AI Capabilities and Firm Performance in Medical Technology

Fazliddin Shermatov*[1], Aldo Geuna[2,3,4], and Stephane Robin[5]

[1]Université Sorbonne Paris Nord
[2]Department of Cultures, Politics and Society, University of Turin, Italy.
[3]Collegio Carlo Alberto, Turin, Italy.,
[4]Innovation, Equity & The Future of Prosperity, CIFAR, Toronto, Canada.
[5]Université Paris 1 Panthéon-Sorbonne.

February 2026

Extended Abstract
Preliminary draft, not for circulation

1 Introduction

The healthcare AI sector is among the fastest-growing segments of the global economy, estimated at $26.69 billion in 2024 and projected to reach $613.81 billion by 2034 (Precedence Research, 2025). Leading applications span medical imaging, natural language processing for clinical documentation, and predictive analytics, with North America capturing the largest share of investment (Landi, 2025; Healthcare Technology Report, 2025). Strategic acquisitions, such as Tempus AI's $625 million purchase of Paige—illustrate an accelerating trend toward platform consolidation and multimodal data integration (Tempus AI, Inc., 2025). Yet AI adoption in healthcare continues to face meaningful headwinds: regulatory complexity, interoperability constraints, and clinician trust remain persistent barriers (Faiyazuddin, 2024; Healthcare Informatics Research, 2024). Reimbursement structures present an additional headwind, as existing time-based and transaction-based payment models were not designed to accommodate AI-enhanced workflows and may inadvertently penalize productivity gains (Vakili et al., 2026).

Against this backdrop, understanding how individual medical technology firms actually build AI capabilities and what those capabilities deliver in terms of commercial outcomes has become a

*Corresponding author: fazliddin.shermatov@edu.univ-paris13.fr

pressing question for both researchers and policymakers. This paper addresses two related questions: *How do medical technology firms develop capabilities to innovate in AI-enhanced medical technologies?* And: *How does AI innovation in medical firms impact their revenue growth, market share expansion, and success in securing public procurement contracts?*

Procurement can itself stimulate innovation. Firms supplying AI-powered equipment to French hospitals, for instance, have been shown to exhibit higher innovation activity, suggesting that information flows from buyers can materially boost firm performance (Patsali et al., 2023). Understanding this dynamic from capability-building inputs through to market outcomes requires a structured empirical approach, which we develop here using a three-stage recursive model grounded in the Crépon-Duguet-Mairesse framework (Crépon et al., 1998).

2 Literature Review

2.1 Innovation and firm performance

Recent research positions firm-level AI capability as a distinct strategic asset that shapes how firms innovate and grow. Drawing on the resource-based view and dynamic capabilities literature (Penrose, 1959; Teece et al., 1997) and the absorptive-capacity concept (Cohen and Levinthal, 1990), scholars show that firms build AI capacity through acquisitions, partnerships, internal hiring, and investments in data and platform infrastructure. Cohen and Levinthal (1990) defined absorptive capacity as a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends: with that capacity depending greatly on prior related knowledge and the diversity of the firm's knowledge base.

AI capability can generate product innovations, process innovations, and organizational innovations. Product innovations are frequently the primary channel for revenue growth and market expansion, while process innovations mainly affect costs and margins. Recent empirical research demonstrates a strong positive relationship between AI investments and product innovation outcomes. Babina et al. (2024) found that AI-investing firms experience higher growth in sales, employment, and market valuations, with that growth channeled primarily through increased product innovation. Their study employed a novel measure of firm-level AI investments constructed from employee resumes, revealing a substantial and broad-based rise in AI investment across sectors.

A substantial body of research confirms that innovation is a central determinant of firm performance, though its effects vary by type, context, and firm capabilities. Product innovations raise revenues and market share by creating diversified and new demand (see for example Sarkar et al., 2024), while process innovations improve cost efficiency and productivity (Baláž et al., 2023; Samperuru et al., 2023). Empirical studies consistently find positive associations between innovation activity and firm outcomes such as profitability, growth, and competitive advantage, with the size and timing of effects depending on resources, industry dynamics, and strategic flexibility (Migdadi, 2020; Al-Hawary, 2021; Kim and Koo, 2020).

