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RESEARCH ARTICLE

Artificial Intelligence and Corporate Customer Stability: Evidence from Industrial Robot Adoption in China

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Abstract

Driven by the initiatives of data-driven intelligence empowerment, robots and artificial intelligence (AI) technology profoundly influence economic and social development. China is the world's largest market for robot adoption. This makes the impact of its industrial robot use on supply chains an important and urgent issue to explore. This paper uses Chinese A-share manufacturing listed firms from 2011 to 2019 to investigate the impact of industrial robot adoption at the enterprise level on customer stability. The empirical results indicate that an increase in the scale of industrial robot adoption will significantly improve the stability of enterprise customers. Mechanism testing shows that industrial robot adoption mainly enhances customer stability through the "technological progress effect" and "risk governance effect." Additionally, the heterogeneity analysis finds that the positive effect of industrial robot adoption on customer stability becomes more potent for firms that are capital-intensive, less digitally transformed, non-state-owned, and trading with younger customers. Finally, applying industrial robots is conducive to adding firm value by strengthening customer stability. This paper enriches the relevant literature on the empowerment of the digital economy and customer governance to some extent. The research also provides a reference for popularizing the adoption of AI technology in enterprises and promoting the high-quality development of supply chains.

Keywords industrial robots; customer stability; artificial intelligence (AI); technological progress; customer relationship

1 Introduction

Robots are hailed as "the pearl at the top of the crown of manufacturing" and play an increasingly vital role in economic and social development. As a major manufacturing country, China places high importance on the healthy development of its industrial robot industry. In 2015, the State Council of China unveiled the "Made in China 2025" plan, designating intelligent manufacturing as a key national initiative. In December 2021, the Ministry of Industry and Information Technology of China, in concert with 12 other ministries and commissions, released the *Robot Industry Development Plan for the "14th*

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Five-Year Plan" Period. The plan set out an ambitious vision: By 2035, China's robotics industry will possess internationally leading capabilities, with robots forming an integral part of economic growth, social governance, and everyday life. The report to the 20th National Congress of the Communist Party of China reiterated the imperative of moving the manufacturing sector toward higher-end, smarter, and greener production. This policy momentum has spurred scholarly interest in the economic implications of widespread industrial robot deployment. Much of the literature has concentrated on employment effects (Acemoglu & Restrepo, 2018; Acemoglu & Restrepo, 2020; Autor & Dorn, 2013; Li et al., 2021; Wang & Dong, 2020; Yu et al., 2021). A smaller body of work, focusing on the firm level, has examined how automation technologies shape managerial decision-making (Graetz & Michaels, 2018; Koch et al., 2021; Zhu et al., 2022). Yet, the potential spillover effects of industrial robot adoption at the enterprise level remain underexplored.

The report to the 20th National Congress of the Communist Party of China further underscored that achieving high-quality development requires making China's industrial and supply chains more resilient and secure (Xi, 2022). The relationship between firms and their customers forms a critical component of supply chain collaboration. The "predatory competition game theory" suggests that customers can erode a firm's profits (Dhaliwal et al., 2016), whereas cooperative governance theory contends that long-term, stable partnerships, underpinned by substantial relationship-specific investment, enhance mutual gains and bolster collective competitiveness. Stable customer relationships not only help secure steady operating returns (Gosman et al., 2004) but also serve as a mechanism of external oversight (Wang & Peng, 2016) and a catalyst for innovation (Wen et al., 2022). Against this backdrop, the stability of customer relationships emerges as a strategic concern for both firms and supply chains. Based on techno-economic paradigm theory, the integration of industrial robots may produce supply chain-level spillover effects. Their "employment effect" can lower labor costs, reduce repetitive work, and raise productivity. Moreover, the biased nature of technological progress in industrial intelligence can refine the skill structure of the workforce, strengthen core competitiveness, and foster enduring customer loyalty. Moreover, machine substitution can reshape firms' cash flow profiles, mitigating uncertainty in operating cash flows and thereby influencing customer decision-making. Drawing on panel data from A-share listed manufacturing firms in China, this study investigates the impact of industrial robot adoption on the stability of corporate customer relationships, elucidating its underlying mechanisms and broader economic consequences.

