency of digitalization-related keywords in annual reports as a metric to assess the extent of digitalization within enterprises [38,39]. In 2005, the China Securities Regulatory Commission revised the "Standards for the Content and Format of Information Disclosure by Enterprises Offering Securities to the Public," mandating listed enterprises to review their operational conditions during the reporting period and provide an outlook for future development. If the management of a listed enterprise views digitalization as a pivotal component of its corporate development strategy and formulates corresponding action plans for attaining digital transformation, this strategic emphasis will undoubtedly exert a substantial impact on the enterprise's operations and future prospects. Consequently, such enterprises are expected to disclose pertinent information in their annual reports. Typically, enterprises that prioritize and effectively implement digitalization strategies tend to disclose more information pertaining to digitalization. Following the methodology of [38,39], this study collects and analyzes the annual reports of A-share listed manufacturing enterprises from 2017 to 2022 using Python 3.9's web scraping functionalities. By applying Chinese word segmentation techniques, the text of the annual reports is processed to extract the frequency of digitalization-related keywords. This frequency is then utilized as a proxy for the degree of digitalization within the manufacturing enterprises. A higher index value signifies a more advanced level of enterprise digitalization.

3.3.3. Other Control Variables

This study identifies a series of control variables that potentially influence the level of green technological innovation within enterprises. These include the lagged green technological innovation level (*L.envpat*), defined as the natural logarithm of the count of green patent applications submitted by the enterprise in the preceding period; enterprise size (*Size*), measured by the natural logarithm of its annual total assets; return on assets (*ROA*), computed as earnings before interest and taxes divided by the average total assets; Tobin's Q (*TobinQ*), represented by the natural logarithm of the enterprise's Tobin's Q value; capital accumulation rate (*RCA*), determined by the ratio of the current year's owner's equity to the previous year's owner's equity minus one; financial leverage (*FL*), calculated as the sum of net profit, income tax expense, and financial expense divided by the sum of net profit and income tax expense; and the asset-liability ratio (*Lev*), which is the total liabilities at year-end divided by the total assets at year-end.

Firstly, the lagged green technology innovation level (*L.envpat*) serves as an indicator of the enterprise's green innovation capability in the preceding period and constitutes a crucial benchmark for assessing its current innovation potential. The size of the enterprise (*Size*) determines its resource endowment and R and D capacity, which exert a direct influence on green technology innovation.

Secondly, the return on assets (*ROA*) and Tobin's Q value (*TobinQ*) mirror the profitability and market valuation of the enterprise, respectively. These factors are likely to shape the enterprise's investment decisions and commitment to green technology innovation.

Furthermore, the capital accumulation rate (*RCA*) reflects the growth trajectory of the enterprise's capital, while financial leverage (*FL*) and the debt-to-asset ratio (*Lev*) unveil the enterprise's financial structure and risk appetite. These elements can either constrain or stimulate the enterprise's innovation endeavors.

Consequently, it is imperative to control for these potential confounding factors, thereby ensuring the accuracy and reliability of the research findings.

4. Empirical Test Results of the Effect of Enterprise Digitalization on Green Technological Innovation

4.1. Baseline Regression Test

The descriptive statistics of the main variables are shown in Table 1. The sample comprises a total of 20,558 observations, which is both representative and substantial. The means for the three green technological innovation variables are 0.411, 0.272, and 0.254, respectively, suggesting that the overall performance of enterprises is moderate, with variations in strength across different aspects. The mean value for the variable (Dig) is

0.963, indicating that enterprises have made considerable progress in digitalization. The standard deviations for the four variables are relatively large. Specifically, the standard deviations for the three green technological innovation variables range between 0.613 and 0.843, while the standard deviation for the variable (Dig) is 0.955. This indicates significant disparities among enterprises. Overall, the data adequately reflect the characteristics and differences among enterprises, providing a reliable foundation for subsequent analysis.

Table 1. The descriptive statistics of the main variables—Stata Regression Results.

Variables	Obs	Mean	Std.dev.	Min	Max
envpat_total	20,558	0.411495	0.8433444	0	6.848005
envpat_inv	20,558	0.2723811	0.6857515	0	6.327937
envpat_uti	20,558	0.2538172	0.6128195	0	5.948035
Dig	20,558	21.89005	0.9554922	0	5.615149

Considering the inherent differences in innovation levels between invention patents and utility model patents, the mechanisms by which digitalization impacts these distinct patent types may vary. Accordingly, this study examines the influence of enterprise digitalization on both the aggregate measure of green technological innovation and the specific metrics for each patent type. Table 2 displays the regression outcomes detailing the effect of enterprise digitalization on green technological innovation, utilizing Model 1. Specifically, columns (1), (2), and (3) in Table 2 present the regression results for the overall innovation indicator, invention patents, and utility model patents, respectively. The regression coefficients are 0.0481, 0.0395, and 0.0236, all of which exhibit statistical significance at the 1% level. These findings suggest that digitalization significantly enhances both green invention innovations and green utility model innovations within enterprises. Nonetheless, the regression coefficient for utility model patents is lower than that for invention patents, thereby lending support to Hypothesis 1.

