The Impact of Industrial Robot Application on the Quality of Corporate Financial Reporting in the Context of High Economic Quality

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Abstract: In promoting high-quality economic development, industrial robots, the fruit of technological innovation, are landed and applied in manufacturing enterprises. This paper takes the manufacturing enterprises listed on China's A-share stock market from 2013 to 2019 as a research sample, empirically explores the relationship between the application of industrial robots and the quality of corporate financial reporting, and analyzes the path mechanisms involved. The results show that the application of industrial robots can significantly reduce the level of surplus management and thus improve the financial reporting quality of listed companies. In terms of heterogeneity, the enhancement effect of industrial robots on financial reporting quality is more obvious in high-tech, non-labor-intensive and non-polluting enterprises. In terms of mechanism analysis, the application of industrial robots enhances financial reporting quality mainly by improving the quality of internal control, and the effect of internal control effect is more obvious in small-sized, high-growth non-state-owned enterprises. Finally, based on the conclusions of the article, this paper puts forward feasible suggestions for accelerating the application of AI innovations in the manufacturing sector to improve the quality of corporate financial reporting and realize the high-quality development of the economy from the perspectives of the government, the industry and the enterprises.

Keywords: Application of Industrial Robots; Financial Reporting Quality; Internal Control

1. Presentation of the Issue

China’s economy has transitioned to high-quality development, prioritizing the real economy and new industrialization by 2035. Manufacturing, bolstered by industrial robots, is central to this goal, with robots driving cost reduction, innovation, and green development. China, the largest robot adopter in Asia per the International Federation of Robotics, aims for global leadership in robotics by 2035 under the “14th Five-Year Plan.” However, robots alter enterprise operations, impacting internal control quality and potentially financial reporting quality[3]. While macro-level studies dominate, micro-level impacts on financial reporting remain underexplored. This study empirically examines how industrial robot adoption affects corporate financial reporting quality, addressing theoretical gaps in AI’s micro-governance effects. It clarifies internal control’s mediating role, offering insights for enhancing financial reporting through robust internal controls. Additionally, it explores variations across enterprises, providing empirical support for precise government policies and corporate AI strategies. By focusing on industrial robots as a specific innovation, this study bridges gaps in understanding AI’s impact on financial transparency, supporting high-quality economic development[2].

2. Literature Review

2.1 Literature Review on the Application of Industrial Robots

The International Organization for Standardization (ISO) and China’s Ministry of Industry and Information Technology define industrial robots as reprogrammable, multi-functional machines for industrial tasks, pivotal to China’s manufacturing strength. Literature measures robot adoption via enterprise-level data like the China Enterprise-Labor Matching Survey, using binary variables or micro-indicators such as robot equipment value and density[4,43], or the International Federation of Robotics (IFR) data for penetration indices to address endogeneity

[36]. Macro-level studies highlight robots' labor market impacts, including substitution, creation, and neutrality effects, enhancing human capital, labor productivity, and industrial upgrades [12,16,27,36,37]. Micro-level research shows robots drive organizational change by reducing costs, optimizing internal controls, and enabling human-machine collaboration, improving resource allocation[1,10,19]. However, the impact on financial reporting quality remains underexplored, despite its link to governance effectiveness, forming the theoretical basis for this study.

2.2 Literature Review on the Quality of Financial Reporting

Financial reporting quality, crucial for investors, lacks consensus on measurement variables. Surplus quality, widely used for its continuity in assessing earnings, serves as this study's proxy [45]. Literature identifies three impact mechanisms: technological innovation, where new technologies like digital transformation enhance disclosure by curbing surplus management [3,35]; internal governance, where improved internal controls and governance reduce surplus manipulation [6,8,9,28,31]; and external supervision, where audits and reputation pressures ensure reliability[5,41,42,44]. Industrial robots, reshaping internal controls and information accuracy, may influence financial reporting quality, a mechanism requiring empirical exploration.

2.3 Literature Review

Existing research overlooks the link between AI applications, like industrial robots, and financial reporting quality, focusing on innovation broadly [3]. Studies emphasize macro-level impacts, neglecting micro-level governance effects of robots. The multidimensional framework for financial reporting quality fails to address robots' influence on organizational control and information generation. As AI carriers, industrial robots reshape financial information ecosystems via improved internal controls and information accuracy, offering a valuable scenario to explore the "technology-governance-information quality" transmission mechanism[13,14].