The marginal contributions of this paper are mainly the following three aspects. Firstly, it demonstrates that industrial robot adoption strengthens the stability of corporate customer relationships, thereby extending the literature on the economic consequences of robotics. The proliferation of robots influences not only macro-level labor markets and firm-level decision-making, but also generates positive supply chain spillovers, thereby lending empirical support to the proposition that industrial robots enhance corporate value creation

(Koch et al., 2021). Secondly, it broadens the inquiry into the determinants of customer stability. While existing studies have largely examined its economic consequences, and a small subset has explored its drivers from the perspectives of internal and external governance (Bauer et al., 2018; Pan & Zhang, 2020; Zhang & Shao, 2022), few have considered the lens of technological transformation brought about by artificial intelligence (AI). This study sheds light on the mechanisms and governance pathways through which industrial robot adoption shapes customer stability. Thirdly, it enriches research on technological progress and digital transformation at the firm level. Prior scholarship has tended to proxy technological progress with relatively narrow metrics such as research and development (R&D) spending or patent counts. Industrial robots, by contrast, offer a direct and tangible measure of technological change, transforming an abstract concept into one that is internationally comparable (Graetz & Michaels, 2018). Moreover, their adoption signals the depth of a firm's digital transformation, offering a valuable extension to research on its measurement and its broader economic implications.

2 Theoretical Framework and Research Hypotheses

2.1 The Economic Consequences of Robot Adoption

The literature on the economic consequences of robot adoption, both domestic and international, falls into two streams. The first examines macro-level effects on employment. Drawing on the "task-based model" of economic growth (Autor & Dorn, 2013), some scholars contend that robots exert a substitution effect on labor. Given their comparative advantage over human workers, robots lower labor costs and boost productivity (Koch et al., 2021). With labor supply held constant, this dynamic reduces labor demand and depresses wages (Acemoglu & Restrepo, 2020; Wang & Dong, 2020). Others adopt a more optimistic view, arguing that robots need not trigger widespread unemployment. While they displace jobs in manufacturing, they simultaneously create new roles in services, high-tech sectors, and other non-automatable occupations (Mokyr et al., 2015), albeit at the cost of widening wage inequality (Autor & Dorn, 2013). Studies in the Chinese context that reflect its distinct institutional and industrial conditions generally find that the expansion of industrial robot use markedly reduces employment, with particularly pronounced crowding-out effects for low-skilled workers, which yields a pattern of employment polarization (Kong et al., 2020). The second stream has emerged alongside richer and more granular robot data, enabling a shift from regional or industry-level analysis to the firm level. This line of research explores how automation shapes corporate behavior, finding that large-scale robot adoption can enhance productivity (Li & Xu, 2020), improve product and service quality (Dixon et al., 2021), spur innovation through the twin channels of efficiency gains and skill complementarity (Zhu et al., 2022), and promote environmentally sustainable production (Nie et al., 2022).

2.2 Customer Stability

Previous studies suggest that the concentration of major customers exerts a dual influence on corporate performance. The "integration effect" view holds that a higher share of sales to key customers can reduce transaction costs, safeguard revenues, enhance asset specificity and utilization (Patatoukas, 2012), and lower financing costs (Chen et al., 2015). In contrast, the "risk effect" perspective warns that heavy reliance on a small number of customers may erode bargaining power, heighten cash flow volatility and financing costs, and threaten business sustainability (Dhaliwal et al., 2016). Beyond simply establishing ties with large customers, scholars emphasize the importance of maintaining relationship stability. Stable partnerships can bolster firms' risk-bearing capacity (Bao et al., 2020) and improve the quality of accounting information (Qiu & Cheng, 2022). They also yield spillovers, such as improving analysts' earnings forecast accuracy (Wang & Peng, 2016), dampening share price volatility (Peng & Zhang, 2022), and reducing the cost of equity capital (Li et al., 2023). Yet stability is not without drawbacks. Some research shows it can amplify relational risks, foster complacency in innovation, and diminish customers' appetite for novel solutions, thereby curbing firms' innovative drive (Liu et al., 2018). As for determinants, opportunistic earnings smoothing, litigation-related negative information, and weak internal controls have been found to undermine relationship stability (Bauer et al., 2018). In contexts of high customer concentration, the loss of executive-customer connections significantly reduces stability (Pan & Zhang, 2020). Disclosure quality is positively associated with stability (Sun & Wang, 2021), and firms backed by venture capital tend to exhibit greater stability (Zhang & Shao, 2022).

In summary, while existing literature has explored the economic consequences of robot adoption and the influencing factors of customer stability from diverse perspectives, it still exhibits certain limitations. Firstly, research has focused largely on robots' employment effects and firm-level operational changes, with limited attention to their spillover effects on customer relationships, particularly from the vantage point of supply chain governance. Secondly, although close economic linkages make customer governance critical (Bauer et al., 2018), determinants of vertical customer attributes such as stability remain underexplored, especially from the standpoint of AI adoption in the digital economy. Thirdly, the heterogeneity, mechanisms, and economic consequences of customer relationship governance in the era of "machine substitution" warrant further investigation. This study addresses these gaps by examining the supply chain spillover effects of AI technology adoption, with a focus on how industrial robot use shapes the stability of corporate customer relationships.