The CDM framework (Crépon et al., 1998) gives a structured way to capture this link between innovation and performance. The model emphasizes a sequential process where firms' R&D investments build innovation capabilities, which in turn generate innovation outputs that ultimately enhance firm performance through higher productivity, sales, or market share.

2.2 AI as a general-purpose technology across sectors

There is a broad case for treating AI as a general-purpose technology (Agrawal et al., 2019; Klinger et al., 2018; Yang et al., 2022), a large technical system (Vannuccini and Prytkova, 2021), or a general method of invention (Bianchini et al., 2022; Cockburn et al., 2018). Regardless of framing, its impact on science and innovation is considerable, and it is expected to reshape almost every sector of the economy, from manufacturing, healthcare, and retail to transportation and finance (Davenport and Ronanki, 2018).

AI's economic benefits are evident across measured deployments and broader economy-wide transformations. Systematic reviews highlight how AI raises productivity, spurs new business models, and shifts industrial structure while also influencing labor markets and governance frameworks (Yuan et al., 2024). Case studies give tangible evidence: a 40% emergency wait-time reduction achieved through AI scheduling in telemedicine (Saini et al., 2025), AI-enabled UAVs improving occupational safety in mining and construction (Chowdhury, 2024), and in manufacturing, a shift toward predictive, data-driven Industry 4.0 operations. At a macro level, bibliometric analyses reveal geographically uneven gains, with Europe and Asia showing the strongest measured impacts (Espina-Romero et al., 2023).

Taken together, this literature points to a set of open questions particularly salient for the

medtech sector. Firms in this space must navigate simultaneous pressures: the need to acquire or build AI capabilities quickly, the technical challenge of integrating those capabilities into regulated devices, and the commercial imperative to translate innovation outputs into market and procurement success. How they manage this process, and which capability-building strategies prove most effective, remains underexplored empirically.

3 Data

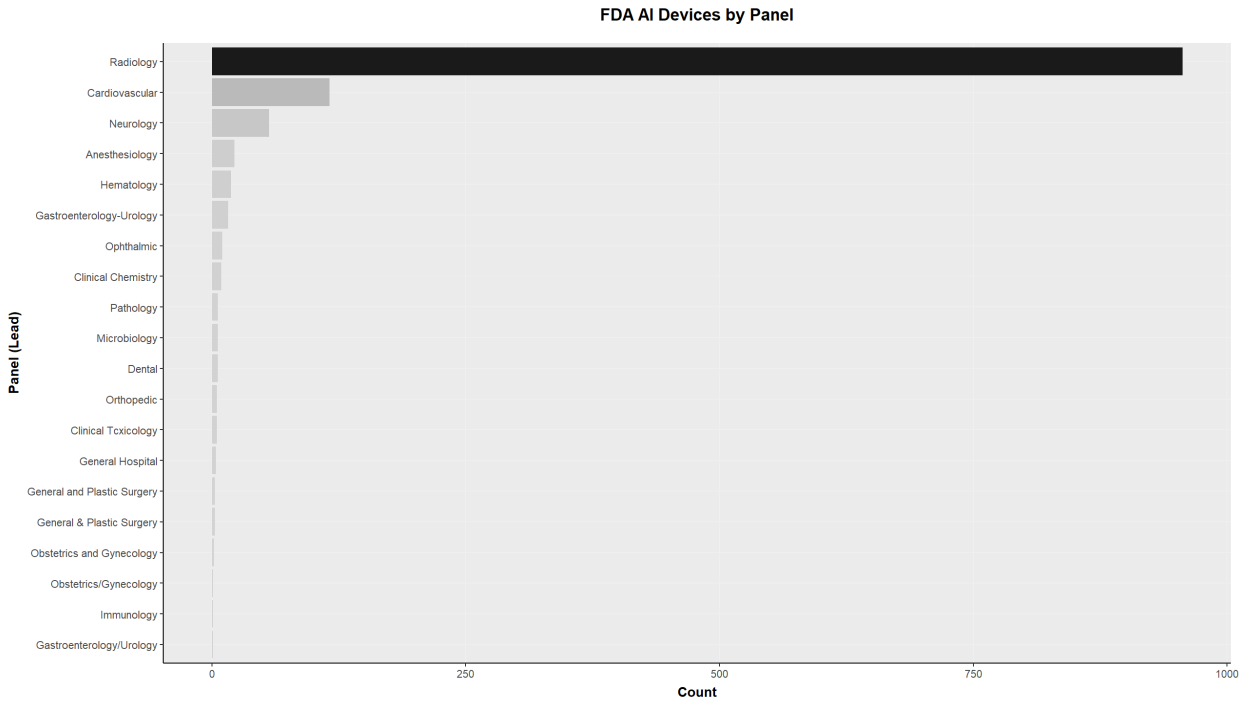
We analyze the US medical device market using a matched firm-level dataset constructed from several primary sources.

