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Unveiling Synergies: The Mediating Role of China's OFDI and Intelligent Transformation in Advancing Green Total Factor Productivity

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ABSTRACT

This research focuses on the impact of intelligent transformation on green total factor productivity (GTFP) within China's manufacturing enterprises from 2010 to 2022. To assess the extent of intelligent transformation across the sector, the study adopts natural language processing and the non-radial SBM-ML index to measure GTFP. Utilizing threshold and mediation analysis, we explore how outward foreign direct investment (OFDI) affects intelligent transformation and GTFP while additional robustness tests supplement the analysis. The study also considers the variability in the impact of intelligent transformation at enterprise, industry, and regional levels. The results reveal a significant positive relationship between intelligent transformation and GTFP, notably stronger in non-OFDI firms and more pronounced in heavily polluting industries. In particular, enterprises with smaller scale of FDI and those in China's middle region see more substantial benefits.

JEL Classification: F21, L6, O33, O38

1 | Introduction

Undoubtedly, foreign direct investment (FDI) is crucial for China's pursuit of high-quality economic progress. Nonetheless, it is currently facing a "dual pressure" from both external challenges such as geopolitical risks and trade disputes, as well as internal hurdles like rising costs of factors and stringent environmental regulations. These pressures have reduced the inclination of foreign companies to augment their investments in China, leading to an annual increase in the volume of FDI withdrawals marked by swift capital inflows and outflows. These dynamics profoundly impact employment, exports, and domestic research (Shi and Zhu 2023).

Previous studies have produced mixed findings regarding the relationship between two-way FDI and green total factor productivity (GTFP) in China. For instance, Zheng and Ran (2018) found that outward FDI (OFDI) may act as a "stumbling block," hindering GTFP growth. In contrast, more recent research by He and Ma (2024) suggests that increased FDI inclusiveness enhances firms' ESG performance, with managerial green attention and innovation capability serving as mediating factors, and investor attention playing a positive moderating role. These divergent perspectives highlight the complexity of the issue and point to a gap in existing research. Under such conditions, the actual effect of intelligent transformation in manufacturing enterprises on GTFP—especially in the context of growing OFDI—remains unclear and warrants further investigation.

The existing body of research on the nexus between digital transformation, green energy efficiency, and productivity predominantly resides in the realm of Ecological Modernization Theory (EMT) (Enrique et al. 2022); particularly its second and third phases, which emphasize the role of industrialism and high technology, including artificial intelligence (AI), in addressing environmental challenges. While this theoretical focus

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underscores the potential of modern society to balance economic and environmental objectives, there remains a substantial gap in the literature—characterized by a lack of quantitative analyses that empirically explore how intelligent transformation influences green productivity. This research seeks to fill this gap by leveraging EMT as its conceptual foundation and conducting empirical investigations to evaluate the impact of intelligent technologies on green productivity in enterprises.

While the extant literature on threshold effects of outward foreign direct investment (OFDI) at the national (Götz and Jankowska 2022), provincial, and city levels (Sinha et al. 2022; Zhang and Wang 2023) is tilting toward a more macro view, this study uses micro-level data from the manufacturing sector spanning the period 2010 to 2022. By leaning on a more granular perspective, the study aims to illuminate the intricate mechanisms underpinning the extant but ambiguous relationships. Furthermore, considering the dearth of literature exploring the synergistic impacts of OFDI and intelligent transformation on GTFP, the study embarks on uncharted territory, pushing the boundaries of our comprehension and unraveling the potential mediating effects at play.

In this direction, we examine the impact of intelligent transformation on GTFP in manufacturing enterprises by utilizing NLP techniques to conduct text mining on companies' annual reports to gauge the extent of digital transformation. Additionally, the study uses the non-radial SBM-ML index (hereinafter referred to as the "ML index") to measure the indices of GTFP, green efficiency change (GEC), and green technical change (GTC). An empirical analysis is then conducted using Heckman methodology to address endogeneity issues, followed by a series of robustness checks to validate the findings.

One notable, among the few contributions of this study lies in its innovative approach to identifying the level of intelligent transformation. Specifically, through the examination of annual reports of publicly traded firms and employing text mining and machine learning techniques to extract relevant content pertaining to intelligence, digitization, and information technology, this research significantly improves the accuracy of measuring companies' intelligent transformation while minimizing potential errors in data computation (Chen et al. 2024; Chen and Alexiou 2025). Furthermore, the introduction of OFDI as a threshold variable represents an additional advancement, as it allows for an exploration of the influence of intelligent transformation on GTFP within the manufacturing sector, accounting for variations in OFDI among publicly traded companies in China. This novel approach offers a fresh perspective on GTFP dynamics within the context of green transformation and the era of "intelligent overseas expansion." Finally, the paper investigates the heterogeneity of intelligent transformation's impact on manufacturing firms' GTFP by considering industry and regional differences, particularly within high-polluting enterprises, thus enhancing our understanding of the nuanced effects across various sectors and geographical locations.

The rest of the paper is organized as follows: Section 2 touches on the theoretical framework and pertinent literature, while Section 3 details the empirical investigation, describing the methodology and data collection processes used in the study. Section 4 presents the empirical results, offering a comprehensive analysis of the findings which are further discussed in Section 5. Finally, Section 6 concludes, summarizing the research findings as well as presenting relevant policy recommendations.

2 | Theoretical Framework and Pertinent Literature

Ecological modernization refers to the process of addressing ecological crises through radical improvements in resource efficiency and the substitution of environmentally harmful industrial processes with less harmful alternatives, all without compromising economic growth or other capitalist imperatives (Bugden 2022). As a key perspective within environmental sociology, EMT is intellectually aligned with global environmental policies that aim to achieve decoupling, green growth, and sustainable development. While critiques of ecological modernization highlight its limitations in effectively mitigating environmental impacts, its core hypothesis—that technological innovation can reduce the ecological footprint—remains central to understanding the role of innovation in sustainability efforts.

As shown in Figure 1, the theoretical framework in this paper combines Modernization Theory and EMT to explore the relationship between digital transformation, green productivity, and China's OFDI. Modernization Theory outlines the progression from Traditional Society (focused on culture) to Modern Society (focused on economy and technological advancements), culminating in a Super-Industrial Society, which prioritizes environmental sustainability. EMT complements this by emphasizing the role of technological advancements, such as AI Transformation, in enhancing green productivity while maintaining economic growth. EMT also highlights innovations like green supply chain management, which facilitates ecological modernization by improving environmental and economic performance simultaneously (Xie et al. 2022). In this context, Chinese OFDI plays a key role in fostering green technological innovation (GTI) and transitioning global industries toward eco-innovation.

In this framework, H1 reflects how digital transformation—especially AI-driven technological upgrades—can directly enhance GTFP through increased efficiency and decoupling of economic growth from environmental degradation. H2, on the other hand, conceptualizes OFDI as a moderating mechanism within EMT. By facilitating the international diffusion of green technologies and best practices, China's OFDI enhances the spillover of eco-innovation across borders, particularly in host countries. EMT highlights innovations like green supply chain management, which facilitate ecological modernization by improving environmental and economic performance simultaneously (Xie et al. 2022). In this context, Chinese OFDI plays a key role in fostering GTI and transitioning global industries toward eco-innovation. OFDI thus does not merely act as a vehicle of capital transfer but contributes strategically to sustainable transitions in global production systems, reinforcing the feedback loop between economic globalization and environmental modernization.

Existing research on the nexus of digital transformation, green energy efficiency, and productivity has largely been theoretical, with limited empirical studies integrating intelligent

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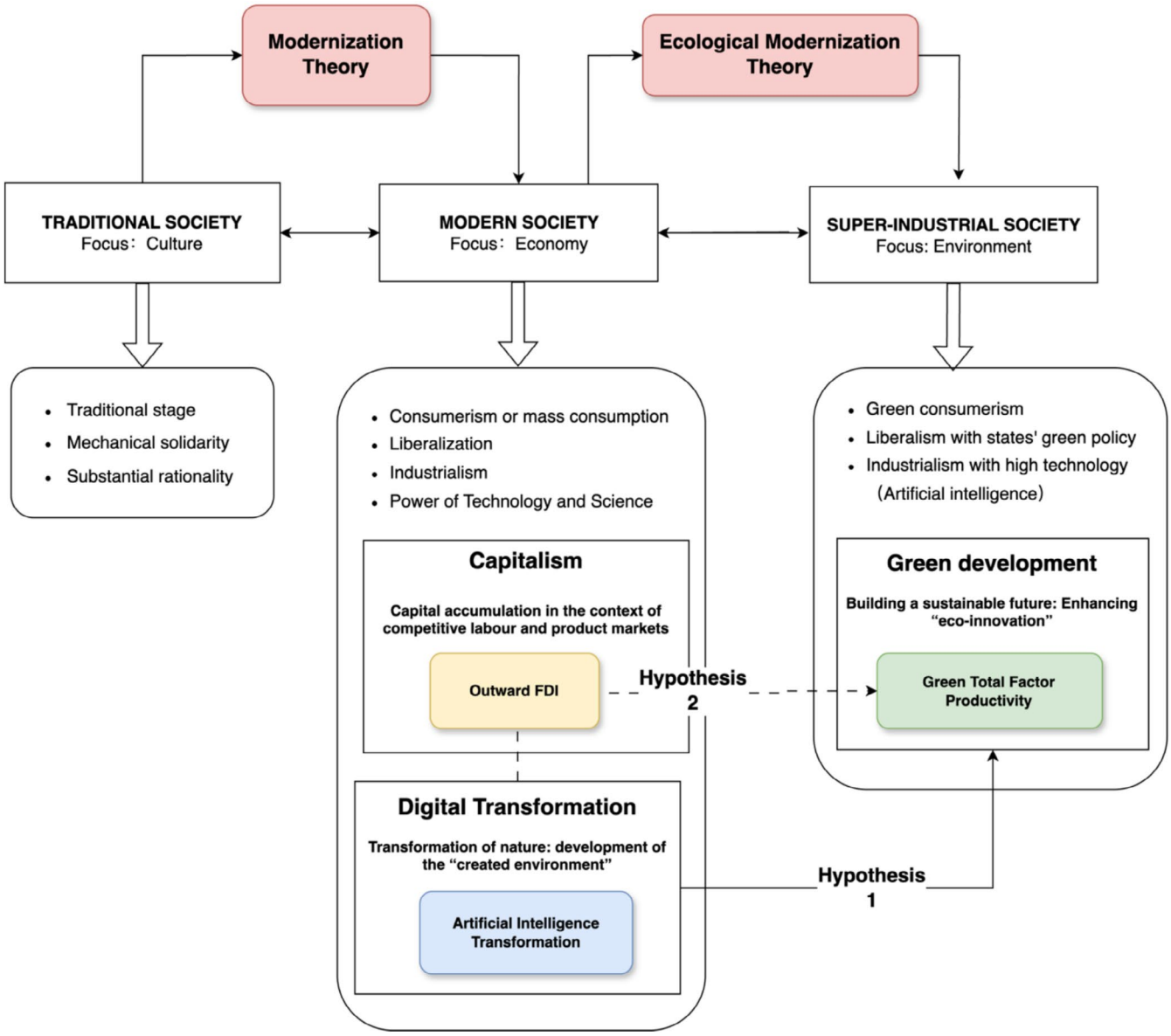


FIGURE 1 | Theoretical framework. [Color figure can be viewed at wileyonlinelibrary.com]

transformation, environmental governance, and economic performance (Enrique et al. 2022). This study addresses that gap by empirically testing how China's OFDI supports green productivity, not only through capital flows but also as a moderating force that amplifies the benefits of digital and ecological modernization. Furthermore, this research acknowledges critiques of EMT, such as its potential to be co-opted into neoliberal frameworks that prioritize market logic over deep environmental reform (Islam 2022). By explicitly linking OFDI to both digital transformation and green productivity within an EMT framework, this study provides a nuanced understanding of how economic globalization can support ecological transitions—when guided by strategic policy and innovation.