2.3 Industrial Robot Adoption and Customer Stability

Within supply chain theory, the cooperative governance view holds that enduring, stable partnerships between firms and customers facilitate information sharing across the supply chain, enhancing its overall competitiveness (Gosman et al., 2004). As the division of labor grows more specialized and asset specificity rises, such stability becomes increasingly vital. Asset specificity theory posits that stable customer relationships entail substantial relationship-specific investments by both parties. For suppliers, replacing a major customer can trigger sharp swings in operating income and elevate business risk; for customers, frequently switching suppliers risks disrupting supply channels and eroding the value of specialized assets. To safeguard supply chain continuity, firms and customers often establish implicit contracts (Li, 2021), with major buyers assessing factors such as product quality, delivery reliability, operational performance, and transparency when deciding whether to maintain a "relational transaction." AI, with its pervasiveness, substitutability, complementarity, and innovativeness, fosters economic growth through efficiency gains, factor substitution, and knowledge creation (Cai & Chen, 2019). Through deep integration with physical production, industrial robots may therefore exert spillover effects on the stability of supply chain relationships.

From the vantage point of techno-economic paradigm theory, robots can strengthen customer stability via a "technological progress effect." Endogenous growth theory identifies technological progress as a primary engine of productivity and economic expansion (Romer, 1986). As an embodiment of tangible technological advance, industrial robots enhance production efficiency in several ways. Firstly, large-scale automation can substitute for certain labor inputs, reducing marginal production costs and time spent on repetitive tasks, thereby raising labor productivity (Graetz & Michaels, 2018). Secondly, by deploying advanced capital goods and automation technologies, firms can mitigate hidden costs arising from uncertainties such as labor shortages, abnormal losses, or temporary stoppages in manual production, enabling tighter coordination among production factors and boosting input-output efficiency (Koch et al., 2021). Enhanced productivity, in turn, underpins customer relationship stability. From a signaling theory perspective, high productivity conveys positive information to major customers, lowering transaction costs associated with information asymmetries and improving the efficiency of implicit contracts (Christensen et al., 2016). Based on the theory of innovation diffusion, improvements in production efficiency can stimulate enterprise innovation vitality through technology spillover effects, enabling the production of high-quality and specialized products to meet the dedicated investment needs of major clients. This facilitates value creation for customers and promotes the formation of stable client relationships (Zhu et al., 2022). Therefore, a larger scale of industrial robot adoption is more conducive to enhancing enterprise production efficiency, thereby strengthening customer stability.

Moreover, industrial robot adoption affects not only the aggregate demand for labor but also the composition of workforce skills. Task-biased technological change theory suggests that automation and intelligent technologies reshape skill structures via a job polarization effect (Autor & Dorn, 2013). Firstly, the adoption of simple industrial robots generates a substitution effect on codifiable and predictable low-skilled labor, leading to a reduced demand for such labor within enterprises. Secondly, the effective functioning of industrial robots relies on the management and maintenance by relevant specialized personnel, thereby increasing the demand for high-skilled labor involved in R&D innovation and enterprise management (Zhu et al., 2022), which constitutes a creation effect. In this way, robot adoption raises the share of high-skilled employees, fostering skill complementarity and, in turn, strengthening customer stability.

Two mechanisms underpin this effect. Firstly, a workforce rich in high-skilled talent signals to major customers a robust human capital base and a commitment to knowledge-driven, high-end manufacturing. This enhances customer recognition and supports long-term ties. Secondly, under knowledge creation theory, high-skilled employees, particularly in R&D, bring deep expertise, rich knowledge reserves, and active innovation capacity. Their contributions to ambidextrous innovation (Acemoglu et al., 2018) yield products and services that are both distinctive and technologically sophisticated, reducing imitability and substitutability. This strengthens bargaining power in supply chain markets and encourages existing customers to increase relationship-specific investments, insulating the supply chain from shocks by other or new customers and thereby reinforcing long-term relationship stability.

From a psychological perspective on risk perception, robot adoption may also deliver a “risk governance effect.” As fixed assets, robots require substantial up-front investment cash outflows during early production stages, but reduce ongoing operating outflows for wages, bonuses, and benefits. This shift smooths future operating cash flows and improves operational stability. Asset specificity theory holds that customers’ willingness to commit relationship-specific investments depends on their perception of supplier risk (Wang & Peng, 2016). A financially stable supplier signals reliability, timeliness, and quality in its output, dampening negative risk perceptions, encouraging further investment, lowering the likelihood of customer attrition, and fostering durable relationships. Taken together, robot adoption may enhance customer stability through both skill complementarity and risk governance. This leads to the following hypothesis:

H1: The greater the scale of a firm’s industrial robot adoption, the higher its customer stability.