Table 2. The Effect of Enterprise Digitalization on Green Technological Innovation—Stata Regression Results.

Variables	(1) envpat_total	(2) envpat_inv	(3) envpat_uti
Dig	0.0481 ***	0.0395 ***	0.0236 ***
	(0.00977)	(0.00843)	(0.00816)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	16,901	16,901	16,901
R2	0.132	0.161	0.085

Standard errors in parentheses. *** $p < 0.01$. Note: To save space, the coefficients of control variables and the constant term are not reported. The same applies to the tables below.

4.2. Robustness Tests

To further mitigate endogenous issues, this study conducts ratio indicator tests, instrumental variable model tests, and counterfactual tests.

4.2.1. Ratio Indicator Tests

Utilizing ratio indicators to assess the levels of green technological innovation within enterprises aids in further mitigating endogeneity issues. This study develops three distinct ratio indicators, based on various patent types, to gauge the extent of green technological innovation among enterprises: (1) Overall Green Patent Ratio: Calculated as the total number of green patent applications divided by the total number of independent patent applications in the same year (*envpat_total_ratio*). (2) Green Invention Patent Ratio: Determined by the number of independent green invention applications relative to the number of independent invention applications in the same year (*envpat_inv_ratio*). (3) Green Utility Model Patent Ratio: Computed as the number of independent green utility model applications divided by the number of independent utility model applications in the same year (*envpat_uti_ratio*). Table 3 presents the regression outcomes for these ratio indicators, in accordance with Model 1. Specifically, the regression results pertaining to the overall indicator, invention patents, and utility model patents are detailed in Table 3(2) and (3), with corresponding regression coefficients of 0.00458, 0.00474, and 0.00329, respectively. Notably, the coefficients for both the overall green patent ratio and the green invention patent ratio are positive and statistically significant, while the coefficient for the green utility model patent ratio is positive but lacks statistical significance. This observation may stem from the fact that utility model patents typically embody a lower level of innovation, with the majority of innovations centered around the shape and structure of products. Consequently, enterprises encounter fewer obstacles in the R and D process for utility model patents, as compared to invention patents. As a result, the impact of corporate digitalization on green utility model patents is relatively modest.

Table 3. The effect of digitalization on corporate green innovation—Stata regression results of ratio variables.

Variables	**(1)** **envpat_total_ratio**	**(2)** **envpat_inv_ratio**	**(3)** **envpat_uti_ratio**
Dig	0.00458 **	0.00474 **	0.00293
	(0.00195)	(0.00227)	(0.00219)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	16,901	16,901	16,901
R2	0.006	0.003	0.002

Standard errors in parentheses. ** $p < 0.05$.

4.2.2. Instrumental Variable Approach to Address Endogeneity

Digitalization can influence enterprise green technological innovation, and conversely, green technological innovation may also impact digitalization, leading to potential bidirectional causality and endogeneity issues. To address this challenge, the instrumental variable (IV) approach is adopted. Specifically, a two-stage least squares (2SLS) regression model with robust standard errors is utilized.

In this study, the average quantitative digitalization indicator of peer enterprises within the same industry (excluding the focal firm) for the corresponding fiscal year is employed as the instrumental variable, denoted as IV_mean_lnd. Columns (1), (2), and (3) of Table 4 present the results of the 2SLS regression model, which correspond to the impact of digitalization on the overall green innovation index, green invention patents, and green utility model patents, respectively.

The regression coefficients are as follows:

Overall Green Innovation Index: 0.101
Green Invention Patents: 0.0722
Green Utility Model Patents: 0.0685

All coefficients are statistically significant at the 1% level. It is noteworthy that the coefficient for green utility model patents is lower than that for green invention patents, consistent with the findings of previous analyses. These results reinforce the robustness of the study's main conclusions.

Table 4. The effect of digitalization on corporate green innovation—Stata regression results of instrumental variable method.

Variables	(1) envpat_total	(2) envpat_inv	(3) envpat_uti
Dig	0.101 ***	0.0722 ***	0.0685 ***
	(0.00938)	(0.00776)	(0.00714)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	16,900	16,900	16,900
R2	0.619	0.626	0.531

Standard errors in parentheses. *** $p < 0.01$.

4.2.3. Counterfactual Test

To further tackle potential endogeneity concerns arising from unobserved factors, a Difference-in-Differences (DID) approach is adopted.

Experimental and Control Groups:

Enterprises are categorized into an experimental group (treatment = 1) and a control group (treatment = 0). Firms consistently displaying a low frequency of digitalization-related terms in their annual reports across all years are deemed to have not undergone digital transformation and are assigned to the control group. In contrast, enterprises with at least one year exhibiting a high frequency of digitalization-related vocabulary are considered to have undergone digital transformation and are placed in the experimental group.

