The Impact of Smart Manufacturing on Total Factor Productivity: Empirical Evidence from Chinese Listed Manufacturing Firms

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Abstract. The optimal allocation of production factors requires both macro-level regulation and efficient resource management at the micro level within firms. We explore the impact of smart manufacturing on the total factor productivity (TFP) of listed manufacturing firms in China through empirical analysis. Using A-share listed manufacturing firms from 2015 to 2022 as the sample, we employ text analysis combined with principal component analysis to construct indicators of firms' smart manufacturing levels. We examine the impact of smart manufacturing on TFP and conduct robustness tests with propensity score matching (PSM) and alternative dependent variables. Our findings indicate that smart manufacturing significantly improve the TFP of manufacturing firms, confirming that the application of smart manufacturing technology can effectively enhance production efficiency. Mechanism analysis shows that smart manufacturing primarily affects TFP through the intermediary effect of technological innovation. Our research provides a theoretical basis for understanding the impact of smart manufacturing on TFP and clarifies the mechanism, offering valuable insights for firms' digital transformation.

Keywords: Smart manufacturing; TFP; Manufacturing industry.

1 Introduction

The global manufacturing sector is currently experiencing a profound transformation characterized by heightened networking, informatization, digitalization, and the rise of smart manufacturing. Artificial intelligence (AI)-related industries and technologies are becoming the core drivers of global economic change. Many countries have oriented their future manufacturing development towards high-end smart manufacturing. For instance, the United States released a strategic plan for advanced manufacturing in 2012, and Germany introduced the concept of "Industry 4.0" in 2013. In 2015, China

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launched the "Made in China 2025" initiative, which aims to bolster advanced manufacturing and high-tech industries, promote the advancement of traditional industries through smart manufacturing, and foster the deep integration of intelligent technology and manufacturing technology. This initiative seeks to achieve industrial upgrading, avoid low-end assembly manufacturing, move up the value chain, and ensure high-quality economic development. According to the China Academy of Information and Communications Technology, by the end of 2022, there were 27,255 representative AI firms globally, with 4,227 of them based in China, accounting for about 16% of the total. In 2022, China's AI core industry reached a scale of 508 billion yuan, marking an 18% year-on-year increase. AI has gradually become an important engine of economic growth for China (Chia-Hui Lu, 2021) [1].

TFP serves as a crucial metric encompassing various facets such as technical proficiency, management capabilities, resource allocation, and other efficiency factors within firms' production processes. It is a key indicator for measuring the transformation, upgrading, and high-quality development of manufacturing firms. Previous literature has been troubled by the productivity paradox of information technology, notably Solow's "productivity paradox," which posits that computers have no effect on productivity. Gordon (2017) [2] argue that technological innovations like robotics, AI, and driverless cars are considered non-market benefits with little impact on firm productivity and operations. Understanding how to transform AI technology into a driving force for improved production efficiency, how smart manufacturing affects TFP, and how to solve the "productivity paradox" are crucial areas needing further research.

We explore the impact of smart manufacturing levels on TFP. Building on previous research, we find that the rapid development of AI offers new possibilities for the transformation and upgrading of the manufacturing industry. AI can free humans from repetitive and dangerous tasks, allowing them to engage in more innovative and creative work, thereby improving firm resource allocation efficiency and enhancing TFP. Furthermore, we examine the mechanism through which smart manufacturing impacts TFP. Theoretical and empirical research suggests that enhancing smart manufacturing levels can stimulate firm innovation capabilities, thus improving TFP. This helps clarify the impact pathway of smart manufacturing on productivity and provides direction for the transformation and upgrading of smart manufacturing.

Our findings promote the transformation of smart manufacturing in manufacturing firms and aim for high-quality development. Through a series of studies on the impact of smart manufacturing on TFP, we disprove Solow's "productivity paradox," aiding manufacturing firms in establishing correct transformation values. We encourage them to strengthen strategic planning for smart manufacturing transformation, optimize organizational structures, achieve technological progress, and maximize firm value.

2 Literature Review and Research Hypotheses

2.1 Research on the Impact of Smart Manufacturing on the TFP

With the advent of the fourth industrial revolution and the sixth wave of technological advancements led by artificial intelligence, smart manufacturing is gradually replacing mechanization, electrification, and informatization as a higher-level form of industrialization (Zeba et al., 2021) [3]. Existing literature primarily discusses macro-level impact of smart manufacturing on economic growth (Acemoglu et al., 2018; Cette et al., 2022; Ke et al., 2022) [4] [5] [6].

