ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2026.28673

TRADE, AI-ROBOT ADOPTION, AND MANUFACTURING TRANSFORMATION: CROSS-NATIONAL DETERMINANTS OF FIRM-LEVEL AUTOMATION IN HETEROGENEOUS INSTITUTIONAL CONTEXTS

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Article History:

- received 17 October 2025
- accepted 20 August 2026
- first published online 19 October 2026

Abstract. It investigates the multi-dimensional determinants of AI-driven robot adoption among manufacturing firms to examine how perceived benefits, industry peer pressure, and international trade exposure jointly shape firm-level automation decisions across heterogeneous institutional contexts during 2016–2024.

Using a firm-level 12,000 manufacturer panel data, it employs PPML estimation with high-dimensional fixed effects, instrumental variables using historical tariffs and partner-country demand shocks to address trade endogeneity, and System GMM to capture dynamic adjustment. The analytical framework integrates TAM, institutional isomorphism theory, and Melitz's heterogeneous firm model.

Empirical results show the strongest adoption driver, with long-run effects nearly double short-run estimates. Industry peer pressure accelerates diffusion through competitive mimicry and network density. Trade exposure causally stimulates automation, exporters respond to quality demands, import-competing firms automate defensively. Cross-country analysis reveals Germany's highest benefit responsiveness, Korea's strongest peer effects, and China's policy-coordinated balanced patterns.

It provides the first integrated cross-national empirical analysis of behavioral, institutional, and trade-related automation mechanisms within a single framework, demonstrating that effective automation policy must verify benefit perceptions, industry coordination, and trade integration across diverse institutional contexts.

Keywords: AI-robot adoption, technology acceptance, manufacturing automation, cross-country analysis.

JEL Classification: F14, L60, O33, C23.

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1. Introduction

Global manufacturing competitiveness has been reshaped, perhaps irreversibly, by the intersection of artificial intelligence (AI), robotics, and global trade, however, we still do not fully understand what leads individual firms to automate when and how they do. The raw statistics are striking that global industrial robot installations reached over 4 million operational units by 2024, with stock growing at roughly 10% to 4.28 million units. Robot density in factories has doubled in seven years, hitting a record 162 units per 10,000 workers worldwide (International Federation of Robotics, 2024), and 53% of manufacturers now actively pursue new robotic systems, primarily to improve quality, not merely cut costs (ABI Research,

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2025). Today's AI-enhanced systems go far beyond the mechanical automation of earlier decades that machine learning, computer vision, and predictive analytics now combine to create adaptive manufacturing environments capable of autonomous decision-making and continuous self-optimization (Gao et al., 2024). Yet despite this technological momentum, adoption patterns are far from uniform. What we observe instead is significant strategic heterogeneity across countries, industries, and firm types of a pattern that points to something more complex than simple technological determinism (Dachs et al., 2020).

There are three gaps in the existing literature motivate our analysis. First, most technology adoption researches analyzed automation primarily as a wage-driven cost-minimization strategy, largely ignoring the behavioral dimensions captured in perceived benefits, organizational learning, and strategic positioning. The Technology Acceptance Model (TAM) identifies perceived usefulness and ease of use as key adoption drivers (Davis, 1989; Venkatesh et al., 2003), but applications to industrial robotics have rarely engaged with the strategic complementarities – between AI capabilities, human capital, and digital infrastructure – that determine whether productivity gains actually materialize (Rakholia et al., 2024). Second, while institutional academic theory predicts that peer pressure and competitive convergence accelerate technology diffusion through mimetic isomorphism (DiMaggio & Powell, 1983), systematic empirical result evidence across heterogeneous institutional settings remains not to be clear. Recent work confirms that firms do learn from and imitate industry peers (Zhang, 2025; Liao, 2024), yet cross-national comparative analysis is largely absent. Third, the relationship between trade exposure and automation is theoretically ambiguous. Classical comparative advantage logic suggests trade liberalization reduces automation incentives in labor-abundant economies; recent evidence, however, points in the opposite direction such as export-oriented firms automate to meet quality standards, while import-competing firms do so to defend market share (Cao, 2025).

The cross-country dimension is where the gap is most pronounced. Studies of AI-robot adoption typically focus on a single country or treat institutional context as uniform background noise, rather than as a potential moderator of adoption dynamics (Bisio et al., 2025). Germany's high skill-intensive manufacturing economic model, Japan's continuous improvement management philosophy, Korea's dense business-oriented networks, China's state-directed industrial policy, and the United States' decentralized market-driven approach represent genuinely different institutional environments and it is precisely these gap that may explain why the same economic incentives produce different adoption outcomes. Moreover, how firm heterogeneity such as size, technological sophistication, and absorptive capacity interacts with these national contexts is poorly understood, limiting the policy relevance of existing work (Melitz, 2003). One recent study illustrates what this gap costs us that trade liberalization via free trade agreements significantly raises robot adoption among partner countries exporting to China, with effects concentrated in non-automotive sectors and technologically less advanced economies (Zhang et al., 2025) of a finding that existing single-country models cannot easily accommodate.

Our study provides a comprehensive empirical treatment of AI-driven robot adoption across these five economies for the period 2016–2024. We integrate behavioral technology adoption theory (Davis, 1989; Venkatesh et al., 2003) with institutional diffusion mechanisms (DiMaggio & Powell, 1983; Zhang, 2025) and the firm heterogeneity framework from

international trade theory (Melitz, 2003; Cao, 2025), constructing a unified empirical model in which perceived benefits, industry adoption pressure, and trade exposure are simultaneously identified. Estimation proceeds via PPML with high-dimensional fixed effects (Correia et al., 2020) and instrumental variables, drawing on approximately 12,000 firm-year observations merged with industry-level robotics statistics, bilateral trade flows, and national AI capability indicators.

What distinguishes our contribution is not the proposal of a new theory of automation but rather the integrated empirical validation of how behavioral, institutional, and trade forces interact within a single framework. Rather than treating each mechanism as a self-contained explanation, we probe the underlying channels: specifically, whether AI-robot benefits are conditional on human capital (a complementarity mechanism) and whether peer pressure operates through industry network density (a social learning mechanism). On the theoretical side, this work extends TAM to cross-national contexts, advances the trade-technology complementarity literature by demonstrating substitution is the exception rather than the rule, and provides fresh evidence that AI-robot productivity gains require concurrent human capital and digital infrastructure, consistent with complementarity theory (Milgrom & Roberts, 1995; Gao et al., 2024).

2. Literature review

2.1. From behavioral technology acceptance to strategic automation

TAM established the foundational logic for technology adoption, arguing that perceived usefulness and perceived ease of use are the primary determinants of individual and organizational acceptance decision making (Davis, 1989; Davis et al., 1989). In the original formulation, adoption follows a cognitive-affective sequence that external stimuli shape perceived ease of use and usefulness, which in turn form attitudes, behavioral intentions, and ultimately actual usage. Venkatesh et al. (2003) broadened this framework through the Unified Theory of Acceptance and Use of Technology (UTAUT), adding organizational capacity, facilitating conditions, and social influence as additional determinants.

When applied to industrial robotics, TAM's behavioral logic holds up, but it requires substantial reconceptualization for technologies as organizationally complex as AI-integrated systems. Evidence from Chinese manufacturers shows that adoption willingness depends more on perceived benefits and peer pressure than on rising labor costs, directly challenging wage-driven automation narratives. This is significant that firms adopting robots do not necessarily reduce wages, contradicting the labor substitution assumption embedded in classical models. Instead, adoption decisions reflect strategic positioning that robots are seen as enablers of quality enhancement, production flexibility, and competitive differentiation, not merely cost-reduction instruments (Bisio et al., 2025).