3. Theoretical Analysis and Research Hypotheses

3.1 Theoretical Analysis of the Impact of the Application of Industrial Robots on the Quality of Corporate Financial Reporting

Industrial robots, embodying corporate innovation, influence financial reporting quality by curbing surplus management and enhancing audit quality. Innovation, including robot adoption, reduces surplus manipulation by maintaining corporate reputation and mitigating agency issues [11,46,47]. Robots improve production efficiency, reducing management's incentive for manipulation, while automation minimizes manual intervention, lowering information asymmetry [1,4]. Additionally, robots enhance audit quality by improving data timeliness, accuracy, and verifiability [25,38]. Standardized, traceable production processes and real-time ERP integration strengthen audit evidence, boosting financial report reliability [1]. Thus, Hypothesis 1 posits that industrial robot application improves firms' financial reporting quality.

3.2 Improved Quality of Financial Reporting Through Enhanced Quality of Internal Controls as a Result of the Application of Industrial Robots

Industrial robots, as "artificially intelligent employees," enhance internal control quality by transforming organizational operations [19,26]. They drive human capital upgrades, increasing high-skilled staff and optimizing structures, thus strengthening risk assessment [12,33]. Integration with IoT and big data improves real-time data processing and decision-making, boosting internal control synergy [7,19]. Strong internal controls reduce surplus management, enhancing financial reporting quality [6,35]. Thus, Hypothesis 2 states: industrial robot applications improve financial reporting quality by enhancing internal control quality.

4. Research Design

4.1 Data Sources

This study uses CSMAR database data, focusing on A-share manufacturing listed companies from 2013–2019. Industrial robot data from the International Federation of Robotics (IFR) is matched with industry categories per GB/T4754-2011 and ISIC standards [24]. Listed company data ensure quality and variability, while robots significantly impact manufacturing. Exclusions include delisted firms, missing data, and outliers trimmed at 1% and 99% quartiles, yielding 9658 observations.

