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Research paper

The Impact of AI and Information Disclosure Quality on Manufacturers' TFP

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Abstract

Artificial intelligence (AI) has emerged as a pivotal driver in promoting the efficiency of economic growth. The existing studies have predominantly focused on macro- or cross-industry perspectives, and research targeting manufacturers remains relatively limited. This study, based on data from Chinese manufacturing enterprises, elaborates on the impact of AI on total factor productivity (TFP) to address the role of information disclosure quality (IDQ) in this relationship from a non-technical perspective. The findings indicate that AI significantly promotes TFP in manufacturing, a conclusion that holds through a series of robustness checks. And the underlying mechanisms of such promotion lie in increased R&D investment and enhanced innovation output. Heterogeneity analysis reveals that the positive effect of AI is more pronounced in younger manufacturers and those with lower tax burdens. Further analysis suggests that high-quality information disclosure amplifies the productivity-enhancing effect of AI. These findings provide new empirical evidence for understanding the effectiveness of AI applications in manufacturing in an information context, and offer insights for policy-making aimed at advancing intelligent manufacturing transformation, particularly in countries where manufacturing plays a vital role in the national economy.

Keywords: *Artificial Intelligence(AI); Total Factor Productivity(TFP); Information Disclosure Quality(IDQ); Manufacturer.*

1. Introduction

The rapid development of Artificial Intelligence (AI) technology in recent years has lifted AI as a new driving force behind technological breakthroughs, and industrial transformation and upgrading. With its shift from laboratory research to practical application, it has exerted profound impacts on reshaping traditional production models, optimizing resource allocation, and enhancing economic operational efficiency, making a significant contribution to the global economy and social activities [1], [2]. Against the backdrop of the current global economic slowdown, more and more countries have recognized AI as a key engine for new economic growth points and economic expansion. In the global technology ecosystem, proprietary models such as GPT-4 and Sora dominate the technological roadmap of general-purpose language models worldwide. In China, AI development stresses the integration of open-source collaboration and industrial application, providing easy access to the intelligent upgrading of various industries. In this context, it is of great significance to dig into AI's impact on the economy, a rising hot topic in today's academic research.

Previous studies have examined the economic impacts of AI from multiple perspectives. However, most of them focus on macroeconomic growth [2], employment structure adjustments [3], [4], and income distribution [5], or investigate the effect of AI on total factor productivity (TFP) from an industry-wide approach [6], [7], leaving micro-level empirical evidence concerning AI's impact on TFP in manufacturing enterprises relatively ignored. The case is particularly true in China, where manufacturing serves as a cornerstone of the national economy, and much has yet to be done to effectively leverage AI technologies to enhance TFP throughout the intelligent transformation of manufacturing.

Additionally, more studies focus on the impact of AI from a technical perspective, keeping non-technical research in the dark [8], [9]. Prior studies find that information disclosure quality (IDQ) plays a crucial role in enterprise investment, innovation, and performance [10], [11], [12]. Improved IDQ not only mitigates information asymmetry between enterprises and external stakeholders but also builds on investor confidence and financing conditions, thereby providing more stable resource support for technological innovation. Thus, in the context of deepening integration between AI and corporate management practices, it is promising to elaborate on the potential reinforcing effect of IDQ [13], [14].

In view of the foregoing discussion, this study, based on the textual information related to AI from the annual reports of Chinese manufacturing listed companies, constructs a specialized lexicon and quantifies the extent of AI adoption to determine a manufacturer AI development indicator to find out the impact of AI on TFP and its underlying mechanisms. The findings indicate that AI significantly enhances manufacturers' TFP, a result that holds after a series of robustness tests. Furthermore, this study identifies that the increased R&D investment and innovation output serve as important mechanisms through which AI promotes TFP. Heterogeneity analysis finds that the positive effect of AI on TFP is more pronounced among younger manufacturers and those with lower tax burdens. More importantly, the results

also show that higher IDQ significantly strengthens the TFP-enhancing effect of AI, suggesting that a transparent information environment facilitates the full realization of AI's technological benefits.
The marginal contributions of this study are threefold. First, the study, which focused on manufacturing, a typical domain for technology application, offers a novel micro-level evidence from the Chinese context on the productivity-enhancing effects of AI, thereby strengthening the empirical support for the economic consequences of AI. Second, the study goes beyond the purely technical practice prevalent in existing research and introduces IDQ as a non-technical factor to reveal its significant role in amplifying the relationship between AI and TFP, offering a fresh analytical perspective and empirical support for future studies. Third, the findings from manufacturers in China are based on the inherent logic and mechanism that ensure broader applicability. Specifically, AI boosts TFP by directing R&D investments and enhancing innovation output, and high IDQ helps firms strengthen AI's productivity effects. They offer valuable insights for economies seeking to enhance manufacturing productivity through intelligent transformation and information environment development.

