An Exploratory Study on the Relationship Between Manufacturing Intelligence Index and Enterprise Performance Based on GMM Model

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Abstract. This paper constructs indicators to measure the degree of enterprise intelligence based on the annual reports of Chinese manufacturing listed companies from 2015–2021, and tests the impact of enterprise intelligence on enterprise performance through empirical analysis. The results show that 1. The intelligent development of manufacturing enterprises can significantly improve enterprise value; 2. Total factor productivity and operating cost rate play a significant mediating role in the influence of intelligence on manufacturing enterprise value.

Keywords: degree of intelligence · firm performance · mediating effect

1 Introduction

With the development of digital technology, theoretical research on the connotation and implementation path of intelligent transformation has gone through a process from simple technology application to collocation with organizational change. Chen et al. [2] pointed out that there is a trade-off between the potential cost of inefficiency and ineffectiveness of the traditional model and the additional cost of intelligent upgrading. As smart manufacturing remains a groundbreaking topic, academic research will continue to focus on building smart manufacturing systems, how to implement smart manufacturing, and assessing smart manufacturing at the macro level. Research on the economic impact of smart manufacturing, especially empirical research, is still lacking, and whether and how smart manufacturing can generate revenue has become a need in the context of smart transformation of contemporary Chinese manufacturing enterprises A realistic problem to be solved. Therefore, this paper builds variable indicators based on existing studies, combines text mining and other methods to construct variable indicators, selects data of A-share manufacturing listed companies for the past seven years as samples, and adds mediating variables of both cost and efficiency to test the relationship between intelligent transformation and enterprise performance.

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2 Analytical Framework and Research Hypothesis

2.1 Degree of Intelligence and Business Performance

The current research on the intelligent transformation of companies at the micro level focuses more on the measurement of digital transformation. Ferreira [3] conducted a telephone survey of several companies to understand how well they implemented digital transformation. In terms of measuring intelligent change, a comparison of relevant national and international research findings shows that there is more research on the level of intelligence at the macro level, but relatively little research at the micro level.

Based on the theory of value co-creation, the intelligent transformation of traditional manufacturing enterprises helps to improve the performance level. On the one hand, smart technologies can help traditional manufacturing companies make accurate decisions and improve productivity. On the other hand, the application of smart technologies is helping companies, consumers and others to create an intelligent ecosystem that can effectively reduce transaction costs while responding quickly to individual users' needs and increasing value co-creation.

Based on the above discussion, the paper presents the core hypothesis that.

H1: Other things being equal, intelligent corporate transformation can effectively improve corporate performance.

2.2 Channels of Impact of Intelligent Transformation on Enterprise Performance

On the one hand, smart manufacturing increases the digital control of critical processes and reduces the percentage of defective products and risk losses due to human errors [7]. Regarding energy costs, smart manufacturing can independently optimize the energy losses in manufacturing processes [15]. On the other hand, some researchers point out that smart manufacturing may also increase the burden on companies. First, the lack of proper advanced design and inappropriate smart device selection strategies may hinder the desired goals of smart manufacturing models [5]. Second, smart manufacturing increases the demand for human capital, requiring companies to improve employee skills [9] to meet the development requirements of smart manufacturing, thus increasing the cost of doing business.

Based on the above discussion, hypothesis 2 is proposed in this paper.

H2: Smart manufacturing improves firm performance by reducing operating costs.

In addition, one of the studies on enterprise efficiency suggests that intelligence can significantly contribute to the growth of total factor productivity in manufacturing. Qiao Xiaonan and Xi Yanping [10] argue that AI technology can improve firm productivity through the "complementary effect" and "substitution effect" on labor. Acemoglu and Restrepo [1] argue that the negative impact of intelligence on productivity is mainly due to lagging effects and misalignment.

Based on the above discussion, hypothesis 3 is proposed in this paper.

H3: Intelligent transformation of enterprises can improve enterprise performance by affecting efficiency.

3 Data and Model Setting

3.1 Data Source and Processing Description

In this study, A-share manufacturing enterprises with the sample period of 2015–2021 were selected as the respondents, and enterprises listed or delisted within the sample area, those in the ST or ST* category, and those with missing key variables were excluded to obtain data for a total of 1291 enterprises over 7 years. In order to reduce the influence of outliers or outliers on the empirical results, a two-tailed (Winsorise) treatment at the 1% level is applied to all continuous variables in this paper.

3.2 Data Sources and Settings

Explanatory Variables

The explanatory variable is firm performance, and drawing on existing research [14], this paper uses return on assets (ROA) to measure the performance of an entity.