FDA AI-enabled medical devices. The FDA maintains a regularly updated list of AI/ML-enabled medical devices. As of October 2025, 1,247 devices are listed, with approximately 90% concentrated in three categories: Radiology (956 devices), Cardiovascular (116 devices), and Neurology (56 devices). We focus our analysis on companies operating in device categories with more than 50 AI devices. This yields a sample of 5,653 companies active in these fields. Among these companies, 650 have introduced at least one AI/ML-enhanced device.

Patent portfolio. We extracted the complete patent portfolio of the 5,653 companies from the United States Patent and Trademark Office (USPTO). The sample includes 1,355,091 patents in total as of 2025. These patents give a measure of each firm's innovation activity, technological trajectory, and knowledge accumulation over time.

Scientific publications and collaborations. From Scopus, we retrieved 1,062,119 papers in total as of 2025. These publications allow us to construct firm-level measures of AI research engagement and collaboration intensity. We identify AI-focused publications and AI collaborations using the methodology developed by Bianchini et al. (2025). This approach distinguishes publications that explicitly engage with AI methods or applications from the broader publication portfolio, enabling us to isolate AI-specific knowledge flows and external collaboration patterns.

Figure 1: FDA AI Devices per Categories



Financial and procurement data. Firm-level financial data (revenues, employment, assets) are drawn from ORBIS.

4 Methodology

Our empirical strategy is grounded in the Crépon-Duguet-Mairesse (CDM) framework (Crépon et al., 1998), which models the innovation process as a sequential, multi-stage system linking R&D inputs to innovation outputs and ultimately to firm performance. We adapt this to the medtech AI context through a three-stage recursive model, where the predicted output of each stage enters as a key input to the next. This structure traces the path from capability-building investment through to market outcomes, while addressing the endogeneity inherent in the innovation process: rather than treating innovation and performance as jointly determined, the sequential structure ensures we capture the effect of innovation on performance rather than the reverse.

4.1 Stage 1: AI Capability Building

The first stage models how firms build AI capabilities through academic and commercial collaboration. For firm i at time t:

$$\text{Collaboration}_{it}^{*} = \alpha_0 + \alpha_1 \text{R\&D}_{i,t-1} + \mathbf{X}_{it}'\alpha_2 + \epsilon_{it} \tag{1}$$

Collaboration is measured as a count of AI-focused co-authored publications or co-filed patents, estimated via Poisson or Negative Binomial regression. The predicted value $\widehat{\text{Collaboration}}_{it}$ represents the firm's expected collaboration intensity, net of idiosyncratic shocks, and serves as the capability-building input to Stage 2.

4.2 Stage 2: AI Innovation Output

The second stage links built-up capabilities to observable innovation outputs, estimated using count data models:

$$\text{AI_Innovation}_{it} = \beta_0 + \beta_1 \widehat{\text{Collaboration}}_{it} + \mathbf{Z}_{it}'\beta_2 + \mu_{it} \tag{2}$$

Innovation output is measured either as the number of AI-related patents filed by firm i in year t, or as the number of new AI-enhanced medical devices registered by the firm. The coefficient β_1 captures the effectiveness of academic collaboration in generating innovation output, conditional on firm size, age, R&D intensity, and accumulated knowledge stock. Stage 2 yields predicted innovation output $\widehat{\text{AI_Innovation}}_{it}$.