2. Literature Review

AI, as a key driving force behind the new wave of industrial transformation, plays a critical role in improving manufacturers' TFP when a deep integration is available [6], [7]. Some studies suggest that while TFP growth stems primarily from technological progress and efficiency improvements, AI, in contrast, largely reshapes the innovation paradigms and production processes of manufacturing enterprises, thereby creating new conditions for expanding the production possibility [15]. Most studies examine the economic effects of AI through a macro-level or economy-wide analysis, leaving a great potential for micro-mechanism research focused specifically on manufacturing—a typical technology application scenario [16]. In the context of ongoing transformation and upgrading in China's manufacturing industry, it is of theoretical and practical significance to further investigate the impact of AI on the TFP of manufacturers. This study, based on the operational characteristics of manufacturing enterprises, extends the research in two dimensions: AI-enabled empowerment and the synergistic role of the information disclosure environment.
Previous studies hold that the positive impact of AI on TFP is primarily materialized in enhancing technological innovation capability [17]. First, AI significantly promotes both the willingness and efficiency of resource allocation in corporate R&D, the capacity of which is a key determinant of its sustained competitive advantage [18]. Through machine learning and deep learning algorithms, AI can collect, process, and analyze market information, enabling accurate identification of market demands and technological opportunities. This helps reduce uncertainties and mitigate the risks of sunk costs in the R&D process [19]. From an accounting perspective, the integration of AI technology with information disclosure can have profound implications for a manufacturer's cost management practices, as AI optimizes resource allocation and allows for precise control of production parameters, thereby streamlining both R&D and administrative processes, like intelligent project management systems that allow real-time monitoring and dynamic adjustment of R&D progress, whereby minimizing resource waste and improving the efficiency of R&D resource allocation. This increase in management efficiency encourages firms to expand their R&D expenditures, thereby accumulating technological capital that contributes to TFP growth.
AI facilitates the immediate transformation of technological achievements into outputs by enhancing the efficiency of innovation production. Studies indicate that AI meets the three criteria of a General-Purpose Technology (GPT): it is pervasive, capable of enabling sustainable innovation, and inducing complementary innovations across various application scenarios [20]. Within this framework, manufacturers can utilize AI-aided design technologies to shorten R&D cycles and reduce trial-and-error costs in product design. Additionally, AI-powered knowledge management allows manufacturers to systematically restructure and reuse both internal innovation information and external intelligence, helping to avoid redundant R&D efforts and accelerating technological iteration and convergence [21]. As a result, AI not only enhances the efficiency of innovation resource utilization but also broadens and deepens the technological portfolio of manufacturing enterprises. These outcomes are ultimately reflected in increased patent outputs, thereby fully unleashing the potential of AI to boost TFP.
It is noteworthy that the effective deployment of AI technologies relies not only on the technology itself but is also profoundly shaped by the manufacturers' internal and external information scenario [22], [23]. Among other things, information disclosure quality (IDQ), a critical non-technical element, may promote the positive effect of AI on TFP.
First, high IDQ sends positive messages to the market regarding a producer's technological and governance capability, enhancing external investor confidence. This helps alleviate financing constraints for AI-related innovation activities, thereby providing stable funding support for technology development and industrial application [24]. Second, information disclosure as a crucial part of internal corporate governance, once improved, strengthens oversight from society, shareholders, and the board of directors over management, curbing short-termist operations [25], [26] and encouraging a stronger focus on the long-term value of AI projects. This leads to better allocation of R&D resources and higher innovation efficiency. Moreover, a robust disclosure mechanism facilitates knowledge sharing and cross-department collaboration within manufacturers [27], enhancing the integration and coordination of AI technologies across operational units and laying a foundation for further TFP gains. Finally, elevated disclosure quality helps manufacturers build up a more favorable external cooperative environment and promote resource acquisition capabilities. Based on signaling theory, high-quality disclosures convey positive signals about a company's technological competence and developmental momentum to potential innovation partners. This enhances the credibility of AI-related information released by the manufacturers and boosts partners' confidence, thereby reducing collaboration costs [28].
Under these conditions, manufacturers gain access to richer external knowledge sources and technical resources, making it easier to leverage AI technologies and generate innovative outcomes. Therefore, the combination of AI technology and a high-quality information environment—fostered by transparent disclosure—can further accelerate technological iteration and output transformation, effectively amplifying the productivity dividends of AI. Furthermore, from an accounting standpoint, high IDQ—synonymous with greater transparency—allows AI-active firms to more credibly convey their technological progress and profit potential to the market [29,30], thereby mitigating investor and creditor risk perceptions and improving financing terms [31]. Placing AI, IDQ, and efficiency within a unified framework thus allows this research to simultaneously examine AI's productivity gains and address the fundamental accounting question of its impact on information quality and its ensuing economic effects.
Based on the above analysis, this study proposes the following hypotheses:
H1: AI promotes the TFP of manufacturing enterprises.
H2: IDQ positively moderates the interplay between AI and TFP.

3. Data And Methodology

3.1. Data sources

The samples of this study are collected from A-share listed companies on the stock exchanges from 2007 to 2023. The year 2007 was chosen as the starting point, given that, as stated in the 2017 China Artificial Intelligence Industry Research Report, the current wave of AI development is largely attributed to the introduction of deep learning algorithms in 2006, which laid the foundation for contemporary advances in AI. The basic and financial data of Manufacturing enterprises are primarily sourced from the China Stock Market & Accounting Research Database (CSMAR). To ensure data quality, the samples, in line with established research practices [32], [33], were processed as follows: (1) only manufacturers were selected; and (2) those under Special Treatment (ST) or *ST status each year were excluded.

3.2. Variable definitions

3.2.1. Dependent variable

Total Factor Productivity (TFP). Following the approach of Olley and Pakes (1996) [34], the manufacturer TFP is calculated through the method proposed by Olley and Pakes (OP method), and the methodology of Levinsohn and Petrin (2003) (LP method) is adopted for robustness checks. In terms of variable determinant, enterprise output is represented by the natural logarithm of total sales; labor input by the natural logarithm of the number of employees; and capital input by the natural logarithm of net fixed assets. The approach of Olley and Pakes (1996) [35] also involves an investment index, which is captured by the natural logarithm of cash spent on intangible assets and other long-term assets.

3.2.2. Independent variable

Artificial Intelligence (AI). Drawing upon the methodology of previous studies [36], the extent of AI application by enterprises is measured by the frequency of AI-related keywords in their annual reports, a critical source for investors to assess a company's operational performance and strategic orientation. AI, as a transformative technology, empowers technological and industrial upgrading and competitive advantage, endowing listed companies with strong incentives to disclose their AI development and application activities in annual reports to win over investor support. Moreover, under regulatory requirements for information disclosure and reporting quality, the frequency of AI-related terms in such reports highlights the importance of AI in the company's operations and management. Therefore, this study takes the count of AI-related words in the annual reports of listed companies to proxy for the level of AI development. In the empirical model, the variable is transformed by taking the natural logarithm of one plus the raw keyword count.