Pre- and Post-Experiment Periods:

For enterprises in the experimental group, the year when the digital transformation index first surpasses a specific threshold is designated as the onset of digital transformation (period = 1). The years preceding this point constitute the pre-experiment period (period = 0). This design accounts for variations in the timing of an enterprise's digital transformation.

Results:

Table 5 presents the regression outcomes of Model 1 utilizing the Difference-in-Differences (DID) method. Columns (1), (2), and (3) illustrate the impacts of digital transformation on the overall green innovation index, green invention patents, and green utility model patents, respectively. The results are as follows:

Table 5. The effect of digitalization on corporate green innovation—Stata regression results of the double difference method.

Variables	(1) envpat_total	(2) envpat_inv	(3) envpat_uti
_diff	0.236 ***	0.212 ***	0.0848 **
	(0.0567)	(0.0463)	(0.0421)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	18,566	18,566	18,566
R2	0.126	0.130	0.086

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Overall Green Innovation Index: Coefficient = 0.236, significant at the 1% level.

Green Invention Patents: Coefficient = 0.212, significant at the 1% level.

Green Utility Model Patents: Coefficient = 0.0848, significant at the 5% level.

These findings indicate that digitalization within enterprises significantly contributes to promoting green technological innovation. Furthermore, consistent with the results of prior studies, the impact on green utility model patents is less pronounced than that on green invention patents.

5. Mechanism Test

Based on the preceding analysis, digitalization has the potential to optimize an enterprise's technological innovation resources by enhancing human capital and fostering business model innovation, thereby encouraging enterprises to engage in green innovation activities. This section empirically examines the aforementioned mechanisms.

5.1. Human Capital Optimization Effect

Human capital represents the aggregate of employees' knowledge and skills. During the process of digital transformation, it encourages enterprises to adopt advanced equipment, increases the demand for highly educated talents, facilitates knowledge sharing, and contributes to green technological innovation. It is commonly measured by the proportion of R and D personnel. The following model is employed to examine the mediation mechanism:

(1) Regress digitalization on the mediator variable. A significant coefficient indicates that digitalization influences the mediator variable.
(2) Regress digitalization on green technological innovation within enterprises. A significant coefficient suggests that digitalization affects green technological innovation.
(3) Simultaneously regress digitalization, the mediator variable, and green technological innovation. If the coefficient of digitalization becomes insignificant or remains significant but with a reduced absolute value, while the coefficient of the mediator variable is significant, this confirms that enterprise digitalization impacts green technological innovation through the mediation mechanism.

Adhering to these testing steps, the model for assessing the mediation mechanism is formulated as follows:

Test the effect of digitalization on the mediator variables.

$$mechanism_{it} = \alpha 0 + \alpha 1 Dig_{it} + \rho X + \delta t + \theta_i + \varepsilon_{it} \tag{2}$$

Test the effect of digitalization on green technological innovation.

$$envpat\_total_{it} = \beta 0 + \beta 1 Dig_{it} + \rho X + \delta t + \theta i + \varepsilon_{it} \tag{3}$$

Incorporate both the digitalization and the mediator variables into the model simultaneously.

$$envpat\_total_{it} = \sigma 0 + \sigma 1 Dig_{it} + \sigma 2 mechanism_{it} + \rho X + \delta_t + \theta_i + \varepsilon_{it} \tag{4}$$

Among these, the term "mechanism" encompasses two mediator variables: *Human Capital* and *Enterprise Business Models (EBM)*. The definitions of other variables remain consistent with those in Model (1). Specifically, *Human Capital* is the variable utilized to test the mediation mechanism related to the human capital improvement effect, whereas *Enterprise Business Models (EBM)* is the variable used to examine the mediation mechanism associated with the business model innovation effect.

This study conducts a mediation mechanism test focusing on human capital. The empirical results of the first step are presented in Column (1) of Table 6. It is evident that digitalization significantly enhances human capital. The regression results of the second step are displayed in Column (2) of Table 6, indicating that digitalization significantly promotes green technological innovation. The estimation results of the third step are shown in Column (3) of Table 6, where the coefficient of Human Capital is significantly positive, and the absolute value of the coefficient for Dig (digitalization) decreases. These empirical findings align with the mechanism analysis presented earlier, suggesting that digitalization substantially improves enterprises' green technological innovation levels by enhancing human capital.

Table 6. Stata Regression results of human capital mediating effect.

Variables	**(1) Human Capital**	**(2) envpat_total**	**(3) envpat_total**
Dig	0.471 ***	0.0515 ***	0.0245 *
	(0.156)	(0.00968)	(0.0127)
Human Capital			0.00503 ***
			(0.00157)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	12,180	16,901	11,705
R2	0.032	0.131	0.045

Standard errors in parentheses. * $p < 0.1$, *** $p < 0.01$.