2.1 | Intelligent Transformation and GTFP

Intelligent transformation, characterized by the integration of AI and advanced manufacturing technologies, has been found to significantly improve the quality of green innovation and overall GTFP in enterprises across different sectors, particularly in the manufacturing industry (Han and Mao 2023; Wei et al. 2024). The enhancement of GTFP is achieved through several mediating factors, including increased human capital, research and development expenditure, efficient factor allocation, and enhanced information sharing (Yang and Shen 2023). Furthermore, intelligent transformation creates conditions for the green development of industries, promoting more sustainable practices (Yu et al. 2021). The extant empirical studies reveal that intelligent manufacturing contributes to corporate environmental performance through a variety of mechanisms, including improved investment in environmental protection, increased green technology innovation, and the agglomeration of producer service industries (Wei et al. 2024). Additionally, government policies such as technology subsidies, green tax standards, and support for green intelligent ports can further amplify the positive effects of intelligent transformation on GTFP (Meng et al. 2020, 2023).

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In the context of contemporary industrial policy, the pursuit of sustainability has become increasingly intertwined with efforts to enhance productivity and efficiency. Amidst growing concerns over environmental degradation and resource scarcity, the manufacturing sector stands at a pivotal juncture, tasked with reconciling traditional productivity metrics with environmental stewardship imperatives. As industries embrace digitalization and automation to bolster competitiveness and innovation, there arises a compelling inquiry into the potential synergies between intelligent transformation and green productivity. This, in turn, is anticipated to contribute significantly to green productivity, highlighting the potential for innovation and efficiency gains in manufacturing processes to align with environmental sustainability objectives. In view of the above, we develop the following hypothesis:

H1. *The intelligent transformation of manufacturing firms positively influences GTFP, thereby contributing to green productivity.*

2.2 | Intelligent Transformation and GTFP via OFDI

The literature reveals a significant interaction between overseas FDI (OFDI), intelligent transformation, and GTFP. Studies like those by Pantulu and Poon (2003) and Siotis (1999) demonstrate that multinational firms investing in developed nations can achieve reverse innovation spillovers within high-end manufacturing, biomedical, and information sectors, thereby elevating technological innovation levels back in their home countries. This is particularly evident in contexts like China, where OFDI is strategically employed by firms to assimilate advanced technologies and R&D capabilities from developed countries, enhancing their intelligent capacities and fostering green technological spillovers. Recent findings indicate that OFDI contributes to the growth of the parent firm's GTI through scale, competitive, and human capital effects, and that digital transformation positively moderates this relationship by amplifying the reverse green spillover effect of OFDI (Wang et al. 2024).

However, some research suggests that the technological spillover from OFDI may not significantly boost the growth of manufacturing GTFP (Li et al. 2022). Additionally, another study indicates that OFDI in regions with lesser green growth and market development can potentially improve GTFP (Bugden 2022; Tian 2022). While, however, the level of regional marketization can influence the green growth effect of OFDI, in regions where marketization is higher, OFDI is found to negatively affect GTFP (Guo and Wang 2023). The capacity of human capital, FDI, and the level of economic development also influence the green growth impacts of outbound FDI (OFDI) and create a threshold effect on GTFP (Wang, Chen, et al. 2023). Research shows that OFDI exhibits a specific threshold effect on GTFP, with its negative impacts intensifying as environmental regulations are strengthened (Kong et al. 2024).

The preceding research findings underscore the nuanced dynamics shaping the relationship between external factors, such as OFDI and GTFP, within the manufacturing sector. While some studies indicate potential positive effects of OFDI on GTFP under specific conditions, others reveal contrasting outcomes, with varying degrees of impact contingent upon factors like regional marketization and environmental controls. These insights prompt the formulation of a hypothesis aimed at elucidating the role of intelligent transformation amidst the complexities of OFDI influences on GTFP. Hence, based on the above, the following hypothesis emerges:

H2. *The positive impact of intelligent transformation in manufacturing firms on GTFP decreases as the scale of OFDI increases.*

2.3 | Heterogeneous Impact of GTFP

Recent studies have explored the heterogeneous impact of various factors on GTFP across different sectors. For instance, Jia et al. (2024) examine the influence of digital transformation on GTFP, highlighting how its impact varies significantly across enterprises due to sector size, investment levels, and other industry-specific characteristics. Liu et al. (2022) explore how environmental regulation affects green transformation and sustainability in the manufacturing sector, emphasizing the heterogeneous effects of regulatory policies on GTFP. Extant studies also indicate that OFDI's impact on GTFP can be mediated by industrial structure transformation, which may lead to divergent environmental outcomes across different cities (Pei et al. 2021). Additionally, the interplay between OFDI and intelligent transformation in manufacturing firms can shift the attractiveness of regions for investment and innovation (Götz and Jankowska 2022). Further analysis, taking into account the regional heterogeneity, indicates that an inverted U-shaped and a U-shaped curve are still valid but that the mediating effect of OFDI is stronger in different regions (Tang et al. 2022). Based on the above, we hypothesize that:

H3. *The impact of intelligent transformation on GTFP exhibits heterogeneity across different characteristics of the manufacturing sector.*

Based on the above content, the envisaged hypotheses can be summarized and integrated into Figure 2, which illustrates the impact of AI Transformation on GTFP through a Threshold Model, considering various moderating effects and heterogeneity analysis across different industries, sizes, and regions.

3 | Empirical Investigation

3.1 | Methodology

The study examines the impact of intelligent transformation on GTFP in manufacturing enterprises, utilizing panel data from the manufacturing sector from 2010 to 2022. We employ NLP techniques to conduct text mining on companies' annual reports to gauge the extent of digital transformation. Additionally, the study uses the non-radial SBM-ML index (hereinafter referred to as the "ML index") to measure the indices of GTFP, GEC, and GTC. An empirical analysis is then conducted using instrumental variables (IVs) and the Heckman approach to address endogeneity issues, followed by a series of robustness checks to validate the findings. Furthermore, threshold effects and mediation effects

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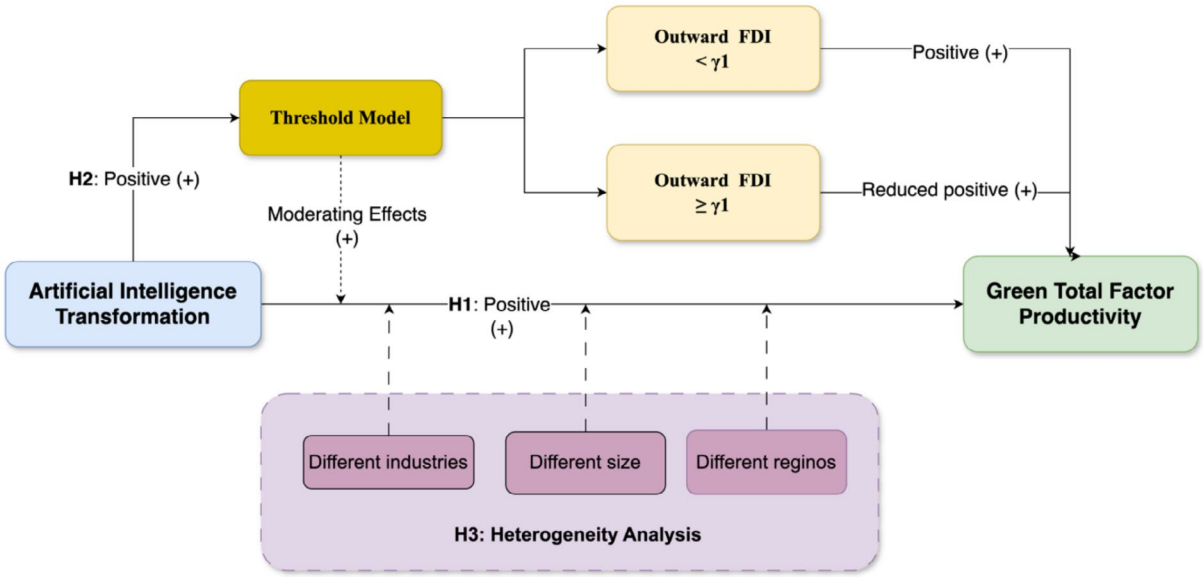


FIGURE 2 | Summary of hypotheses. [Color figure can be viewed at wileyonlinelibrary.com]

methods are used to examine the mechanisms through which OFDI influences intelligent transformation and green GTFP in manufacturing enterprises. Finally, the study investigates the heterogeneity of digital transformation in GTFP at the enterprise, industry, and regional levels.

3.2 | Data

This study examines A-share manufacturing firms listed from 2010 to 2022, when intelligent transformation gained momentum. Data on intelligent investment, financials, governance, and ownership are from the CSMAR database. Information on intelligent technology use comes from company annual reports on the Shenzhen and Shanghai stock exchange websites. Manufacturing and internet data are from the Wind database. OFDI data are sourced from CSMAR's related-party transactions. Regional data come from CNRDS and local statistical yearbooks. ST and *ST firms are excluded. Continuous variables are winsorized at the 1% level to control for outliers.

3.3 | Modeling

In examining the impact of smart transformation of manufacturing firms on GTFP, the following benchmark model is set in Equation (1):

$$GTFP_{i,t} = \beta_0 + \beta_1 IntellTr_{i,t} + \beta_3 Control_{i,t} + \sum Industry + \sum Province + \varepsilon_{i,t} \quad (1)$$

The model's independent variable is the degree of intelligent transformation for manufacturing firms ($IntellTr_{i,t}$), which directly impacts green totally factor productivity ($GTFP_{i,t}$), as represented by its coefficient. Additionally, the model includes control variables that account for other factors influencing $TFP_{i,t}$, along with fixed effects for both industry and province to capture sector-specific and regional influences. An error term is also included to account for any variance not explained by these variables.