3 Research Design

3.1 Sample Selection and Data Sources

China’s adoption of industrial robots has accelerated markedly since 2010, with applications concentrated primarily in manufacturing. Against this backdrop, the study examines A-share listed manufacturing firms from 2011 to 2019. The sample was refined by applying four filters: (1) excluding firms designated ST or ST*; (2) removing observations with missing values; (3) dropping firms that did not explicitly disclose the names of their top five customers; (4) excluding firms that failed to report these names consistently for both the preceding and subsequent years. The resulting panel comprises 2,263 firm-year observations.

Data on industrial robots are drawn from the International Federation of Robotics (IFR). Information on the sales revenue, sales share, and identities of the top five customers is sourced from the China Research Data Service Platform (CNRDS). Data on the proportion of employees in production departments are obtained from the Wind Information database, while other firm-level financial and governance variables come from the China Stock Market & Accounting Research database. To limit the influence of outliers, all continuous variables are winsorized at the 1% level at both ends of the distribution.

3.2 Variable Definitions

3.2.1 Dependent Variable

Customer Stability. Following established measures (Bauer et al., 2018; Pan & Zhang, 2020; Wang & Peng, 2016; Wen et al., 2022; Zhang & Shao, 2022), customer stability is measured by the proportion of stable customers (*Cust*1), defined as the number of the current year's top five customers that also appeared in the previous year, divided by five. The measure ranges from 0 to 1, with higher values denoting greater stability. As a second indicator (*Cust*2), a binary variable is set equal to 1 if more than three of the current year's top five customers are repeats from the prior year, signaling a stable relationship, and 0 otherwise.

3.2.2 Independent Variable

Industrial Robot Adoption. Adapting the approach of Wang and Dong (2020), a firm-level measure of industrial robot penetration is constructed for listed Chinese manufacturers in four steps: (1) Industry categories in the 2002 edition of China's National Industry Classification are harmonized to the 2011 edition, yielding 31 categories. (2) These categories are matched to the industry taxonomy used by the IFR. (3) Industry-level robot penetration is calculated as the stock of industrial robots in manufacturing industry j in year t divided by that industry's 2010 employment (base year). (4) For firm k in industry j, the ratio of its 2011 production-department employee share to the 2011 median for all listed manufacturing firms is multiplied by the industry-level penetration rate, and the product is scaled by dividing by 100. The resulting metric (*Robots*) captures firm-level industrial robot penetration.

3.2.3 Control Variables

Consistent with earlier research (Bauer et al., 2018; Pan & Zhang, 2020), the analysis controls for a range of firm-level characteristics that may influence customer stability: firm size, leverage, ownership nature, age, book-to-market ratio, cash holdings, operating cash flow, return on equity, sales growth, capital expenditure, ownership concentration, and customer concentration. It further accounts for external factors, including industry competition intensity, regional marketization level, and regional economic development level. Industry and year fixed effects are also included. Variable definitions are provided in Table 1.

Table 1 Variable Definition

Variable name	Variable symbol	Definition
Proportion of stable customers	*Cust*1	The number of recurring top-five customers from the previous year divided by five, yielding a value between 0 and 1. A higher value indicates greater customer stability.
Stable customer relationship	*Cust*2	If the number of recurring top-five customers from the previous year exceeds three, it indicates a stable customer relationship and is assigned a value of 1; otherwise, it is considered unstable and assigned a value of 0.
Industrial robot penetration	*Robots*	The firm-level industrial robot penetration rate is obtained by matching with the IFR classification. This rate is then multiplied by the ratio of the manufacturing firm's proportion of production department employees to the median proportion across all manufacturing firms, ultimately yielding the firm-level industrial robot penetration rate.
Firm size	*Size*	Natural logarithm of total assets
Leverage	*Lev*	Total liabilities divided by total assets
Ownership nature	*Soe*	1 for non-state-owned enterprises, 0 for state-owned
Firm age	*Age*	Natural logarithm of years listed plus one
Book-to-market ratio	*Btm*	Total assets divided by year-end market value
Cash holdings	*Cash*	Cash and cash equivalents divided by total assets
Operating cash flow	*Ocf*	Net operating cash flow divided by total assets
Return on equity	*Roe*	Net profit divided by average shareholders' equity
Sales growth rate	*Growth*	Change in sales revenue from the previous year, divided by prior-year sales revenue
Capital expenditure	*Capital*	Cash paid for acquisition or construction of fixed assets, intangible assets, and other long-term assets, scaled by total assets
Ownership concentration	*Top*	Shareholding percentage of the largest shareholder
Customer concentration	*Cuscon*	Sum of squared sales shares of the top five customers
Industry competition intensity	*Comp*	Sum of squared ratios of a firm's main business revenue to total main business revenue in the industry
Regional marketization level	*Market*	Regional marketization index (2019)
Regional economic development level	*Gdp*	Regional per capita GDP (ten-thousand yuan)