5.2. Business Model Innovation Effect

An enterprise's business model encapsulates the manner in which it generates, delivers, and captures value. Amidst the surge of digitalization, businesses are harnessing this trend to revolutionize their value creation processes, leveraging data to inform decision-making, exploring novel market channels, innovating products and services, catering to personalized needs, enhancing competitiveness, and fostering advancements in green technology. Keywords pertinent to enterprise business model innovation encompass: medical digitalization, mobile wallets, barcode payments, NFC payments, smart devices, smart factories, smart terminal products, smart energy solutions, Internet of Things (IoT), smart energy conservation and environmental sustainability, smart logistics, smart healthcare services, smart customer support, smart homes, smart investment advisory services, smart cultural and tourism initiatives, smart power grids, digital control systems, digital retailing, unmanned retail outlets, Internet finance, digital finance solutions, fintech innovations, quantitative finance strategies, open banking practices, electronic medical records (EMR) systems, new retail concepts, B2B, B2C, C2B, C2C, C2M, online-to-offline (O2O) models, online retail platforms, e-commerce, public accounts, WeChat mini-programs, applications (apps), live streaming platforms, microblogs, mobile e-commerce (M-commerce), pre-sales strategies, online office solutions, online education platforms, telemedicine services, and unmanned delivery systems.

In this study, we gathered and systematized annual reports of A-share listed manufacturing enterprises spanning from 2017 to 2022 utilizing Python's web scraping capabilities. Through Chinese word segmentation techniques, we extracted textual content from the annual reports and quantified the extent of enterprise business model innovation (EBM) based on the frequency of keywords associated with business model innovation. A higher index signifies a greater degree of enterprise business model innovation.

This study examines the mediation mechanism centered around business model innovation. Column (1) of Table 7 presents the empirical findings of the initial step. It is evident that digitalization significantly stimulates enterprise business model innovation. The regression outcomes of the second step are outlined in Column (2) of Table 7, indicating that digitalization notably elevates the levels of enterprise green technological innovation. Column (3) of Table 7 showcases the estimation results of the third step; wherein the absolute value of the coefficient for Dig (digitalization) diminishes, and the coefficient for business model innovation (EBM) is markedly positive. This implies that digitalization promotes green technological innovation levels by innovating the enterprise business model.

Table 7. Stata Regression results of the mediating effect of enterprise business model innovation.

Variables	**(1)** **EBM**	**(2)** **envpat_total**	**(3)** **envpat_total**
Dig	0.391 ***	0.0515 ***	0.0446 ***
	(0.0190)	(0.00968)	(0.00976)
EBM			0.0179 **
			(0.00772)
Control Variables	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled
N	18,111	16,901	16,901
R2	0.267	0.131	0.132

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

6. Heterogeneity Test

Manufacturing enterprises display diversity across multiple dimensions, including senior executives' awareness of green issues, availability of green credit, pollution levels, degrees of technological innovation, and enterprise scale. As a result, the impact of digitalization on green technological innovation may differ among these enterprises owing to these disparities. By conducting heterogeneity tests, we can attain a more profound understanding of digitalization's role in enterprises with varying characteristics and offer more tailored recommendations to both enterprises and policymakers.

6.1. Heterogeneity Based on Executives' Green Awareness

Executives' Green Consciousness: Grounded in three dimensions—recognition of green competitive edge, corporate social responsibility, and perception of external environmental pressures—we have selected the following keywords: energy conservation and emission reduction, environmental protection strategy, environmental protection ethos, environmental management framework, environmental technology advancement, environmental auditing, energy efficiency and environmental preservation, environmental conservation policies, environmental conservation authorities, environmental supervision, low-carbon initiatives, conservation programs, environmental stewardship, conservation oversight, environmental protection infrastructure, pertinent environmental protection legislation, and environmental pollution remediation. We construct a variable for executives' green consciousness (GEC) in publicly listed enterprises, based on the prevalence of these keywords in enterprise annual reports, to gauge the emphasis on green considerations in corporate management decisions.

The integration of digital technology enhances technological resources for enterprise green innovation, and an enterprise's commitment to green development directly influences its involvement in green innovation activities. When executives exhibit a high level of green consciousness, the stimulating effect of digitalization on enterprise green innovation becomes more evident. Accordingly, this study classifies enterprises into two categories based on executives' green consciousness: one where executives lack green consciousness and another where executives possess green consciousness. Subsequently, a grouped regression analysis is performed. Columns (1) and (2) of Table 8 display empirical findings. The regression results reveal that for enterprises with executives lacking green consciousness, the regression coefficient is 0.0419, which is statistically significant at the 0.05 level. For enterprises with executives possessing green consciousness, the regression coefficient is 0.0692, with a statistical significance level of 0.01. The research findings suggest that for enterprises whose executives possess green consciousness, i.e., enterprises that prioritize green development, enhancing digitalization levels can more effectively optimize the enterprise's innovative technological resources, thereby more effectively boosting the enterprise's green technological innovation capabilities.

Table 8. Stata Heterogeneity test regression results.