The paper also constructs a panel threshold model, drawing on Hansen's (1999) approach, to investigate the impact of manufacturing enterprises' digital transformation on GTFP. Using OFDI as a threshold variable, the model examines how different levels of OFDI influence the relationship between intelligent transformation and GTFP. Equation (2) provides a comprehensive framework for understanding the sustainable productivity dynamics in the manufacturing sector. Where γ is the threshold to be estimated; I (·) is an indicator function that takes the value of 1 if the corresponding condition is true, and 0 otherwise; the rest of the variables are the same as in benchmark regression (1).

$$\begin{aligned} GTFP_{i,t} = {} & a_0 + a_1 IntellTr_{i,t} \cdot I\left(OFDI_{i,t} \le \gamma_1\right) \\ & + a_2\, IntellTr_{i,t} \cdot I\left(\gamma_1 < OFDI_{i,t} \le \gamma_2\right) \\ & + \cdots + a_n\, IntellTr_{i,t} \cdot I\left(\gamma_{n-1} < OFDI_{i,t} \le \gamma_n\right) \\ & + a_{n+1}\, IntellTr_{i,t} \cdot I\left(OFDI_{i,t} > \gamma_n\right) + \theta Control_{i,t} \\ & + \sum Industry + \sum Province + \varepsilon_{i,t} \end{aligned} \quad (2)$$

This paper outlines a panel threshold model used to evaluate the $GTFP_{i,t}$ of an entity over time. GTFP is explained by intelligent transformation ($IntellTr_{i,t}$), OFDI, and other control variables ($Control_{i,t}$). The model incorporates threshold effects using indicator functions (I), which activate different coefficients (a_1, a_2, ..., a_n, a_{n+1}) based on the value of OFDI compared to predetermined thresholds (γ_1, γ_2, ..., γ_n). These thresholds categorize OFDI into intervals, reflecting the idea that the impact of OFDI on GTFP may differ at various investment levels. The entity-specific fixed effect captures unique, time-invariant characteristics, while the error term ($\varepsilon_{i,t}$) accounts for the variability in GTFP not explained by the model. This approach provides a nuanced understanding of how intelligent transformation, and levels of foreign investment jointly influence a green entity's productivity, adjusted for other factors.

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To further test the impact of the synergistic development between OFDI and digital transformation on $GTFP_{i,t}$, we introduce an interaction term between OFDI and intelligent transformation ($OFDI_{i,t} \times IntellTr_{i,t}$) as expressed in Equation (3):

$$GTFP_{i,t} = \beta_0 + \beta_1 OFDI_{i,t} + \beta_2 IntellTr_{i,t} + \beta_3 \left(OFDI_{i,t} \times IntellTr_{i,t}\right) + \beta_4 Control_{i,t} + \sum Industry + \sum Province + \varepsilon_{i,t} \quad (3)$$

The model includes several predictors: the degree of the firm's OFDI ($OFDI_{i,t}$) and its intelligent transformation ($IntellTr_{i,t}$), both individually and through their interaction term ($OFDI_{i,t} \times IntellTr_{i,t}$) to explore how these factors jointly influence the GTFP. Additionally, the model incorporates various control variables ($Control_{i,t}$) to account for other influences on the dependent variable, as well as categorical variables for industry and province to capture potential fixed effects or regional influences. An error term ($\varepsilon_{i,t}$) represents unexplained variability in the dependent variable, accounting for randomness and unobserved factors.

3.4 | Variables

3.4.1 | Independent Variable: Intelligent Transformation Index

Scholars and practitioners describe digital transformation as encompassing all efforts that utilize digital technologies, including 3-D printing, mobile computing, and AI, to revolutionize processes and organizational structures (Nambisan et al. 2017). This study constructs an Intelligent Transformation Index using a natural language processing (NLP) approach based on corporate annual reports, following the methodology of (Lee and Wang 2022). To identify the relevant terminology, we first applied latent Dirichlet allocation (LDA) topic modeling to extract dominant themes and frequently co-occurring terms from the text corpus. The resulting topics were then manually validated and grouped into three major dimensions of intelligent transformation—Intelligent Technology, Digital and Network Technology, and Automation and Manufacturing—which informed the final selection of 29 keywords (see Table A1). This approach balances data-driven discovery with conceptual clarity grounded in existing literature.

"IntellTr" and "IntellTra" are two indicators used to measure intelligent transformation. "IntellTr" represents the logarithm of the frequency of intelligent-related words plus one, while "IntellTra" denotes the ratio of the frequency of intelligent-related words to the total number of words in the annual report, multiplied by 1000. Specifically, intelligent transformation is measured by the ratio of the total number of intelligent transformation keywords for manufacturing enterprises in a given year to the total number of similar keywords appearing in the same industry enterprises in that year. If $IntelligentTransformation_{i,t}$ ("IntellTr" and "IntellTra") is larger, it means that the company has a higher degree of intelligent transformation. The higher the values of "IntellTr" and "IntellTra," the higher the degree of enterprise intelligence transformation.

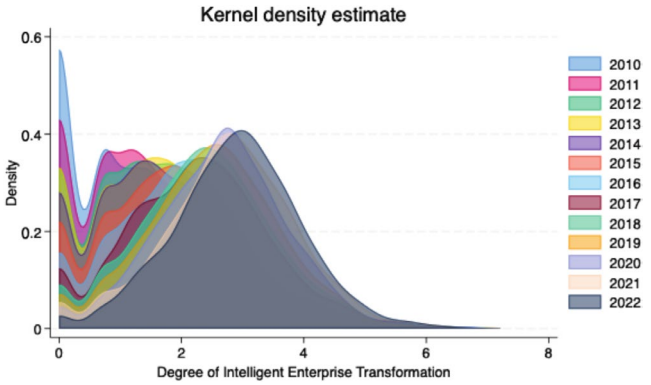


FIGURE 3 | Kernel density estimate (KDE) plot of intelligent transformation. [Color figure can be viewed at wileyonlinelibrary.com]

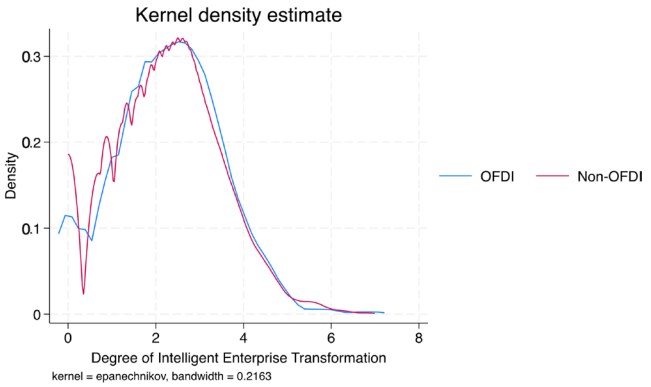


FIGURE 4 | Kernel density estimate (KDE) plot of intelligent transformation different in OFDI. [Color figure can be viewed at wileyonlinelibrary.com]

The kernel density estimate (KDE) plot depicts the distribution of intelligent enterprise transformation (IntellTr) from 2010 to 2022 (Figure 3). It shows that the degree of transformation generally follows a multimodal distribution, with a primary peak between 3 and 4 on the *x*-axis, indicating a moderate level of transformation in most years. Over time, the distribution shifts toward higher values, reflecting a trend toward greater adoption of intelligent processes and technologies. Recent years (2020–2022) exhibit a more concentrated distribution around 3 and 4, suggesting a higher degree of transformation, likely due to technological advancements and increased enterprise adoption of intelligent systems. The KDE plot illustrates that the intelligent transformation of the manufacturing industry has generally increased over time, with a significant shift toward higher values. The shift suggests a broader trend toward technological integration, with enterprises increasingly adopting intelligent systems and processes in recent years.

In Figure 4, the KDE plot shows the distribution of the degree of intelligent enterprise transformation (IntellTr) for manufacturing enterprises, comparing those with OFDI to those without. The distribution indicates that both OFDI and non-OFDI enterprises have similar degrees of transformation, with a primary peak between 2 and 3 on the *x*-axis, reflecting a moderate level of transformation. In the early stages (0–2 on the *x*-axis), the non-OFDI distribution shows a higher density than OFDI

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enterprises, suggesting that a larger proportion of non-OFDI enterprises tend to have lower transformation levels. However, overall, both groups exhibit similar distributions, with a longer tail toward higher transformation levels, particularly for OFDI enterprises, reflecting a broader range of transformation levels. The similar distributions imply that OFDI and non-OFDI enterprises generally share comparable levels of intelligent transformation, but OFDI enterprises may have a broader distribution due to international influences.

3.5 | Intelligent Software Investment Ratio (ISIR)

To assess the degree of enterprise intelligence transformation robustness, this paper also calculates the level of intelligent investment in manufacturing enterprises. Based on the asset names and amounts listed under the fixed assets and intangible assets sections in the financial reports of publicly listed companies, manual collation is used to extract amounts related to AI investments. The intelligent investment level is then measured by calculating the proportion of the combined amounts of AI-related intangible assets and fixed assets to the total annual assets of the company. The intangible assets associated with enterprise intelligence transformation are those with names including keywords such as "intelligent," "software," "system," "information platform," or "data," while the relevant fixed assets include assets with names such as "electronic equipment," "computer," or "data equipment" (Zhang and Li 2022). This leads to the ISIR, representing the proportion of intangible assets related to intelligence transformation to total assets. A higher ISIR indicates a higher degree of intelligence transformation in the enterprise.