3.3 Model Specification

To test *H1* regarding the impact of industrial robot adoption on corporate customer stability, this paper constructs the following empirical model:

$$\begin{aligned}Customer_{i,t} = \alpha_0 + \alpha_1\, Robots_{i,t} + \alpha_2 Size_{i,t} + \alpha_3\, Lev_{i,t} + \alpha_4 Soe_{i,t} + \alpha_5\, Age_{i,t} + \\ \alpha_6 Btm_{i,t} + \alpha_7 Cash_{i,t} + \alpha_8 Ocf_{i,t} + \alpha_9\, Roe_{i,t} + \alpha_{10} Growth_{i,t} + \\ \alpha_{11} Capital_{i,t} + \alpha_{12} Top_{i,t} + \alpha_{13} Cuscon_{i,t} + \alpha_{14} Comp_{i,t} + \\ \alpha_{15}\, Market_{i,t} + \alpha_{16} Gdp_{i,t} + \alpha_j\, Industry + \alpha_k Year + \varepsilon_{i,t}.\end{aligned} \tag{1}$$

In equation (1), *Customer* denotes customer stability, measured by the proportion of repeat customers (*Cust*1) and by a binary indicator of stable customer relationships (*Cust*2). *Robots* measures firm-level industrial robot penetration. The remaining covariates are control variables, while *Industry* and *Year* capture industry and year fixed effects. ε represents the idiosyncratic error term. The model is estimated using ordinary least squares, with robust standard errors to mitigate heteroskedasticity. The coefficient α_1 captures the marginal effect of robot adoption on customer stability, with a positive and statistically significant estimate consistent with *H1*.

4 Empirical Results Analysis

4.1 Descriptive Statistics and Correlation Analysis

Table 2 summarizes the descriptive statistics for the key variables. The mean proportion of stable customers (*Cust*1) is 0.480, implying that on average fewer than three of a firm's top five customers are retained year-on-year. More than half of the firms in the sample thus face the risk of losing major clients, a finding consistent with earlier studies (Bauer et al., 2018; Pan & Zhang, 2020; Wang & Peng, 2016; Wen et al., 2022; Zhang & Shao, 2022). The average value of the industrial robot penetration measure (*Robots*) is 0.197, with a standard deviation of 0.495, indicating that firms operate with fewer than 0.200 robots per employee on average and that adoption levels vary markedly across the sample. Pearson correlations show that *Robots* is significantly and positively correlated with both *Cust*1 and *Cust*2 at the 1% level, providing initial evidence of a positive association between robot adoption and customer stability. Variance inflation factors for all variables have both mean and maximum values well below the conventional threshold of 10, suggesting that multicollinearity is not a concern in the regression analysis.

Table 2 Descriptive Statistics of Main Variables

Variable	Sample size	*M*	*SD*	*Min.*	*Max.*
*Cust*1	2,263	0.480	0.259	0.000	1.000
*Cust*2	2,263	0.475	0.500	0.000	1.000
Robots	2,263	0.197	0.495	0.000	6.014
Size	2,263	21.951	1.150	18.926	25.961
Lev	2,263	0.446	0.209	0.052	0.998
Roe	2,263	0.042	0.164	–0.983	0.506
Top	2,263	0.336	0.144	0.039	0.900
Cuscon	2,263	4.941	8.606	0.000	77.121

4.2 Baseline Regression Results

Table 3 presents the results from estimating equation (1) on the effect of industrial robot adoption on customer stability. According to columns (1) and (3) of Table 3, when other influencing factors are not considered, the regression coefficients of *Robots* on *Cust*1 and *Cust*2 are both significantly positive, providing preliminary evidence that firms with greater industrial robot adoption enjoy higher customer stability. Including control variables, as shown in columns (2) and (4), strengthens both the magnitude and statistical significance of these regression coefficients. The estimates for *Robots* rise to 0.036 for *Cust*1 and 0.075 for *Cust*2, each significant at the 1% level. Economically, a one-unit increase in robot penetration corresponds to an average rise of 7.500% in the proportion of stable customers (0.036/0.480) or a 15.789% increase in the probability of maintaining stable customer relationships (0.075/0.475). These findings indicate that greater integration of industrial robots into production processes enhances the stability of relationships with major customers, providing empirical support for *H1*.