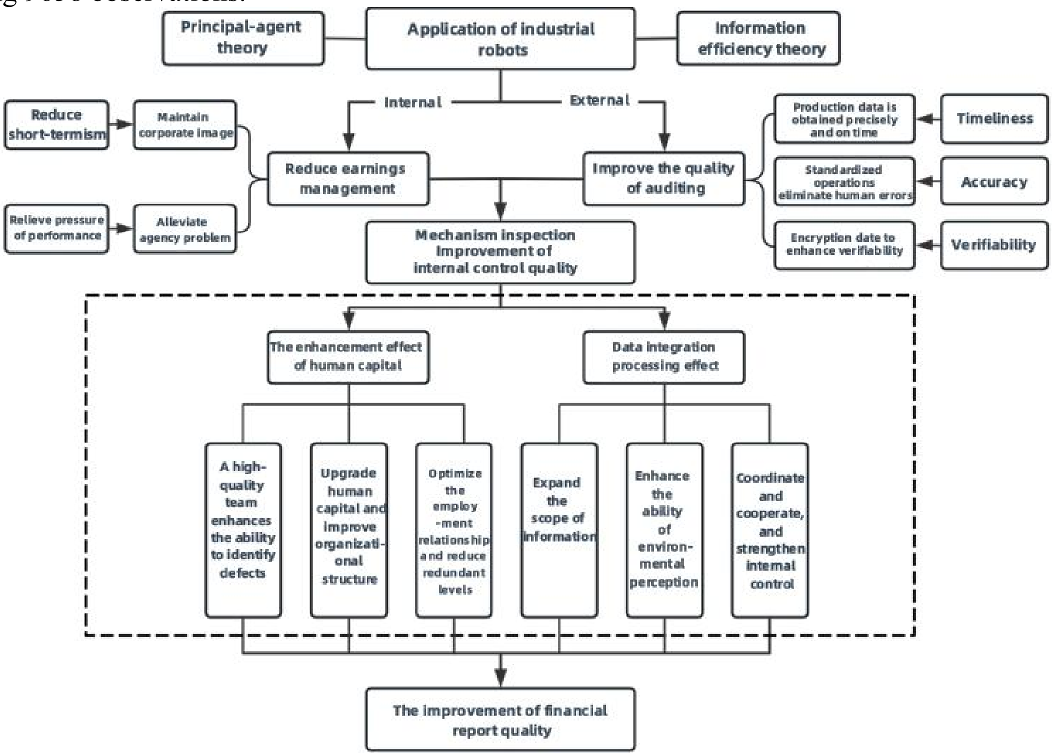

Figure 1. Logic Thought Map

4.2 Definition of Variables

4.2.1 Explained variable: financial reporting quality (*FRQ*)

The explanatory variable is financial reporting quality (FRQ), measured by surplus management per Ball and Shivakumar[40]. A nonlinear accrual model, incorporating a dummy variable (DVAR) for losses, captures the asymmetric recognition of gains and losses. The absolute value of manipulable accruals, derived as the difference between total and normal accruals, reflects accounting information quality.

$$\frac{TA_t}{A_{t-1}} = \beta_0 + \beta_1 \frac{REV_t}{A_{t-1}} + \beta_2 \frac{PPE_t}{A_{t-1}} + \beta_3 \frac{DVAR_t}{A_{t-1}} + \beta_4 \frac{CFO_t \times DVAR_t}{DVAR_t} + \varepsilon_t \quad (1)$$

Where TA_t is the firm's total accrued profit in year t, which is calculated by subtracting operating profit in year t from cash flow from operating activities in year t; A_{t-1} is the firm's total investment in year t-1; ΔREV_t is the change in the firm's main operating income in year t, which is calculated by subtracting main operating income in year t from main operating income in year t; PPE_t is the original book value of the firm's fixed assets in year t; and $DVAR_t$ is the dummy variable representing losses, which equals 1 when CFO is less than zero and 0 when the reverse is true; CFO_t is the firm's operating cash flow in year t; and ε_t is the model's fitting error, which is an estimate of the firm's manipulable surplus in year t. Using industry-by-industry-by-year regressions, the absolute value of the residuals obtained at the end is the degree of surplus management.

4.2.2 Explanatory variables: penetration of industrial robots (*Robot*)

The main hypothesized explanatory variable of this paper is industrial robot penetration (*Robot*), referring to Wang Yongqin and Dong Wen[34], constructing industrial robot penetration indicators of Chinese manufacturing listed companies according to Bartik's instrumental variable idea. The specific steps are:

In the first step, industrial robot penetration (*IR*) is calculated at the industry level:

$$IR_{jt} = \frac{SR_{jt}}{L_{j,t=2011}} \quad (2)$$

Where $IR_{j,t}$ denotes industrial robot penetration in t in the j industry, SR_{jt} denotes industrial robot stock in t in the j industry, and $L_{j,t=2011}$ denotes number of employees in 2011 (base period) in the j industry.

In the second step, the penetration of industrial robots at the firm level was calculated (CR):

$$CR_{ijt} = \left(\frac{W_{ijt=2012}}{ManuW_{t=2012}}\right) \times IR_{jt} \quad (3)$$

Where CR_{ijt} denotes the industrial robot penetration degree of j industry i enterprises t in 2012, and $W_{ijt=2012}/ManuW_{t=2012}$ is the ratio of the ratio of employees in the production department of j industry i enterprises in 2012 (base period) to the median ratio of employees in the production department of all enterprises in the manufacturing industry in 2012. In order to eliminate the effect of heteroskedasticity as much as possible, CR_{ijt} is logarithmized after adding 1 to get the core explanatory variable of this paper-industrial robot penetration degree ($Robot$). This indicator reflects the changes in the technological characteristics of the industrial robot industry, and is not related to the characteristics of the enterprises themselves. Under this main hypothesis, this paper also derives the mediating variable internal control quality.