Explanatory Variables

Firstly, we choose R&D intensity and talent intensity to measure the level of smart technology. Secondly, we measure the level of intelligent technology application of enterprises based on text keyword frequency. In the first step, we download the annual reports of sample enterprises using python, and then convert the annual reports into readable text format. In the second step, we use python software to obtain keywords related to intelligent transformation. Specifically, keywords related to two dimensions of intelligent technology and intelligent technology application were selected based on Yu et al.'s study [1] and important policy documents and research reports such as "Made in China 2025". In the third step, the keyword numbers of the two types of keywords were summed up separately. Finally, the entropy weighting method is used to assign the secondary indicators and calculate the intelligent transformation index of enterprises. Table 1 shows the intelligent transformation index system (Tables 2 and 3).

Control Variables

In this paper, eight control variables are added [14]: firm size (Size), years of IPO (Age), gearing (Leverage), equity concentration (Shareholder), board independence (Indirector), duality (Duality), audit opinion (Audit), and nature of equity (SOE).

Mediating Variables

In this paper, two indicators, enterprise efficiency and operating cost rate, are selected for the mediation effect analysis. Total factor productivity is closely related to resource allocation efficiency [4] and can be used as a proxy indicator of enterprise efficiency. In this paper, with reference to Lu and Lian [8], the LP method [6] is chosen to estimate total factor productivity, with "main business income" denoting total output, capital input denoting "net fixed capital formation", and labor input denoted as "number of employees", and intermediate inputs were estimated on the basis of "operating costs + selling costs + administrative costs + financial costs - depreciation - money paid to and for employees" by referring to the study of Wang and Niu [11].

Table 1. Intelligent transformation index system

Tier 1 Indicators	Secondary indicators	Measurements
Intelligent input	R&D intensity	Enterprise R&D expenses/main business income
	Talent intensity	Number of enterprise R&D personnel/total number of employees
Intelligent Technology Applications	Intelligent technology level	Number of keywords related to smart technology in the text of the company's annual report
	Intelligent technology application depth	Number of keywords related to the application of smart technology in the text of the company's annual report

3.3 Model Setting and Empirical Strategy

According to hypothesis 1, to test the relationship between intelligent transformation and firm performance, this paper constructs OLS benchmark regression models.

$$\begin{aligned} ROA_{it} = & a_0 + a_1 IntelTrans_{it} + \beta_1 Size + \beta_2 Age + \beta_3 Leverage + \beta_4 Shareholder \\ & + \beta_5 Indirector + \beta_6 Duality + \beta_7 SOE + \beta_8 Audit + \beta_9 Year + \beta_{10} Industry + e \end{aligned} \tag{1}$$

In Eq. (1), the explanatory variable is the firm performance and the core explanatory variable represents the degree of intelligent transformation of the firm. In addition to the eight control variables, time (Year) and industry (Industry) variables are introduced in the model to absorb the effects of year and different types of manufacturing firm-level potential factors as much as possible. The coefficient a_1 represents the regression coefficient of the intensity of intelligent transformation, and if the coefficient is significantly positive, it indicates that intelligent transformation can have a positive impact on firm performance.

In testing hypotheses 2 and 3, this study builds on the study of Wen Zhonglin and Ye Baojuan [12] on mediating effects by developing the following regression model to identify the mechanisms and test the channels.

$$\begin{aligned} ROA_{it} = & a_0 + a_1 IntelTrans_{it} + \beta_1 Size + \beta_2 Age + \beta_3 Leverage + \beta_4 Shareholder \\ & + \beta_5 Indirector + \beta_6 Duality + \beta_7 SOE + \beta_8 Audit + \beta_9 Year + \beta_{10} Industry + e_1 \end{aligned} \tag{2}$$

$$\begin{aligned} Mediator_{it} = & b_0 + b_1 IntelTrans_{it} + \theta_1 Size + \theta_2 Age + \theta_3 Leverage + \theta_4 Shareholder \\ & + \theta_5 Indirector + \theta_6 Duality + \theta_7 SOE + \theta_8 Audit + \theta_9 Year + \theta_{10} Industry + e_2 \end{aligned} \tag{3}$$