This study measures the level of AI development by adopting mainstream text analysis methods [36]. First, drawing upon authoritative industry reports (such as the 2024 Report on AI Status Quo and Development Trend by Shenzhen Qianzhan Industry Research Institute) with international organization standards like AI terminologies of WIPO, we systematically compiled a foundational lexicon of core terms. This initial lexicon includes keywords such as "artificial intelligence," "machine learning," "Internet of Things," "cloud computing, etc." Subsequently, the raw keyword frequencies extracted from annual reports underwent a two-step refined cleaning process: (1) eliminating instances where keywords were preceded by negations to ensure the capture of genuine AI adoption, and (2) excluding AI terms describing non-firm entities, thereby focusing the analysis on the firm's own AI activities. Finally, the cleaned, valid keywords were summed to construct a firm-level AI word frequency measure, which was then transformed by taking the natural logarithm of (1 + the total count) in our empirical models.

3.2.3. Moderating variable

Information Disclosure Quality. The Shenzhen Stock Exchange, considering the evaluation criteria based on the information disclosure regulations for listed companies, comprehensively assesses the quality of information disclosure throughout the year—covering both mandatory and voluntary disclosures—across multiple dimensions, including completeness, truthfulness, timeliness, accuracy, fairness, and compliance. Therefore, this study, following previous studies [37], employs the IDQ rating (Grade) of the Shenzhen Stock Exchange to measure disclosure quality. The overall rating is divided into four levels from highest to lowest: "Excellent," "Good," "Pass," and "Fail" with assigned values of 4, 3, 2, and 1, respectively.

3.2.4. Control variable

To mitigate endogeneity concerns arising from omitted variables, this study, drawing upon previous research [38,39], chooses the following control variables: leverage ratio (LEV), return on total assets (ROA), the proportion of fixed assets to total assets (FIXED), management expense ratio (MFR), company size (SIZE), cash flow ratio (Cashflow), and ownership structure (OS). Company size is measured by the natural logarithm of the number of employees, and ownership structure by the percentage of shares held by the largest shareholder.

3.3. Methodology

To examine the impact of AI on manufacturers' TFP, the following empirical model is specified:

$$TFPi,t = \alpha + \alpha 1AIi,t + \sum_{i=1}^{n=7} \beta iCONTROLi,t + year + firm + \delta\, i,t \tag{1}$$

In Equation (1), $TFP_{i,t}$ denotes TPF, α the constant term, $AI_{i,t}$ the artificial intelligence measure, and $CONTROL_{i,\,t}$ the set of control variables. α_1 and β_i are regression coefficients, year and firm represent year and firm fixed effects, and δi,t represents the idiosyncratic error term.

To analyze the impact of AI on TFP from the perspective of IDQ, the baseline model is extended by incorporating both the disclosure quality measure and its interaction term with AI. To mitigate potential multicollinearity concerns before introducing the interaction term, both the AI variable and the IDQ variable are mean-centered following [40]. The extended model is specified as follows:

$$TFPi,t = \alpha + \alpha1AIi,t + a2IDQi,t + a3AI \times IDQi,t + \sum_{i=1}^{n=7} \beta iCONTROLi,t + year + firm + \delta\, i,t \quad (2)$$

In Equation (2), $IDQ_{i,t}$ denotes the information disclosure quality, and $AI \times IDQ_{i,t}$ represents the interaction term between AI and IDQ, and α_2 and α_3 are regression coefficients.

4. Data Analysis and Discussion

4.1. Descriptive statistics

Figure 1 presents the time-varying trends of the average AI word frequency and the average TFP among A-share manufacturers each year. It can be observed that both the average AI word frequency and the average TFP generally exhibit an upward trend over the sample period. This preliminary finding suggests that higher levels of AI development are associated with greater TFP, which is consistent with the theoretical expectations of this study and provides initial empirical support for the subsequent analysis.

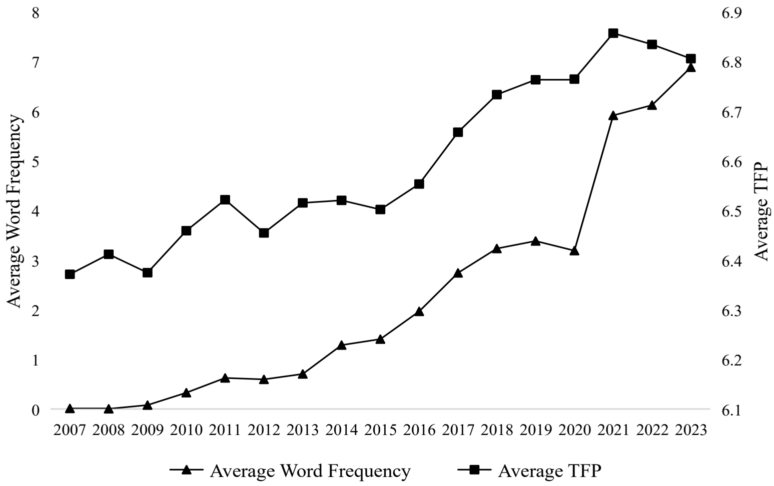

Fig. 1: The Time-Varying Trends of the Word Frequency and TFP.

Table 1 describes the measurement and descriptive statistics of Dependent, Core Independent, Moderating, and Control Variables.

Table 1: Variable Measurement and Descriptive Statistics of Samples

Variable Types and Notation	Variables	Variable Definitions	Mean	SD
Dependent Variable				
TFP_OP	TFP	TFP measured by OP	6.725	0.777
Core Independent Variable				
AI	AI Word Frequency	The AI word frequency from the annual reports of listed companies is transformed by taking the natural logarithm of the raw count + 1	0.665	1.041
Moderator Variable				
IDQ	IDQ	IDQ Rating: Excellent=4；Good=3；Pass=2；Fail=1	3.042	0.599
Control Variables				
LEV	Debt-to-Asset Ratio	Total Debt / Total Assets	0.389	0.196
ROA	Return on Assets	Net Profit / Total Assets	0.044	0.067
FIXED	Fixed Asset Ratio	Fixed Assets / Total Assets	0.224	0.137
MER	Management Expense Ratio	Management Expense/Operating Revenue	0.250	1.668
SIZE	Firm Size	The size is measured by taking the natural logarithm of the number of employees +1	7.601	1.154
Cashflow	Cashflow	Net Cash Flow from Operations / Operating Revenue	0.049	0.067
OS	Ownership Structure	Percentage of Shares Held by the Largest Shareholder	0.334	0.142