Table 1. Variable Definitions

Variable type	variable name	variable symbol	Measurement Methods
explanatory variable	Quality of financial reporting	FRQ	A nonlinear accrual model is chosen to calculate manipulated accrual profits with reference to Ball and Shiwakumar's model.
explanatory variable	Industrial Robot Applications	$Robot$	Drawing on the research methodology of Yongqin Wang and Wen Dong, "robot penetration" is used as a measure of "industrial robot application".
intermediary variable	Quality of internal controls	IC	The "Dibo-China listed companies internal control index" is used as a proxy variable for internal control.
control variable	Company size	$size$	Equal to the natural logarithm of assets at the beginning of the current period
	Company age	age	Independent directors divided by number of directors
	Inventory ratio	IAR	Net cash flows from operating activities/total assets
	solvency	LEV	Gearing ratio, which is equal to the ratio of the firm's total liabilities to the Total assets ratio
	return on net assets	ROA	Net profit for the year of loss is less than 0 take 1, otherwise take 0
	two jobs in one	$Dual$	CEO and Chairman of the Board assigned a value of 1, otherwise 0
	growth capacity	$Growth$	Revenue growth rate
	Percentage of independent directors	$Indr$	Number of independent directors/number of directors
	system of checks and balances on shareholding	EBR	Proportion of shares held by the company's largest shareholder / sum of the proportion of shares held by the company's second to tenth largest shareholders
	Big Four Audit	$BIG4$	If the company is "Big 4" audits take the value of 1; otherwise it takes the value of 0
	shareholding structure	SOE	It takes the value of 1 if the company is a state-owned enterprise; otherwise it takes the value of 0

4.2.3 Control variables

Referring to Yongqin Wang and Wen Dong[34] etc., the following control variables are selected in this paper as shown in Table 1.

4.3 Modeling

To test hypothesis one, we constructed the following empirical model:

$$FRQ = \alpha_0 + \alpha_1 Robot + \sum \alpha_k Control + \sum Year + \sum id + \delta \tag{4}$$

In model (4), $Control$ represents the control variables; $Year$ is the time fixed effect, id is the firm fixed effect, and the selected standard errors are robust standard errors. α_1 It is the core coefficient of interest in this paper. If α_1 is significantly negative, hypothesis H1 is verified; if α_1 is significantly positive, hypothesis H1 is not valid.

5. Empirical Findings

5.1 Descriptive Statistics

Table 2 shows financial reporting quality (FRQ) with a mean of 0.046, median of 0.032, and standard deviation of 0.048, indicating varied quality. Industrial robot penetration (Robot) ranges from 0.000 to 0.013, with a standard deviation of 0.004, reflecting significant differences across manufacturing industries. Most control variables, except DUAL and SOE, are normally distributed.

Table 2. Results of Descriptive Statistics

variant	sample size	average value	upper quartile	(statistics) standard deviation	minimum value	maximum values
FRQ	9658	0.046	0.032	0.048	0.000	0.992
Robot	9658	0.007	0.007	0.000	0.000	0.013
IC	9658	6.394	6.620	1.180	0.000	8.233
size	9658	22.050	21.910	1.126	19.700	26.000
age	9658	18.110	18.000	5.232	6.000	35.000
LEV	9658	0.388	0.378	0.187	0.033	0.980
IAR	9658	0.247	0.223	0.135	0.016	0.828
ROE	9658	0.058	0.063	0.126	1.752	0.416
DUAL	9658	0.293	0.000	0.455	0.000	1.000
Growth	9658	0.256	0.123	0.688	-1.00	10.340
SOE	9658	0.290	0.000	0.454	0.000	1.000
BIG4	9658	0.043	0.000	0.204	0.000	1.000

5.2 Co-Linearity Diagnosis

Table 3. Co-Linearity Diagnostic Results

variant	VIF	1/VIF
size	1.660	0.604
LEV	1.580	0.634
SOE	1.280	0.780
ROE	1.260	0.791
IC	1.170	0.852
BIG4	1.120	0.893
DUAL	1.090	0.916
IAR	1.090	0.920
age	1.080	0.927
Growth	1.010	0.991
Robot	1.000	0.998
Mean	VIF	1.210

As shown in Table 3, before conducting the baseline regression, variance inflation factor (VIF) diagnostics were performed on all explanatory and control variables entered into the model, and the results showed that the maximum value of VIF for each variable was 1.660, and the average value of VIF was 1.21. The VIF was significantly less than 10, which indicated that there was no multicollinearity between the variables, and the test was passed.

5.3 Baseline Regression Results and Analysis

Table 4 shows baseline regression results. Industrial robot penetration (Robot) has a significantly negative coefficient (-0.258 at 10% in column 1; -0.316 at 5% in column 2 with controls and fixed effects), confirming reduced surplus management and improved financial reporting quality, supporting Hypothesis 1. Significant control variables include gearing ratio (LEV, 0.039), inventory ratio (IAR, -0.029), return on equity (ROE, -0.108), and growth (0.005), all at 1%, indicating their impact on financial reporting quality[17].