Table 3 Regression Results: Industrial Robot Adoption and Customer Stability

Variable	(1)	(2)	(3)	(4)
	*Cust*1	*Cust*1	*Cust*2	*Cust*2
Robots	0.029**	0.036***	0.061***	0.075***
	(2.487)	(2.992)	(2.662)	(3.128)
Controls	No	Yes	No	Yes
Industry & Year	Yes	Yes	Yes	Yes
N	2,263	2,263	2,263	2,263
Adj. R^2	0.074	0.134	0.045	0.089

Note. Controls denotes the inclusion of control variables; results for these variables are omitted for brevity but are available from the author on request. *** $p < 0.01$ and ** $p < 0.05$.

4.3 Robustness Checks

4.3.1 Omitted Variable Bias

To address potential omitted variable bias, two instrumental variable strategies are employed. The first uses *Robots_US*, firm-level penetration rates for Chinese manufacturers constructed from U.S. industry-level robot adoption data, as the instrument, following Wang and Dong (2020). The second employs *Peer_Robots*, defined as the mean penetration rate among other firms in the same industry-year, excluding the focal firm, in line with Nie et al. (2022). Additional controls are also included to account for unobserved heterogeneity: accrual-based earnings management, analyst coverage, audit quality, internal control quality, the logarithm of average employee wages, the square of firm age, and region-year interaction fixed effects, as in Li and Xu (2020). Table 4 reports the results. Columns (1) and (4) indicate that in the first-stage regressions, the coefficients of *Robots_US* and *Peer_Robots* are both significantly positive, with *F*-statistics greater than 10. The Kleibergen-Paap rk LM statistics are 72.856 and 12.539, respectively, indicating that the two instrumental variables are not subject to under-identification. According to the second-stage regression results, the coefficients of *Robots* remain significantly positive, indicating that after addressing the omitted variable problem, the results of this study are robust.

Table 4 Instrumental Variable Estimates for Omitted Variable Bias

Variable	Instrumental variable method					
	(1)	(2)	(3)	(4)	(5)	(6)
	Robots	*Cust*1	*Cust*2	*Robots*	*Cust*1	*Cust*2
Robots_US	0.002*** (20.011)					
Peer_Robots				0.840*** (12.465)		
Robots		0.042*** (2.663)	0.080*** (2.739)		0.051** (2.089)	0.084* (1.686)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	2,263	2,263	2,263	2,248	2,248	2,248
Adj. R^2	0.804	0.134	0.089	0.521	0.133	0.087

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.3.2 Sample Selection Bias

Managerial characteristics can shape the trajectory of technological change, and traits such as academic experience or a CEO's multi-functional background (Yang et al., 2022) may influence the extent of industrial robot adoption. This heterogeneity can induce non-randomness in the key explanatory variable, raising concerns about sample selection bias. Three approaches are applied to assess this issue. The first is the Heckman two-step estimation. Following Zhang et al. (2020), managerial attributes such as short-term orientation, proportion of male executives, average age, financial background, overseas experience, and equity holdings are used as instruments for *Robots*. The inverse Mills ratio from the first-stage regression is included as a control in the second stage. The second is the propensity score matching. The control variables from equation (1) serve as covariates in a Probit model to estimate propensity scores. Firms are matched one-to-one using the nearest-neighbor method, and the matched sample satisfies balance requirements. The third is the entropy balancing. Continuous weights are assigned to the control group, and weighted regressions are estimated to account for differences between treated and control units. Across these specifications, the estimated relationship between industrial robot adoption and customer stability remains positive and significant, indicating that the main findings are robust to selection concerns.

To further mitigate reverse causality concerns, the one-period-ahead values of *Cust*1 and *Cust*2 ($t + 1$) are regressed on contemporaneous *Robots* (t). Additional robustness checks utilizing alternative variable measures, sensitivity tests, and subsample analyses produce qualitatively similar results.