Table 1 shows that, regarding the mean of dependent, independent, and moderating variables, the TFP of Chinese listed companies from 2007 to 2023 is 6.725, the AI word frequency in annual reports of these companies is 0.665, and the information disclosure rating of Chinese listed companies is 3.042, suggesting that the average disclosure quality falls at a good level. In terms of control variables, the mean leverage ratio (LEV) of the sample manufacturers is 0.389, indicating a moderate overall debt level with relatively controllable variation in debt structure across companies. The mean return on assets (ROA) is 0.044 with a standard deviation of 0.067, reflecting some divergence in profitability among sample enterprises, with some facing revenue pressure. The average fixed asset ratio (FAR) is 0.224 with a standard deviation of 0.137, implying differences in the scale and strategy of fixed asset investment among manufacturers, though no extreme concentration or dispersion is observed overall. The mean cash flow ratio is 0.049, indicating a relatively low overall capacity to generate cash from operations. The average ownership percentage of the largest shareholder (OS) is 0.334, suggesting that in most sample companies, the largest shareholder maintains the controlling power to a certain extent.

4.2. Baseline regression

The baseline regression of this study examines the impact of AI on the TFP of manufacturers. The results are presented in Table 2. Columns (1) to (2) formulate the key explanatory variable (AI) and the control variables. The findings consistently indicate that AI exerts a statistically significant positive effect on the TFP of manufacturing enterprises, thus supporting Hypothesis 1. Furthermore, this study recalculates TFP based on the Levinsohn-Petrin (LP) method and re-examines the influence of AI. As shown in Columns (3) and (4) of Table 2, AI maintains a significant positive impact on TFP, providing preliminary evidence for the robustness of the results.

Table 2: The Impact of AI on TFP of Manufacturers

Variables	(1) TFP_OP	(2) TFP_OP	(3) TFP_LP	(4) TFP_LP
AI	0.024^{***} (0.006)	0.017^{***} (0.005)	0.045^{***} (0.007)	0.014^{***} (0.005)
LEV		0.621^{***} (0.046)		0.573^{***} (0.044)
ROA		1.954^{***} (0.079)		1.932^{***} (0.077)
FIXED		-0.714^{***} (0.061)		-1.085^{***} (0.060)
MFR		-0.004** (0.002)		-0.004^{**} (0.001)
SIZE		0.062^{***} (0.019)		0.368^{***} (0.018)
Cashflow		0.520^{***} (0.050)		0.530^{***} (0.049)
OS		-0.356^{***} (0.087)		-0.325^{***} (0.083)
Constant	6.708^{***} (0.004)	6.160^{***} (0.148)	8.510^{***} (0.005)	5.727^{***} (0.137)
Observations	27,929	27,929	27,929	27,929
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Note: The clustered standard errors are reported in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Hereinafter the same.

4.3. Robustness checks

To further verify the robustness of our findings, three alternative approaches are adopted to conduct robustness checks.
(1) Introducing city-level control variables and controlling for city fixed effects. Given that cities vary in terms of economic development, fiscal intervention capacity, and industrial structure—factors that may influence the adoption and application of AI technologies and manufacturers' TFP, we introduce three additional control variables: economic development level (lngdp), fiscal expenditure level (lnfinance), and the proportion of secondary industry value-added in GDP (structure). The analysis also covers city fixed effects, with the results presented in Column (1) of Table 3.
(2) Applying a one-period delay to all explanatory variables. Since decisions and characteristics of manufacturers often exhibit delayed effects on output and TFP, current TFP is likely influenced more by the level of AI development in the previous period. The introduction of the delayed term of AI allows us to examine its impact on manufacturer TFP from a dynamic perspective of technology absorption and efficiency transformation. The results are reported in Column (2) of Table 3.
(3) Excluding state-owned enterprises (SOEs) from the sample. SOEs in China often bear certain policy and social obligations, and their investment and innovation decisions may be driven by market efficiency as well as administrative interventions and social development objectives. Therefore, this study removes SOE observations and focuses the analysis on non-SOEs, which tend to exhibit more market-responsive behaviors and operate under governance structures closer to market-oriented principles. This approach allows for a clearer examination of the impact of AI on manufacturer TFP, thereby enhancing the generalizability of the findings. The results are presented in Column (3) of Table 3.

Table 3: Robustness Checks

Variables	(1) TFP_OP	(2) TFP_OP	(3) TFP_OP
AI	0.019^{***} (0.006)	0.011^{*} (0.006)	0.016^{***} (0.006)
LEV	0.690^{***} (0.051)	0.583^{***} (0.045)	0.606^{***} (0.053)
ROA	2.189^{***} (0.094)	1.525^{***} (0.079)	1.811^{***} (0.091)
FIXED	-0.747^{***} (0.072)	-0.296^{***} (0.061)	-0.777^{***} (0.062)
MFR	-0.004^{***} (0.002)	-0.001 (0.001)	-0.007^{***} (0.002)
SIZE	0.085^{***} (0.020)	0.064^{***} (0.016)	0.064^{***} (0.023)
Cashflow	0.551^{***} (0.061)	0.176^{***} (0.051)	0.560^{***} (0.057)
OS	-0.412^{***} (0.095)	-0.216^{**} (0.086)	-0.360^{***} (0.114)
lngdp	0.002 (0.052)		
lnfinance	0.104^{**}		

	(0.043)		
structure	0.003*		
	(0.002)		
Constant	4.125***	6.094***	6.068***
	(0.955)	(0.126)	(0.168)
Observations	20,436	24,651	20,210
Year FE	YES	YES	YES
City FE	YES	NO	NO
Firm FE	YES	YES	YES

The results of the robustness checks demonstrate that AI exerts a statistically significant positive effect on the TFP of manufacturing firms, whether by incorporating city-level controls and city fixed effects, applying a one-period delay to all explanatory variables, or excluding state-owned enterprises from the sample. These findings further confirm the robustness of the analysis.