The shift to Industry 4.0 has profoundly altered what perceived benefits means in this context. Where traditional mechanical robotics offered bounded, predictable productivity gains through task substitution, current AI-integrated systems combine physical robots with machine learning, computer vision, and predictive analytics to create adaptive production environments that self-optimize over time (Gao et al., 2024; OECD, 2024). The implication is

that perceived benefits are no longer static cost savings that they are dynamic capability gains that accumulate through organizational learning and algorithmic improvement.

Behavioral perspectives complicate this picture further. Firms may systematically over- or under-estimate automation benefits due to information asymmetries, technological uncertainty, and cognitive biases when evaluating investments with intangible and difficult-to-quantify ex ante returns (Mai et al., 2025). For AI-integrated robotics specifically, benefits often flow through indirect channels that improved product quality enabling premium pricing, enhanced flexibility facilitating rapid innovation, and data-driven optimization generating continuous incremental gains.

A critical moderator is firm heterogeneity. Firms with larger size, stronger human capital, and greater absorptive capacity are better positioned to convert perceived benefits and industry pressure into actual adoption. This raises a research gap that has not been adequately addressed that vocational training systems reduce implementation barriers for smaller firms and business network structures shape knowledge diffusion about automation benefits across the firm-size distribution.

Cross-national applications of TAM reveal that cultural and institutional context significantly moderates the benefits-adoption relationship. Individualism-collectivism orientations, power distance, and uncertainty avoidance influence how organizations assess strategic necessity, legitimacy, and readiness for technological change (Hofstede, 2001). In robotics settings, these cultural factors shape whether firms approach automation proactively for competitive positioning or reactively under competitive pressure with higher-skilled sectors showing more proactive orientations.

Yet virtually all TAM applications to industrial robotics are single-country studies that cannot disentangle universal behavioral mechanisms from country-specific institutional effects. Whether perceived benefits constitute a universal primary driver or whether different national systems elevate peer pressure, trade exposure, or state policy to comparable importance – remains an open empirical question.

2.2. Complementarity theory and the AI-robotics capability integration

Complementarity theory, developed by Milgrom and Roberts (1995), provides a crucial corrective to the assumption that perceived benefits alone should predict adoption success. The core argument is that productivity gains from any new technology depend on concurrent investments in complementary inputs like human capital, organizational capabilities, and supporting infrastructure. For AI-robotics, this implies that the marginal return to automation investment rises with the level of complementary investment, creating strong incentives for comprehensive technological transformation rather than isolated automation projects (Jimeno & Lamo, 2024).

Several empirical channels confirm this logic. Manufacturing firms in advanced economies generate significant robotics-related productivity gains primarily when they also have strong human capital, R&D intensity, and digital infrastructure (Bisio et al., 2025). A refined capital-skill complementarity hypothesis within structural transformation contexts holds that AI and skilled labor are complements those innovations in AI-augmented technologies stimulate

skilled labor deployment across sectors (Zhang et al., 2024). This extends to organizational capabilities as well: firms with strong quality management, flexible production processes, and continuous improvement cultures extract substantially larger returns from robotics, suggesting that competitive advantage comes from integrated complementary resources, not from any single technology.

AI introduces a temporal dimension that traditional complementarity models did not anticipate. AI-enabled robotic systems generate continuous data streams that feed back into production optimization, predictive maintenance, and quality improvement. This data loop creates cumulative returns: early adopters gain informational advantages that compound as algorithms accumulate operational experience (Loaiza & Rigobon, 2024). Productivity benefits can continue expanding well after initial installation, provided firms maintain data infrastructure and analytical capacity. Notably, complex, hard-to-codify tasks show greater potential for human-AI collaboration than routine tasks, implying that complementarity strength varies systematically with task structure (Jimeno & Lamo, 2024).

Cohen and Levinthal's (1990) absorptive capacity concept illuminate the firm-level mechanisms through which these complementarities operate. Absorptive capacity – the ability to recognize, assimilate, and apply external knowledge that depends on prior related knowledge, R&D investment, and organizational learning routines. In AI-robotics settings, it manifests through a firm's ability to interpret machine learning outputs, adapt production processes to AI insights, and integrate automated systems with human workflows (Mubarik et al., 2023; Arcidiacono et al., 2022). Digitalization competencies further enhance this capacity by facilitating learning from external sources such as industry benchmarks, technological advancements, and collaborative networks (Ng et al., 2021).

Complementarity magnitudes vary with firm characteristics and industry context. Large firms typically exhibit stronger effects due to greater resources for comprehensive transformation. That said, cloud-based AI services and digital platforms are beginning to erode these scale advantages, making sophisticated AI-robotics systems accessible to smaller firms without prohibitive fixed costs. Effects are largest in industries marked by complex production processes, stringent quality requirements, and rapid product innovation cycles.

2.3. Institutional isomorphism and peer pressure mechanisms

DiMaggio and Powell's (1983) institutional isomorphism framework shifts the analysis from efficiency calculations alone to the social and institutional pressures that also drive organizational behavior. From this perspective, firms adopt technologies not solely because they have demonstrated efficiency advantages, but also to gain legitimacy and maintain competitive parity in their institutional environment.

Industrial robot diffusion exhibits classic isomorphism patterns along three dimensions. Coercive pressures arise from regulatory requirements, customer demands, and supply chain mandates that effectively require automation that automotive supply chains being the most visible example, where lead firms' quality and delivery standards compel suppliers to adopt compatible technologies. Mimetic pressures emerge under conditions of technological uncertainty, where firms imitate successful peers to reduce decision-making risk (Liu, 2022).

Empirical evidence confirms that firms adopt robots partly in response to perceived pressure from industry peers, combining proactive benefit-driven adoption with reactive pressure-driven acceptance. Normative pressures stem from professional communities, industry associations, and educational institutions that frame certain technologies as best practice.

Empirical evidence on peer effects in robot adoption is compelling. Firms located in regions with high robot density are significantly more likely to adopt robotics themselves, even after controlling for industry characteristics, firm size, and economic conditions (Zhang, 2024; Liao, 2024). This spatial clustering reflects multiple reinforcing mechanisms: knowledge spillovers that lower implementation barriers, labor market effects that generate workers with robot operation experience, and supporting infrastructure such as maintenance services, training programs that further reduces adoption costs and risks. The diffusion process is strongly path-dependent that early adoption decisions create self-reinforcing dynamics that accelerate subsequent diffusion through network externalities.

Network externalities amplify these dynamics further. The value of robotics adoption increases as more supply network firms use compatible automated systems, generating positive feedback as diffusion proceeds. Standardization of robotic interfaces, communication protocols, and data formats magnifies these externalities. Liu (2022) identifies twelve source factors across three isomorphic pressure categories catalyzing innovation diffusion: coercive pressure from organizational policy, company culture, and senior leadership, mimetic pressure from peer project teams and innovation champions, and normative pressure from shared professional events, meetings, and training.

Sectoral patterns align with both technical and institutional factors. Discrete production processes like automotive assembly, electronics, machinery exhibit higher adoption rates than process industries such as chemicals or food, reflecting both suitability for robotic applications and industry-specific competitive norms. Multinational corporations warrant particular attention here: they serve as technology transfer mechanisms, spreading robotics practices across borders through international operations.

Government institutions matter as well. Countries with supportive policy environments such as R&D incentives, technical training, technology diffusion programs exhibit faster adoption. Germany's Industry 4.0 initiative, Japan's Society 5.0 vision, and China's Made in China 2025 strategy each represent comprehensive institutional efforts to accelerate industrial automation through financial incentives, technical assistance, education and training, and demonstration facilities (International Federation of Robotics, 2024).