Variables	**(1) envpat_total (GEC_no)**	**(2) envpat_total (GEC_yes)**	**(3) envpat_total**	**(4) envpat_total (Pollute_yes)**	**(5) envpat_total (Pollute_no)**
Dig	0.0419 **	0.0692 ***	0.0439 ***	0.0510 **	0.0409 ***
	(0.0171)	(0.0140)	(0.00986)	(0.0229)	(0.0106)
Dig×GLR			0.194 ***		
			(0.0732)		
GLR			−0.278		
			(0.219)		
Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled
N	4750	12,151	16,758	5321	11,580
R2	0.110	0.116	0.132	0.063	0.150

Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

6.2. Heterogeneity Based on Green Credit

The Green Credit Ratio (GLR), which measures the extent of green credit, is computed as the Green Credit Amount divided by the aggregate of Long-term and Short-term Borrowings. By offering financial support, green credit empowers enterprises to harness digital technology, thereby accelerating the research and application of green technologies and fostering green and low-carbon development. Enterprises with a high level of green credit experience a heightened incentive effect of digitalization on their green innovation endeavors. Consequently, this study adopts a moderation effect model for regression analysis. The empirical results, presented in Column (3) of Table 7, reveal that the regression coefficient for the interaction term (Dig×GLR) is 0.194, with a statistical significance level of 0.01. These findings suggest that green credit positively moderates the impact of digitalization on green technological innovation.

6.3. Heterogeneity Based on Whether the Enterprise Is in a Heavily Polluting Manufacturing Industry

An enterprise is classified as highly polluting if it is assigned a value of 1; otherwise, it is assigned a value of 0. The empirical findings are detailed in Columns (4) and (5) of Table 7. For heavily polluting enterprises, the regression coefficient stands at 0.051, with a statistical significance of 0.05. In contrast, the regression coefficient for non-heavily polluting enterprises is 0.0409, exhibiting a statistical significance of 0.01. These findings suggest that, relative to other manufacturing enterprises, the impact of digitalization on fostering green technological innovation is less pronounced in heavily polluting manufacturing enterprises. This can be primarily ascribed to the high technological hurdles for transformation, significant capital investment needs, prolonged technological innovation cycles, and the inconspicuous short-term economic returns. Furthermore, stringent environmental regulations impose additional challenges and pressures on these enterprises.

6.4. Heterogeneity Based on Different Levels of Innovation

Quantile regression is utilized to investigate the variation in the impact of digitalization on green technological innovation across different levels of innovation (q.5, q.6, q.7, and q.8). The findings of the quantile regression analysis, categorized by levels of green technological innovation, are presented in Table 9. Specifically, for the lower innovation level groups (q.5 and q.6) and the higher innovation level groups (q.7 and q.8), the regression coefficients are 0.134, 0.107, 0.308, and 0.359, respectively. It is evident that as the level of green technological innovation rises, the regression coefficients shift from a positive yet statistically non-significant association in the lower groups to a strongly positive and statistically significant association in the higher groups. This suggests that the influence of digitalization on green technological innovation becomes more prominent when the level of green technological innovation is high.

Table 9. Stata Quantile regression results of corporate green innovation level.

Variables	**(1) envpat_total (.5)**	**(2) envpat_total (.6)**	**(3) envpat_total (.7)**	**(4) envpat_total (.8)**
Dig	0.134 (0.381)	0.107 (0.0954)	0.308 *** (0.0885)	0.359 *** (0.0707)
Control Variables	Controlled	Controlled	Controlled	Controlled
Enterprise Fixed Effects	Controlled	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled	Controlled
N	18,105	18,105	18,105	18,105
R2				

Standard errors in parentheses. *** $p < 0.01$.

6.5. Heterogeneity Based on Enterprise Size

The relationship between enterprise digitalization and green technological innovation is unlikely to be strictly linear, and a threshold effect may exist that is contingent upon enterprise size. Through the implementation of a threshold effect test, the specific threshold value of enterprise size can be determined, facilitating an examination of how digitalization impacts green technological innovation across various scale ranges. This enhances our understanding of how enterprise size influences the efficacy of digitalization in fostering green technological innovation, thereby enabling the development of tailored policies for enterprises of different sizes and improving the effectiveness and precision of these policies. To explore the presence of this threshold effect, a single-threshold effect regression model, predicated on enterprise size, is formulated as follows:

$$envpat\_total_{it} = c_1 Dig_{it}\ (Size < Y) + c_2 Dig_{it}\ (Y < Size\ ) + \rho X + \delta t + \theta i + \varepsilon it. \quad (5)$$

Among the variables, Enterprise Size (Size), measured by total assets, serves as the threshold variable, and Y denotes the threshold value to be estimated. Following 300 Bootstrap sampling iterations, the results of the threshold effect test are presented below. In Table 10, the *p*-value for the threshold effect test is 0.000, indicating a significant threshold effect with a threshold value of 25.2484. According to the regression results of the scale threshold effect, when the total asset size is below the threshold of 25.2484, the coefficient is 0.0278053 (p-value = 0.032). Conversely, when the total asset size surpasses the threshold of 25.2484, the coefficient rises to 0.3325333 (p-value = 0.000), suggesting that digitalization has a more substantial impact on green technological innovation in larger enterprises. Generally, the effect of digitalization on green technological innovation demonstrates a threshold effect, characterized by an abrupt change in the magnitude of the positive effect, rather than a sudden shift in its direction (positive or negative).