4.4. Mechanism analysis

To further investigate the mechanisms through which AI enhances TFP in manufacturing firms, this study selects R&D investment (RD) and innovation output (Patent) as moderating variables. The measurement of R&D investment follows previous research [41] and is defined as the ratio of R&D expenditure to operating revenue. Innovation output is measured by taking the natural logarithm of one plus the number of invention patent applications filed by the manufacturer. The results are presented in Table 4.

Table 4: Mechanism Analysis

Variables	(1) RD	(2) RD	(3) Patent	(4) Patent
AI	0.002**	0.002*	0.055***	0.042***
	(0.001)	(0.001)	(0.015)	(0.014)
LEV		-0.047***		-0.066
		(0.017)		(0.090)
ROA		-0.204***		0.005
		(0.038)		(0.150)
FIXED		0.001		-0.048
		(0.009)		(0.117)
MFR		0.003		-0.014***
		(0.003)		(0.004)
SIZE		0.002		0.209***
		(0.004)		(0.028)
Cashflow		-0.051***		-0.270**
		(0.009)		(0.114)
OS		0.017***		0.435**
		(0.007)		(0.180)
Constant	0.058***	0.067**	1.866***	0.168
	(0.001)	(0.034)	(0.011)	(0.214)
Observations	19,025	19,025	23,427	23,427
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

The results of the mechanism analysis indicate that AI significantly enhances both manufacturer R&D investment and the output of innovation. This suggests that AI, through means such as machine learning and deep learning algorithms, enables manufacturers to collect, process, and analyze market information more effectively, thereby allowing them to identify product quality demands and customer needs in a more timely and accurate manner. As a result, AI helps reduce the risks associated with R&D investments and encourages enterprises to increase their spending in this area. Furthermore, with AI-aided design technologies, enterprises can shorten R&D cycles and reduce trial-and-error costs in product design, resulting in many more invention patents. These findings indicate that increased R&D investment and enhanced innovation output serve as important mechanisms through which AI promotes TFP in manufacturing enterprises.

4.5. Heterogeneity analysis

To find out the heterogeneous effects of AI on TFP of manufacturing firms, the first step is to calculate the mean of manufacturers' age across the sample. Those with an age above the mean are classified as the higher group (H-age), while those below the mean the lower group (L-age). The impact of AI on TFP is then analyzed separately across these two groups. Additionally, corporate tax burden is used as another indicator for heterogeneity analysis. Following previous studies [42], tax burden is measured as the sum of value-added tax and corporate income tax divided by operating revenue. Manufacturers with a tax burden above the sample average are assigned to the high-tax-burden group (H-tax), while those below the average the low-tax-burden group (L-tax). The results of the heterogeneity analysis are presented in Table 5.

Table 5: Heterogeneity Analysis

Variables	(1) H-age	(2) L-age	(3) H-tax	(4) L-tax
AI	0.009	0.025***	0.002	0.024***
	(0.007)	(0.008)	(0.008)	(0.007)
LEV	0.536***	0.708***	0.691***	0.498***
	(0.069)	(0.057)	(0.063)	(0.057)
ROA	1.883***	2.039***	2.557***	1.564***
	(0.116)	(0.106)	(0.131)	(0.102)
FIXED	-0.601***	-0.846***	-0.663***	-0.745***
	(0.086)	(0.083)	(0.072)	(0.079)
MFR	-0.005**	-0.002	-0.004	-0.003*

	(0.002)	(0.002)	(0.003)	(0.002)
SIZE	0.043	0.073***	0.020	0.066***
	(0.030)	(0.023)	(0.028)	(0.024)
Cashflow	0.530***	0.492***	0.549***	0.423***
	(0.068)	(0.073)	(0.082)	(0.058)
OS	-0.310**	-0.323***	-0.352***	-0.275**
	(0.124)	(0.117)	(0.123)	(0.107)
Constant	6.316***	6.041***	6.217***	6.286***
	(0.231)	(0.176)	(0.214)	(0.187)
Observations	14,540	13,389	9,936	17,161
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

The results of the heterogeneity analysis reveal significant variations across manufacturers in the productivity-enhancing effects of AI. Specifically, the positive impact of AI on TFP is more pronounced in younger companies and those with lower tax burdens, whereas no consistent effect is observed in older ones or those subject to heavier tax obligations. This divergence may stem from differences in enterprises' adaptive capacities and institutional constraints. Younger manufacturers, often in rapid growth, exhibit stronger motivation for efficiency improvement and technological transformation, while facing fewer internal barriers to technology adoption; hence, they are more likely to benefit from AI applications [43]. Manufacturers with lighter tax burdens generally possess more substantial internal capital, enabling them to commit more resources to long-term and high-risk innovation activities—such as AI adoption—thereby more effectively translating technological advantages into actual TFP gains.

In contrast, firms with higher tax burdens operate under stronger financial constraints and greater agency costs, both of which may impair their ability to allocate resources efficiently toward AI-related initiatives. Consequently, the effect of AI on TFP becomes less evident or consistent in these enterprises.

4.6. Further analysis

To investigate the role of IDQ in the interplay between AI and TFP in manufacturing firms, this study extends the baseline regression by incorporating both IDQ and the interaction term between AI and disclosure quality into the model. This part of the analysis chooses only listed companies from the Shenzhen Stock Exchange, which is the only provider of public disclosure quality ratings.

First, the analysis goes to the evolving trends of the average of the AI word frequency-IDQ interaction term and the average TFP by year for our sample of A-share manufacturers (see Figure 2). A discernible upward co-movement is observed, providing initial graphical support for our core premise that their synergy enhances productivity, thereby laying the groundwork for the rigorous tests that follow.

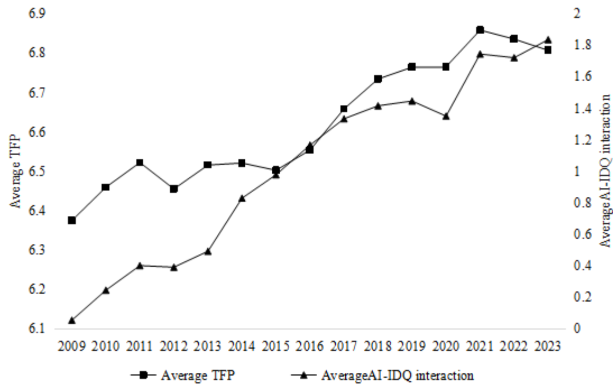

Fig. 2: The Time-Varying Trends of the Interaction Term and TFP.