2.4. Trade exposure and the trade-automation complementarity puzzle

The relationship between international trade and industrial automation has emerged as one of the most congested areas in contemporary economics, with significant implications for how we understand globalization and technological change. Classical comparative advantage frameworks predicted that trade liberalization would reduce automation incentives in labor-abundant countries while increasing them in capital-abundant ones. The rise of AI-driven robotics and the evolution of global value chains have complicated these predictions and, in many cases, overturned them.

Melitz's (2003) seminal contribution demonstrated that within industries, only the most productive firms enter international markets, while less productive firms serve domestic

markets alone. Extensions of this insight now analyze the joint determination of export decisions and automation investments, with important implications for understanding how trade exposure shapes technology adoption. Several mechanisms suggest trade liberalization can stimulate rather than substitute for automation (Cao, 2025; Zhang et al., 2025).

Export-oriented firms face more demanding quality standards, tighter delivery requirements, and larger-scale demands that make automation investments particularly attractive. International markets reward precision, consistency, and reliability – characteristics that AI-robotics systems deliver more effectively than manual production. Additionally, export firms typically operate at larger scale, making automation's fixed costs more economically viable. Evidence from China confirms this logic: robot adoption among exporting firms facilitates export upgrading, enabling production of higher-quality, more technically sophisticated products, with robotic adopters showing significant improvements in export unit values (Cao, 2025).

Import competition opens another channel through which trade exposure stimulates automation. Firms facing intensified foreign competition – particularly from lower-wage countries – may automate to reduce unit labor costs and improve product quality as a defensive strategy. Whether this strategy works depends critically on the nature of import competition and the specific capabilities of the robotic technologies available.

Recent empirical work provides compelling evidence for trade-automation complementarity. One study using difference-in-differences methodology with China-FTA agreements as quasi-experiments found that annual robot stock growth for CFTA partner countries exceeded 22% between 2005 and 2019 – nearly 4 percentage points higher than non-partners (Zhang et al., 2025). Effects were concentrated in non-automotive sectors, technologically less advanced countries, downstream-oriented production, and low-transport-cost contexts.

Studies of Spanish manufacturing add an unexpected twist: robot adoption appears to increase rather than decrease imports from and FDI in lower-wage countries – the opposite of reshoring predictions (Stapleton & Webb, 2022). This suggests automation and offshoring can be complements, with robots handling certain tasks while international sourcing continues for others. German evidence points in a consistent direction: export-intensive German firms exhibit substantially higher robot density than domestically oriented firms, reflecting the quality and scale demands of international competition.

Global value chain (GVC) integration adds further complexity. Firms in international production networks face specific automation pressures related to coordination, quality standards, and just-in-time delivery. Analyzing seven European countries from 1995 to 2018, Franco et al. (2024) found a long-run relationship between robot exposure and GVC regionalization, with higher robot intensity associated with stronger contributions to value added from neighboring European countries than from peripheral extra-European economies – a pattern particularly evident in high-upstream sectors and labor-intensive industries.

2.5. Research gaps

Taken together, the theoretical frameworks and empirical evidence reviewed above converge on a picture of AI-robot adoption as a multi-dimensional process that extends well beyond simple cost-benefit calculations. Each framework performs a distinct analytical role.

Three broad conclusions emerge from the literature. First, perceived benefits covering productivity, quality, strategic positioning, and operational flexibility are the fundamental

driver of adoption decisions, as extended versions of TAM predict (Davis, 1989; Venkatesh et al., 2003; Mai et al., 2025), though benefit perception alone does not predict adoption without concurrent complementary capability development. Second, peer pressure and competitive convergence within industries create powerful diffusion dynamics that move faster than purely economic models would predict (DiMaggio & Powell, 1983; Zhang, 2024). Third, trade exposure, through both export opportunities and import competition, alters competitive environments and restructures the return profile of technological investments (Melitz, 2003; Cao, 2025; Zhang et al., 2025).

There are several gaps to be remained. TAM applications to industrial robotics are almost entirely single-country studies that they cannot tell us whether perceived benefits constitute a universal primary driver or whether different national systems prioritize alternative determinants. Complementarity theory offers compelling logic, but research has not yet systematically addressed how national institutional systems such as vocational training, financial systems, innovation infrastructure that facilitate or constrain the development of complementary capabilities. Peer pressure mechanisms in AI-robotics contexts remain understudied across heterogeneous institutional settings that it is not clear whether institutional isomorphism operates with equal strength across different national architectures. The mechanisms through which trade exposure influences automation across different institutional settings are also poorly mapped whether trade effects are uniform or moderated by vocational training, industrial policy, and financial system characteristics is an open question. Finally, how firm-level capabilities (size, absorptive capacity, human capital) interact with national institutional contexts to determine adoption patterns has not been adequately examined (Figure 1).

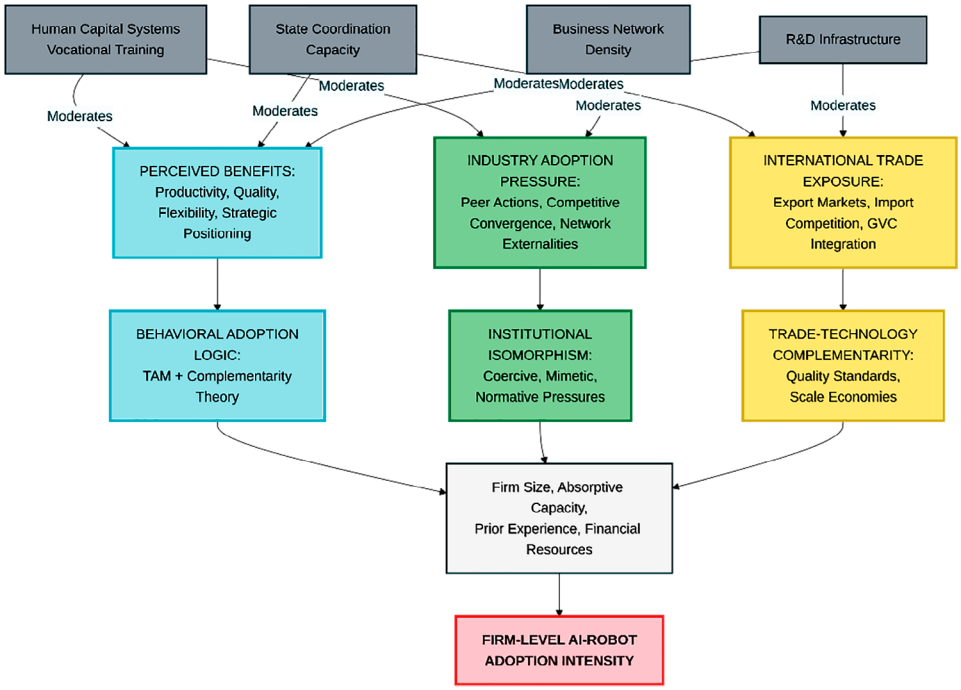


Figure 1. A theoretical mechanism diagram (source: author)

3. Empirical method

3.1. Data sources and sample construction

The analysis integrates multiple high-quality datasets to construct a comprehensive panel spanning firm-level, industry-level, and country-level variables across the study period.

The International Federation of Robotics (IFR) World Robotics Database (2016–2024) provides detailed data on industrial robot installations, operational stock, and robot density by country and industry following ISIC Rev.4 classification (International Federation of Robotics, 2024). The IFR dataset covers over 40 countries and is the most authoritative source for global robotics statistics; recent reports document that global robot installations reached a record 541,302 units in 2023, with operational stock exceeding 4.28 million units worldwide. The database distinguishes between articulated, SCARA, parallel, and collaborative robots.