4.3 Stage 3: Firm Performance

The final stage connects AI innovation output to firm productivity. Following the CDM tradition, we estimate a production function augmented with the predicted innovation output from Stage 2:

$$\ln(\text{Productivity})_{it} = \gamma_0 + \gamma_1 \widehat{\text{AI_Innovation}}_{it} + \mathbf{W}_{it}'\gamma_2 + \nu_{it} \tag{3}$$

$$\ln(\text{Procurement})_{it} = \gamma_0 + \gamma_1 \widehat{\text{AI_Innovation}}_{it} + \mathbf{W}_{it}'\gamma_2 + \nu_{it} \tag{4}$$

Productivity is measured as log value-added per employee. The coefficient γ_1 captures the output-side return to AI innovation, holding firm size, capital intensity, and sector fixed effects constant. Using the predicted innovation output from Stage 2 as the key right-hand side variable ensures that the estimated performance effect reflects the innovation component attributable to collaboration intensity, rather than unobserved firm-level factors that may independently drive both innovation and productivity.

4.4 Identification

Endogeneity remains the central identification challenge. Unobservable firm characteristics such as managerial quality, corporate culture, or privileged access to scientific networks could simultaneously drive AI adoption, innovation output, and performance, generating omitted variable bias. Reverse causality is also plausible: high-performing firms may simply have more resources to invest in AI, or firms anticipating strong public procurement demand may innovate preemptively.

To address endogeneity in the collaboration-innovation link, we employ an instrumental variables strategy. The instrument is the firm's geographical proximity to AI research clusters—universities and research centers with high concentrations of AI talent and publication output. Distance to the nearest AI hotspot plausibly affects how intensively firms collaborate with academic partners, but has no direct channel to device registration or revenue growth beyond that collaboration effect. We measure proximity using the log-transformed distance in kilometres between the firm's registered address and the nearest qualifying AI research institution (distance_km_qlt), complemented by the log count of AI-related publications of the companies ($\log(\text{n_publications_ai} + 1)$).

5 Results

5.1 Preliminary IV estimates

So far, we can present results for the first two equations. Tables 1 and 2 show the effect of academic AI collaboration on firms' probability of introducing an AI-enhanced medical device. We use Two-Stage Least Squares estimates across four samples, with year, country, and sector fixed effects throughout. In the second stage, the outcome is whether the firm registered an AI device that year. In the first stage, the outcome is the firm's average AI collaboration score. We use two instruments: distance to

the nearest AI research cluster, and the log count of AI publications. The instruments perform well, with first-stage F-statistics ranging from 416.0 to 1,658.6, well above standard weak-instrument thresholds.

The Wu-Hausman test rejects the null in all specifications, confirming that the collaboration variable is endogenous and that OLS would produce inconsistent estimates. The Sargan overidentification test does not reject in any specification, supporting instrument validity.