3.5.1 | Dependent Variable: GTFP

The GTFP index is an effective scientific tool for studying green development, and it is commonly employed to assess whether an economy is undergoing a transformation and upgrading toward greener practices (L. Chen et al. 2019). In line with Cui et al. (2023), this paper applies the SBM directional distance function and the whole-domain Malmquist-Luenberger productivity index, and incorporates the enterprise environmental pollution into the evaluation system to measure the enterprise GTFP. The input and output indicators of the enterprise GTFP are measured as follows. Labor input is measured by using the number of employees as a proxy variable; capital input is measured by using the net fixed assets of the enterprise; energy input is measured by using the industrial electricity consumption of the city where the enterprise is located, converted by the proportion of employees in the employment of urban workers in the city, as a proxy variable; business revenue is chosen as the desired output; the proportion of employees in the employment of urban workers in the city is chosen as the proxy variable for the "three industrial wastes"; and the proportion of employees in the employment of urban workers in the city is chosen as the proxy variable. The "three industrial wastes," that is, industrial sulfur dioxide, industrial wastewater, and industrial smoke and dust emissions, are converted as the proxy variables for the non-desired output of enterprises. The specific equation is shown in Equation (4) below:

$$\mathrm{GML}_{\mathrm{i}}^{\mathrm{t+1}}=\left\{\frac{\left[1+\vec{D}_0^{\,t}\left(x_i^t,y_i^t,b_i^t;p_i^t\right)\right]}{\left[1+\vec{D}_0^{\,t}\left(x_i^{t+1},y_i^{t+1},b_i^{t+1};p_i^{t+1}\right)\right]}\times\frac{\left[1+\vec{D}_0^{\,t+1}\left(x_i^t,y_i^t,b_i^t;p_i^t\right)\right]}{\left[1+\vec{D}_0^{\,t+1}\left(x_i^{t+1},y_i^{t+1},b_i^{t+1};p_i^{t+1}\right)\right]}\right\}^{\frac{1}{2}} \tag{4}$$

GML_i^{t+1} denotes the change in GTFP from time t to time $t+1$; $\vec{D}_0^{\,t}$ is a directional distance function that captures the distance of a firm's production activities from the production possibility boundary, taking into account both desired and non-desired outputs; and x_i^t, y_i^t, b_i^t represent the inputs of labor, capital, and energy, respectively; and p_i^t is a parameter related to environmental pollution (Zhang and Wang 2023). Combined with the GML index calculation, the GTFP index of A-share listed companies from 2010 to 2022, which can also be decomposed into the green technical efficiency change index (GEC) and the green technological progress change index (GTC), as shown in Equation (5):

$$GML_t^{t+1}=GEC_t^{t+1}\times GTC_t^{t+1} \tag{5}$$

GEC measures the change in green technology efficiency over time; when GEC > 1, it indicates an improvement in efficiency; when GEC < 1, it indicates a decrease in efficiency; GTC measures the change in the dynamics of green technology progress; when GTC > 1, it indicates an outward shift of the production frontier in the direction of an increase in desired output rather than a decrease in undesired output; when GTC < 1, it indicates a reversal of the direction of inward shift of the production frontier. When GML > 1, GTFP increases; when GML < 1, GTFP decreases.

3.5.2 | Mediating Variables: OFDI

Chinese accounting standards require listed companies to disclose information about their related companies. This article defines whether a listed company engages in FDI based on specific information about its related companies. The specific data comes from the CSMAR database on related-party transactions of Chinese listed companies, which provides basic information on related companies of Chinese listed enterprises, including their place of registration, registered capital (including currency type), relationships, and the proportion of equity controlled by the listed company.

In line with Liu et al. (2015) research, this article considers the following relationships: "subsidiaries of the listed company," "joint ventures of the listed company," and "associates of the listed company," where the related party's place of registration is outside mainland China, and the equity control ratio exceeds 10%. This is regarded as the listed company's FDI, leading to data on whether there is foreign investment, the number of foreign investments, and the amount of foreign investment. The variables in this data set relate to OFDI as follows: "FDInum" indicates the number of OFDI transactions, ranging from 0 to 6; "FDIsca" represents the monetary amount invested in these transactions, calculates the size of OFDI by OFDI enterprises in RMB for the year using the annual average official exchange

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rate provided by the World Bank; and "FDIsta" is a binary variable that shows whether the company has engaged in OFDI activities.

3.5.3 | Control Variables

This study comprehensively considers both internal and external characteristics of enterprises by selecting key variables as control variables. These include Size, Top1, ROA1, TobinQ, Growth, and Lev. These variables represent various aspects of enterprise performance and financial stability, from the enterprise's size and profitability to its market value, growth rate, and leverage. By considering these factors, the study provides a comprehensive understanding of how enterprises perform and maintain their stability (see Tables A2–A4 for the definition of variables, descriptive statistics, and cross-correlations).

TABLE 1 | Baseline regression (GTFP).

	(1)	(2)	(3)	(4)	(5)	(6)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP
IntellTr	0.0372***					
	(57.8050)					
IntellTra		0.0260***				
		(16.5685)				
ISIR			3.3669***			
			(28.1412)			
L.IntellTr				0.0375***		
				(54.4085)		
L.IntellTra					0.0276***	
					(15.6027)	
L.ISIR						3.7189***
						(27.6800)
Size	0.0919***	0.1146***	0.1155***	0.0937***	0.1166***	0.1181***
	(88.8168)	(112.0061)	(115.2067)	(82.4452)	(103.0334)	(106.7872)
Top1	−0.0025***	−0.0028***	−0.0026***	−0.0024***	−0.0027***	−0.0025***
	(−33.6858)	(−35.3988)	(−33.3828)	(−29.5651)	(−31.2269)	(−29.4366)
ROA1	−0.1728***	−0.1897***	−0.1561***	−0.1416***	−0.1690***	−0.1582***
	(−18.2809)	(−18.6002)	(−15.4677)	(−13.9661)	(−15.4365)	(−14.7090)
TobinQ	0.0065***	0.0069***	0.0063***	0.0054***	0.0057***	0.0056***
	(14.9452)	(14.5366)	(13.5337)	(11.1509)	(10.9949)	(10.8991)
Growth	−0.0171***	−0.0197***	−0.0201***	−0.0150***	−0.0201***	−0.0206***
	(−13.7020)	(−14.6252)	(−15.1269)	(−11.0356)	(−13.7291)	(−14.2623)
Lev	−0.0596***	−0.0820***	−0.0816***	−0.0797***	−0.1014***	−0.1058***
	(−12.4723)	(−15.9649)	(−16.0996)	(−15.1672)	(−17.8988)	(−18.9633)
_cons	−1.0682***	−1.4859***	−1.4962***	−1.1377***	−1.5634***	−1.5781***
	(−33.1532)	(−43.9797)	(−44.9899)	(−32.5676)	(−42.5871)	(−43.7512)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,414	21,414	21,336	18,661	18,661	18,551
R^2	0.610	0.546	0.561	0.593	0.524	0.542
Adj. R^2	0.546	0.471	0.489	0.520	0.438	0.459

Note: $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. *t* statistics in parentheses.

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4 | Empirical Results

4.1 | Baseline Results

The baseline regression analysis explores how the intelligent transformation of Chinese enterprises impacts GTFP and green technology efficiency change (GEC). Key indicators such as the frequency and proportion of intelligent terms in company annual reports, along with investment in intelligent software, demonstrate a statistically significant positive correlation with GTFP and GEC. This indicates that intelligent transformations contribute to sustainable growth in Tables 1 and 2. Additionally, lagged variables show a delayed yet consistent impact, suggesting a sustained influence on productivity. The findings

TABLE 2 | Baseline regression (GEC).

	(1)	(2)	(3)	(4)	(5)	(6)
	GEC	GEC	GEC	GEC	GEC	GEC
IntellTr	0.0372***					
	(57.8106)					
IntellTra		0.0257***				
		(16.3624)				
ISIR			3.4190***			
			(28.6224)			
L.IntellTr				0.0373***		
				(54.1555)		
L.IntellTra					0.0275***	
					(15.5162)	
L.ISIR						3.7141***
						(27.6680)
Size	0.0924***	0.1151***	0.1159***	0.0943***	0.1171***	0.1186***
	(89.3097)	(112.5182)	(115.8125)	(82.9796)	(103.5469)	(107.2792)
Top1	−0.0025***	−0.0028***	−0.0026***	−0.0024***	−0.0027***	−0.0025***
	(−33.7102)	(−35.4238)	(−33.4210)	(−29.5195)	(−31.1881)	(−29.4017)
ROA1	−0.1670***	−0.1839***	−0.1500***	−0.1361***	−0.1634***	−0.1530***
	(−17.6716)	(−18.0320)	(−14.8901)	(−13.4230)	(−14.9319)	(−14.2368)
TobinQ	0.0065***	0.0069***	0.0063***	0.0054***	0.0057***	0.0055***
	(14.9354)	(14.5291)	(13.4527)	(11.1214)	(10.9718)	(10.7856)
Growth	−0.0166***	−0.0192***	−0.0196***	−0.0146***	−0.0197***	−0.0201***
	(−13.3594)	(−14.3096)	(−14.7916)	(−10.7786)	(−13.4841)	(−13.8762)
Lev	−0.0582***	−0.0807***	−0.0802***	−0.0775***	−0.0991***	−0.1036***
	(−12.1907)	(−15.7049)	(−15.8435)	(−14.7521)	(−17.5077)	(−18.5803)
_cons	−1.0902***	−1.5083***	−1.5166***	−1.1619***	−1.5858***	−1.5986***
	(−33.8463)	(−44.6468)	(−45.6748)	(−33.2605)	(−43.2222)	(−44.3569)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,414	21,414	21,336	18,661	18,661	18,551
R^2	0.611	0.547	0.564	0.594	0.526	0.543
Adj. R^2	0.548	0.473	0.492	0.521	0.440	0.461

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *t* statistics in parentheses.

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TABLE 3 | Heckman regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
	IntTrDum	**GTFP**	**GEC**	**IntTrDum**	**GTFP**	**GEC**
Main						
IntellTr		0.0302***	0.0304***		0.0197***	0.0197***
		(46.0495)	(46.3769)		(32.4049)	(32.4970)
IVte	5.31e−06***					
	(14.5234)					
IVint				0.7525***		
				(24.1363)		
Size	0.2122***	0.0408***	0.0414***	0.1081***	0.0436***	0.0442***
	(12.2774)	(30.6615)	(31.1310)	(5.5588)	(40.7052)	(41.2610)
Top1	−0.0020*	−0.0018***	−0.0018***	0.0007	−0.0017***	−0.0017***
	(−1.7694)	(−24.3382)	(−24.4030)	(0.5841)	(−24.7810)	(−24.6569)
ROA1	0.5454*	−0.2274***	−0.2196***	1.4792***	−0.2059***	−0.1977***
	(1.9580)	(−23.8221)	(−23.0034)	(4.7445)	(−23.8255)	(−22.8871)
TobinQ	−0.0355***	0.0121***	0.0120***	−0.0641***	0.0095***	0.0094***
	(−3.1814)	(27.4010)	(27.1085)	(−5.2812)	(24.3664)	(24.1561)
Growth	−0.0287	−0.0103***	−0.0100***	−0.0209	−0.0058***	−0.0056***
	(−0.7180)	(−8.2795)	(−8.0560)	(−0.4855)	(−5.2390)	(−5.0359)
Lev	−0.6281***	0.0795***	0.0805***	−0.2538**	0.0356***	0.0344***
	(−6.5553)	(15.0133)	(15.2072)	(−2.3831)	(7.9014)	(7.6287)
imr		−0.7032***	−0.6991***		−0.3676***	−0.3668***
		(−59.5831)	(−59.2369)		(−88.7234)	(−88.5584)
_cons	−4.1473***	0.2402***	0.2065***	−6.2450***	0.2159***	0.1475***
	(−10.6709)	(6.1810)	(5.3144)	(−13.9368)	(4.0553)	(2.7719)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17,551	17,551	17,551	14,421	14,421	14,421
R^2		0.682	0.683		0.759	0.759
Adj. R^2	0.149	0.630	0.631	0.1971	0.716	0.716

Note: t statistics in parentheses.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

highlight that continued investment in intelligent technologies and strategic transformation measures play a crucial role in driving both immediate and long-term sustainable productivity for Chinese enterprises. Modern human capital theory suggests that, in comparison to unskilled labor, high-skilled labor possesses greater knowledge and professional expertise, making it more suitable for the intelligent transformation of enterprises. Additionally, it offers the necessary talent support for the extensive green innovation activities required for enhancing environmental performance (Galor and Moav 2000).