5 Extended Analysis

5.1 Mechanism Tests

The theoretical framework suggests two pathways through which industrial robot adoption may strengthen customer stability: a technological progress effect and a risk governance effect. These mechanisms are examined by splitting the sample along three dimensions: total factor productivity (*TFP*), proportion of high-skilled labor, and cash flow volatility. *TFP* is estimated using the Levinsohn-Petrin method, with total output regressed on labor, capital, and intermediate inputs; the residual serves as the *TFP* measure. The proportion of high-skilled labor (*Labor*) is calculated as the ratio of year-end R&D staff to total employees. Cash flow volatility (*Cashvol*) is the standard deviation, over the period from $t - 2$ to t, of net operating cash flow scaled by average total assets. For each variable, firms are classified into high and low groups using the industry-year median as the cutoff. Results in Table 5 indicate that the estimated coefficient on *Robots* is larger and more significant for firms with low *TFP*, low proportions of high-skilled labor, and high cash flow volatility. These patterns are consistent with the proposed mechanisms of the "technological progress effect" and the "risk governance effect."

Table 5 Mechanism Test Results

Variable	Total factor productivity		Proportion of high-skilled labor		Cash flow volatility	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1
Robots	0.014	0.078***	0.014	0.124**	0.034**	0.031
	(0.912)	(2.690)	(0.877)	(2.541)	(2.186)	(1.539)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	1,045	1,046	786	1,477	1,119	1,144
Adj. R^2	0.117	0.163	0.193	0.123	0.163	0.111
P-value	0.000		0.000		0.414	

Note. *** $p < 0.01$ and ** $p < 0.05$.

5.2 Heterogeneity in the Effect of Industrial Robot Adoption on Customer Stability

5.2.1 Factor Intensity

Given that industrial robot adoption in China remains in its early stages, the short-term dividends from “machine substitution” are limited for labor-intensive firms. For such firms, large and sustained capital expenditures may increase operating costs and heighten the risk of unsuccessful digital transformation. By contrast, capital-intensive firms typically possess greater expertise in fixed asset investment and management, along with more substantial financial reserves, equipping them with both the capacity and the incentive to implement intelligent manufacturing. To capture factor intensity, *Density* is defined following Li et al. (2021) as the ratio of net fixed assets at year-end to total employees. Firms with *Density* above the industry-year median are classified as capital-intensive; those below are classified as labor-intensive. The estimates in Table 6 (columns 1 and 2) show that the coefficient on *Robots* is significantly more positive for capital-intensive firms than for labor-intensive firms. A between-group coefficient difference test yields a *P*-value of 0.000, indicating that greater capital intensity amplifies the positive effect of industrial robot adoption on customer stability.

5.2.2 Degree of Digital Transformation

Data has emerged as a critical factor of production. Firms that leverage data assets effectively can improve the coordination of capital, labor, and technology, thereby enhancing firm value (Wu et al., 2021). The deployment of industrial robots represents a concrete application of digital technology. When digital transformation is already advanced, the incremental benefits of robot adoption, through efficiency gains, skill complementarity, and cash flow stabilization, may be reduced, weakening its contribution to customer stability. In this sense, digital transformation and robot adoption can act as substitutes. The degree of digital transformation (*Digital*) is calculated using the approach of Wu et al. (2021). Firms are classified into high and low groups based on the industry-year median. As shown in columns 3 and 4 of Table 6, the coefficient on Robots is positive and significant at the 1% level in the low-digital-transformation group. Moreover, it is significantly larger than the corresponding coefficient in the high-digital-transformation group. This result suggests that the positive impact of industrial robot adoption on customer stability is more pronounced in firms with lower levels of digital transformation.

5.2.3 Ownership Nature

Ownership nature is a key internal governance factor shaping industrial robot adoption. In state-owned enterprises, senior executives who are subject to political promotion criteria often prioritize preserving and increasing state capital, resulting in underinvestment in high-risk AI technologies. By contrast, non-state-owned enterprises, constrained by resources and exposed to competitive pressures, have stronger incentives to pursue automation-driven transformation as a means of leapfrogging competitors. State-owned enterprises’ superior access to government resources and implicit guarantees provides them with inherently more stable customer relationships (Pan & Zhang, 2020). Non-state-owned enterprises, facing greater operational uncertainty, must rely more heavily on digital transformation to establish and maintain stable customer ties, thereby allowing industrial robots to exert a stronger influence. The expectation, therefore, is that robot adoption will have a more pronounced positive effect on customer stability in non-state-owned enterprises. Table 6 (columns 5 and 6) supports this proposition: The *Robots* coefficient for state-owned enterprises is positive but statistically insignificant, while for non-state-owned enterprises it is positive and significant at the 1% level.