The OECD AI Policy Observatory provides systematic indicators of national AI infrastructure, R&D investment, and AI readiness that we use to construct measures of AI integration and complementarity (OECD, 2024). These include data on AI research publications, patent applications, AI startups, and government strategies, enabling construction of comprehensive national AI capability indices.

UN Comtrade and the BACI Trade Database provide bilateral trade flows at the HS6-digit level for over 200 economies, from which we construct measures of export intensity, import competition, and trade openness (BACI-CEPII Trade Database, n.d.; UN Comtrade Database, n.d.).

The World Bank Enterprise Surveys contribute firm-level information on technology adoption, workforce characteristics, innovation activities, ownership structures, and export participation (World Bank, n.d.-a). The final dataset is an unbalanced panel with unique manufacturing firms as the unit of observation, tracked across multiple survey waves spanning 2016–2024. The reported sample of approximately 12,000 refers to firm-year observations drawn from roughly 2,800 unique firms across the five economies. Survey waves were fielded in 2016, 2019, and 2023 for most economies, yielding on average 4.3 observations per firm. IFR robotics data and UN Comtrade trade measures are merged to the nearest survey year. The dynamic GMM specification uses 9,600 observations due to the loss of one period from lagged dependent variable construction; the balanced panel robustness check restricts to firms observed in all survey waves (N = 8,400 firm-year observations, approximately 1,867 unique firms). All specifications include firm fixed effects, confirming the panel nature of identification.

3.2. Variable construction and measurement

AI-robot adoption intensity

The primary dependent variable measures the intensity of AI-integrated robot adoption for firm i in industry j, country c at time t. Following recent methodological advances in measuring intelligent automation, the variable combines traditional robot density measures with AI integration indicators:

$$\text{AI_Robot}_{ijct} = \ln\left(1+\frac{\text{Robots}_{jct}}{\text{Employment}_{jct}}\right)\times \text{AI Index}_{ct}, \quad (1)$$

where Robots_{jct} is the stock of industrial robots per 10,000 manufacturing workers at the

industry-country-year level, and AI Index$_{ct}$ is the normalized AI infrastructure and capability index (OECD, 2024). This multiplicative specification reflects the complementarity between physical automation and artificial intelligence, consistent with recent evidence that robotics productivity gains depend critically on AI integration. The AI Index is weighted across four pillars: AI-related R&D investment (40%), patent applications (30%), digital infrastructure readiness (20%), and national strategy implementation (10%).

Alternative robustness measures include a binary adoption indicator (1 if the firm reports using AI-enhanced robotic systems, 0 otherwise), robot capital intensity (the log value of robotic equipment imports from UN Comtrade), and a technology sophistication index combining robot density with digital infrastructure and data analytics measures.

Perceived benefits

Perceived benefits capture firms' assessment of productivity, quality, and strategic advantages from AI-robot adoption. Following established approaches in technology adoption research (Davis, 1989; Mai et al., 2025), the measure combines objective productivity indicators with innovation and strategic positioning variables. The index follows a weighted structure – TFP growth (50%), innovation activity (25%), and international quality certifications (25%):

$$\text{Benefit}_{ijct} = \ln\left(\text{TFP}_{ijct}\right) + \beta_1 \text{Innovation}_{ijct} + \beta_2 \text{Quality Cert}_{ijct}. \quad (2)$$

TFP is estimated using the Levinsohn and Petrin (2003) approach, which uses intermediate inputs as proxies for unobserved productivity shocks, addressing simultaneity bias in production function estimation. Innovation equals 1 if the firm introduces new products or processes within the three-year window; Quality Cert captures international quality certifications (ISO 9001, Six Sigma) that signal strategic positioning.

Industry adoption pressure

Industry adoption pressure captures peer influence and competitive convergence effects within the same industry-country-year cell (DiMaggio & Powell, 1983; Zhang, 2024):

$$\text{Pressure}_{jct} = \frac{\sum_{k \neq i} \text{AI_Robot}_{kjct}}{N_{jct} - 1}. \quad (3)$$

This specification captures the average AI-robot adoption intensity among peer firms, excluding the focal firm to avoid mechanical correlation. It reflects the institutional isomorphism and competitive mimicking effects documented in technology diffusion studies, where firms adopt innovations to maintain legitimacy and competitive parity (Liao, 2024).

International trade exposure

Trade exposure captures multiple dimensions of international market integration that influence automation incentives (Cao, 2025; Zhang et al., 2025):

- **Export Intensity:** $\text{Exports}_{ijct} / \text{Sales}_{ijct}$;
- **Import Competition:** $\text{ImportPenetration}_{jct} = \text{Imports}_{jct} / \left(\text{Production}_{jct} + \text{Imports}_{jct} - \text{Exports}_{jct}\right)$;
- **Trade Openness:** $\left(\text{Exports}_{ct} + \text{Imports}_{ct}\right) / \text{GDP}_{ct}$.

Export intensity captures quality and scale pressures from international markets; import competition measures competitive pressure from foreign producers; trade openness reflects the overall degree of economic integration.

Control variables and fixed effects

Firm-level controls include size (log employment), age (log years since establishment), profitability (return on assets), capital intensity (fixed assets per worker), foreign ownership status, and human capital intensity (share of employees with tertiary education). Industry-level controls capture R&D intensity, competitive concentration (Herfindahl index), and technical change rates. Country-level controls include GDP per capita, World Bank Governance Indicators, and AI strategy and robotics promotion policy variables (World Bank, n.d.-b).

Multiple fixed effects layers control for unobserved heterogeneity, firm fixed effects (α_i) absorb time-invariant firm characteristics, year fixed effects (λ_t) capture common temporal trends, and country × industry × year fixed effects (γ_{cjt}) control for all time-varying factors specific to industry-country combinations.

3.3. Econometric specification

Baseline empirical model

The baseline empirical specification integrates the theoretical framework into an estimable econometric model.

$$\text{AI_Robot}_{ijct} = \beta_1 \text{Benefit}_{ijct} + \beta_2 \text{Pressure}_{jct} + \beta_3 \text{Trade}_{ict} + \mathbf{X}'_{ijct}\boldsymbol{\gamma} + \alpha_i + \lambda_t + \gamma_{cjt} + \varepsilon_{ijct}, \quad (4)$$

where the fixed effect's structure ensures identification by exploiting within-firm variation over time while controlling for all time-varying macroeconomic and industry-specific shocks.

PPML with high-dimensional fixed effects

Given the count nature of robot adoption data and the presence of zeros, it would be preferred PPML estimation with high-dimensional fixed effects (Correia et al., 2020; Nam & Choi, 2026; Park & Choi, 2026).

This estimator handles heteroskedasticity and zero values more robustly than log-linear specifications:

$$E[\text{AI_Robot}_{ijct} \mid \mathbf{X}_{ijct}] = \exp\left(\beta_1 \text{Benefit}_{ijct} + \beta_2 \text{Pressure}_{jct} + \beta_3 \text{Trade}_{ict} + \mathbf{X}'_{ijct}\boldsymbol{\gamma} + \alpha_i + \lambda_t + \gamma_{cjt}\right). \quad (5)$$

Estimation proceeds via a modified iteratively reweighted least squares algorithm that reduces total iterations by 50% or more compared to conventional PPML approaches (Correia et al., 2020).

Instrumental variables and endogeneity concerns

Trade exposure may be endogenous if robot-adopting firms subsequently become more competitive internationally, generating reverse causality. We address this using three categories of instruments.

