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The Heterogeneous Effects of Artificial Intelligence on Enterprise Total Factor Productivity: Key Mechanisms and Strategic Implications

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Abstract: While Artificial Intelligence (AI) is recognized as a catalyst for productivity, prior research often assumes homogeneous effects or views heterogeneity in one dimension, overlooking interdependencies among firm traits. Using panel data of 3366 Chinese A-share listed firms from 2015 to 2023, this study examines how AI adoption affects Total Factor Productivity (TFP) and explores heterogeneous effects through a multidimensional clustering based on firm size, age, market competitiveness, and digital infrastructure. Our findings challenge the notion of a universal technological dividend and show that AI adoption yields asymmetric productivity gains depending on firms resource constraints and competitive environments. Firms constrained by limited intangibles, outdated hardware, or weak human capital benefit most when AI mitigates bottlenecks, while technologically advanced firms in hypercompetitive markets gain little, reflecting diminishing returns from capability saturation. Mechanism tests reveal two key pathways: efficiency gains via automation in constrained firms and innovation stagnation in mature firms with redundant AI. These findings underscore AI's contingent productivity effects and the need for digital strategies aligned with firm resources and market context.

Keywords: AI adoption, Chinese A-share listed firms, clustering analysis, firm heterogeneity, productivity mechanisms, total factor productivity

1 INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative technology that reshapes economic structures and firm-level productivity. Governments and international organizations have launched major AI initiatives, such as the EU AI Act [1], underscoring a broad consensus on AI's strategic role in long-term competitiveness. Recent surveys show that most global firms have adopted AI in at least one business function and plan further investment [2]. These developments highlight the urgency of understanding how AI adoption influences firm performance, particularly Total Factor Productivity (TFP), a key indicator of operational and technological efficiency.

A growing body of research affirms that AI boosts productivity through technological upgrading, process automation, human-capital reallocation, and market efficiency [3]. Yet these benefits are not uniform. Firm-level heterogeneity, stemming from structural attributes (e.g., size, ownership), capability endowments (e.g., technological position), and external contingencies (e.g., market concentration), critically shapes AI's productivity effects [4, 5].

While existing research provides valuable perspectives, four critical limitations warrant scholarly attention. First, the predominant theoretical framework implicitly assumes linear AI productivity effects, overlooking the law of diminishing marginal returns that characterizes technological adoption processes. Second, current empirical approaches typically examine firm-level heterogeneity through unidimensional lenses (e.g., firm size or industry classification), failing to capture the multidimensional nature of organizational adaptation capabilities. Third, mediating mechanisms such as innovation absorption and resource reallocation are examined apart from firm traits, obscuring the causal mechanisms through which heterogeneous organizational attributes differentially capitalize on AI-enabled productivity pathways. Finally, methodological constraints persist as extant studies predominantly rely on perceptual measures derived from managerial surveys or context-specific case analyses, introducing risks of systematic measurement errors and compromised external validity for cross-country comparisons.

To address these gaps, this study examines how AI adoption affects firm-level TFP through an integrated framework combining the Resource-Based View (RBV) [6] and Dynamic Capabilities Theory (DCT) [7], which explain productivity gains from resource orchestration. We argue that AI's productivity impact is contingent on firms' internal resources and external competition.

This study advances four contributions: (1) integrating RBV and DCT to reveal the duality of AI's efficiency potential and saturation limitations; (2) building a multidimensional classification model for firm heterogeneity, including enterprise scale and digital infrastructure, that overcomes the limitations of traditional single-dimensional analyses; (3) confirming that AI may fail under the constraints of technological saturation and intense competition, thereby challenging the perception of a "universal technological dividend"; and (4) elucidating the mechanisms by which different enterprises realize AI value through differentiated pathways, thereby establishing a dynamic link between heterogeneity and productivity.

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework and hypotheses; Section 3 outlines the research design; Section 4 reports the clustering results; Section 5 reports the empirical results; and Section 6 concludes with implications.

2 THEORETICAL BACKGROUND AND HYPOTHESES

Total Factor Productivity (TFP) serves as a critical barometer of a firm's operational efficiency and technological advancement, capturing its ability to integrate heterogeneous resources capital, labor, and managerial competencies into a unified production system [8]. While conventional frameworks emphasize incremental process optimization, recent studies suggest that sustained productivity growth stems from systemic organizational restructuring, adaptive governance, and strategic realignment in response to competitive dynamics

[9]. This reconceptualization positions TFP as a dual construct: it measures not only tangible asset accumulation but also a firm's dynamic capability to orchestrate knowledge-based resources, including data analytics, intellectual capital, and innovation ecosystems, into enduring competitive advantages [10].

Building on this view, the RBV and DCT provide complementary explanations for sustainable productivity gains. RBV highlights how AI enhances value extraction from firm-specific resources, whereas DCT emphasizes the roles of sensing, seizing, and reconfiguring capabilities in adapting to environmental change. This integrated framework helps explain why AI adoption generates heterogeneous productivity effects across firms with different resource endowments and adaptive capacities.