Based on the preliminary analysis as shown in Figure 2, we incorporate IDQ and its interaction term with AI into the empirical model. The results are reported in Table 6.

Table 6: Further Analysis

Variables	(1) TFP_OP	(2) TFP_OP	(3) TFP_OP	(4) TFP_LP
AI	0.033***	0.030***	0.022***	0.018***
	(0.008)	(0.008)	(0.007)	(0.007)
IDQ	0.070***	0.091***	0.054***	0.050***
	(0.008)	(0.012)	(0.011)	(0.011)
AI×IDQ		0.020**	0.016**	0.015**
		(0.009)	(0.008)	(0.007)
LEV			0.691***	0.647***
			(0.056)	(0.053)
ROA			1.821***	1.809***
			(0.109)	(0.105)
FIXED			-0.794***	-1.171***
			(0.074)	(0.072)
MFR			-0.005**	-0.005**
			(0.002)	(0.002)
SIZE			0.069***	0.378***
			(0.024)	(0.022)
Cashflow			0.571***	0.574***
			(0.070)	(0.068)
OS			-0.398***	-0.359***

			(0.109)	(0.104)
Constant	6.377^{***}	6.315^{***}	5.843^{***}	5.408^{***}
	(0.026)	(0.039)	(0.181)	(0.166)
Observations	12,670	12,670	12,670	12,670
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

The results in Table 6 indicate that an improvement in IDQ significantly promotes the TFP of manufacturing firms. And the interaction term between AI and IDQ is found to exert a statistically significant positive influence on TFP. This result remains robust after control variables are included and the dependent variable is replaced with TFP calculated by the Levinsohn-Petrin (LP) method. These findings suggest that higher IDQ strengthens the positive effect of AI on manufacturers' TFP, thereby supporting Hypothesis H2. The further analysis underscores that, among non-technological factors, the quality of the information environment plays a crucial role in shaping the impact of AI on production efficiency in manufacturing enterprises. It highlights that IDQ—an essential non-technological factor—should not be overlooked in the intelligent transformation and upgrading of the manufacturing industry.

5. Conclusion

AI holds significant potential for driving economic growth and enterprise production efficiency. Based on textual analysis of annual reports from Chinese listed manufacturers, this study constructs an AI word frequency indicator and examines the impact of AI on TFP at the micro level, as well as its underlying mechanisms. It finds out the role of IDQ in shaping the relationship between AI and TFP in manufacturers from a non-technical perspective.

5.1. Key findings and discussion

1) AI significantly promotes the TFP of manufacturing enterprises, a conclusion that remains robust after a series of robustness checks. This finding offers micro-level evidence that AI embodies the defining features of a GPT—characterized by its pervasive penetrability and powerful spillover effects[20, 44]. It drives sustained expansion of the production possibility by reconfiguring production processes and innovation paradigms.
2) Mechanism analysis shows that AI primarily enhances TFP by incentivizing increased R&D investment and boosting innovation output, which aligns with the predictions of GPT theory, positing that AI catalyzes not merely sustained innovation but also widespread complementary innovations [22,45], thereby establishing a virtuous cycle between technological change and productivity enhancement.
3) Heterogeneity analysis indicates that the positive effect of AI on TFP is more pronounced in younger enterprises, which exhibit stronger motivation to improve productivity, as well as in those with lower tax burdens.
4) Further analysis confirms that superior IDQ significantly strengthens the productivity-enhancing effect of AI. This finding provides compelling empirical evidence for Signaling Theory [29,46], i.e., high IDQ effectively mitigates information asymmetry between a firm and external stakeholders, sending positive signals to the market regarding its technological capabilities and growth prospects. In this way, it helps improve financing conditions, enhances corporate governance, and underscores the critical role of IDQ during the intelligent transformation of manufacturing, thereby creating a favorable information environment for fully unleashing AI's technological dividends.

5.2. Practical implications

1) It is advisable that the government continue to promote the adoption and integration of AI technologies in manufacturing through technical guidance and optimization of market institutions. Based on existing policies, priority support should target AI fields directly linked to industrial production—such as industrial intelligent robotics and smart production data analytics. Guiding manufacturers to embed AI applications into R&D, production, and organizational management will further unleash its efficiency potential. Meanwhile, the government is expected to encourage firms to increase R&D investment and establish industry-university-research collaboration mechanisms through legislation and policies, facilitating partnerships between manufacturers, universities, and research institutions to enhance AI development efficiency and patent output.
2) Regarding accounting practice and regulation, standard-setters and regulators are advised to consider issuing targeted guidance to encourage or require firms to disclose their AI strategies, primary application scenarios, achieved efficiency gains (e.g., cost savings, capacity utilization changes), and associated risks. Specific disclosure indicators may include amounts of capitalized/front-loaded versus expensed R&D expenditures related to AI; key efficiency improvements driven by AI applications, such as reduction rates in unit product costs, increases in production line capacity utilization, and declines in product defect rates; and major AI application scenarios (e.g., intelligent quality inspection, predictive maintenance) with corresponding estimated returns on investment. Such disclosures would significantly enhance the comparability and decision-usefulness of AI-related information across firms, furnishing market participants with more effective benchmarks for evaluation.
3) This research provides a key implication beyond the Chinese context: the returns on AI investment are shaped not merely by technological advancement but by the interplay between innovation and the institutional setting, particularly the quality of the information ecosystem. Our findings underscore that enhanced IDQ is critical to leveraging the full productivity potential of AI. Therefore, a synergistic, co-evolutionary framework integrating technology incentives with information infrastructure is essential for policy, rather than treating them in isolation. This "technology-institution" synergy, empirically validated in China, offers a generalizable paradigm for global manufacturing economies to optimize policy impacts in their intelligent transformations.