4.2 | Robustness Check

4.2.1 | Heckman Test

The fact that some enterprises have undertaken intelligent transformation without, however, disclosing it in their annual reports leads to a lack of observable data for certain samples. To mitigate this issue, the paper employs the Heckman two-stage method, with results presented in Table 3. In the first stage, a probit regression model is constructed to calculate the inverse Mills ratio (Imr),

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TABLE 4 | Robustness check: Excluding 2015 (China's stock market crash).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP	GEC	GEC	GEC	GEC	GEC	GEC
IntellTr	0.0379***						0.0379***					
	(56.4722)						(56.5089)					
IntellTra		0.0274***						0.0273***				
		(16.4080)						(16.3768)				
ISIR			3.3347***						3.4104***			
			(26.7966)						(27.4723)			
L.IntellTr				0.0355***						0.0351***		
				(48.9217)						(48.4068)		
L.IntellTra					0.0269***						0.0258***	
					(14.6648)						(14.0070)	
L.ISIR						3.5589***						3.5476***
						(24.7445)						(24.7631)
Size	0.0935***	0.1170***	0.1181***	0.0954***	0.1171***	0.1183***	0.0941***	0.1176***	0.1186***	0.0961***	0.1177***	0.1190***
	(87.1400)	(110.5227)	(113.9736)	(77.7133)	(96.9520)	(99.9330)	(87.7781)	(111.1763)	(114.7500)	(78.4166)	(96.7093)	(100.0362)
Top1	−0.0024***	−0.0028***	−0.0026***	−0.0024***	−0.0027***	−0.0025***	−0.0024***	−0.0028***	−0.0026***	−0.0024***	−0.0027***	−0.0025***
	(−31.9258)	(−33.6503)	(−31.6068)	(−27.9507)	(−29.4233)	(−27.9755)	(−31.8368)	(−33.5675)	(−31.5228)	(−27.9037)	(−29.3735)	(−27.8811)
ROA1	−0.1810***	−0.2022***	−0.1679***	−0.1328***	−0.1587***	−0.1486***	−0.1763***	−0.1975***	−0.1626***	−0.1307***	−0.1561***	−0.1465***
	(−18.3537)	(−18.9847)	(−15.9018)	(−12.7050)	(−14.0789)	(−13.3693)	(−17.8951)	(−18.5590)	(−15.4371)	(−12.5218)	(−13.9399)	(−13.2802)
TobinQ	0.0099***	0.0105***	0.0096***	0.0088***	0.0097***	0.0091***	0.0100***	0.0106***	0.0096***	0.0089***	0.0096***	0.0089***
	(19.5531)	(19.2235)	(17.6401)	(15.3152)	(15.6991)	(14.8596)	(19.7344)	(19.3903)	(17.7638)	(15.4246)	(15.5740)	(14.6091)
Growth	−0.0187***	−0.0215***	−0.0219***	−0.0159***	−0.0203***	−0.0211***	−0.0181***	−0.0210***	−0.0212***	−0.0151***	−0.0191***	−0.0198***
	(−14.1145)	(−15.0248)	(−15.4739)	(−10.5577)	(−12.4930)	(−13.1155)	(−13.6964)	(−14.6380)	(−15.0563)	(−10.0022)	(−11.8234)	(−12.3896)
Lev	−0.0632***	−0.0882***	−0.0894***	−0.0660***	−0.0862***	−0.0925***	−0.0626***	−0.0877***	−0.0887***	−0.0646***	−0.0835***	−0.0896***
	(−12.6217)	(−16.3867)	(−16.7971)	(−11.7120)	(−14.2595)	(−15.4561)	(−12.5157)	(−16.2903)	(−16.7211)	(−11.4790)	(−13.8449)	(−15.0497)
_cons	−1.1135***	−1.5480***	−1.5592***	−1.1839***	−1.5191***	−1.5370***	−1.1365***	−1.5710***	−1.5801***	−1.2112***	−1.6081***	−1.6206***
	(−33.5362)	(−44.4801)	(−45.4653)	(−30.3409)	(−45.0062)	(−46.2133)	(−34.2611)	(−45.1766)	(−46.1870)	(−31.0866)	(−39.3860)	(−40.3026)

(Continues)

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TABLE 4 | (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GTFP	**GTFP**	**GTFP**	**GTFP**	**GTFP**	**GTFP**	**GEC**	**GEC**	**GEC**	**GEC**	**GEC**	**GEC**
Industry FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,120	20,120	20,048	16,491	16,491	16,427	20,120	20,120	20,048	16,491	16,491	16,427
R^2	0.623	0.559	0.573	0.593	0.523	0.539	0.624	0.561	0.576	0.594	0.532	0.548
Adj. R^2	0.556	0.482	0.498	0.509	0.426	0.444	0.558	0.484	0.501	0.511	0.435	0.454

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. *t* statistics in parentheses.

testing whether common characteristics of listed companies influence the intelligent transformation dummy variable (IntTrDum). Due to the impact of fixed telephone and internet users on a company's intelligent transformation, the interaction term with 1984 telephone data and internet users of each city (IVte), along with the logarithm of broadband access ports (IVint), are selected as exclusion restriction variables (Zhang and Li 2022). Considering the correlation, the placement of post offices might influence the availability of landline telephones, which in turn could affect early Internet access and the subsequent widespread adoption and growth of the Internet (Huang et al. 2019). In the second stage, Imr is added as a control variable to Models 2–3 and 5–6, testing for selective errors affecting research conclusions. The results show that the Imr coefficient is significant at the 1% level, indicating selection bias. However, after controlling for Imr, the coefficient for intelligent transformation remains significantly positive, affirming the conclusion's validity despite sample selection bias.

Table 3 presents results from a Heckman two-stage model examining the impact of intelligent transformation on GTFP and GEC. The coefficients for "Intelligent Transformation" (IntellTr) in both Model (2) and Model (5) are positive and highly significant, indicating that as companies undergo intelligent transformation, their GTFP improves. This positive effect is robust across models, demonstrating that intelligent transformation has a meaningful and consistent influence on GTFP. Moreover, the significant and negative coefficients for the inverse Mills ratio (IMR) in these models indicate the presence of selection bias, which is accounted for in the analysis. This correction ensures that the relationship between intelligent transformation and GTFP is valid and not confounded by selection bias, reaffirming the positive impact of intelligent transformation on green productivity outcomes for companies.

4.2.2 | Other Robustness Check

Tables 4 and 5 provide robust regression models that explore the relationship between intelligent transformation (IntellTr and IntellTra) and GTFP. Two key robustness checks strengthen these findings. In Table 4, the exclusion of data from 2015 (see Wang, Chen, et al. 2023; Wang, Liu, et al. 2023), which corresponds to significant financial stock crises, maintains the positive relationship between intelligent transformation and GTFP. Table 5 incorporates additional fixed effects, such as company, enterprise, province, and city-level effects, further affirming the robustness of this relationship. Across various models, IntellTr and IntellTra consistently show positive and statistically significant associations with GTFP, demonstrating that intelligent transformation efforts contribute to enhanced green productivity. Additionally, factors such as ISIR and lagged variables of IntellTr and IntellTra show varying significance, adding depth to the relationship dynamics. This consistency indicates that intelligent transformation efforts steadily contribute to green productivity improvements, even when adjusting for external influences.

4.3 | Threshold Effect: OFDI

This paper also examines the relationship between intelligent transformation (IntellTr) in companies and their GTFP and

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TABLE 5 | Robustness check: Fixed effects model (individual firms, enterprises, provinces, and cities).

	(1)	(2)	(3)	(4)	(5)	(6)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP
IntellTr	0.0372***					
	(57.7850)					
IntellTra		0.0282***				
		(17.2856)				
ISIR			3.3650***			
			(28.0814)			
L.IntellTr				0.0351***		
				(50.6030)		
L.IntellTra					0.0271***	
					(15.1783)	
L.ISIR						3.5918***
						(26.7779)
Size	0.0919***	0.1146***	0.1156***	0.0936***	0.1149***	0.1160***
	(88.1786)	(111.1629)	(114.4242)	(78.5016)	(96.7333)	(99.8221)
Top1	−0.0025***	−0.0028***	−0.0026***	−0.0024***	−0.0027***	−0.0025***
	(−33.4922)	(−35.1228)	(−33.0535)	(−29.4366)	(−30.9711)	(−29.2407)
ROA1	−0.1688***	−0.1850***	−0.1516***	−0.1199***	−0.1426***	−0.1341***
	(−17.8352)	(−18.1272)	(−15.0029)	(−11.9278)	(−13.2037)	(−12.6249)
TobinQ	0.0064***	0.0067***	0.0062***	0.0048***	0.0051***	0.0053***
	(14.6624)	(14.2173)	(13.2629)	(9.8990)	(9.6534)	(10.1881)
Growth	−0.0174***	−0.0199***	−0.0204***	−0.0146***	−0.0185***	−0.0193***
	(−13.9502)	(−14.8083)	(−15.3703)	(−10.2630)	(−12.1829)	(−12.8397)
Lev	−0.0601***	−0.0825***	−0.0818***	−0.0631***	−0.0805***	−0.0851***
	(−12.5626)	(−16.0440)	(−16.1090)	(−11.7422)	(−13.9670)	(−14.9662)
_cons	−0.9796***	−1.3746***	−1.4231***	−1.0927***	−1.4812***	−1.5105***
	(−18.7844)	(−24.6736)	(−26.0191)	(−20.7577)	(−26.4855)	(−27.5457)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,414	21,414	21,336	17,596	17,596	17,529
R^2	0.615	0.552	0.567	0.586	0.521	0.539
Adj. R^2	0.550	0.477	0.494	0.505	0.428	0.449

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *t* statistics in parentheses.