Table 10. Stata Regression results of the scale threshold effect.

Category	Indicator	Value
Threshold Effect Test (bootstrap = 300)		
	RSS	3371.3356
	MSE	0.4062
	Fstat	48.98
	Prob	0
	Crit10	13.74
	Crit5	16.983
	Crit1	22.737
Threshold Estimation (level = 95%)		
	Model	Th-1
	Threshold	25.2484
	Lower	25.057
	Upper	25.4287
Threshold effect regression results		
Coefficient	0 (below the threshold)	0.0278053
	1 (above the threshold)	0.3325333
std. err.	0 (below the threshold)	0.0129763
	1 (above the threshold)	0.0681101
t	0 (below the threshold)	2.14
	1 (above the threshold)	4.88
$p > \|t\|$	1 (below the threshold)	0.032
	1 (above the threshold)	0.000
[95% conf. interval]	0 (below the threshold)	0.0023461 0.0532644
	1 (above the threshold)	0.1989035 0.4661632

7. Discussion

7.1. Implications of the Findings

Based on the research findings presented herein, we ascertain that the digitalization of manufacturing enterprises exerts a profound promoting effect on green technological innovation. Specifically, digitalization has significantly facilitated green technological innovation by enhancing human capital levels and fostering innovative business models. The heterogeneity test further indicates that manufacturing enterprises with high levels of green awareness among executives and ample green credit experience a more pronounced effect of digitalization on green technological innovation. Conversely, the incentive effect of digitalization on green technological innovation in heavily polluting manufacturing enterprises is relatively muted, due to challenges such as high technical transformation barriers, substantial capital investment needs, prolonged technological innovation cycles, and stringent environmental protection regulations. Moreover, as the green technological innovation capabilities of manufacturing enterprises improve, the corresponding impact of digitalization on green technological innovation also intensifies. For large-scale manufacturing enterprises, the influence of digitalization on green technological innovation is particularly noteworthy. Consequently, our research objectives have been successfully achieved.

Based on these findings, we propose the following policy recommendations: First, the manufacturing industry is characterized by complex production processes. Digital technology can precisely reduce energy consumption and offer opportunities for exploring efficient energy-saving models. To this end, the government should enhance its policy support for the digital transformation of manufacturing enterprises. This can be achieved through specific measures such as fiscal subsidies, tax incentives, and technical assistance, guiding enterprises to leverage digital technology to optimize their production processes. Secondly, the manufacturing industry is a significant consumer of resources. Therefore, the government should refine its green credit policies. It should also increase financing support for green technology transformation and upgrading projects in manufacturing enterprises, encouraging them to utilize digital means to enhance resource utilization efficiency. In addition, the manufacturing industry experiences rapid product updates. Digital technology can promote green product innovation within enterprises. To facilitate this, the government and enterprises should collaborate closely, enhancing the green awareness of corporate executives through training programs, seminars, and other initiatives. Finally, the government should implement differentiated policies tailored to the size of enterprises. Small enterprises should be provided with additional technical support and training to bolster their digital and green technology innovation capabilities. Conversely, large enterprises should be encouraged to leverage their scale advantages, taking the lead in driving the trend of green technology innovation across the entire industry.

7.2. Potential Limitations and Future Research Directions

7.2.1. Potential Limitations

This study utilized microdata in combination with a variety of statistical regression analysis techniques, encompassing fixed effects models, instrumental variable approaches, counterfactual analyses, threshold effect models, and quantile regressions, to guarantee the reliability and robustness of the research outcomes. Nevertheless, the study does have certain limitations pertaining to sample selection and the temporal scope of the data. In particular, the sample is confined to manufacturing enterprises in China. Future research endeavors could be broadened to include other types of enterprises, so as to offer a more comprehensive examination of whether industry-specific disparities exist in the impact of enterprise digitalization on green technological innovation. Moreover, the restricted temporal range of the data constrains the observation and analysis of long-term trends. To derive more nuanced conclusions over an extended period, further studies may be conducted in the future.

7.2.2. Future Research Directions

Future research endeavors will delve into digital technologies, encompassing big data, artificial intelligence, and blockchain, from the vantage point of technology transfer (TT). The study will explore avenues for comprehensively optimizing various facets of technology transfer, such as enhancing the efficiency of knowledge dissemination, improving the accuracy of technology assessments, refining partner matching processes, and streamlining transaction procedures, all while fostering advancements in enterprise green technological innovation. Specifically, the research will concentrate on elucidating how enterprise digitalization expedites and enhances the overall procedure and tangible outcomes of technology transfer (TT), particularly within the pivotal domain of green technological innovation. Furthermore, the study will scrutinize the potential impact of digital methodologies on accelerating the pace of green technology transfer and facilitating its widespread implementation. In the course of this investigation, we will assess how digital technology precisely affects the efficacy of green technology transfer, elucidate the significance and functions of digital platforms in this process, and actively investigate the existence of particular digital tools or strategies capable of markedly elevating the success rate of green technology transfer. This research is geared towards providing a robust scientific foundation and practical direction for the accelerated development and extensive application of green technology.