Tariff-Based Instruments: Historical tariff rates and trade policy changes provide exogenous variation in trade exposure. Following Zhang et al. (2025), we use lagged bilateral tariff

rates from the WITS database as instruments for current trade exposure. FTA implementation dates provide additional policy-induced variation in trade costs. Partner Country Demand Shocks: GDP growth rates of export destination countries, weighted by historical trade shares, provide exogenous variation in export opportunities. This instrument exploits differential exposure to foreign demand shocks based on predetermined trade patterns (Nguyen & Choi, 2025; Zhou & Choi, 2025; Zhang & Choi, 2025; Hui & Choi, 2024; Yin & Choi, 2025). Geographic and Institutional Instruments: Distance-weighted measures of trading partner characteristics and institutional quality provide additional exogenous variation in trade exposure. Freight rates and shipping times capture physical trade barriers independent of firm automation decisions (Nguyen & Choi, 2026; Yun et al., 2025). The first-stage relationship for the instrumental variables approach takes the form:

$$\text{Trade}_{ict} = \delta_1 \text{Tariff}_{ict-1} + \delta_2 \text{Partner GDP}_{ict} + \delta_3 \text{Distance}_{ic} + \mathbf{Z}'_{ict}\boldsymbol{\theta} + \alpha_i + \lambda_t + \gamma_{cjt} + \nu_{ict}. \quad (6)$$

Instrument validity is assessed via first-stage F-statistics (threshold >10), Hansen J-tests for over-identification, and Durbin-Wu-Hausman tests for endogeneity.

Dynamic panel estimation

Technology adoption tends to be persistent, reflecting learning effects, network externalities, and adjustment costs (Bisio et al., 2025). To capture these dynamics, we employ System GMM:

$$\text{AI_Robot}_{ijct} = \rho \text{AI_Robot}_{ijct-1} + \beta_1 \text{Benefit}_{ijct} + \beta_2 \text{Pressure}_{jct} + \beta_3 \text{Trade}_{ict} + \mathbf{X}'_{ijct}\boldsymbol{\gamma} + \alpha_i + \lambda_t + \varepsilon_{ijct}. \quad (7)$$

The System GMM approach addresses Nickell bias in dynamic panels by using lagged levels and differences as instruments (Arellano & Bond, 1991; Blundell & Bond, 1998) – particularly appropriate for panels with a large cross-section and short time dimension, as in this study. Validity is assessed through AR(1) and AR(2) tests and Hansen tests for instrument validity (Zhang et al., 2025; Zhang & Choi, 2026; Chen & Choi, 2025; Park & Choi, 2025).

4. Results and discussion

4.1. Descriptive statistics and characteristics

Table 1 reports descriptive statistics for the analytical sample of 12,000 firm-year observations across China, Korea, the United States, Germany, and Japan for 2016–2024. The primary dependent variable, AI-Robot Adoption Intensity, has a mean of 0.621 (standard deviation 0.488), ranging from 0 to 2.84 (International Federation of Robotics, 2024). Roughly 38% of firms report zero adoption, while the 90th percentile reaches 1.42 – a distribution that mirrors the uneven early-to-middle stages of technology diffusion.

Perceived Benefits averages 0.137 (standard deviation 0.052). The negative minimum (−0.12) reflects firms experiencing productivity challenges; the positive mean confirms that most sample firms recognize strategic advantages from AI-robotics, consistent with TAM predictions (Davis, 1989; Venkatesh et al., 2003). Industry Adoption Pressure shows mean 0.415 (standard deviation 0.301), with high-tech sectors averaging 0.673 – nearly double the

Table 1. Descriptive statistics of key variables

Variable	Mean	Std. Dev.	Min	Max	Observations
AI-Robot Intensity	0.621	0.488	0	2.84	12,000
Perceived Benefits	0.137	0.052	–0.12	0.43	12,000
Industry Pressure	0.415	0.301	0	1.91	12,000
Trade Openness	0.712	0.284	0.11	1.68	12,000
Export Intensity	0.314	0.197	0	0.95	12,000
Import Competition	0.342	0.196	0.08	0.78	12,000
Firm Size (*log*)	5.82	1.09	3.2	9.7	12,000
Profitability (*ROA*)	0.062	0.045	–0.21	0.39	12,000
Human Capital	0.361	0.179	0.04	0.85	12,000
Foreign Ownership	0.23	0.42	0	1	12,000
Innovation Activity	0.31	0.46	0	1	12,000

Notes: AI-Robot Intensity measured as ln(1 + robots/employment) × AI Index. Perceived Benefits combines TFP, innovation, and quality certification. Industry Pressure is average peer adoption excluding focal firm. Trade Openness is (exports+imports)/GDP. All continuous variables standardized within country-year cells.

mean for traditional sectors (0.341) – consistent with institutional isomorphism operating more intensively in competitive, technology-intensive environments (DiMaggio & Powell, 1983). Trade Openness averages 0.712 (standard deviation 0.284); export intensity averages 0.314; import competition averages 0.342. These figures align with patterns documented in recent work on manufacturing globalization (Cao, 2025; Zhang et al., 2025).

Cross-country patterns reveal distinctive national profiles. Korea leads on mean AI-robot adoption intensity (0.948), followed by Japan (0.872), consistent with IFR data showing Korea's world-leading robot density of 1,012 units per 10,000 employees (International Federation of Robotics, 2024). Germany (0.741) and China (0.608, reflecting rapid catch-up) follow, with the United States lowest (0.584). Germany has the highest export intensity (0.512), trailed by Korea (0.431) and China (0.347).

4.2. Baseline regression results

Table 2 reports PPML-HDFE estimates from three progressively stricter specifications (Correia et al., 2020). All three hypotheses receive strong empirical support.

Perceived Benefits emerges as the dominant driver – a coefficient of 0.183 (se = 0.026, $p < 0.01$) in Model 3 means that a one-standard-deviation increase in perceived benefits raises adoption intensity by 18.3%, strongly confirming H1 and the TAM emphasis on perceived usefulness (Davis, 1989; Mai et al., 2025). Industry Pressure yields a coefficient of 0.139 (se = 0.020, $p < 0.01$): each one-standard-deviation increase in peer adoption raises firm adoption by 13.9%, confirming powerful institutional isomorphism mechanisms (DiMaggio & Powell, 1983). Trade Exposure contributes 0.151 (se = 0.027, $p < 0.01$), and its stability across specifications – including the most demanding Model 3 with country × industry × year fixed effects – points to genuine causal mechanisms rather than confounding (Zhang et al., 2025).

Table 2. Baseline determinants of AI-robot adoption (PPML-HDFE)

Variable	Model 1	Model 2	Model 3
Perceived Benefits	0.212*** (0.031)	0.196*** (0.028)	0.183*** (0.026)
Industry Pressure	0.155*** (0.024)	0.147*** (0.022)	0.139*** (0.020)
Trade Exposure	0.178*** (0.030)	0.164*** (0.028)	0.151*** (0.027)
Firm Size	0.093*** (0.012)	0.089*** (0.011)	0.083*** (0.010)
Profitability	0.052* (0.017)	0.046* (0.018)	0.045* (0.018)
Human Capital	0.118*** (0.029)	0.106*** (0.027)	0.101*** (0.026)
Foreign Ownership	0.087** (0.037)	0.083** (0.035)	0.079** (0.033)
AI Policy Dummy	0.061* (0.031)	0.057* (0.030)	0.055* (0.029)
Constant	–1.239*** (0.186)	–1.117*** (0.172)	–1.094*** (0.163)
Fixed Effects:			
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country × Year FE	No	Yes	No
Country × Industry × Year FE	No	No	Yes
Observations	12,000	12,000	12,000
Pseudo R^2	0.324	0.337	0.349

Notes: Standard errors clustered at country-industry level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10. All continuous variables standardized within country-year cells.