GEC, with a focus on how this relationship is influenced by the scale of FDI (FDIsca). We applied the threshold effect defined by FDIsca, splitting companies into two groups: those with FDIsca below a threshold (γ1) and those with FDIsca equal to or above this threshold. The threshold test *p* values indicate this split is significant, emphasizing its relevance.

The threshold values for FDIsca are around 14.7677 and 9.5285 for the two models, with *p* values indicating that these thresholds are significant at the 0.05 level in Table 6. This implies that the scale of FDI divides companies into two distinct groups, which is meaningful in analyzing the effect of intelligent transformation on GTFP. This threshold regression analyzes the relationship

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TABLE 6 | Threshold regressions.

	(1)	(2)	(3)	(4)
	GTFP	GEC	GTFP	GEC
Size	0.0926***	0.0927***	0.1164***	0.1167***
	(37.5047)	(37.7522)	(44.3875)	(44.9613)
Top1	−0.0025***	−0.0025***	−0.0028***	−0.0028***
	(−16.7234)	(−16.6881)	(−17.0159)	(−17.0641)
ROA1	−0.1653***	−0.1591***	−0.1812***	−0.1751***
	(−11.0878)	(−10.6977)	(−10.9440)	(−10.6086)
TobinQ	0.0063***	0.0063***	0.0067***	0.0067***
	(8.7285)	(8.6272)	(8.3905)	(8.3253)
Growth	−0.0179***	−0.0173***	−0.0203***	−0.0197***
	(−11.2101)	(−10.6883)	(−12.0796)	(−11.5662)
Lev	−0.0644***	−0.0628***	−0.0877***	−0.0866***
	(−5.9508)	(−5.8480)	(−7.0741)	(−7.0350)
IntellTr (FDIsca < γ1)	0.0384***	0.0388***		
	(30.9656)	(30.8362)		
IntellTr (FDIsca ≥ γ1)	0.0343***	0.0339***		
	(24.5619)	(24.8060)		
IntellTra (FDIsca < γ1)			0.0261***	0.0260***
			(4.9808)	(4.7994)
IntellTra (FDIsca ≥ γ1)			0.0252***	0.0249***
			(4.7077)	(4.6283)
_cons	−1.0043***	−1.0065***	−1.4338***	−1.4431***
	(−18.8018)	(−18.9789)	(−24.6975)	(−25.0919)
N	20,827	20,827	20,827	20,827
R^2	0.610	0.612	0.543	0.544
adj. R^2	0.610	0.612	0.543	0.544
Firms	2864	2864	2864	2864
Threshold value	14.7677**	9.5285**	14.7677	9.5285*
Threshold test *p* value	0.022	0.008	0.130	0.087

Note: t statistics in parentheses.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

between intelligent transformation (IntellTr and IntellTra) in companies and their GTFP and GEC, with FDI (FDIsca) acting as a threshold variable. The data show a significant threshold effect, with a threshold value of 14.7677 for GTFP and 9.5285 for GEC, indicating that the impact of intelligent transformation on these indices differs between companies with FDIsca below and above these thresholds. For companies with FDIsca below γ1, the coefficients for IntellTr and IntellTra are positive and highly significant. This indicates that a higher degree of intelligent transformation corresponds to an increase in GTFP. The coefficients for IntellTr and IntellTra are 0.0384 and 0.0343, respectively. For companies with FDIsca equal to or above γ1, the coefficients remain positive and significant, but with lower values (0.0261 and 0.0252), suggesting the positive effect of intelligent transformation on GTFP diminishes slightly as the scale of OFDI increases, which is consistent with Zhang (2021) empirically testing the effect of digital trade openness on GTFP and finding that the growth of digital trade has a dampening effect on GTFP.

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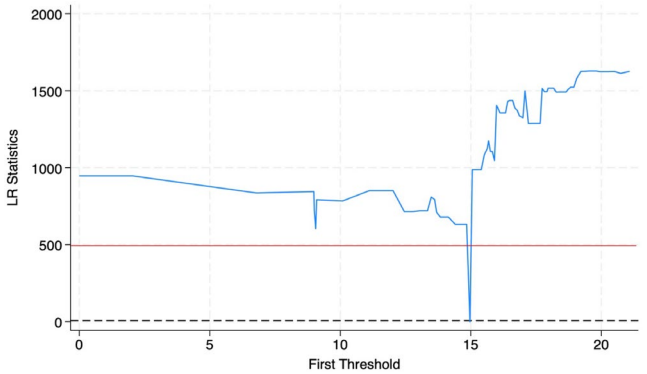


FIGURE 5 | Threshold-based LR statistics. [Color figure can be viewed at wileyonlinelibrary.com]

A threshold value of 14.7677 indicates that only firms with relatively high levels of outward investment—likely large and internationally competitive firms—experience a stronger positive effect of intelligent transformation on GTFP (Chen et al. 2023). This threshold may correspond to a substantial investment size in the context of China's outward FDI landscape, where most small and medium-sized enterprises (SMEs) engage in OFDI at much lower levels. Compared to macro-level averages, these threshold values suggest that only firms with sufficiently large OFDI can fully benefit from intelligent transformation in improving productivity. Digital industrial clusters—composed of leading firms and supporting institutions—have become global hubs of innovation, increasingly recognized by governments and international organizations (Zhang et al. 2024).

In conclusion, the data show that intelligent transformation positively affects GTFP, and this relationship is moderated by the scale of FDIsca, with a diminishing effect for companies with higher FDIsca. This highlights the importance of intelligent transformation in contributing to green productivity, even as FDI increases.

Figure 5 illustrates the likelihood ratio (LR) statistics for various threshold values of the FDIsca. The *x*-axis represents potential thresholds ranging from 0 to over 20, while the *y*-axis shows the LR statistics, indicating the statistical significance of these thresholds. A critical value line demonstrates the point above, where the LR statistics indicate a significant divide between companies with FDIsca below and above the threshold. For thresholds below 15, the LR statistics fluctuate but remain relatively stable. A sharp drop and subsequent rise around the threshold of 15 suggest a significant separation effect, reinforcing the importance of this threshold in dividing companies into two meaningful groups, which impacts how intelligent transformation affects green productivity measures such as GTFP and GEC. This visual representation confirms the threshold's role in moderating the relationship between intelligent transformation and green productivity.

4.4 | Moderating Effect

The moderating model examines the relationship between intelligent transformation (IntellTr) in companies and their GTFP, with a focus on how FDI variables influence this relationship.

In Table 7, the interaction terms between IntellTr and FDI variables indicate that as FDI status (FDIsta) and FDI number (FDInum) increase, the positive impact of intelligent transformation on GTFP diminishes. The interaction terms have negative coefficients (−0.0019 for FDIsta and −0.0008 for FDInum), highlighting a moderating effect of FDI variables on the relationship between intelligent transformation and green productivity. The relationship between intelligent transformation and GTFP is moderated by FDI variables. The negative interaction terms indicate that as FDI status and number increase, the positive impact of intelligent transformation on GTFP diminishes, suggesting a nuanced relationship influenced by external investments. In conclusion, the moderating effect shows that intelligent transformation has a positive relationship with GTFP, but this relationship is moderated by OFDI. Significantly, there is another result that the influence of FDI on environmental outcomes is nonlinear and is shaped by various factors, including human capital, environmental regulations, and intellectual property rights protection (Feng et al. 2019; Zeng et al. 2021).

4.5 | Heterogeneity Analysis

4.5.1 | OFDI and Non-OFDI

The heterogeneity analysis explores the impact of intelligent transformation on GTFP across companies with and without OFDI. OFDI Companies: For companies involved in OFDI (Models 1–3) in Table 8, both IntellTr and IntellTra show positive and significant associations with GTFP. For instance, in Model 1, IntellTr has a coefficient of 0.0308, and IntellTra shows a coefficient of 0.0312 in Model 2, both significant at the 1% level. This indicates that intelligent transformation contributes to higher GTFP for these firms. Non-OFDI Companies: In contrast, for companies not engaged in OFDI (Models 4–6), the coefficients for IntellTr and IntellTra are also positive and significant, but with different magnitudes. The coefficients for IntellTr and IntellTra are 0.0376 and 0.0246, respectively, demonstrating a nuanced impact on GTFP.

Generally, non-OFDI companies show slightly larger coefficients for IntellTr and IntellTra, indicating that the impact of intelligent transformation on GTFP might be stronger for companies focusing domestically. This suggests that companies not engaged in OFDI might realize more immediate gains in green productivity from their intelligent transformation efforts compared to those that expand internationally. In conclusion, the analysis shows that intelligent transformation positively impacts GTFP for both OFDI and non-OFDI companies, but the magnitude of this impact is greater for non-OFDI companies. This highlights the importance of considering a firm's international strategy when evaluating the benefits of intelligent transformation on green productivity.

4.5.2 | Heavily Polluting Industries

Table 9 examines the impact of intelligent transformation on GTFP in Chinese manufacturing companies, dividing the

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TABLE 7 | Moderating effect regressions.

	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
IntellTr	0.0373***	0.0378***	0.0372***	0.0376***
	(57.5976)	(54.0325)	(57.4024)	(55.3132)
FDIsta	−0.0163***	−0.0121***		
	(−11.2538)	(−4.5929)		
IntellTrxFDIsta		−0.0019*		
		(−1.9298)		
FDInum			−0.0065***	−0.0048***
			(−11.2624)	(−4.4080)
IntellTrxFDInum				−0.0008*
				(−1.9445)
Size	0.0923***	0.0923***	0.0923***	0.0923***
	(87.9284)	(87.9067)	(87.8824)	(87.8908)
Top1	−0.0024***	−0.0024***	−0.0024***	−0.0024***
	(−32.9219)	(−32.9160)	(−33.0088)	(−33.0080)
ROA1	−0.1618***	−0.1620***	−0.1605***	−0.1607***
	(−16.7076)	(−16.7312)	(−16.5707)	(−16.5872)
TobinQ	0.0061***	0.0061***	0.0061***	0.0061***
	(13.7673)	(13.7655)	(13.7134)	(13.7164)
Growth	−0.0179***	−0.0179***	−0.0180***	−0.0180***
	(−14.1440)	(−14.1193)	(−14.1745)	(−14.1791)
Lev	−0.0614***	−0.0615***	−0.0608***	−0.0609***
	(−12.5860)	(−12.6114)	(−12.4753)	(−12.4949)
_cons	−1.1018***	−1.1032***	−1.1049***	−1.1061***
	(−33.0857)	(−33.1232)	(−33.1928)	(−33.2252)
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
N	20,827	20,827	20,827	20,827
R^2	0.617	0.617	0.617	0.617
Adj. R^2	0.555	0.555	0.555	0.555

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. *t* statistics in parentheses.

analysis into heavily polluting and non-heavily polluting industries. The independent variables include the degree of intelligent transformation (IntellTr) and the proportion of ISIR, along with another metric related to transformation (IntellTra). For heavily polluting industries, IntellTr and IntellTra show a significant positive effect on GTFP, with coefficients of 0.0399 and 0.0557, respectively, indicating a stronger relationship. In non-heavily polluting industries, IntellTr and IntellTra also have positive and significant effects, though less pronounced, emphasizing the varying impacts of intelligent transformation strategies across different segments. The positive coefficients and higher values for heavily polluting industries demonstrate a stronger positive impact of intelligent transformation on GTFP in these companies. This underscores the critical role of intelligent transformation in driving GTFP, particularly in industries with significant environmental challenges.