Table 4. Benchmark Regression Results

variant	Explained variable: *FRQ*	
	(1)	(2)
Robot	-0.294**	-0.316**
	(-2.132)	(-2.317)
size		0.001
		(0.485)
age		-0.006
		(-0.449)
LEV		0.039***
		(4.160)
IAR		-0.029 ***
		(-2.833)
ROE		-0.093***
		(-9.402)
DUAL		-0.002
		(-0.819)
Growth		0.007***
		(2.714)
SOE		-0.004
		(-0.655)
BIG4		-0.002
		(-0.340)
constant term (math.)	0.047***	0.108
	(28.344)	(0.496)
Year fixed effects	uncontrolled	containment
individual fixed effect	uncontrolled	containment

N	9658	9658
r2	0.012	0.083
r2_a	0.011	0.081

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

5.4 Robustness Tests

Benchmark regression analysis proves the role of industrial robot application and financial report quality improvement, in order to verify the robustness of the conclusions of this paper, this paper adopts three methods of robustness test by replacing the explanatory variables, changing the sample period and reducing the control variables[20].

5.4.1 Replacement of explanatory variables

Referring to the proxies for financial reporting quality in the existing literature, the modified Jones model *FRQ1* proposed by Dechow and the cash flow Jones model *FRQ2* proposed by Dechow and Dichev are used as proxies for financial reporting quality *FRQ*, respectively. Table 5 Column (1) shows the results of the benchmark regression, and columns (4) and (5) show the results of the regression of the proxy variables in place of The results show that the regression coefficients of the application of industrial robots, *Robot*, on the financial reporting quality, *FRQ1* and *FRQ2*, are significantly negative, i.e., the application of industrial robots is still able to significantly improve the quality of financial reporting, which further verifies the robustness of the results of the benchmark regression[21].

5.4.2 Change of sample period

The article shortens the sample period to 2015 to 2019, as shown in column (3) of Table 5 , the regression coefficient of the application of industrial robots (*Robot*) on financial reporting quality (*FRQ*) is significantly negative, indicating that the application of industrial robots reduces surplus management behaviors and thus improves financial reporting quality.

Table 5. Robustness Tests

variant	*FRQ*			*FRQ1*	*FRQ2*
	(1)	(2)	(3)	(2)	(3)
Robot	-0.316**	-0.309*	-0.311**	-0.169*	-0.944*
	(-2.317)	(-1.926)	(-2.267)	(-1.741)	(-1.910)
controls	containment	containment	containment	containment	containment
Year fixed effects	containment	containment	containment	containment	containment
individual fixed effect	containment	containment	containment	containment	containment
constant term (math.)	0.108	0.094	0.212	0.024	-1.041
	(0.496)	(0.225)	(0.934)	(0.173)	(-1.476)
N	9658	5893	9658	9658	9658
r2	0.083	0.150	0.049	0.030	0.092
r2_a	0.081	0.148	0.048	0.029	0.090

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

5.4.3 Reduction of control variables

Replacing return on equity (*ROE*) with *return* on total net assets (*ROA*) and deleting firm size (*SIZE*), nature of equity (*SOE*), and Big 4 International (*BIG4*), Table 5 Column (2) of the results shows that the regression of the application of industrial robots (*Robot*) on the quality of financial reporting (*FRQ*) is significantly negative, which is basically the same as that of the benchmark regression.

5.5 Heterogeneity Analysis

The previous empirical results based on the full sample show that the application of industrial robots has an enhancing effect on the quality of financial reporting, but considering that there may be asymmetry in the impact of the application of industrial robots on the quality of financial reporting in different internal environments, this part examines the performance of such an enhancing effect in firms with different technological intensities, pollution levels, and labor intensities in terms of the firms' own micro characteristics[29].

5.5.1 Whether it is a High-tech Industry

Table 6. Technology Intensity

variant	high tech	non-high tech
	(1)	(2)
Robot	-0.296**	-0.557
	(-2.125)	(-1.369)
controls	containment	containment
Year fixed effects	containment	containment
individual fixed effect	containment	containment

constant term (math.)	-0.025	0.319
	(-0.076)	(1.074)
N	7651	2007
r2	0.100	0.044
r2_a	0.098	0.037

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

Table 6 shows subgroup regressions for high-tech and non-high-tech firms [30]. Industrial robot penetration (Robot) significantly improves financial reporting quality (FRQ) in high-tech firms (coefficient -0.276, 5% level), but is insignificant in non-high-tech firms. High-tech firms benefit from better technological integration, mature digital infrastructure, and policy-driven disclosure incentives, enabling seamless robot data integration into financial systems. Non-high-tech firms face manual intervention, fragmented systems, and lower transparency requirements, limiting robots' impact on FRQ[22].