Table 2. Variable design and meaning

	Variables	Variable Symbols	Variable Definition
Explained variables	Corporate Performance	ROA	Net profit after tax/total assets
Explanatory variables	Intelligent Transformation	Intel Trans	Intelligent transformation indicators constructed using the entropy weight method
Intermediate variables	Operating cost ratio	Cost ratio	Operating Costs / Operating Revenue
	Enterprise efficiency	Efficiency	Total factor productivity (the combined efficiency of each resource development and utilization)
Control variables	Enterprise size	Size	Logarithmic processing of the size of the company's workforce
	Business Age	Age	Logarithmic processing of the number of years the company has been listed
	Gearing ratio	Leverage	Total liabilities at end of period/total assets at end of period
	Shareholding Concentration	Shareholder	Percentage of shareholding of the largest shareholder
	Board Independence	Indirector	Number of independent directors as a percentage of the total number of board of directors
	Two jobs in one	Duality	The value is 1 if the chairman is also the general manager, otherwise it is 0
	Nature of shareholding	SOE	State-controlled enterprises take the value of 1, otherwise it is 0
	Audit Opinion	Audit	Standard unqualified opinion takes the value of 1, otherwise it is 0

Table 3. Descriptive statistics results

Variable Name	Variable Symbols	Average value	Standard deviation	Minimum value	Maximum value
Intelligence Index	Intel Trans	0.145	0.117	0	0.931
ROA	ROA	0.053	0.100	-1.079	0.480
Operating cost ratio	OCR	0.705	0.171	0.036	1.862
Total Factor Productivity	TFP	0.745	0.160	-2.117	2.513
Number of employees	Size	5904.830	13654.365	0	288186
Company Age	Age	19.000	5.274	6	54
Gearing ratio	Leverage	0.390	0.178	0.014	0.989
Shareholding Concentration	Shareholder	32.250	13.898	2.431	89.093
Two jobs in one	Duality	0.290	0.452	0	1
Audit Opinion	Audit	0.980	0.137	0	1
Board Independence	Indirector	0.380	0.057	0	1
Nature of shareholding	SOE	0.300	0.456	0	1

$$\begin{aligned} ROA_{it} =& c_0 + c_1 Mediator_{it} + a_0^{'} IntelTrans_{it} + \delta_1 Size + \delta_2 Age + \delta_3 Leverage + \delta_4 Shareholder \\ &+ \delta_5 Indirector + \delta_6 Duality + \delta_7 SOE + \delta_8 Audit + \delta_9 Year + \delta_{10} Industry + e_3 \end{aligned} \tag{4}$$

In the equation, the main explanatory variable is Intel Trans, the mediating variable is Mediator, the explanatory variable is ROA, a_1 represents the path coefficient, and $a_0{'}$ represents the direct effect. Since there is no third variable involved in the mediating effect, a_1 represents the total effect of the explanatory variable on the explanatory variable. After controlling for intervening variables, the relationship between the explanatory variable Intel Trans and the explanatory variable ROA is such that the explanatory variable Intel Trans affects the explanatory variable ROA through the explanatory mediating variable.

4 Empirical Study and Analysis of Results

4.1 Descriptive Statistics

The minimum value of ROA is -1.079, the maximum value is 0.480, and the standard deviation is 0.1, which indicates that there is a large gap between the enterprise values of manufacturing enterprises in China, and also indicates that the sample data selected in this paper is broad and diverse. The mean value of the index used to measure the level of intelligence is 0.145, compared with the United States and other developed countries, the level of intelligence of Chinese manufacturing enterprises is still in the initial stage and relatively low; the maximum and minimum values of this index are 0.931 and 0, respectively, and the standard deviation is 0.117, which indicates that the differences in the application of intelligence among different manufacturing enterprises are very obvious.

4.2 Table of Empirical Studies on the Degree of Intelligence and Firm Performance

Table 4 reports the results of the impact of smart transformation on ROA. The results in columns (1) and (2) show that the estimated coefficient of intelligent transformation is 0.335, which is significant at the 1% level, after controlling for firm- and region-level control variables, indicating that intelligent transformation of manufacturing firms can significantly increase net profit after tax; in column (3), the p-values of firm age, dual employment and equity nature are greater than 0.01, and there is no significant correlation between them and changes in ROA. There is no statistical correlation between them and the change in ROA. In column (5), the VIF value of each variable is less than 2, indicating that there is no significant multicollinearity among the variables and the model is acceptable. ROA is the company performance and Intel Trans represents the degree of intelligent transformation of the company. The coefficient a_1 represents the regression coefficient of Intel Trans, which is significantly positive, indicating that intelligent transformation can have a positive impact on firm performance.