Table 1: Two-Stage Least Squares Regression Results: All Countries

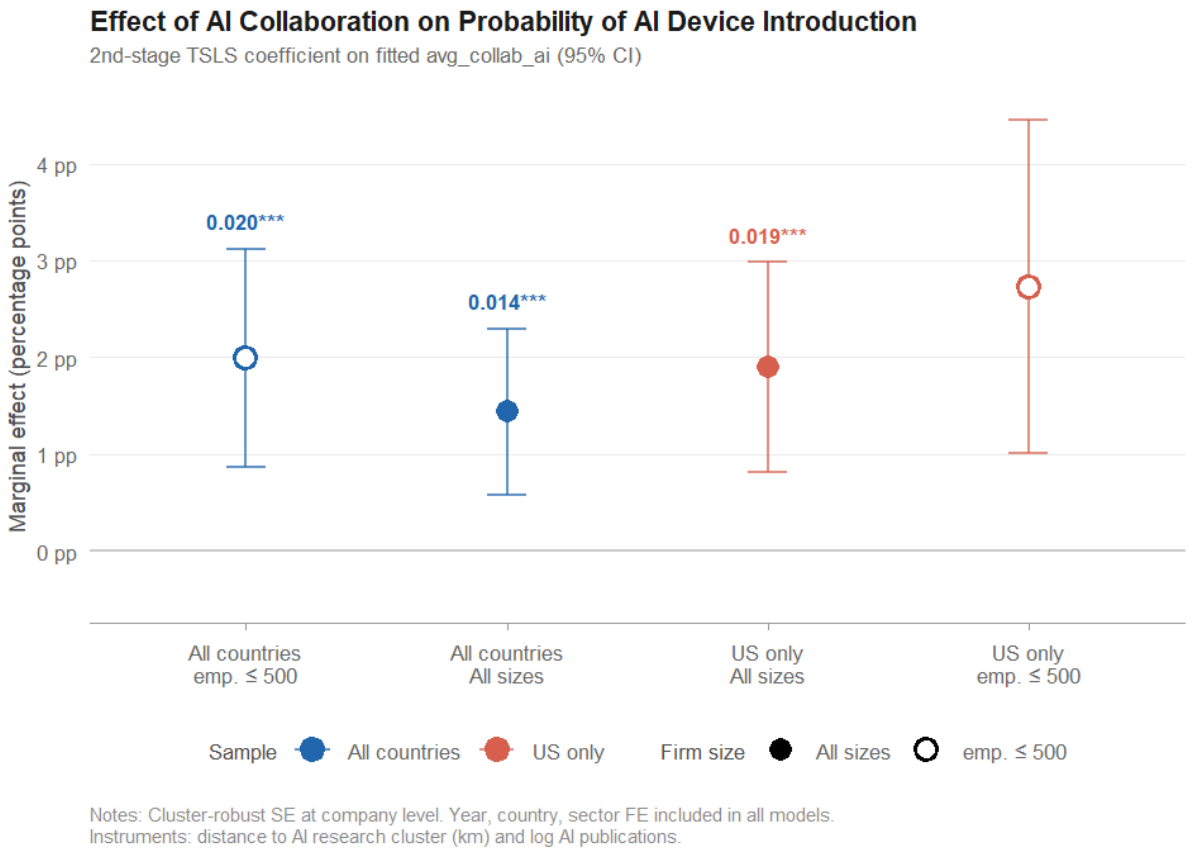
	All Sizes		emp. < 501	
	avg_collab	ai_device	avg_collab	ai_device
	1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)
distance_km_qlt	-0.00006^{*}		$-0.00003^{\cdot}$	
	(0.00003)		(0.00002)	
log(n_pub_ai + 1)	1.914^{***}		2.673^{***}	
	(0.204)		(0.250)	
fit_avg_collab_ai		0.014^{**}		0.020^{***}
		(0.004)		(0.006)
log(emp. + 1)	$0.041^{\cdot}$	0.001	0.039^{**}	0.007^{**}
	(0.022)	(0.001)	(0.013)	(0.002)
log((pat + 1)/(rev + 1))	0.011	0.0003	0.001	0.003^{**}
	(0.008)	(0.001)	(0.005)	(0.001)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES
Observations	8,724	8,724	7,062	7,062
R^2 (Within)	0.253	0.011	0.329	0.021
Adjusted R^2	0.271	0.023	0.345	0.030
RMSE	1.547	0.134	1.080	0.127
F-test (1st stage)	$1{,}155.7^{***}$		$1{,}658.6^{***}$	
Wu-Hausman	24.74^{***}		63.71^{***}	
Sargan	2.705		0.229	

Notes: Cluster-robust standard errors in parentheses (clustered at company level). Endogenous variable: avg_collab_ai. Instruments: distance_km_qlt, log(n_publications_ai + 1). All models include year (14), country, and sector fixed effects. Significance level: $^{\cdot}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

The main finding is clear. Higher predicted AI collaboration raises the probability of introducing an AI device. Figure 2 shows the second-stage coefficients and 95% confidence intervals across all

four specifications. In the full cross-country sample, a one-unit increase in collaboration intensity raises the probability of AI device introduction by 1.4 percentage points ($p < 0.01$). For firms with fewer than 501 employees, the effect is larger, at 2.0 percentage points ($p < 0.001$). US-only estimates follow the same pattern: the effect stands at 1.9 percentage points for all firm sizes, and rises to 2.7 percentage points for small US firms ($p < 0.01$ in both cases).