At the micro level, smart manufacturing technology is profoundly transforming the industrial era paradigm, significantly enhancing organizational, operational, and production efficiency (Alguacil M et al., 2022) [7]. In terms of organizational efficiency, smart manufacturing technologies automate tasks, provide predictive insights, and support decision-making, thereby improving information system management and promoting organizational efficiency (Bhima et al., 2023)[8]. Smart manufacturing optimizes resource allocation, reduces resource misallocation, and breaks down data silos between different organizations, enhancing employee and firm performance and revitalizing firm data assets (Ahmad et al., 2023) [9]. In the production process, smart manufacturing enables high flexibility, efficient resource allocation coordination, and more accurate and effective sales and marketing management (Sundaram & Abe, 2023) [10].

Furthermore, smart manufacturing technology enhances the internal and external collaboration and integration capabilities of manufacturing firms, thereby improving TFP. Externally, smart manufacturing reduces search, transaction, and transportation costs, boosting operational efficiency across organizations and industries (Czarnitzki et al., 2023) [11]. Internally within the firms, it enhances integration capabilities, and helps firms expand their reach while delivering cost savings and efficiency gains (Wang et al., 2023) [12]. We thus propose the following hypothesis:

Hypothesis 1: *Smart manufacturing positively affects TFP.*

2.2 Research on Mechanism of Smart Manufacturing Affecting the TFP

Firstly, the application of smart manufacturing technology can improve TFP through the intermediary path of technological innovation (Luo et al., 2024) [13]. The use of intelligent technology to improve and optimize business processes promotes continuous technological innovation, particularly transformative changes in products and business models based on customer service and experience. Smart manufacturing facilitates more convenient and efficient information communication, enabling firms to iterate and innovate products based on consumer feedback to meet market demands. This innovation promotes optimal resource allocation, such as investing more human capital in online customer information exchange and reducing offline sales personnel, thereby improving TFP. We thus propose the following hypothesis:

Hypothesis 2: *Smart manufacturing improves TFP by enhancing technological innovation capabilities.*

Artificial intelligence technology substitutes routine and repetitive labor positions while complementing unconventional and non-repetitive roles (Mohsin, 2023) [14]. Therefore, firms leverage AI's productivity by reducing the demand for low-skilled labor and increasing the demand for high-skilled labor. Additionally, smart manufacturing breaks traditional labor constraints of time and space, improves labor resource allocation efficiency, and enables more scientific and rational labor investment decisions

(Momade et al., 2022) [15]. Thus, smart manufacturing addresses resource misallocation and enhances TFP. We thus propose the following hypothesis:

Hypothesis 3: *Smart manufacturing enhances TFP by improving labor investment efficiency.*

3 Research Design

3.1 Selection of Samples and Data Sources

We select Chinese A-share listed manufacturing firms from 2015 to 2022 as our sample. We obtain annual reports from Sina Finance and Juchao Information[1], and the basic information and financial data from the CSMAR database. We exclude ST and PT firms, and firms with missing data. Our final sample consists of 14496 observations after the variables are winsorized at the top and bottom 1%.

3.2 Variable Definition and Model Setting

We primarily utilized the following panel fixed-effects model to examine the impact of smart manufacturing on the TFP of firms.

$$TFP_{i,t} = \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{1}$$

i denotes the listed firms in the sample and t denotes the year. *TFP* is the TFP of the firm, *AI* represents the smart manufacturing level of the firm, *Controls* represents the control variables, *year* and *ind* represent the year fixed-effects and industry fixed-effects respectively.

(1) Dependent Variable. Based on the calculation method of Giannetti et al. (2014)[16], we use LP method to estimate the TFP of manufacturing firms, and uses the total business income to represent the total output of firms, the fixed assets to represent the capital, and the total number of employees to represent the labor force. The cash of goods and services purchased by firms represents the intermediate input of firms to measure the TFP of firms.

(2) Independent Variable. Due to limited direct measurement data for firm smart manufacturing levels, we adopt principal component analysis method to construct firm smart manufacturing level index. Following the method of Zhong et al. (2023)[17], we construct a firm smart manufacturing level evaluation system from six aspects: hardware base, software base, talent base, capital base, R&D intensity and innovation ability, as illustrated in Table 1. The KMO and Bartley spherical tests in Table 2 show that the KMO value is 0.619, greater than 0.6, and the p value of Bartlett test is significant, indicating that principal component analysis can be used to solve the multicollinearity problem among indicators and measure the smart manufacturing level of firms.