5.5.2 Whether it is a heavily polluting enterprise

Table 7 shows regressions for heavily and non-heavily polluting firms [23]. Industrial robot penetration (Robot) significantly enhances financial reporting quality (FRQ) in non-heavily polluting firms (coefficient -0.342, 5% level), but is insignificant in heavily polluting firms. Non-heavily polluting firms benefit from easier equipment upgrades and green policy support, like subsidies for cleaner production, optimizing financial structures. Heavily polluting firms face high fixed asset barriers, limited financing, and view robot investment as compliance, lacking incentives to improve FRQ.

Table 7. Pollution Levels

variant	heavy pollution	non-heavy pollution
	(1)	(2)
Robot	-0.393	-0.342**
	(-1.216)	(-2.336)
controls	containment	containment
Year fixed effects	containment	containment
individual fixed effect	containment	containment
constant term (math.)	0.129	0.076
	(0.251)	(0.322)
N	2840	6818
r2	0.082	0.099
r2_a	0.077	0.097

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

5.5.3 Whether it is a labor-intensive enterprise

Table 8 shows regressions for labor-intensive and non-labor-intensive firms [32]. Industrial robot penetration (Robot) significantly improves financial reporting quality (FRQ) in non-labor-intensive firms (coefficient -0.266, 10% level), but is insignificant in labor-intensive firms. Non-labor-intensive firms, with higher investment returns, integrate robots for complex financial reporting, leveraging real-time data for R&D and supply chain metrics. Labor-intensive firms, with lower returns and simpler cost-focused indicators, see limited robot-driven optimization, restricting financial reporting improvements.

Table 8. Labor Intensity

variant	labor-intensive	non-labor-intensive
	(1)	(2)
Robot	-0.353	-0.266*
	(-1.262)	(-1.754)
controls	containment	containment
Year fixed effects	containment	containment
individual fixed effect	containment	containment
constant term (math.)	-0.244	0.160
	(-1.202)	(0.531)
N	2038	7620
r2	0.116	0.082
r2_a	0.109	0.081

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

5.6 Transmission Path Analysis

5.6.1 Path mechanism analysis

The results of the previous study show that the application of industrial robots can help improve the quality of corporate financial reporting. As "artificially intelligent employees", industrial robots, on the surface, are only involved in operation control, and the path of their influence on the quality of financial reporting is not clear, and exploring this path will help to deeply understand the micro-governance effect of industrial robots' application and open the black box of the relationship between the application of industrial robots and the quality of corporate financial reporting. Therefore, the following section will focus on examining the mechanism of the path of industrial robot application to improve the quality of corporate internal control.

The mechanism variable of this paper, internal control quality (*IC*), measures the quality of internal control by the internal control index of listed companies published by Dibble Big Data Research Center, drawing on Zhou, Weihua and Liu, Yilin (2022)[34], which is divided by 100 and expressed as IC. The larger the value, the higher the quality of internal control of the firm.

Referring to the riverboat[15], the following model was developed to test hypothesis 2:

$$IC=\theta_0+\theta_1 Robot+\sum\theta_k Control+\sum Year+\sum Industry+\psi \quad (5)$$

Based on the validation of the above empirical results, if the coefficient α_1 in model (1) and the coefficient θ_1 in model (2) are significant, it indicates that the variable IC is a mediating variable of the application of industrial robots affecting the quality of corporate financial reporting.

Table 9. Effect of Intermediate Model Test

variant	*IC*
Robot	6.699**
	(2.121)
controls	containment
Year fixed effects	containment
individual fixed effect	containment
constant term (math.)	6.955***
	(3.207)
N	9658
r2	0.091
r2_a	0.089

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10% confidence levels, respectively.

Table 9 shows that industrial robot application (Robot) significantly enhances internal control quality (IC) (coefficient 6.699, 5% level), improving financial reporting quality (FRQ) by strengthening internal controls. High-quality internal controls curb surplus management, aligning with principal-agent theory and studies confirming their role in enhancing FRQ[6,9,31]. Thus, robots reduce surplus management via improved internal controls, verifying Hypothesis 2.