Figure 2: Second-stage TSLS coefficients on fitted `avg_collab_ai`



Notes: Cluster-robust SE at company level. Year, country, sector FE included in all models.
Instruments: distance to AI research cluster (km) and log AI publications.

These results suggest that collaboration with academic AI research clusters matters for innovation output. The consistently larger effects among smaller firms point to a compensating role for external knowledge: firms with limited internal R&D capacity appear to rely more heavily on academic ties to build the capabilities needed to bring an AI device to market.

The first-stage results reinforce this interpretation. Figure 3 shows the coefficient on log AI publications across specifications. Proximity to research clusters, captured through both the distance instrument and the publication stock, strongly predicts collaboration intensity in all samples. No-

tably, the publication coefficient is larger for small firms (2.67 in the all-countries small-firm sample versus 1.91 across all sizes), again consistent with smaller firms drawing more extensively on external knowledge stocks when internal capacity is constrained.

Figure 3: First-stage TSLS coefficients on log(n_publications_ai + 1)

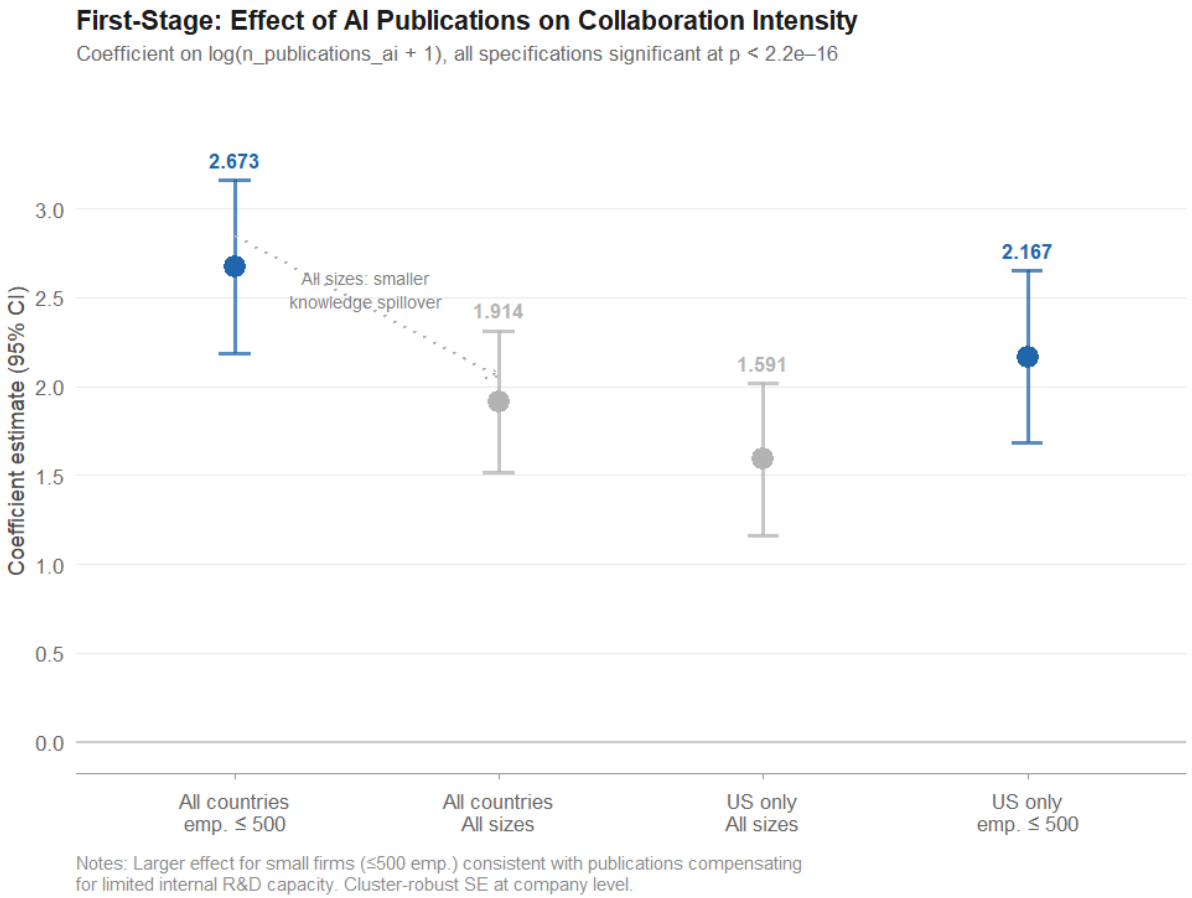


Table 2: Two-Stage Least Squares Regression Results: US Only

	All Sizes		emp. < 501	
	avg_collab	ai_device	avg_collab	ai_device
	1st Stage	2nd Stage	1st Stage	2nd Stage
	(5)	(6)	(7)	(8)
distance_km_qlt	−0.00009·		−0.00004·	
	(0.00006)		(0.00004)	
log(n_pub_ai + 1)	1.591***		2.167***	
	(0.218)		(0.246)	
fit_avg_collab_ai		0.019***		0.027**
		(0.006)		(0.009)
log(emp. + 1)	0.065·	0.0005	0.031*	0.008*
	(0.036)	(0.002)	(0.015)	(0.004)
log((pat + 1)/(rev + 1))	0.018	0.001	0.003	0.002
	(0.014)	(0.001)	(0.008)	(0.002)
Year FE	YES	YES	YES	YES
Country FE	NO	NO	NO	NO
Sector FE	YES	YES	YES	YES
Observations	4,565	4,565	3,761	3,761
R^2 (Within)	0.202	0.017	0.307	0.028
Adjusted R^2	0.214	0.024	0.305	0.029
RMSE	1.815	0.137	1.068	0.130
F-test (1st stage)	416.0***		788.9***	
Wu-Hausman	15.98***		33.96***	
Sargan	0.424		0.180	