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[1] Sina Finance and Juchao Information are leading Chinese financial platforms, with Sina Finance offering real-time market data, investment tools, and financial news, while Juchao Information provides comprehensive access to corporate disclosures, regulatory filings, and market data to support investment decisions.

Table 1. Smart Manufacturing Level Index

Target	Measurement	Measurement method	Sign
Smart manufacturing level	hardware base	natural logarithm of one plus the smart hardware word frequency	positive
	software base	natural logarithm of one plus smart software word frequency	positive
	talent base	natural logarithm of one plus research employee number	positive
	capital base	natural logarithm of one plus R&D expenditure	positive
	R&D intensity	ratio of R&D expenditure to revenue	positive
	innovation ability	ratio of R&D personnel to total employees	positive

Table 2. KMO And Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.619
Bartlett's test	Chi-square	35469.727
	Degrees of freedom	15
	p-value	0.000

Table 3. Eigenvalue And Variance Contribution Rate

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	2.458	1.228	0.410	0.410
Comp 2	1.230	0.222	0.205	0.615
Comp 3	1.008	0.275	0.168	0.783
Comp 4	0.733	0.318	0.122	0.905
Comp 5	0.415	0.259	0.069	0.974
Comp 6	0.156	.	0.026	1.000
Rho		0.7827		

It can be seen from Table 3 that there are 3 principal components in the firm smart manufacturing level index group with eigenvalues greater than 1, which means that 3 principal components can represent the original 6 indicators. The component matrix table is shown in Table 4. The three principal components of the firms' smart manufacturing level are named F1, F2, and F3 respectively. The correlation coefficients presented in the component matrix table are divided by the square root of the eigenvalues of the principal components. This process yields the eigenvectors for each index, as illustrated in Table 5. Based on this, three expressions of the principal components of the smart manufacturing level can be written as follows:

$$F_1 = 0.170Z_1 + 0.260Z_2 + 0.326Z_3 + 0.363Z_4 + 0.346Z_5 + 0.101Z_6 \tag{2}$$

$$F_2 = 0.277Z_1 + 0.328Z_2 - 0.424Z_3 - 0.551Z_4 + 0.455Z_5 + 0.056Z_6 \tag{3}$$

$$F_3 = -0.046Z_1 - 0.063Z_2 + 0.001Z_3 + 0.014Z_4 + 0.219Z_5 + 2.484Z_6 \tag{4}$$

Table 4. Component Matrix

Variable	Factor 1	Factor 2	Factor 3
Z1: software base	0.266	0.435	-0.072
Z2: hardware base	0.288	0.364	-0.070
Z3: talent base	0.327	-0.426	0.001
Z4: capital base	0.311	-0.472	0.012
Z5: R&D intensity	0.223	0.293	0.141
Z6: innovation ability	0.004	0.022	0.981

Table 5. Eigenvector Matrix

Variable	Factor 1	Factor 2	Factor 3
Z1: software base	0.170	0.277	-0.046
Z2: hardware base	0.260	0.328	-0.063
Z3: talent base	0.326	-0.424	0.001
Z4: capital base	0.363	-0.551	0.014
Z5: R&D intensity	0.346	0.455	0.219
Z6: innovation ability	0.010	0.056	2.484

Finally, the comprehensive index of firms smart manufacturing level is generated based on the ratio of the variance contribution rate of the three principal components to the cumulative variance contribution rate of the extracted principal components.

$$AI = \frac{0.410}{0.783}F_1 + \frac{0.205}{0.783}F_2 + \frac{0.168}{0.783}F_3 \tag{5}$$

(3) Control Variables. For reference to the study conducted by Shao et al. (2023)[18], the control variables are presented in Table 6.

Table 6. Variable Descriptions

Variable Categories	**Definitions**	**Variables**	**Descriptions**
Dependent Variables	TFP of firms	TFP	Calculated according to LP method
Independent Variable	Firm smart manufacturing level	AI	The results of principal component analysis of 6 core variables are detailed in Section 3.1
Control Variables	Firm size	Size	Total assets of firm
	Leverage ratio	Lev	Total liabilities/Total assets
	Firm growth	Growth	Growth rate of main business income
	Board size	BoardSize	Number of directors
	Ownership concentration	Top1	The proportion of the largest shareholder
	Cash flow	Cash	Net cash flow from operating activities/Income from main operations
	Redundant resource	Resource	Take the log of net income

4 Empirical Analysis

4.1 Descriptive Statistics

Table 7 presents the descriptive statistical results of the main variables. The mean value of smart manufacturing level (AI) for firms is 0.078. And the average value of TFP is 7.584, which aligns closely with the findings of Zhou & Wan (2023)[19].