5.6.2 Further analysis: the effectiveness of internal control effects in different enterprises

(1) Nature of equity

Table 10 shows industrial robot penetration (Robot) significantly improves internal control quality (IC) in non-state-owned enterprises (coefficient 6.721, 10% level), but not in state-owned enterprises (SOEs). Non-SOEs, with flexible employment and stronger risk management, leverage robots to enhance governance and internal controls, substituting low-end labor with high-skilled staff [18,24]. SOEs, with longer agency chains, face persistent agency issues, limiting robots' impact on internal control quality [18].

(2) Growth capacity

Table 10 shows industrial robot penetration (Robot) significantly enhances internal control quality (IC) in high-growth-capacity firms (coefficient 6.905, 5% level), but not in low-growth-capacity firms. High-growth firms, with stronger financial and technological resources, treat robots as strategic investments, optimizing internal controls via automation. They boast adaptable, skilled workforces and agile structures. Conversely, low-growth firms face cash flow constraints, limited talent, rigid hierarchies, and weaker market pressures, hindering robot integration and internal control improvements.

Table 10. Results of Further Analysis

variant	*IC*					
	nationalized business	non-state enterprise	High growth capacity	Low growth capacity	broad scale	limited scale
Robot	7.130	6.721*	6.905**	-7.018	5.689	7.486*
	(1.209)	(1.861)	(2.418)	(-0.232)	(1.292)	(1.677)
controls	containment	containment	containment	containment	containment	containment
Year fixed effects	containment	containment	containment	containment	containment	containment
individual fixed effect	containment	containment	containment	containment	containment	containment
constant term (math.)	-4.792**	9.406 ***	4.885 ***	-3.676	0.887	7.313 ***
	(-2.215)	(4.413)	(2.855)	(-0.420)	(0.275)	(2.889)
N	2803	6855	8829	829	4831	4827
r2	0.091	0.105	0.033	0.103	0.120	0.064
r2_a	0.086	0.103	0.031	0.087	0.117	0.061

Note: t-values are in parentheses; ***, **, and * indicate significant at 1%, 5%, and 10%

confidence levels, respectively.

(3) Enterprise size

Table 10 shows industrial robot penetration (Robot) significantly enhances internal control quality (IC) in small-scale firms (coefficient 7.486, 5% level), but not in large-scale firms. Small firms focus robot investments on key processes, rapidly improving internal controls via automation. Their flat structures and short payback cycles enable quick optimization. Large firms, with scattered investments and complex hierarchies, face integration challenges and long payback cycles, diluting internal control improvements.

6. Conclusions and Insights

6.1 Conclusions of the Study

This paper utilizes industrial robot data from the International Federation of Robotics and micro data from Chinese A-share manufacturing listed companies to construct an industrial robot penetration index, and examines the impact of industrial robot application on the quality of firms' financial reporting, and the main conclusions are as follows: the results of the benchmark regression show that the application of industrial robots contributes to the improvement of the quality of firms' financial reporting, and this is still valid after the robustness test. Heterogeneity analysis shows that the effect of industrial robots on the improvement of financial reporting quality is more obvious in high-tech, non-labor-intensive and non-polluting enterprises. Mechanism analysis reveals that the application of industrial robots enhances the quality of financial reporting mainly by improving the quality of internal control quality, and that the effect of internal control effect is more pronounced in small-sized, high-growth, non-state-owned firms[33,39].

6.2 Policy Recommendations

To enhance financial reporting quality (FRQ) in manufacturing, enterprises should leverage industrial robots and AI, focusing on employee training and long-term robot deployment to boost brand image and adapt to intelligent manufacturing. For firms, state-owned enterprises (SOEs) should pursue mixed ownership reforms to align robot use with internal control optimization, while low-growth firms need to address financial and talent constraints through phased robot adoption. Large firms should prioritize high-value automation links and industry standards. Policymakers should support robot adoption via subsidies and tax incentives, tailoring policies to local conditions. For labor-intensive and heavily polluting firms, policies should promote digital transformation and “robotics+environmental accounting” projects to enhance FRQ and financing. High-tech, non-SOE, small-scale, high-growth firms excel in robot use; policies should lower entry barriers through funds and technical consulting to maximize FRQ improvements.

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