Notes: Cluster-robust standard errors in parentheses (clustered at company level). Endogenous variable: avg_collab_ai. Instruments: distance_km_qlt, log(n_publications_ai + 1). All models include year (14), and sector fixed effects. Significance level: ·p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Control variables behave as expected. Firm size is positively associated with AI device introduction in several specifications, though the association is not uniform across samples, suggesting that resource endowments matter but do not fully explain the pattern.

Acknowledgements

The authors declare no conflicts of interest. The views expressed are those of the authors and do not necessarily reflect those of any affiliated institution.

References

Agrawal, A., J. Gans, and A. Goldfarb (2019). *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press.

Babina, T., A. Fedyk, A. He, and J. Hodson (2024). "Artificial intelligence, firm growth, and product innovation." *Journal of Financial Economics* 151, 103745. 10.1016/j.jfineco.2023.103745.

Baláž, V., T. Jeck, and M. Balog (2023). "Firm performance over innovation cycle: Evidence from a small European economy." *Journal of Innovation and Entrepreneurship* 12(1), 17. 10.1186/s13731-023-00298-9.

Bianchini, S., S. Kiefer, and M. Müller (2022). "Artificial intelligence as a general method of invention." *Industrial and Corporate Change* 31(4), 875–899.

Bianchini, S., A. Geuna, and F. Shermatov (2025). "AI and Supercomputing are Powering the Next Wave of Breakthrough Science - But at What Cost?" *ArXiv* abs/2511.12686.

Chowdhury, R. H. (2024). *AI-powered Industry 4.0: Pathways to economic development and innovation*. Research report. Available via ResearchGate.

Cockburn, I. M., R. Henderson, and S. Stern (2018). "The impact of artificial intelligence on innovation." In: *The Economics of Artificial Intelligence*. Ed. by A. Agrawal, J. Gans, and A. Goldfarb. University of Chicago Press, 115–146.

Cohen, W. M. and D. A. Levinthal (1990). "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35(1), 128–152. 10.2307/2393553.

Crépon, B., E. Duguet, and J. Mairesse (1998). "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7(2), 115–158. 10.1080/10438599800000031.

Davenport, T. H. and R. Ronanki (2018). "Artificial intelligence for the real world." *Harvard Business Review* 96(1), 108–116.

Espina-Romero, L. C. et al. (2023). "Which industrial sectors are affected by artificial intelligence? A bibliometric analysis of trends and perspectives." *Sustainability* 15(16), 12176. 10.3390/su151612176.