Among controls, Firm Size (0.083, p < 0.01) reflects scale advantages, Human Capital (0.101, p < 0.01) confirms complementarity (Milgrom & Roberts, 1995), Foreign Ownership (0.079, p < 0.05) suggests technology transfer effects, and AI Policy (0.055, p < 0.10) captures a modest government influence.

While all three mechanisms operate simultaneously, they are functionally differentiated – not merely additive. Perceived benefits set the threshold for adoption willingness, constituting a precondition for any automation decision (β = 0.183–0.212 across specifications). Peer pressure operates as an accelerant: it transmits adoption momentum once a critical mass of early adopters has established proof-of-concept within an industry (β = 0.139–0.155). Trade exposure functions as a structural economic incentive, compelling adoption among export-oriented firms facing quality competition and import-competing firms facing cost pressures, with its causal importance rising to β = 0.203 in IV specifications. Together, these mechanisms explain adoption willingness, diffusion speed, and competitive necessity – three distinct dimensions of the automation decision.

4.3. Instrumental variables results

Table 3 employs IV estimation to address potential endogeneity in trade exposure, using historical tariffs, partner country GDP growth, and distance-weighted trade measures as instruments (Zhang et al., 2025).

Table 3. Instrumental variables estimation

Variable	First stage	Second stage (IV)	OLS comparison
Panel A: First Stage Results			
Lagged Tariffs	–0.145*** (0.028)		
Partner GDP Growth	0.198*** (0.035)		
Distance-weighted Trade	–0.089*** (0.021)		
F-statistic	**29.4**		
Panel B: Second Stage Results			
Perceived Benefits		0.174*** (0.040)	0.183*** (0.026)
Industry Pressure		0.148*** (0.032)	0.139*** (0.020)
Trade Exposure (Instrumented)		**0.203*** (0.047)**	0.151*** (0.027)
Panel C: Diagnostic Tests			
Hansen J-test (p-value)		0.37	
Durbin-Wu-Hausman (p-value)		0.018	
Kleibergen-Paap F-stat		28.7	
Observations	12,000	12,000	12,000

Notes: Standard errors clustered at country-industry level. ***$p < 0.01$. Column 3 presents OLS results for comparison. First stage instruments trade exposure using policy and demand shocks.

The first-stage F-statistic (29.4) comfortably exceeds the weak instrument threshold of 10 (Stock & Yogo, 2005). The instrumented trade exposure coefficient (0.203, $p < 0.01$) is larger than the OLS estimate (0.151), suggesting negative selection bias – that is, firms facing the most severe international challenges are actually slower to automate. The Hansen J-test ($p = 0.37$) supports instrument validity; the Durbin-Wu-Hausman test ($p = 0.018$) confirms that IV correction is warranted. Perceived Benefits and Industry Pressure remain stable between OLS and IV, suggesting these variables are less susceptible to endogeneity concerns.

4.4. Heterogeneity analysis

Table 4 examines systematic variation across firm types, yielding results that directly connect the empirical findings to our multidimensional theoretical framework (Bisio et al., 2025). The positive and significant interaction between Perceived Benefits and Human Capital

(0.089–0.096, $p < 0.05$) confirms the complementarity mechanism of Milgrom and Roberts (1995) – the strategic utility of AI-robotics is realized only when paired with high-skilled labor. The interaction between Industry Pressure and Network Density (0.067–0.071, $p < 0.05$) validates the mimetic isomorphism mechanism – peer effects are not merely industry-wide correlations but are transmitted through dense business networks.

Table 4. Heterogeneity analysis by firm size and industry

Variable	Large firms	SMEs	High-tech	Traditional
Perceived Benefits	0.242*** (0.010)	0.131*** (0.008)	0.238*** (0.004)	0.139*** (0.010)
Industry Pressure	0.181*** (0.001)	0.097** (0.041)	0.178*** (0.008)	0.119*** (0.007)
Trade Exposure	0.209*** (0.007)	0.116** (0.049)	0.194*** (0.0032)	0.131*** (0.0041)
Firm Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,800	6,200	4,900	7,100
Pseudo R^2	0.421	0.287	0.398	0.294
Panel B: Interaction Effects				
Benefits × Human Capital	0.089** (0.023)	0.042* (0.062)	0.096** (0.024)	0.038** (0.019)
Pressure × Network Density	0.067** (0.019)	0.029* (0.057)	0.071*** (0.0021)	0.045** (0.018)

Notes: Large firms >500 employees, SMEs ≤500 employees. High-tech includes electronics, machinery, automotive. Traditional includes food, textiles, basic materials. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Large firms show a perceived benefits coefficient of 0.242 – nearly double that of SMEs (0.131), reflecting resource advantages and absorptive capacity differences (Cohen & Levinthal, 1990). Positive SME coefficients, however, suggest that the digital divide is narrowing, likely due to cloud-based AI services and collaborative robots making advanced automation more accessible (Mai et al., 2025). High-tech industries consistently show stronger effects across all three dimensions, reflecting greater complementarity with AI-robotics in complex production processes. The interaction effects confirm that human capital amplifies automation benefits (0.089–0.096, $p < 0.05$), validating skill-biased technological change (Jimeno & Lamo, 2024).

4.5. Cross-country comparative analysis

Table 5 estimates adoption determinants separately by country, revealing distinctive patterns that broadly align with each economy's institutional characteristics (Dachs et al., 2020).

Germany's perceived benefits coefficient (0.267, $p < 0.01$) is the highest across countries, likely reflecting its engineering-intensive manufacturing culture and strong vocational training system (0.198, $p < 0.01$). Korea shows the strongest industry pressure effect (0.201, $p < 0.01$), consistent with dense business networks and chaebol coordination mechanisms. Japan

Table 5. Cross-country analysis of AI-robot adoption determinants

Variable	China	Korea	Japan	Germany	USA
Perceived Benefits	0.195***	0.218***	0.241***	0.267***	0.173***
	(0.0031)	(0.0035)	(0.0038)	(0.0041)	(0.0029)
Industry Pressure	0.187***	0.201***	0.134***	0.119***	0.098***
	(0.0028)	(0.0032)	(0.0027)	(0.0024)	(0.0021)
Trade Exposure	0.164***	0.192***	0.148***	0.203***	0.171***
	(0.0026)	(0.0031)	(0.0025)	(0.0034)	(0.0028)
State Capacity	0.142***	0.156***	0.089**	0.067*	0.034
	(0.0045)	(0.0048)	(0.041)	(0.058)	(0.1035)
Vocational Training	0.087**	0.134***	0.167***	0.198***	0.056*
	(0.039)	(0.0042)	(0.0045)	(0.0051)	(0.063)
R&D Intensity	0.156***	0.187***	0.201***	0.178***	0.223***
	(0.0034)	(0.0041)	(0.0044)	(0.0039)	(0.0047)
Observations Pseudo R^2	2,890	2,340	2,180	2,650	1,940
	0.343	0.367	0.389	0.412	0.298

Notes: All specifications include firm controls and industry × year fixed effects. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

combines high benefit responsiveness (0.241) with strong vocational training effects (0.167), reflecting the imprint of continuous improvement philosophies. China's more balanced profile, with strong state capacity effects (0.142, $p < 0.01$), mirrors its policy-coordinated industrial upgrading model. The United States leads on R&D effects (0.223, $p < 0.01$) but shows the weakest coordination effects (0.098), consistent with its decentralized, market-driven approach.