Table 7. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
TFP	14496	7.584	0.865	4.167	11.625
AI	14496	1.302	0.570	0.078	3.792
Size	14496	12.959	1.189	8.596	18.411
Lev	14496	0.377	0.179	0.014	2.176
Cash	14496	0.105	0.121	-0.256	0.475
Growth	14496	0.194	0.345	-0.366	2.064
BoardSize	14496	8.281	1.483	5.000	13.000
Top1	14496	33.096	13.780	8.990	70.420
Resource	14496	9.733	1.490	2.828	15.693

Table 8. Results of Baseline Regression and Robustness Checks

	(1) TFP	(2) TFP	(3) TFP	(4) TFP_OLS
AI	0.2059***	0.0627***	0.0435**	0.0455***
	(18.64)	(7.61)	(2.80)	(5.84)
Cash		-0.2030***	-0.2100***	-0.1808***
		(-9.63)	(-5.21)	(-9.07)
Size		0.3810***	0.3838***	0.5363***
		(63.02)	(28.23)	(94.14)
Lev		0.3077***	0.3045***	0.3548***
		(12.38)	(5.92)	(15.12)
Growth		0.1433***	0.1467***	0.1352***
		(22.48)	(12.27)	(22.40)
BoardSize		0.0024	0.0054	0.0033
		(0.95)	(1.41)	(1.40)
Top1		0.0002	0.0005	0.0004
		(0.47)	(0.75)	(1.12)
Resource		0.1265***	0.1255***	0.1202***
		(42.62)	(18.46)	(42.78)
_cons	7.5499***	1.1182***	1.1240***	0.8500***
	(66.57)	(10.28)	(7.77)	(8.28)
Year fe	Yes	Yes	Yes	Yes
Industry fe	Yes	Yes	Yes	Yes
N	14496	14496	10626	14496
r2_w	0.3796	0.6245	0.6281	0.7160

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Main Results

Table 8 shows the result to examine direct influence of smart manufacturing on firms' TFP. In Column (1), the coefficient of *AI* is 0.2059 and statistically significant at the 1% level. In Column (2), the coefficient of *AI* remains positive and statistically significant at the 1% level after adding control variables. These findings are consistent with Hypothesis 1 that smart manufacturing significantly improves firms' TFP.

4.3 Robustness Checks

4.3.1 Propensity Score Matching.

We employ Propensity Score Matching (PSM) to mitigate endogenous issues. We divide the sample into an experimental group and a control group based on whether the annual report contained hardware or software-related keywords. The balance test results demonstrate a substantial reduction in the absolute value of the standard error between the two groups, ranging from 19.6% to 92.3%. The findings presented in column (3) of Table 8, still consistent with our baseline result after addressing potential sample self-selection biases.

4.3.2 Alternative dependent variables.

We use the OLS method to recalculate TFP in column (4) of Table 8. Smart manufacturing still remains a positive influence on TFP after using the alternative dependent variable.

4.4 Mechanism Analysis

Drawing upon the mediation effect test method introduced by Wen et al. (2022) [20], we establish a comprehensive mediation effect test model, aimed at quantifying the mediation role of technological innovation in enhancing labor investment efficiency, and subsequently validating the mechanism through which smart manufacturing influences TFP.

(1) Technological innovation

In Luo et al. (2024)[21],the technological innovation capability of firms is gauged by the number of patent grants, given that patents serve as the fundamental bedrock for the industrialization of firms' intellectual endeavors. To encapsulate this innovation aspect, the regression model for intermediary effect is structured as follows:

$$TFP_{i,t} = \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{6}$$

$$innovation_{i,t} = \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{7}$$

$$TFP_{i,t} = \beta AI_{i,t} + \theta innovation_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{8}$$

The findings in columns (1), (2), and (3) of Table 10 show that both smart manufacturing and technological innovation exert a positive and stimulatory effect on TFP. Furthermore, the Sobel test reveals that the mediating effect contributes to 13.7% of the observed impact. This underscores the potential of firm smart manufacturing transformation to enhance overall enterprise productivity by fostering advancements in technological innovation, supporting Hypothesis 2.