4.5.3 | Regional Heterogeneity

Table 10 analyzes the impact of intelligent transformation on GTFP across China's manufacturing sector, divided into three regions: West, Middle, and East. In the Mid region, intelligent transformation (IntellTr) has a significant positive impact

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TABLE 8 | Heterogeneity analysis: OFDI and non-OFDI.

	(1)	(2)	(3)	(4)	(5)	(6)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP
		OFDI			Non-OFDI	
IntellTr	0.0308***			0.0376***		
	(24.9244)			(48.5564)		
IntellTra		0.0312***			0.0246***	
		(9.5320)			(13.3799)	
ISIR			2.4379***			3.9757***
			(12.9451)			(24.5754)
Size	0.0964***	0.1153***	0.1188***	0.0939***	0.1175***	0.1179***
	(42.4356)	(51.4681)	(54.3497)	(73.7277)	(93.0531)	(95.1496)
Top1	−0.0024***	−0.0026***	−0.0025***	−0.0025***	−0.0028***	−0.0025***
	(−15.7099)	(−16.4311)	(−16.1518)	(−28.4691)	(−29.3764)	(−26.8180)
ROA1	−0.1390***	−0.1444***	−0.1285***	−0.1583***	−0.1722***	−0.1354***
	(−7.4916)	(−7.3508)	(−6.5785)	(−14.0427)	(−14.1223)	(−11.2898)
TobinQ	0.0041***	0.0040***	0.0040***	0.0063***	0.0066***	0.0059***
	(4.5180)	(4.0793)	(4.1317)	(12.4426)	(12.1551)	(10.9881)
Growth	−0.0156***	−0.0163***	−0.0158***	−0.0173***	−0.0200***	−0.0204***
	(−6.1032)	(−6.0162)	(−5.8778)	(−11.7556)	(−12.6013)	(−13.0955)
Lev	−0.0241**	−0.0360***	−0.0448***	−0.0650***	−0.0867***	−0.0819***
	(−2.4025)	(−3.3995)	(−4.2429)	(−11.3771)	(−14.0900)	(−13.5468)
_cons	−1.0963***	−1.4669***	−1.5256***	−1.1698***	−1.5931***	−1.5957***
	(−17.7795)	(−23.2899)	(−24.6009)	(−28.3967)	(−36.6580)	(−37.4099)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5564	5564	5553	15,263	15,263	15,201
R^2	0.619	0.573	0.581	0.604	0.536	0.556
Adj. R^2	0.506	0.446	0.456	0.521	0.440	0.464

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. *t* statistics in parentheses.

on GTFP, with a coefficient of 0.1453 and a *t* value of 14.9103, suggesting a strong relationship. ISIR also contributes significantly, with a coefficient of 5.3525 and a *t* value of 10.8024, indicating another substantial positive impact. In the West and East regions, intelligent transformation also shows positive impacts on GTFP. In the West, IntellTr has a coefficient of 0.0413 with a *t* value of 25.1007, while IntellTra contributes positively with a coefficient of 0.0435 and a *t* value of 9.6185. In the East, IntellTr has a coefficient of 0.0340 and a *t* value of 45.1462, while IntellTra contributes positively with a coefficient of 0.0209 and a *t* value of 12.1283. The overall findings underscore the pivotal role of intelligent transformation in driving sustainable productivity across China's manufacturing sector, with a notably strong impact observed in the central region. This can be partly attributed to the "Rise of Central China" strategy (Jiang 2023), which has promoted industrial upgrading, encouraged technological innovation, and enhanced digital infrastructure in the region—creating a fertile ground for intelligent transformation. Spatially, this transformation follows a distinctive "One Core, Three Poles, and Multiple Strongholds" pattern—Beijing serves as the central core, while Shanghai, Shenzhen, and Hangzhou emerge as dynamic growth poles, supported by several other robust regional hubs (Zhang et al. 2024).

5 | Discussion of Results

For H1, the baseline regression suggests that intelligent transformation has a positive relationship with GTFP, reflecting its contribution to green productivity. Manufacturing, through

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TABLE 9 | Heterogeneity analysis: Heavily polluting industries in the manufacturing sector.

	(1)	(2)	(3)	(4)	(5)	(6)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP
	Heavily polluting industries in the manufacturing sector			Non-heavily polluting industries in the manufacturing sector		
IntellTr	0.0399***			0.0346***		
	(32.2553)			(46.0843)		
IntellTra		0.0557***			0.0227***	
		(11.6252)			(13.6442)	
ISIR			6.8061***			2.9554***
			(16.1528)			(24.5408)
Size	0.0947***	0.1209***	0.1239***	0.0918***	0.1120***	0.1122***
	(44.5433)	(57.7491)	(59.9587)	(76.6928)	(94.7929)	(97.2253)
Top1	−0.0026***	−0.0029***	−0.0028***	−0.0023***	−0.0026***	−0.0024***
	(−19.0887)	(−20.1401)	(−19.3037)	(−26.1072)	(−27.1890)	(−25.7026)
ROA1	−0.1425***	−0.1611***	−0.1139***	−0.1822***	−0.1983***	−0.1667***
	(−7.2878)	(−7.6240)	(−5.4561)	(−17.1275)	(−17.4195)	(−14.7673)
TobinQ	0.0080***	0.0083***	0.0062***	0.0059***	0.0061***	0.0059***
	(7.7224)	(7.4114)	(5.5581)	(12.3769)	(12.0056)	(11.9021)
Growth	−0.0181***	−0.0192***	−0.0208***	−0.0179***	−0.0210***	−0.0212***
	(−7.0594)	(−6.8997)	(−7.5938)	(−12.7487)	(−13.9807)	(−14.2619)
Lev	−0.1382***	−0.1787***	−0.1669***	−0.0117**	−0.0226***	−0.0278***
	(−14.6906)	(−17.7427)	(−16.8149)	(−2.0910)	(−3.7794)	(−4.6997)
_cons	−1.0631***	−1.5595***	−1.6074***	−1.0182***	−1.3712***	−1.3885***
	(−19.4191)	(−27.6480)	(−28.8043)	(−21.8917)	(−27.9639)	(−28.8443)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6061	6061	6024	15,353	15,353	15,312
R^2	0.582	0.511	0.531	0.625	0.571	0.584
Adj. R^2	0.513	0.430	0.452	0.561	0.497	0.513

Note: $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. *t* statistics in parentheses.

intelligent transformation, can usually enhance efficiency and environmental performance because intelligent technologies can use resources more effectively, reduce waste and emissions, thereby improving GTFP. This includes adopting automated, informatized, and efficient production technologies. The research findings are consistent with previous similar studies. Intelligent manufacturing (IM) has emerged as a key strategy for technological advancement and industrial competitiveness across various nations. In China, which boasts the largest manufacturing infrastructure globally, the government has actively implemented numerous industrial policies to promote and support the intelligent transformation of manufacturing enterprises (Wei et al. 2024).

For H2, the threshold model shows that the positive effect of intelligent transformation on GTFP diminishes slightly as the scale of OFDI increases. The negative interaction terms indicate that as FDI status and number increase, the positive impact of intelligent transformation on GTFP diminishes. The intelligent transformation of the manufacturing industry positively impacts GTFP; however, this benefit is reduced as the scale of enterprises' OFDI increases. As firms expand their foreign investments, they may shift parts of their production to countries with more lenient environmental regulations or to less technologically advanced regions, potentially causing a decrease in overall GTFP. This "pollution haven" effect can undermine the positive impacts of intelligent transformation on environmental and production efficiency. Moreover, OFDI can present several risks and challenges. It might contribute to resources and brain drain, which can impact the economic growth of the home country (Buckley and Casson 1998; Driffield and

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TABLE 10 | Regional heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP	GTFP
		West			Mid			East	
IntellTr	0.0413***			0.0445***			0.0340***		
	(25.1007)			(25.1049)			(45.1462)		
IntellTra		0.0435***			0.1453***			0.0209***	
		(9.6185)			(14.9103)			(12.1283)	
ISIR			4.7380***			5.3525***			3.0535***
			(10.6378)			(10.8024)			(24.3776)
Size	0.1010***	0.1272***	0.1304***	0.0925***	0.1144***	0.1256***	0.0885***	0.1085***	0.1085***
	(39.0029)	(50.6843)	(51.3200)	(30.8548)	(38.2646)	(42.7138)	(72.5291)	(89.6112)	(91.9583)
Top1	−0.0018***	−0.0021***	−0.0021***	−0.0026***	−0.0028***	−0.0026***	−0.0027***	−0.0030***	−0.0028***
	(−9.4992)	(−10.2883)	(−9.9047)	(−12.4632)	(−12.7817)	(−11.7192)	(−31.2041)	(−32.8055)	(−31.1049)
ROA1	−0.1386***	−0.1479***	−0.1148***	−0.1400***	−0.1627***	−0.1501***	−0.1791***	−0.1946***	−0.1589***
	(−5.6884)	(−5.6123)	(−4.3483)	(−5.1398)	(−5.5616)	(−5.1105)	(−16.3846)	(−16.6391)	(−13.6972)
TobinQ	0.0046***	0.0046***	0.0047***	0.0123***	0.0125***	0.0105***	0.0054***	0.0058***	0.0057***
	(4.0838)	(3.8147)	(3.8487)	(10.3915)	(9.8416)	(8.1348)	(10.5448)	(10.5125)	(10.4492)
Growth	−0.0194***	−0.0205***	−0.0227***	−0.0124***	−0.0144***	−0.0148***	−0.0186***	−0.0213***	−0.0216***
	(−6.4981)	(−6.3461)	(−6.9859)	(−3.9201)	(−4.2602)	(−4.3637)	(−12.2744)	(−13.1485)	(−13.4866)
Lev	−0.0472***	−0.0727***	−0.0725***	−0.1572***	−0.1895***	−0.1802***	−0.0350***	−0.0520***	−0.0549***
	(−3.8071)	(−5.4364)	(−5.4233)	(−12.4452)	(−14.0684)	(−13.2259)	(−6.1965)	(−8.6335)	(−9.2441)
_cons	−1.3239***	−1.8408***	−1.9191***	−1.0931***	−1.4992***	−1.7221***	−0.9762***	−1.3270***	−1.3348***
	(−16.5417)	(−22.1759)	(−23.2235)	(−12.7583)	(−16.7916)	(−19.3665)	(−26.9533)	(−35.1179)	(−36.0446)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3581	3581	3551	2787	2787	2763	15,040	15,040	15,016
R^2	0.616	0.551	0.556	0.618	0.559	0.554	0.619	0.563	0.577
Adj. R^2	0.554	0.479	0.484	0.559	0.490	0.485	0.553	0.488	0.505

Note: $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. *t* statistics in parentheses.