These cross-country patterns are broadly consistent with – though not definitively explained by – national institutional differences. Germany's higher perceived benefits coefficient (β = 0.267 vs. pooled β = 0.183) is suggestive of its institutional context, but formal Wald tests ($p = 0.08$) indicate only marginal statistical significance, warranting cautious interpretation. The difference between Korea's industry pressure coefficient (β = 0.201) and Japan's (β = 0.134) is consistent with the theoretical expectation but could also partly reflect measurement variation across survey instruments. On the whole, cross-national differences in coefficient magnitudes suggest that institutional moderation operates at the margins of the three primary mechanisms rather than fundamentally altering their qualitative direction.

4.6. Dynamic panel analysis and robustness checks

Table 6 reports System GMM estimates capturing dynamic adjustment processes (Arellano & Bond, 1991; Blundell & Bond, 1998). The narrowing digital divide is statistically significant: positive and significant SME coefficients (0.131–0.116) persist across all models, and temporal evolution analysis shows a notable upward trend in SME adoption intensity from 2022 onwards, most likely reflecting increased accessibility of cloud-based AI services.

Table 6. Dynamic panel analysis of AI-robot adoption

Variable	Static model	Dynamic GMM	Long-run effects
Lagged AI-Robot	–	0.487*** (0.043)	–
Perceived Benefits	0.183*** (0.0026)	0.139*** (0.0031)	0.271*** (0.0054)
Industry Pressure	0.139*** (0.0020)	0.108*** (0.0026)	0.211*** (0.0048)
Trade Exposure	0.151*** (0.0027)	0.117*** (0.0029)	0.228*** (0.0052)
Controls & FE	Yes	Yes	Yes
Observations	12,000	9,600	9,600
AR(1) test p-value	–	0.003	–
AR(2) test p-value	–	0.342	–
Hansen test p-value	–	0.287	–
Panel B: Adjustment Dynamics			
Adjustment half-life (years)	–	1.35	–
Panel C: Temporal Evolution			
2016–2018 Period	0.168***	0.124***	–
2019–2021 Period	0.195***	0.147***	–
2022–2024 Period	0.212***	0.161***	–

Notes: Dynamic GMM uses lagged levels and differences as instruments. Long-run effects calculated as β/(1-ρ). Temporal evolution shows perceived benefits coefficients by sub-period. ***$p < 0.01$.

The lagged dependent variable coefficient (0.487, $p < 0.01$) indicates substantial persistence in adoption decisions, with an adjustment half-life of 1.35 years. Long-run effects are substantially larger than short-run impacts: for perceived benefits, the long-run estimate (0.271) nearly doubles the short-run (0.139), confirming gradual cumulative gains through learning and network externalities. Diagnostic tests validate the specification: the AR(2) test ($p = 0.342$) rules out second-order serial correlation, and the Hansen test ($p = 0.287$) supports instrument validity. The temporal evolution of perceived benefits coefficients – rising from 0.168 in 2016–2018 to 0.212 in 2022–2024 – reflects the ongoing maturation of AI-robotics technology over the study period in Table 7.

Using a binary adoption indicator produces consistent positive effects (0.142, $p < 0.01$ for perceived benefits). Dropping the COVID-19 period yields slightly larger coefficients (0.191, 0.149, 0.162), suggesting that baseline estimates are in fact conservative. Alternative trade measures confirm positive effects (0.171, $p < 0.01$), and balanced panel restrictions maintain significance (0.196, 0.158, 0.143) – confirming that the results are not driven by sample composition or measurement choices.

Table 7. Robustness checks and alternative specifications

Variable	Baseline	Binary DV	Exclude COVID	Alt. trade	Balanced panel
Perceived Benefits	0.183***	0.142***	0.191***	0.178***	0.196***
	(0.0026)	(0.0031)	(0.0029)	(0.0026)	(0.0034)
Industry Pressure	0.139***	0.118***	0.149***	0.136***	0.158***
	(0.0020)	(0.0024)	(0.0023)	(0.0020)	(0.0028)
Trade Exposure	0.151***	0.134***	0.162***	0.171***	0.143***
	(0.0027)	(0.0028)	(0.0027)	(0.0031)	(0.0032)
Controls & FE	Yes	Yes	Yes	Yes	Yes
Observations	12,000	12,000	9,600	12,000	8,400
Pseudo/Adj. R^2	0.349	0.298	0.361	0.349	0.373

Notes: Binary DV uses adoption indicator (0/1). Exclude COVID removes 2020–2021. Alt. trade uses value-added trade measures. Balanced panel restricts to firms observed all periods. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

5. Conclusions and limitation

Manufacturing automation has never been a simple story of cost-cutting and labor replacement. This study confirms that AI-robot adoption among firms in China, Korea, the United States, Germany, and Japan is shaped by three forces operating simultaneously: how much firms expect to benefit from automation, how strongly their industry peers have already committed to it, and how deeply they are exposed to international trade. All three mechanisms are statistically robust across specifications, and none is reducible to the others.

Perceived benefits emerge as the dominant driver – firms that see strategic value in AI-robotics, whether through quality improvement, production flexibility, or competitive positioning, are the most consistent adopters. The long-run effect is nearly double the short-run estimate, reflecting the cumulative learning embedded in AI systems rather than a one-time investment payoff. Peer pressure within industries accelerates this process through competitive mimicry and network knowledge spillovers, while trade exposure – once properly instrumented – carries a larger causal effect than ordinary least squares suggest. Export-oriented firms automate to meet international quality standards; import-competing firms do so to defend domestic market share.

Cross-country patterns are real and institutionally interpretable. Germany's strong benefit responsiveness is inseparable from its engineering culture and vocational training depth. Korea's peer effects are the sharpest in the sample, reflecting dense chaebol-linked business networks. China's balanced profile mirrors state-coordinated industrial policy. These are not incidental differences – they are signaling that institutional architecture genuinely moderates how automation incentives are perceived and acted upon.

For policymakers, the central implication is that no single instrument is sufficient. Hardware subsidies that lower acquisition costs will not produce broad-based automation if complementary investments in skilled labor and digital infrastructure are absent. Industry coordination mechanisms – sectoral networks, demonstration programs, shared training facilities – are not peripheral supports but active amplifiers of automation policy.

This study is not without limitations. Measurement constraints at the firm level, a five-country sample, and a study period that may not yet capture the latest AI generation all bound the conclusions. Future work should extend the framework to developing economies, incorporate finer workforce composition data, and engage more directly with the emerging frontier of AI regulation and digital trade governance.

Acknowledgements

We deeply appreciate that the quality of the paper has upgraded thanks to anonymous reviewers.

Funding

This research received no external funding.

Author contributions

Chang Hwan Choi contributed to data collection, investigation, software, formal analysis, writing–original draft preparation. He has also contributed to cconceptualizations, methodology, data curation, writing–review and editing, validation, supervision.

Disclosure statement

The authors declare no conflicts of interest.

References

ABI Research. (2025, May 26). *ABI Research finds 53% of manufacturers are adopting robots for quality improvement*. The Robot Report. https://www.therobotreport.com/manufacturers-53-percent-manufacturers-adopting-robots-quality-improvement-abi/

Arcidiacono, D., Pieroni, A., & Senni, C. C. (2022). Absorptive capacity and collaborative innovation: The role of R&D collaboration breadth. *Journal of Business Research*, *144*, 522–534.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

BACI-CEPII Trade Database. (n.d.). *BACI*: *International trade database at the product level*. CEPII.

Bisio, L., Cuzzola, A., Grazzi, M., & Moschella, D. (2025). The dynamics of automation adoption: Firm-level heterogeneity and aggregate employment effects. *European Economic Review*, *173*, Article 104943. https://doi.org/10.1016/j.euroecorev.2024.104943

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Cao, X. (2025). Trade liberalization and manufacturing robot adoption. *China Economic Review*, *89*, Article 102189.