Faiyazuddin, M. (2024). "The impact of artificial intelligence on healthcare: a comprehensive review of advancements in diagnostics, treatment, and operational efficiency." *Health Science Reports*. 10.1002/hsr2.70312.

Al-Hawary, S. I. (2021). "The mediating role of innovation capability on the relationship between strategic agility and organizational performance." *Sustainability* 13(14), 7564. 10.3390/su13147564.

Healthcare Informatics Research (2024). *Status and trends of the digital healthcare industry*. https://synapse.koreamed.org/upload/synapsexml/1088hir/pdf/hir-2024-30-3-172.pdf.

Healthcare Technology Report (2025). *The Top 25 Healthcare AI Companies of 2025*. https://thehealthcaretechnologyreport.com/the-top-25-healthcare-ai-companies-of-2025/.

Kim, J. H. and I. S. Koo (2020). "The impact of innovation capability of SMEs companies on corporate performance: Focusing on the mediating effect of competitive advantage." *Korean Small Business Studies* 22(1), 51–70. 10.12812/KSMS.2020.22.1.051.

Klinger, J., J. Mateos-Garcia, and K. Stathoulopoulos (2018). *Mapping the diffusion of AI in science*. Working Paper. Nesta.

Landi, H. (2025). *Healthcare AI rakes in nearly $4B in VC funding, buoying the digital health market in 2025*. https://www.fiercehealthcare.com/health-tech/healthcare-ai-rakes-nearly-4b-vc-funding-buoying-digital-health-market-2025.

Migdadi, M. M. (2020). "Knowledge management processes, innovation capability and organizational performance." *International Journal of Productivity and Performance Management* 70(2), 357–379. 10.1108/IJPPM-04-2020-0154.

Patsali, S., M. Pezzoni, and J. Krafft (2023). *Healthcare Procurement and Firm Innovation: Evidence from AI-powered Equipment*. Working Paper.

Penrose, E. T. (1959). *The Theory of the Growth of the Firm*. Oxford: Basil Blackwell.

Precedence Research (2025). *Artificial Intelligence in Healthcare Market Size to Hit USD 613.81 Bn by 2034*. https://www.precedenceresearch.com/artificial-intelligence-in-healthcare-market. Accessed on 27.07.2025.

Saini, B., D. Singh, K. C. Sharma, and B. Saini (2025). "AI-enhanced telemedicine: transforming resource allocation and cost-efficiency analysis via advanced queueing model." *Scientific Reports*. 10.1038/s41598-025-15664-8.

Samperuru, E. S., J. Jusni, and A. Aswan (2023). "The influence of innovation strategy on improving company performance by PT. Kencana Energi Lestari, Tbk." *Economos* 6(3), 269–280. 10.31850/economos.v6i3.2694.

Sarkar, A., O. M. Hazhar, A. M. Rawa, and F. O. Rezhwan (2024). "The importance of product innovation in maintaining a competitive advantage." *Mednarodno inovativno poslovanje* 16(2), 45–56. 10.32015/jibm.2024.16.2.4.

Teece, D. J., G. Pisano, and A. Shuen (1997). "Dynamic Capabilities and Strategic Management." *Strategic Management Journal* 18(7), 509–533. 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Tempus AI, Inc. (2025). *Tempus announces the acquisition of Paige*. https://www.tempus.com/news/tempus-announces-the-acquisition-of-paige/.

Vakili, S., A. Nayak, A. Conrad, and K. Schulman (2026). "Artificial Intelligence in the Clinic: Don't Pay for the Tool, Pay for the Care." *NEJM Catalyst* 7(3). 10.1056/cat.25.0338.

Vannuccini, S. and E. Prytkova (2021). "AI as a large technical system: The case for innovation studies." *Research Policy* 50(7), 104286.

Yang, G. et al. (2022). "Artificial intelligence as a general-purpose technology: Evidence and policy implications." *Technological Forecasting and Social Change* 178, 121576.

Yuan, C., J. Tang, Y. Cao, T. Z. Wei, and W. Shen (2024). "The impact of artificial intelligence on economic development: A systematic review." *Itphss* 1(1). 10.70693/itphss.v1i1.57.