4.3 Dynamic Panel Regression Model

The sample itself in this paper has endogeneity, and the traditional panel regression model cannot fit the relationship between the explanatory variables and the explained variables well. In order to reduce the effect of endogeneity, the following model is developed in this paper, combined with the consideration of the inertial behavior of economic phenomena, and the following dynamic panel regression model is re-established using the Generalized Method of Moments (GMM).

$$\begin{aligned} ROA_{it} =& \alpha + a_0 ROA_{it-1} + a_1 IntelTrans_{it} + \beta_1 Size + \beta_2 Age + \beta_3 Leverage + \beta_4 Shareholder \\ &+ \beta_5 Indirector + \beta_6 Duality + \beta_7 SOE + \beta_8 Audit + \beta_9 Year + \beta_{10} Industry + e \end{aligned} \tag{5}$$

Table 5 reports the results of the regressions using differential generalized moment estimation and systematic generalized moment estimation, respectively.

From the statistical results, it can be seen that the P-values of Arellano-Bond tests for all models are greater than 0.01 at the 1% significance level, and there is no autocorrelation in the disturbance terms, so the GMM method can be used to estimate the dynamic model of the panel data in this paper; from Table 5, it can be seen that the P-values of Sargan tests for all models in this paper are greater than 0.01, and the original hypothesis is accepted, i.e., the selected instrumental variables are valid in all models.

Table 4. Baseline regression results

	(1)	(2)	(3)	(4)	(5)
	ROA	TFP	Cost ratio	ROA	ROA
Intel Trans	0.335***	-0.023*	-0.167***	0.339***	0.315***
	(51.791)	(-1.657)	(-11.859)	(58.332)	(50.041)
TFP				0.205***	
				(45.999)	
Cost ratio					-0.116***
					(-24.880)
Size	5.580E-7***	6.226E-7***	4.859E-8	4.304E-7***	5.636E-7***
	(9.882)	(5.186)	(0.395)	(8.455)	(10.318)
Age	3.128E-4	-0.001***	-9.475E-5	0.001***	3.02E-4
	(2.011)	(-4.163)	(-0.280)	(4.246)	(2.006)
Leverage	-0.139***	-0.307***	0.374***	-0.076***	-0.095***
	(-31.373)	(-32.605)	(38.776)	(-18.037)	(-20.624)
Shareholder	0.001***	0.001***	-0.001***	3.75E-4***	0.001***
	(10.942)	(9.392)	(-5.063)	(7.573)	(9.971)
Duality	-0.001	0.002	-0.017***	-0.001	-0.003
	(-0.400)	(0.535)	(-4.632)	(-0.703)	(-1.624)
Audit	0.072***	0.063***	0.020	0.059***	0.075***
	(13.356)	(5.477)	(1.728)	(12.167)	(14.256)
Indirector	-0.051***	-0.032	-0.025	-0.045***	-0.054***
	(-3.919)	(-1.168)	(-0.868)	(-3.788)	(-4.278)
SOE	-0.102***	-0.008**	0.039***	-0.101***	-0.098***
	(-57.461)	(-2.042)	(10.066)	(-62.835)	(-56.444)
N	9037	9037	9037	9037	9037
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
R2	0.510	0.133	0.209	0.603	0.541

Note: The values of each statistic are in parentheses, *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively

The baseline regression uses two methods for its dynamic panel estimation, and its significance and the positive and negative coefficients do not change, so the model is robust and will not be tested separately for robustness.

The results show that the intelligence index can significantly and positively affect firm performance. This result can test hypothesis H1.

Table 5. Comparison of diffGMM and sysGMM

	diffGMM	sysGMM
L.roa	roa	roa
	0.104***	0.148***
Intel trans	(3.613)	(5.707)
	0.166***	0.249***
size	(3.742)	(12.160)
	0.000	0.000*
age	(0.631)	(1.693)
	0.003***	0.002***
leverage	(5.015)	(4.773)
	-0.299***	-0.283***
shareholder	(-10.058)	(-10.589)
	0.000	0.001*
duality	(1.620)	(1.948)
	-0.000	-0.004
audit	(-0.090)	(-0.796)
	0.031*	0.033**
indirector	(1.829)	(2.016)
	-0.067*	-0.066*
soe	(-1.752)	(-1.772)
	0.004	0.015*
Constant	(0.531)	(1.935)
	0.040	0.028
	(1.470)	(1.078)
AR(2)	0.1320	0.0612
sargan	1.0000	1.0000
Observations	6,455	7,746
Number of code	1,291	1,291

Note: The values of each statistic are in parentheses, *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively

4.4 Analysis of Mediating Effects

According to column (3) of Table 6, the relationship between total factor productivity and intelligence index is significant at the 5% level. In column (4), it shows that there is a significant relationship between both the intelligence index and total factor productivity and ROA. Therefore, TFP is a mediating variable between firm performance and the intelligence index, with a partial mediating effect. The correlation coefficient between TFP and the intelligence index is negative, but the correlation coefficient between ROA and the intelligence index is positive, which may be related to the fact that the mediating effect of TFP is masked by the high degree of explanation of the intelligence index itself. In general, total factor productivity can still be considered as a proxy variable between ROA and the intelligence index.