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Girma 2003). Furthermore, OFDI can be subject to legal, political, and financial uncertainties, creating instability (Agosin and Machado 2005; Yang et al. 2016).

For H3, intelligent transformation positively affects GTFP for both OFDI and non-OFDI companies, with non-OFDI firms seeing a stronger impact, suggesting greater green productivity benefits for non-OFDI companies. Additionally, intelligent transformation has a greater positive impact on GTFP in heavily polluting sectors. The regional heterogeneity results highlight the significant role of intelligent transformation in promoting sustainable productivity across China's manufacturing sector, with particularly strong influences in the middle region. First, firms not engaged in OFDI may concentrate more resources and investment in the domestic market, including in intelligent technologies and environmental measures. This focused investment enables these companies to implement technological upgrades and optimize production processes more effectively, thereby achieving better outcomes in production efficiency and environmental performance. In contrast, enterprises engaged in OFDI may need to disperse their attention and resources across multiple countries and regions, which could lead to a relative decrease in domestic investments in intelligence and environmental protection. Additionally, these enterprises' operations abroad might face varying environmental regulations and production conditions, which could impact their improvements in GTFP. Second, intelligent transformation has a distinct impact on heavily polluting industries, such as chemicals, steel, and paper manufacturing. Due to the high energy consumption and emissions in their production processes, there is a pressing need for environmental technologies and efficient production techniques. Intelligent transformation enhances resource efficiency, reduces waste and emissions, and significantly boosts GTFP in these industries, reflecting the critical role of intelligent technologies in addressing environmental issues. Finally, the impact of intelligent transformation varies by region, particularly noticeable in the central areas of China. This variation is linked to the industrial structure of the region, support for environmental policies, and the adaptation and adoption of intelligent and environmental technologies. The central region may place a higher emphasis on upgrading manufacturing and environmental protection, thus investing more in intelligent transformation, which results in more significant gains in production efficiency and environmental benefits.

Finally, one limitation of the study might be the exclusive focus on A-share listed manufacturing firms, which may not fully represent the broader industrial landscape in China. As such, smaller enterprises and private firms not listed on the stock exchange are excluded from the analysis. These firms may have different digital adoption capabilities, OFDI behaviors, and environmental practices, which could affect the generalizability of the findings. Future research could expand the sample scope to include non-listed and private-sector firms to provide a more comprehensive understanding of the relationship between intelligent transformation, OFDI, and green productivity across diverse enterprise types.

6 | Conclusion

Given the rapid development of intelligent transformation and the increasing importance of green growth in the manufacturing industry, it is critical to investigate how the intelligent shift influences green productivity growth in the manufacturing industry. The study's findings provide compelling evidence that intelligent transformation is a critical driver of GTFP in the manufacturing industry. By implementing advanced technologies and innovative practices, firms not only enhance their operational efficiency but also contribute significantly to environmental sustainability. Furthermore, this study makes an important theoretical contribution by extending EMT, addressing its underexplored hypothesis on the relationship between technological innovation and environmental impacts. By empirically demonstrating how intelligent transformation drives green productivity, this research provides new insights into EMT, which traditionally focuses on quantitative and theoretical discussions. The positive association between intelligent transformation and GTFP was consistent across various robustness checks, reinforcing the robustness of the results. Intelligent transformation proves particularly beneficial for non-OFDI companies, which experience a more pronounced increase in GTFP. This suggests that firms focusing on domestic markets and operations might gain more from green technologies and practices compared to those engaged in overseas direct investments. Moreover, the impact of intelligent transformation on GTFP is more substantial in heavily polluting sectors, highlighting its potential as a critical lever in mitigating environmental impacts within these high-risk industries. The regional analysis further underscores the significant role of intelligent transformation in promoting sustainable productivity across different areas of China, with the middle region showing especially strong effects. This regional heterogeneity indicates that local economic conditions and industrial policies play crucial roles in the effectiveness of intelligent transformation initiatives.

This paper has several practical and policy implications. For policymakers, the results suggest that supporting intelligent transformation initiatives in manufacturing can be an effective strategy to enhance GTFP and achieve sustainability goals. Policies that encourage the adoption of smart technologies and practices in heavily polluting industries and non-OFDI firms could be particularly impactful. For businesses, the findings indicate that investing in intelligent transformation not only complies with global sustainability standards but also enhances productivity and operational efficiency. Companies, especially those in regions with less developed infrastructure, stand to benefit significantly from tailored strategies that align with regional capabilities and growth objectives.

Governments should enact stringent environmental regulations and enforce these standards among both domestic and international businesses, incentivizing the adoption of green technologies through tax reliefs and subsidies. They should promote international environmental cooperation, establish common environmental standards with other countries, and include environmental clauses in trade agreements. Furthermore, governments should invest in the development and commercialization of green technologies, supporting collaborations between universities and businesses to accelerate the application and widespread adoption of environmental technologies. It is recommended to promote internationally recognized environmental standards and certification systems, such as green labels, to enhance the international competitiveness of products.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A

TABLE A1 | Dimensions and associated keywords for intelligent transformation.

Dimension	Keywords
Intelligent Technology	Intelligentization, Intelligent Digitization, Intelligent Manufacturing, Intelligent Enterprise, Intelligent Recognition, Smart Terminal, Robots, Industry 4.0, Sensing Technology, Human-Machine Interaction
Digital and Network Technology	Digitization, Networking, Informatization, Cloud Computing, Cloud Platform, Internet of Things, Cyber-Physical System, Network Physical System, Big Data, Data Visualization
Automation and Manufacturing	Automation, Cloud Manufacturing, Proactive Manufacturing, Smart Manufacturing, Industrial Internet, Internet+, Sensors, Controllers, Data Mining

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TABLE A2 | Definition of Variables.

Variable type	Variable name	Variable symbol	Variable definition
Independent variable	Intelligent Transformation Index	IntellTr	Intelligent word frequency plus 1 to take the logarithm
		IntellTra	The ratio of intelligent word frequency to the total number of words in the annual report is multiplied by 1000
		ISIR	Intelligent software investment proportion
Dependent variable	Green Total Factor Productivity Index	GTFP	Green total factor productivity
		GEC	Green Technology Efficiency Change Index
Mediating variables	OFDI Index	FDInum	Foreign Direct Investment Number
		FDIsca	Foreign Direct Investment Scale (Calculate the size of OFDI by OFDI enterprises in RMB for the year using the annual average official exchange rate provided by the World Bank) (Liu et al. 2015)
		FDIsta	Foreign Direct Investment Status
Control variable		Size	Enterprise size
		Top1	Number of shares held by the largest shareholder/total number of shares
		ROA1	Net profit divided by average total assets
		TobinQ	Tobin's *Q* value
		Growth	Operating income growth rate
		Lev	Assets and liabilities

TABLE A3 | Descriptive statistics.

Descriptive statistics									
Variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**p1**	**p99**	**Skew.**	**Kurt.**
GTFP	21,755	1.018	0.099	0.8	1.176	0.813	1.172	−0.367	2.032
GEC	21,755	1.018	0.099	0.8	1.176	0.813	1.171	−0.363	2.025
IntellTr	21,755	2.22	1.254	0	7.209	0	5.342	0.16	2.85
IntellTra	21,755	0.363	0.843	0	21.085	0	3.544	10.625	179.459
ISIR	21,673	0.003	0.006	0	0.061	0	0.033	5.175	38.561
FDInum	21,142	0.501	1.094	0	6	0	6	3.007	13.038
FDIsca	21,142	4.312	7.366	0	21.091	0	21.091	1.213	2.636
FDIsta	21,142	0.267	0.443	0	1	0	1	1.052	2.107
Size	21,755	22.082	1.176	19.585	26.452	19.997	25.659	0.785	3.7
Top1	21,755	33.184	14.055	8.02	75.843	9	71.315	0.557	2.854
ROA1	21,755	0.043	0.066	−0.373	0.247	−0.175	0.215	−0.881	8.111
TobinQ	21,415	2.139	1.374	0.802	15.607	0.879	7.974	2.896	15.302
Growth	21,754	0.17	0.38	−0.658	4.024	−0.467	1.812	3.432	25.105
Lev	21,755	0.399	0.192	0.027	0.908	0.059	0.864	0.243	2.346

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TABLE A4 | Cross correlations: Pearson correlation.

	(1)												
	GTFP	**IntellTr**	**IntellTra**	**ISIR**	**FDInum**	**FDIsca**	**FDIsta**	**Size**	**Top1**	**ROA1**	**TobinQ**	**Growth**	**Lev**
GTFP	1.000												
IntellTr	0.427***	1.000											
IntellTra	0.109***	0.597***	1.000										
ISIR	0.159***	0.233***	0.124***	1.000									
FDInum	−0.084***	0.024***	−0.000	0.053***	1.000								
FDIsca	−0.061***	0.027***	0.002	0.042***	0.791***	1.000							
FDIsta	−0.073***	0.026***	0.004	0.046***	0.758***	0.969***	1.000						
Size	0.141***	0.099***	−0.025***	−0.022***	0.164***	0.157***	0.115***	1.000					
Top1	−0.114***	−0.037***	−0.033***	−0.035***	0.049***	0.029***	0.032***	0.105***	1.000				
ROA1	−0.020***	0.034***	−0.005	−0.106***	0.029***	0.014**	0.015**	0.054***	0.144***	1.000			
TobinQ	0.006	−0.055***	0.010	0.045***	−0.065***	−0.070***	−0.057***	−0.305***	−0.062***	0.208***	1.000		
Growth	−0.039***	0.015**	0.001	−0.035***	0.011	0.005	0.012*	0.064***	0.012*	0.289***	0.066***	1.000	
Lev	−0.035***	−0.010	−0.012*	−0.003	0.082***	0.078***	0.062***	0.453***	−0.006	−0.361***	−0.218***	0.046***	1.000

*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

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Unveiling synergies: the mediating role of China's OFDI and intelligent transformation in advancing green total factor productivity

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