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References

1. Yuan, Q.; Zhang, G.; Wang, R.; Ma, X.; Niu, J. Does technological innovation in National Sustainable Development Agenda Innovation Demonstration Zones promote green development?—The case from Chengde City, China. *PLoS ONE* **2024**, *19*, e0300315. [CrossRef] [PubMed]
2. Wang, Q.; Wei, Y. Research on the Influence of Digital Economy on Technological Innovation: Evidence from Manufacturing Enterprises in China. *Sustainability* **2023**, *15*, 4995. [CrossRef]
3. Fang, X.; Liu, M. How does the digital transformation drive digital technology innovation of enterprises? Evidence from enterprise's digital patents. *Technol. Forecast. Soc. Change* **2024**, *204*, 123428. [CrossRef]
4. Liu, C.; Sheng, Z.; Hu, X.; Tian, C. Hand in hand or left behind: The dual impact of leading firms' digital technologies on industry digital transformation. *N. Am. J. Econ. Financ.* **2025**, *75*, 102305. [CrossRef]
5. Liu, H.; Wang, P.; Li, Z. Is There Any Difference in the Impact of Digital Transformation on the Quantity and Efficiency of Enterprise Technological Innovation? Taking China's Agricultural Listed Companies as an Example. *Sustainability* **2021**, *13*, 12972. [CrossRef]
6. Li, J.; Dong, K.; Dong, X. Green energy as a new determinant of green growth in China: The role of green technological innovation. *Energy Econ.* **2022**, *114*, 106260. [CrossRef]
7. Li, M.; Guo, S.; Wang, X.; Liu, Y. Increase or decrease: Customer digital transformation and supplier cost stickiness. *Pac.-Basin Financ. J.* **2024**, *87*, 102507. [CrossRef]
8. Du, X.; Jiang, K.; Zheng, X. Reducing asymmetric cost behaviors: Evidence from digital innovation. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 682. [CrossRef]
9. El-Kassar, A.N.; Singh, S.K. Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 483–498. Available online: https://www.webofscience.com/wos/woscc/full-record/WOS:000471735700044 (accessed on 29 January 2025). [CrossRef]
10. Ma, J.; Yang, X.; Li, M. Are Data Assets Useful?—Evidence Based on Corporate Cost Stickiness. *Emerg. Mark. Finance Trade* **2024**, *60*, 3734–3752. [CrossRef]
11. Qureshi, K.M.; Mewada, B.G.; Kaur, S.; Alghamdi, S.Y.; Almakayeel, N.; Almuflih, A.S.; Qureshi, M.R.N.M. Sustainable Manufacturing Supply Chain Performance Enhancement through Technology Utilization and Process Innovation in Industry 4.0: A SEM-PLS Approach. *Sustainability* **2023**, *15*, 15388. [CrossRef]
12. Wang, F.; Wang, H.; Li, J. The effect of cybersecurity legislation on firm cost behavior: Evidence from China. *Pac.-Basin Finance J.* **2024**, *86*, 102460. [CrossRef]
13. Jiao, J.; Zhang, X.; Tang, Y. What factors determine the survival of green innovative enterprises in China?—A method based on fsQCA. *Technol. Soc.* **2020**, *62*, 101314. [CrossRef] [PubMed]
14. Tian, H.; Han, J.; Sun, M.; Lv, X. Keeping pace with the times: Research on the impact of digital leadership on radical green innovation of manufacturing enterprises. *Eur. J. Innov. Manag.* **2023**. *ahead-of-print*. [CrossRef]
15. Liu, J.; Wang, Q.; Wei, C. Unleashing Green Innovation in Enterprises: The Transformative Power of Digital Technology Application, Green Human Resource, and Digital Innovation Networks. *Systems* **2024**, *12*, 11. [CrossRef]
16. Fan, W.; Wu, H.; Liu, Y. Does Digital Finance Induce Improved Financing for Green Technological Innovation in China? *Discret. Dyn. Nat. Soc.* **2022**, *2022*, 6138422. [CrossRef]