5.2.4 Customer Age

Corporate life cycle theory suggests that older customers tend to have stronger operational resilience and stability, generating steady cash inflows for upstream suppliers. However, their stronger bargaining power can weaken the incremental effect of industrial robot adoption on customer stability. By contrast, younger customers, typically at a competitive disadvantage, are more responsive to the economic gains from suppliers' robot adoption, which can increase their commitment to relationship-specific investments. Customer age (*Cus_age*) is calculated from the basic information of each firm's top five customers. It is measured as the natural logarithm of the average years these customers have been in operation since their founding. Firms are grouped into high and low categories based on the median value. Table 6 (columns 7 and 8) shows that for the low customer age group, the *Robots* coefficient is significantly positive, while for the high customer age group, it is statistically insignificant. A between-group coefficient difference test (*P*-value = 0.000) confirms that robot adoption is more effective in strengthening the stability of younger customers.

5.3 Economic Consequences of Industrial Robot Adoption on Customer Stability

Stable customer relationships help enhance corporate value, but they can also lead to the risk of over-reliance on major clients, which may suppress the dynamism of innovative thinking, hinder the improvement of innovation performance, and ultimately damage corporate value (Liu et al., 2018). To address this, drawing on the research of He et al. (2019), this paper adopts the Tobin's Q indicator to measure corporate value, calculated as the ratio of a company's total market value to the book value of its total assets. A higher value indicates greater corporate value. To examine how industrial robot adoption affects corporate value by enhancing customer stability, this study draws on methods from existing literature and constructs two regression models (Zhang & Shao, 2022). The first regresses Tobin's Q on *Robots* to test for a direct effect. The second introduces interaction terms between robot adoption and customer stability (*Robots* × *Cust*1 and *Robots* × *Cust*2), with the interaction coefficients capturing the degree to which the effect on firm value operates via customer stability. The results show that *Robots* is positive and significant at the 1% level, implying

Table 6 Heterogeneity Analysis Results

Variable	Capital-intensive	Labor-intensive	High digital transformation	Low digital transformation	Non-state-owned enterprises	State-owned enterprises	Older customers	Younger customers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1	*Cust*1
Robots	0.063***	0.008	0.014	0.052***	0.043***	0.026	–0.017	0.107**
	(3.496)	(0.531)	(0.718)	(3.195)	(2.877)	(0.948)	(–1.055)	(2.096)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,206	1,055	758	1,475	1,393	870	501	500
Adj. R^2	0.142	0.144	0.141	0.141	0.172	0.085	0.092	0.066
P-value	0.000		0.000		0.170		0.000	

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

that robot adoption directly enhances firm value. More notably, $Robots \times Cust2$ is positive and significant at the 5% level, indicating that the stabilizing effect on customer relationships contributes to value creation. For brevity, regression tables are omitted but are available from the authors upon request.

6 Conclusions and Policy Implications

6.1 Conclusions

Drawing on panel data from Shanghai and Shenzhen A-share manufacturing firms over 2011–2019, the analysis shows a robust positive association between industrial robot adoption and customer stability: Greater use of robots corresponds to higher stability in client relationships. Mechanism tests indicate that this effect is more pronounced among firms with lower total factor productivity, a smaller share of high-skilled workers, and higher cash flow volatility, consistent with the view that robots enhance stability through both “technological progress effect” and “risk governance effect” channels. Heterogeneity analysis further reveals stronger effects in capital-intensive firms, those with lower levels of digital transformation, non-state-owned enterprises, and firms serving younger clients. Finally, economic consequence tests show that robot adoption increases firm value by reinforcing customer stability.

6.2 Policy Implications

First, the government should intensify support for the intelligent and green robotics industries and foster the robotics labor service market, thereby enhancing society’s overall digital literacy. Greater fiscal and tax incentives should be provided for the intelligent and green robotics industries to ease firms’ operating costs and financing constraints, and to stimulate innovation in high-end robotics. Moreover, the “machine substitution” wave is forcing transformation in the labor market, making it essential to train more high-skilled workers compatible with robotics technologies, thereby improving digital literacy across the population.

Second, manufacturing enterprises should expand their industrial robot adoption, using automation and AI technologies to improve the efficiency of production factor allocation, optimize human capital structures, and continuously adjust and manage cash flow distribution. This study shows that robot adoption significantly enhances customer stability and increases firm value. Manufacturing firms can leverage robotics to empower production and operations, lower operating costs, alleviate the adverse effects of external financing constraints, and channel the savings into product R&D and innovation.

Finally, customers may choose to establish partnerships with suppliers that have a larger scale of robot adoption. However, given that robotics technologies remain far from mature and are still subject to technological, ethical, and moral risks and are shaped by factors such as engineers’ and managers’ cognition level, customers should carefully assess a supplier’s corporate culture, social responsibility practices, and governance environment before forming a relationship. Such due diligence can minimize transaction costs, maximize the benefits of AI-driven technological transformation, and strengthen the coordination of supply chains, industrial chains, and global value chains, thereby promoting high-quality economic and social development.

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