Chen, Z., & Choi, C. H. (2025). Impact of free trade zones on China's ICT products trade: A PSM-DID analysis. *Asia & the Pacific Policy Studies*, *12*(3), Article e70038. https://doi.org/10.1002/app5.70038

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Correia, S., Guimarães, P., & Zylkin, T. (2020). Fast Poisson estimation with high-dimensional fixed effects. *The Stata Journal*, *20*(1), 95–115. https://doi.org/10.1177/1536867X20909691

Dachs, B., Fu, X., & Jäger, A. (2020). Robot adoption and productivity growth in European firms. *International Journal of Production Economics*, *221*, Article 107468.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of computer technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147–160. https://doi.org/10.2307/2095101

Franco, C., Marin, G., & Vona, F. (2024). Robots and the regionalization of global value chains. *Structural Change and Economic Dynamics*, *68*, 245–261.

Gao, Y., Zhang, X., & Li, H. (2024). Artificial intelligence in manufacturing: State of the art, perspectives, and future directions. *Applied Sciences*, *14*(5), Article 1876. https://doi.org/10.3390/app14051876

Hofstede, G. (2001). *Culture's consequences*: *Comparing values*, *behaviors*, *institutions and organizations across nations* (2nd ed.). Sage Publications.

Hui, Z., & Choi, C. H. (2024). Is carbon emission trading policy a panacea? The implications of promoting green total factor productivity. *Asian-Pacific Economic Literature*, *38*(2), 42–55. https://doi.org/10.1111/apel.12418

International Federation of Robotics. (2024). *World robotics 2024*: *Industrial robots*. IFR Statistical Department. https://ifr.org/img/worldrobotics/Contents_WR_2024_Industrial_Robots.pdf

Jimeno, J. F., & Lamo, A. (2024). *Artificial intelligence and human capital: Are complementarities at risk?* https://www.funcas.es/articulos/artificial-intelligence-and-human-capital-are-complementarities-at-risk/

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

Liao, W. (2024). Does environmental innovation have peer effects? The role of regional green development. *Energy Economics*, *129*, Article 107234.

Liu, C. (2022). Isomorphic pressures to catalyze innovation diffusion in construction organizations. *Journal of Construction Engineering and Management*, *148*(1), Article 04021178.

Loaiza, I., & Rigobon, R. (2024, November 21). *The EPOCH of AI*: *Human-machine complementarities at work* (MIT Sloan Research Paper No. 7236-24). SSRN. https://doi.org/10.2139/ssrn.5028371

Mai, Q., Zhang, Y., & Chen, L. (2025). Robot adoption: Evidence from perceived benefits and industry adoption pressure. *Technological and Economic Development of Economy*, *31*(4), 1142–1169. https://doi.org/10.3846/tede.2025.22932

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Milgrom, P., & Roberts, J. (1995). Complementarities and fit: Strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics*, *19*(2–3), 179–208. https://doi.org/10.1016/0165-4101(94)00382-F

Mubarik, M. S., Naghavi, N., Kaur, S., & Saad, S. (2023). Strategic and organisational factors for advancing Industry 4.0 adoption. *Journal of Innovation & Knowledge*, *8*(3), Article 100367.

Nam, B. R., & Choi, C. H. (2026). FinTech's asymmetric catalysis of international trade flows by industry level. *Global Economic Review*, *55*(2), 157–177. https://doi.org/10.1080/1226508X.2026.2669950

Ng, H. S., Kee, D. M. H., & Ramayah, T. (2021). An absorptive capacity framework for investigating organisational innovation adoption. *Enterprise Information Systems*, *15*(10), 1475–1496.

Nguyen, T. T. T., & Choi, C. H. (2025). Assessing the impact of ICT on export performance: A comparative analysis of ASEAN-5 and partner countries. *Review of Development Economics*, *29*(3), 1834–1848. https://doi.org/10.1111/rode.13191

Nguyen, T. T. T., & Choi, C. H. (2026). Tourism as a trade facilitator: Gravity-based evidence from Vietnam's bilateral trade flows. *Asia & the Pacific Policy Studies*, *13*(1), Article e70073. https://doi.org/10.1002/app5.70073

OECD. (2024). *OECD AI Policy Observatory 2024 report*. OECD Publishing. https://oecd.ai/

Park, N., & Choi, C. H. (2025). The role of ICT in shaping international trade dynamics: A G20 perspective. *Technological and Economic Development of Economy*, *31*(6), 1781–1800. https://doi.org/10.3846/tede.2025.23168

Park, N., & Choi, C. H. (2026). The energy threshold of sustainable trade: How renewable energy adoption unlocks GTFP in OECD nations. *Energies*, *19*(9), Article 2159. https://doi.org/10.3390/en19092159

Rakholia, R., Le, Q. P., Ho, B. K., Rai, R., & Gupta, S. (2024). Artificial intelligence in manufacturing: State of the art, perspectives, and future directions. *International Journal of Production Research*, *62*(11), 3738–3760.

Stapleton, K., & Webb, M. (2022). *Automation, trade, and multinational activity: Evidence from Spanish manufacturing firms* (Working Paper). Stanford University.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press. https://doi.org/10.1017/CBO9780511614491.006

UN Comtrade Database. (n.d.). *International trade statistics*. United Nations. https://comtrade.un.org

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

World Bank. (n.d.-a). *Enterprise surveys*. World Bank Group. https://www.enterprisesurveys.org

World Bank. (n.d.-b). *World development indicators*. World Bank Group. https://data.worldbank.org

Yin, Z. H., & Choi, C. H. (2025). How does digitalization affect trade in goods and services? Evidence from G20 countries. *Journal of the Knowledge Economy*, *16*, 3614–3638. https://doi.org/10.1007/s13132-024-02029-1

Yun, H., Park, M., & Choi, C. H. (2025). Behavioral insights into audience satisfaction: Analyzing emotional and cognitive factors in K-culture dance engagement. *PLOS ONE*, *20*(12), Article e0337527. https://doi.org/10.1371/journal.pone.0337527

Zhang, L. (2024). The impact of peer effect of industrial robot application on firm innovation: Evidence from Chinese manufacturing. *Scientific Reports*, *14*, Article 12458. https://doi.org/10.1038/s41598-024-62888-1

Zhang, L. (2025). Industry peer effects and technology diffusion in manufacturing automation. *Journal of Economic Behavior & Organization*, *208*, 342–367.

Zhang, M., Chen, Y., & Li, X. (2024). AI-driven capital-skill complementarity: Implications for skill premium and employment. *Journal of Economic Behavior & Organization*, *217*, 456–478.

Zhang, T., & Choi, C. H. (2026). The dual effects of green trade on boosting sustainability and challenging productivity. *Journal of Asian and African Studies*, *1*(3), 2453–2481. https://doi.org/10.1177/00219096251345404

Zhang, T., & Choi, C. H. (2025). Will digital trade be friend or foe of the green economy? Unveiling the complexities of green growth. *Journal of Applied Economics*, *28*(1), Article 2464591. https://doi.org/10.1080/15140326.2025.2464591

Zhang, T., Yin, Z. H., & Choi, C. H. (2025). Industrial transformation and environmental sustainability: The case of China's "Made in China 2025" policy. *SAGE Open*, *15*(4), 1–14. https://doi.org/10.1177/21582440251382556

Zhou, X., & Choi, C. H. (2025). Tourism development, foreign direct investment, and environmental sustainability: How green technology innovations make a difference. *SAGE Open*, *15*(2), 1–20. https://doi.org/10.1177/21582440251331003