17. Zhou, Y. The Application Trend of Digital Finance and Technological Innovation in the Development of Green Economy. *J. Environ. Public Health* **2022**, *2022*, 1064558. [CrossRef] [PubMed]
18. Chen, W.; Wang, X.; Peng, N.; Wei, X.; Lin, C. Evaluation of the Green Innovation Efficiency of Chinese Industrial Enterprises: Research Based on the Three—Stage Chain Network SBM Model. *Math. Probl. Eng.* **2020**, *2020*, 3143651. [CrossRef]
19. Zhao, X.; Qian, Y. Does Digital Technology Promote Green Innovation Performance? *J. Knowl. Econ.* **2024**, *15*, 7568–7587. Available online: https://www.webofscience.com/wos/woscc/full-record/WOS:000994740700003 (accessed on 29 January 2025). [CrossRef]
20. Wu, W.; Shi, J.; Liu, Y. The impact of corporate social responsibility in technological innovation on sustainable competitive performance. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 707. [CrossRef]
21. Sun, D.; Yu, B.; Ma, J. Research on the Impact of Digital Empowerment on China's Human Capital Accumulation and Human Capital Gap between Urban and Rural Areas. *Sustainability* **2023**, *15*, 5458. [CrossRef]
22. He, Z.; Kuai, L.; Wang, J. Driving mechanism model of enterprise green strategy evolution under digital technology empowerment: A case study based on Zhejiang Enterprises. *Bus. Strategy Environ.* **2023**, *32*, 408–429. [CrossRef]
23. Kulangara, N.P.; Jackson, S.A.; Prater, E. Examining the impact of socialization and information sharing and the medi- ating effect of trust on innovation capability. *Int. J. Oper. Prod. Manag.* **2016**, *36*, 1601–1624. [CrossRef]
24. Li, W.; Yang, X.; Yin, X. Digital transformation and labor upgrading. *Pac.-Basin Financ. J.* **2024**, *83*, 102280. Available online: https://www.webofscience.com/wos/woscc/full-record/WOS:001178462100001 (accessed on 29 January 2025). [CrossRef]
25. Lewbel, A. Constructing instruments for regressions with measurement error when no additional data are available, with an application to patents and R&D. *Econometrica* **1997**, *65*, 1201–1213.
26. Lin, C.; Liu, S.B.; Manso, G. Shareholder litigation and corporate innovation. *Manag. Sci.* **2021**, *67*, 3346–3367. [CrossRef]
27. Grimpe, C.; Sofka, W.; Kaiser, U. Competing for digital human capital: The retention effect of digital expertise in MNC subsidiaries. *J. Int. Bus. Stud.* **2023**, *54*, 657–685. [CrossRef]
28. Mooi, E.A.; Frambach, R.T. Encouraging innovation in business relationships: A research note. *J. Bus. Res.* **2012**, *65*, 1025–1030. [CrossRef]
29. Mubarak, M.F.; Tiwari, S.; Petraite, M.; Mubarik, M.; Raja Mohd Rasi, R.Z. How Industry 4.0 technologies and open innovation can improve green innovation performance? *Manag. Environ. Qual.* **2021**, *32*, 1007–1022. [CrossRef]
30. Li, Z.; Xie, W.; Wang, Z.; Wang, Y.; Huang, D. Antecedent configurations and performance of business models of intelligent manufacturing enterprises. *Technol. Forecast. Soc. Chang.* **2023**, *193*, 122550. Available online: https://www.webofscience.com/wos/woscc/full-record/WOS:001009447400001 (accessed on 29 January 2025). [CrossRef]
31. Schoenecker, T.; Swanson, L. Indicators of firm technological capability: Validity and performance implications. *IEEE Trans. Eng. Manag.* **2002**, *49*, 36–44. [CrossRef]
32. Strambach, S. Combining knowledge bases in transnational sustainability innovation: Microdynamics and institutional change. *Econ. Geogr.* **2017**, *93*, 500–526. [CrossRef]
33. Yang, J.; Zhang, X.; Pei, Y. Digital transformation of the business models of Chinese sporting goods enterprises in the post-COVID-19 era: A knowledge-management perspective. *J. Knowl. Manag.* **2023**, *ahead-of-print*. Available online: https://www.webofscience.com/wos/woscc/full-record/WOS:000973714300001 (accessed on 29 January 2025). [CrossRef]
34. Subramaniam, M.; Youndt, M.A. The influence of intellectual capital on the types of innovative capabilities. *Acad. Manag. J.* **2005**, *48*, 450–463. [CrossRef]
35. Craiut, L.; Bungau, C.; Bungau, T.; Grava, C.; Otrisal, P.; Radu, A.-F. Technology Transfer, Sustainability, and Development, Worldwide and in Romania. *Sustainability* **2022**, *14*, 15728. [CrossRef]
36. Li, X.; Cao, J.; Liu, Z.; Luo, X. Sustainable Business Model Based on Digital Twin Platform Network: The Inspiration from Haier's Case Study in China. *Sustainability* **2020**, *12*, 936. [CrossRef]
37. Bungau, C.C.; Bungau, T.; Prada, I.F.; Prada, M.F. Green buildings as a necessity for sustainable environment development: Dilemmas and challenges. *Sustainability* **2022**, *14*, 13121. [CrossRef]
38. Yuan, C.; Xiao, T.; Geng, C. Digital transformation and enterprise division of labor: Specialization or vertical integration. *China Ind. Econ.* **2021**, *9*, 137–155.
39. Xiao, T.; Sun, R.; Yuan, C. Enterprise digital transformation, human capital structure adjustment and labor income share. *Manag. World* **2022**, *38*, 220–237.