Table 6. Total factor productivity regression results

VARIABLES	(2) roa	(3) tfp	(4) roa
L.roa	0.148***		0.075***
	(5.707)		(3.058)
Intel trans	0.249***	-0.050**	0.296***
	(12.160)	(-2.150)	(15.385)
tfp			0.221***
			(10.683)
size	0.000*	0.000	0.000
	(1.693)	(1.490)	(1.620)
age	0.002***	0.005***	-0.000
	(4.773)	(6.328)	(-0.764)
leverage	-0.283***	-0.153***	-0.237***
	(-10.589)	(-4.866)	(-9.362)
shareholder	0.001*	0.001*	0.000
	(1.948)	(1.886)	(1.322)
duality	-0.004	-0.005	-0.003
	(-0.796)	(-0.997)	(-0.611)
audit	0.033**	0.003	0.016
	(2.016)	(0.202)	(1.212)
indirector	-0.066*	-0.110**	-0.061*
	(-1.772)	(-2.168)	(-1.947)
soe	0.015*	-0.008	0.015**
	(1.935)	(-0.869)	(2.080)
L.tfp		0.524***	
		(18.707)	
Constant	0.028	0.340***	-0.083***
	(1.078)	(9.949)	(-3.420)
Observations	7,746	7,746	7,746

(*continued*)

Table 6. (*continued*)

VARIABLES	(2) roa	(3) tfp	(4) roa
Number of code	1,291	1,291	1,291

Note: The values of each statistic are in parentheses, *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively

According to column (3) of Table 7, the relationship between operating cost rate and intelligence index is significant at the 1% level. In column (4), it shows that there is a significant relationship between both the intelligence index and the operating cost rate and the ROA of corporate performance. Therefore, it can be judged that the operating cost rate is a mediating variable between corporate performance ROA and intelligence index with partial mediation effect. The coefficients b_1*c_1 and α_0 have the same sign, which indicates that the intelligence index may negatively regulate the corporate performance ROA by reducing the operating cost rate. Collectively, both firm-wide productivity and operating cost rate are mediating variables between the explanatory variable corporate performance ROA and the explanatory variable intelligence index. Therefore, H2 cannot be rejected, and it can be argued that smart manufacturing improves firm performance by reducing firm operating costs.

Table 7. Operating cost ratio regression results

VARIABLES	(2) roa	(3) Cost ratio	(4) roa
L.roa	0.148***		0.077***
	(5.707)		(3.004)
Intel trans	0.249***	-0.009	0.204***
	(12.160)	(-0.639)	(7.910)
Cost ratio			-0.387***
			(-10.228)
size	0.000*	0.000	0.000**
	(1.693)	(0.151)	(2.238)
age	0.002***	0.003***	0.004***
	(4.773)	(6.558)	(7.374)
leverage	-0.283***	0.071***	-0.250***
	(-10.589)	(4.468)	(-9.992)
shareholder	0.001*	-0.000	0.000

(*continued*)

Table 7. (*continued*)

VARIABLES	(2) roa	(3) Cost ratio	(4) roa
	(1.948)	(-1.122)	(0.705)
duality	-0.004	0.001	-0.002
	(-0.796)	(0.375)	(-0.546)
audit	0.033**	0.000	0.027*
	(2.016)	(0.036)	(1.890)
indirector	-0.066*	-0.003	-0.045
	(-1.772)	(-0.092)	(-1.353)
soe	0.015*	-0.008	0.019**
	(1.935)	(-1.236)	(2.476)
L.cost ratio		0.772***	
		(29.333)	
Constant	0.028	0.096***	0.276***
	(1.078)	(3.172)	(8.880)
Observations	7,746	7,746	7,746
Number of code	1,291	1,291	1,291

Note: The values of each statistic are in parentheses, *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively

5 Conclusions

The following conclusions are drawn from the empirical analysis: (1) Intelligent transformation is an important influencing factor to improve enterprise performance under the same control conditions; (2) Intelligent manufacturing can improve enterprise performance by reducing operating costs; (3) Intelligent transformation of enterprises can improve enterprise performance by affecting enterprise efficiency.

The following recommendations are made based on the findings of the study.

(1) Intelligent transformation of enterprises should be value benefit-oriented and clear transformation objectives.
(2) Enterprises should establish reliable intelligent management and decision support systems to support improved technical efficiency.
(3) Enterprises should increase investment in R&D and increase the role of intelligence in promoting industrial total factor productivity.

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