5.3. Limitations and suggestions for future research

It must be admitted that this study has limitations that point to promising avenues for future research. First, while we construct a firm-level AI indicator using text analysis and confirm its positive impact on TFP, the measurement approach does not distinguish between different types of AI technologies or their specific application scenarios. Future research could employ surveys and patent data to classify AI technologies, thereby examining the heterogeneous effects of various AI applications across different value chain segments on firm productivity. Second, as this study focuses on the broader context of Chinese manufacturing, further theoretical and empirical evidence is needed to verify whether our finding—that higher IDQ amplifies AI's positive effect on TFP—holds in other technology-intensive industries, such as information technology services and biopharmaceuticals. Subsequent studies could extend our analytical framework to these and other specific sectors, using comparative analysis to uncover the boundary conditions of AI's economic effects across different industries and application contexts.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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References

[1] Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics (No. w24001). *National Bureau of Economic Research*. https://doi.org/10.3386/w24001.

[2] Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation policy and the economy*, 19(1), 161-191. https://doi.org/10.1086/699936.

[3] Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488-1542. https://doi.org/10.1257/aer.20160696.

[4] Zhang, Z. (2023). The impact of the artificial intelligence industry on the number and structure of employments in the digital economy environment. *Technological Forecasting and Social Change*, 197, 122881. https://doi.org/10.1016/j.techfore.2023.122881.

[5] Goyal, A., & Aneja, R. (2020). Artificial intelligence and income inequality: Do technological changes and worker's position matter? *Journal of Public Affairs*, 20(4), e2326. https://doi.org/10.1002/pa.2326.

[6] Wang, K. L., Sun, T. T., & Xu, R. Y. (2023). The impact of artificial intelligence on total factor productivity: empirical evidence from China's manufacturing enterprises. *Economic Change and Restructuring*, 56(2), 1113-1146. https://doi.org/10.1007/s10644-022-09467-4.

[7] Zhong, Y., Xu, F., & Zhang, L. (2024). Influence of artificial intelligence applications on total factor productivity of enterprises—evidence from textual analysis of annual reports of Chinese-listed companies. *Applied Economics*, 56(43), 5205-5223. https://doi.org/10.1080/00036846.2023.2244246.

[8] Korinek, A., & Stiglitz, J. E. (2021). Artificial intelligence, globalization, and strategies for economic development (No. w28453). *National Bureau of Economic Research*. https://doi.org/10.3386/w28453.

[9] Qin, Y., Xu, Z., Wang, X., & Skare, M. (2024). Artificial intelligence and economic development: An evolutionary investigation and systematic review. *Journal of the Knowledge Economy*, 15(1), 1736-1770. https://doi.org/10.1007/s13132-023-01183-2.

[10] Lu, J., Li, B., Li, H., & Zhang, Y. (2020). Sustainability of enterprise export expansion from the perspective of environmental information disclosure. *Journal of Cleaner Production*, 252, 119839. https://doi.org/10.1016/j.jclepro.2019.119839.

[11] Wang, Y., & He, P. (2024). Enterprise digital transformation, financial information disclosure and innovation efficiency. *Finance Research Letters*, 59, 104707. https://doi.org/10.1016/j.frl.2023.104707.

[12] Dzhereleyko, S., Pysarenko, N., Poltinina, O., Nesterenko, O., & Kolomiiets, V. (2025). Digital Economy and Its Effect on Financial Market Structures: Analyzing Key Trends And Future Opportunities. *International Journal of Accounting and Economics Studies*, 12(4), 747-759. https://doi.org/10.14419/9gya2n94.

[13] Weshah, S., Altal, A., & Obeidat, Z. (2019). The impact of information systems disclosures as a part of structural capital on banks' profitably: a case study of Islamic banks in Jordan. *International Journal of Accounting and Economics Studies*, 7(1), 6-10. https://doi.org/10.14419/ijaes.v7i1.28717.

[14] Gupta, D. A., Hashmi, D. S., Prusty, R., Khilla, D. G., Allamprabhu, D., Bareja, L., & Vashisht, N. (2025). Sustainability Accounting: A Comparative Study of Corporate Environmental Disclosures. *International Journal of Accounting and Economics Studies*, 12(SI-1), 5-8. https://doi.org/10.14419/t8gtjw91.

[15] Han, F., & Mao, X. (2024). Artificial intelligence empowers enterprise innovation: evidence from China's industrial enterprises. *Applied Economics*, 56(57), 7971-7986. https://doi.org/10.1080/00036846.2023.2289916.

[16] Zhang, Y., Chang, Y., Zhang, X., & Zhou, H. (2025). Artificial Intelligence and Enterprise Technological Innovation: Evidence from China. *Managerial and Decision Economics.* https://doi.org/10.1002/mde.70002.

[17] Zhou, W., Zhang, Y., & Li, X. (2024). Artificial intelligence, green technological progress, energy conservation, and carbon emission reduction in China: An examination based on dynamic spatial Durbin modeling. *Journal of Cleaner Production*, 446, 141142. https://doi.org/10.1016/j.jclepro.2024.141142.

[18] Song, M., Peng, L., Shang, Y., & Zhao, X. (2022). Green technology progress and total factor productivity of resource-based enterprises: A perspective of technical compensation of environmental regulation. *Technological Forecasting and Social Change*, 174, 121276. https://doi.org/10.1016/j.techfore.2021.121276.

[19] Miao, H., Guo, X., & Yuan, F. (2021). Research on identification of potential directions of artificial intelligence industry from the perspective of weak signal. *IEEE Transactions on Engineering Management*, 71, 465-480. https://doi.org/10.1109/TEM.2021.3123639.

[20] Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211, 188-205. https://doi.org/10.1016/j.jebo.2023.05.008.

[21] Li, C., Xu, Y., Zheng, H., Wang, Z., Han, H., & Zeng, L. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resources Policy*, 81, 103324. https://doi.org/10.1016/j.resourpol.2023.103324.

[22] Sahoo, S., Das, S., Neyyila, S., Chaitanya, N., Kumar, T. V., & Penta, S. (2025). Forging Circuits and Bytes: The Mediator with Moderating Effects of Digital Transformation on The Circular Economy and Sustainable Entrepreneurship. *International Journal of Accounting and Economics Studies*, 12(5), 397-410. https://doi.org/10.14419/tv3wzg33.