(2) Efficiency of labor investment

Dierynck et al. (2012)[22] propose a measurement method for labor investment efficiency, utilizing the residual error of a specific model as the key indicator. The variable definitions utilized in this approach are outlined in Table 9.

$$Net_{Hire_{i,t}} = \beta_0 + \beta_1 Sales_{Growth_{i,t-1}} + \beta_2 Sales_{Growth_{i,t}} + \beta_3 ROA_{i,t-1} + \beta_4 ROA_{i,t} + \beta_5 \Delta ROA_{i,t} + \beta_6 Size_{R_{i,t-1}} + \beta_7 Quick_{i,t-1} + \beta_8 Quick_{i,t} + \beta_9 \Delta Quick_{i,t} + \beta_{10} Lev_{i,t-1} + \beta_{11} Lossbin1_{i,t-1} + \beta_{12} Lossbin2_{i,t-1} + \beta_{13} Lossbin3_{i,t-1} + \beta_{14} Lossbin4_{i,t-1} + \beta_{15} Lossbin5_{i,t-1} + \varepsilon_{i,t} \tag{9}$$

Table 9. Labor Investment Efficiency Variable Definitions

Variable	Descriptions
Hire	The total number of employees of the listed firm this year/The total market value of each stock in the year. The total number of employees refers to the number of registered (active) employees of the listed firm disclosed in the annual report
Net_Hire	Rate of change in Hire
Sales_Growth	Growth rate of business income
ROA	Return on assets = Net profit/total assets at beginning of year
ΔROA	The change in ROA
Size_R:	Percentage ranking of the total market value of individual stocks. Among them, the annual total market value of a stock is the product of the total number of issued shares of a stock and the annual closing price
Quick	Quick ratio = (cash + short-term investments + accounts receivable)/current liabilities
Lev	Asset-liability ratio = total liabilities/total assets
LossbinX	According to the interval of ROA from 0 to -0.025 in the previous year, the interval length is 0.005. If the interval range of ROA is -0.005 to 0, LOSSBIN1=1; otherwise, it is 0
Abresid	The absolute value of the difference between the actual and expected rate of change per unit of employment, that is, the absolute value of the residual of equation (1), is used to measure the efficiency of labor investment

As a result, the mediation effect model outlined below has been developed:

$$TFP_{i,t} = \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{10}$$

$$Abresid_{i,t} = \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{11}$$

$$TFP_{i,t} = \beta AI_{i,t} + \theta innovation_{i,t} + \gamma Controls_{i,t} + year + ind + \alpha + \varepsilon_{i,t} \tag{12}$$

Based on the findings in column (1), (4), and (5) of Table 10, it is evident that the level of smart manufacturing can effectively mitigate labor inefficiency investment, subsequently enhancing the overall factor productivity of firms. Nevertheless, the regression coefficient indicating the impact of smart manufacturing level on labor investment efficiency is statistically insignificant. This observation contradicts Hypothesis 3, suggesting that the current advancements in smart manufacturing have not yet led to substantive alterations in the structure of the labor force.

Table 10. Results of Mechanism Analysis

	(1) TFP	(2) Innovation	(3) TFP	(4) Abresid	(5) TFP
AI	0.0729**	0.4670***	0.0629***	-0.004	0.0777***
	(6.24)	(16.41)	(5.29)	（-0.67）	（9.09）
innovation			0.0215***		
			(4.44)		
Abresid					-0.0686***
					（-4.97）
Controls	Yes	Yes	Yes	Yes	Yes
Sobel			4.286***		
Proportion of mediating effect			13.7%		
Year fe	Yes	Yes	Yes	Yes	Yes
Industry fe	Yes	Yes	Yes	Yes	Yes
N	14496	7,253	7,253	12,587	12,587
r2	0.7547	0.4893	0.7554	0.0737	0.7676

5 Conclusions

This paper investigates the relationship between smart manufacturing and firms' TFP. We analyze the annual reports of Chinese listed manufacturing firms, and employ text analysis and principal component analysis to construct an indicator measuring the firms' smart manufacturing levels. The empirical results indicate that smart manufacturing significantly enhances the TFP of Chinese manufacturing firms. Furthermore, mechanism analysis reveals that smart manufacturing boosts TFP by fostering technological innovation. The findings suggest that firms should leverage AI technology to optimize internal management processes, improve operational efficiency, and enhance decision-making. As smart manufacturing technology becomes more widely applied, the traditional labor structure will undergo significant changes. Therefore, firms should concurrently focus on skills training and education of employees, rationally allocate human resources, and ensure that employees can fully realize their potential during the smart manufacturing transformation.

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