[23] Azadi, M., Moghaddas, Z., Farzipoor Saen, R., & Hussain, F. K. (2024). Financing manufacturers for investing in Industry 4.0 technologies: internal financing vs. External financing. International *Journal of Production Research*, 62(22), 8056-8072. https://doi.org/10.1080/00207543.2021.1912431.

[24] Meng, X., Chen, L., & Gou, D. (2023). The impact of corporate environmental disclosure quality on financing constraints: the moderating role of internal control. *Environmental Science and Pollution Research*, 30(12), 33455-33474. https://doi.org/10.1007/s11356-022-24510-7.

[25] Liu, Q., Wang, J., & Qiu, Z. (2023). Data as evidence: Research on the influencing factors and mechanisms of coal mine safety supervision effect in China. *Resources Policy*, 81, 103298. https://doi.org/10.1016/j.resourpol.2023.103298.

[26] Hu, Z., & Liu, L. (2025). Female executives' influence on competitive strategies in tourism enterprises: A study on the moderating role of managerial shortsightedness. *Finance Research Letters*, 76, 106992. https://doi.org/10.1016/j.frl.2025.106992.

[27] Lindblom, J., & Martins, J. T. (2022). Knowledge transfer for R&D-sales cross-functional cooperation: Unpacking the intersections between institutional expectations and human resource practices. *Knowledge and Process Management*, 29(4), 418-433. https://doi.org/10.1002/kpm.1726.

[28] Du, Y. G., He, Y., & Guo, M. N. (2024). Disclosure of strategic collaborative agreements and the cost of equity capital. *Journal of International Financial Management & Accounting*, 35(1), 68-114. https://doi.org/10.1111/jifm.12191.

[29] Karim, H. M., & Mohsin, M. A. (2025). The Impact of IT Governance Dimensions on Enhancing the Quality of Accounting Information in Economic Units. *International Journal of Accounting and Economics Studies*, 12(4), 562-573. https://doi.org/10.14419/ac3cxk72.

[30] Alfartoosi, A. M. huseein, & Mohsin, H. J. (2025). The Impact of The Transition from Traditional Accounting to Cloud Accounting on The Accuracy of Financial Statements: A Field Study At Rafidain and Rashid Banks/Babylon Branch. *International Journal of Accounting and Economics Studies*, 12(5), 1029-1037. https://doi.org/10.14419/9n83ay28.

[31] Iashchenko, O., Chupryna, O., Maksymov, S., Zemlianska, N., Afanasieva, O., & Popova, Y. (2025). Information Noise in Marketing Analytics: Implications for Financial Reporting and Economic Decision-Making. *International Journal of Accounting and Economics Studies*, 12(5), 702-709. https://doi.org/10.14419/qk1f2333.

[32] Ye, J., & Xu, W. (2023). Carbon reduction effect of ESG: empirical evidence from listed manufacturing companies in China. *Frontiers in Ecology and Evolution*, 11, 1311777. https://doi.org/10.3389/fevo.2023.1311777.

[33] Chen, G., & Yu, Z. (2024). Digital finance, value cocreation, and supply chain resilience: Evidence from listed manufacturing firms in China. *Finance Research Letters*, 70, 106322. https://doi.org/10.1016/j.frl.2024.106322.

[34] Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263-1297. https://doi.org/10.2307/2171831.

[35] Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2), 317-341. https://doi.org/10.1111/1467-937X.00246.

[36] Yang, C. H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy*, 51(6), 104536. https://doi.org/10.1016/j.respol.2022.104536.

[37] Yang, S., & Zhou, N. (2025). Artificial Intelligence and the Quality of Corporate Accounting Information Disclosure. *Finance Research Letters*, 108136. https://doi.org/10.1016/j.frl.2025.108136

[38] Li, Q., Li, W., & Liu, J. (2025). Government subsidies and total factor productivity: The conflict between economic and social objectives. *Finance Research Letters*, 108024. https://doi.org/10.1016/j.frl.2025.108024.

[39] Xu, J., & Sim, J. W. (2017). Are costs really sticky and biased? Evidence from manufacturing listed companies in China. *Applied Economics*, 49(55), 5601-5613. https://doi.org/10.1080/00036846.2017.1316823.

[40] Iacobucci, D., Schneider, M. J., Popovich, D. L., & Bakamitsos, G. A. (2016). Mean centering helps alleviate "micro" but not "macro" multicollinearity. *Behavior research methods*, 48(4), 1308-1317. https://doi.org/10.3758/s13428-015-0624-x.

[41] Wang, H., Liang, P., Li, H., & Yang, R. (2016). Financing sources, R&D investment and enterprise risk. *Procedia Computer Science*, 91, 122-130. https://doi.org/10.1016/j.procs.2016.07.049.

[42] Tang, W., Zhao, X., Zhai, S., & Cao, L. (2023). Local government debt and corporate tax burden: A perspective based on the trade-off of government tax collection and management. *Plos one*, 18(7), e0287763. https://doi.org/10.1371/journal.pone.0287763.

[43] Arum, E. D. P., Wijaya, R., & Wahyudi, I. (2025). Tax aggressiveness in the energy industry: insights of emerging countries. *International Journal of Accounting and Economics Studies*, 12(2), 35-42. https://doi.org/10.14419/2eq43940.

[44] Gutierrez, C. I., Aguirre, A., Uuk, R., Boine, C. C., & Franklin, M. (2023). A proposal for a definition of general purpose artificial intelligence systems. *Digital Society*, 2(3), 36. https://doi.org/10.1007/s44206-023-00068-w.

[45] Farayola, O. A., Abdul, A. A., Irabor, B. O., & Okeleke, E. C. (2023). Innovative business models driven by AI technologies: A review. Computer Science & IT *Research Journal*, 4(2), 85-110. https://doi.org/10.51594/csitrj.v4i2.608

[46] Yao, L., Li, A., & Yan, E. (2025). Research on digital infrastructure construction empowering new quality productivity. *Scientific Reports*, 15(1), 6645. https://doi.org/10.1038/s41598-025-90811-9.