Artificial Intelligence (AI) has emerged as a transformative enabler of such knowledge-based resource orchestration. Mounting empirical evidence shows that AI can transcend conventional productivity frontiers through the reconfiguration of organizational capabilities [11]. By leveraging AI's dual capacity to process high-velocity, heterogeneous data and automate cognitively intensive tasks, firms can mitigate inefficiencies rooted in fragmented information architectures and suboptimal labor allocation [8]. Specifically, AI-enabled analytics identify latent market trends and guide precise resource reallocation, while robotic process automation releases human capital from routine work, fostering creativity and strategic experimentation [9, 12]. These mechanisms jointly drive two transformations: operational upgrading via real-time optimization and strategic renewal through adaptive reconfiguration of organizational routines [7]. Consequently, firms achieve discontinuous TFP improvements that incremental adjustments cannot replicate, particularly when AI adoption aligns with their resource endowments and competitive contexts [13]. Hence, in light of the above discussion, this study proposes the following hypothesis:

Hypothesis 1.AI adoption generates a statistically significant improvement in TFP across firms.

2.1 Enterprise Heterogeneity and AI Applicability

While RBV and DCT emphasize AI as a source of strategic advantage, the technology redundancy perspective cautions that excessive AI investment may produce diminishing or even negative returns [14]. Consequently, productivity enhancement follows a nonlinear trajectory. Resource-constrained firms tend to realize accelerating returns from AI-driven efficiency gains, whereas technologically mature firms face diminishing benefits due to capability saturation and redundant deployments [14]. This inverted U-shaped relationship underscores the need for strategic selectivity in AI deployment [7].

Firms with underdeveloped digital infrastructure, such as low robotic penetration or R&D intensity, gain most from closing capability gaps, while hypercompetitive firms at the technological frontier often experience innovation stagnation from overlapping AI functionalities [15]. Such variation necessitates a contingency framework in which productivity outcomes depend on firms' resource configurations and market positioning [16].

Accordingly, the impact of AI on TFP is moderated by firm heterogeneity: attributes such as size, age, and competitive intensity shape absorptive capacity and technology adoption efficiency [17]. Larger firms typically invest more in innovation, whereas smaller firms adapt faster [18]; younger firms exhibit lower inertia than older counterparts [19]; and intense competition affects innovation sustainability [20]. These differences in resources, routines, and environments generate asymmetric productivity effects from AI adoption [21]. Therefore, we propose:

Hypothesis 2a. The relationship between AI adoption and TFP follows a multidimensional contingency framework, where firm size, age, industry competitiveness, and digital foundations (hardware infrastructure, human capital quality, and basic innovation capabilities) jointly moderate the magnitude and direction of productivity returns.

Building on the technology redundancy perspective, we further posit that firms with insufficient technological infrastructure benefit most from AI adoption, as it compensates for capability gaps. In contrast, firms with mature technological systems experience limited or no additional gains due to saturation effects, overlapping functionalities, or strategic rigidity [14].

Hypothesis 2b. The positive effect of AI adoption on TFP is significant among technologically underdeveloped firms, but becomes statistically insignificant in technologically mature firms.

2.2 Mechanisms

The mechanisms through which AI influences TFP are inherently heterogeneous and contingent on firms' multidimensional resource configurations. Building on the RBV and DCT, this study identifies four distinct mechanistic pathways that mediate AI's impact on productivity, each governed by nonlinear interactions between technological readiness and organizational attributes. Specifically, this study examines four mechanisms: human capital augmentation, innovation capability reinforcement, operational efficiency optimization, and managerial decision-making enhancement.

2.2.1 Human Capital Augmentation

Human capital, encompassing employees' skills, knowledge, and competencies, is fundamental to firm productivity and innovation [22]. AI enhances human capital through three mechanisms: skill alignment, as AI-driven HRM systems detect mismatches and optimize workforce allocation to improve efficiency [23]; targeted training, where machine learning diagnoses skill gaps in real time, enabling personalized programs that elevate performance; and talent management, as AI analytics refine recruitment and competency evaluation, reducing turnover and enhancing resource efficiency [24].

Overall, AI-driven analytics improve skill alignment and training efficiency, allowing firms with constrained human capital to achieve faster TFP growth. By automating assessments and tailoring learning interventions, AI transforms latent human potential into measurable productivity gains. These improvements in workforce capability translate directly into higher TFP.

Hypothesis 3a. AI adoption promotes firm TFP through enhancing human capital.

2.2.2 Innovation Capability Reinforcement

Innovation capability, the capacity to integrate and reconfigure knowledge resources, is central to sustainable advantage and productivity growth [10]. Firms use AI to strengthen innovation via three mechanisms: (1) accelerated knowledge integration, as machine learning and natural language processing assimilate heterogeneous data to enhance exploratory innovation [11, 25]; (2) resource allocation optimization, as AI analytics reduce uncertainty in R&D investment, shortening innovation cycles and lowering experimental costs [26]; and (3) Adaptive Business Model Innovation, as AI anticipates market dynamics and customer needs, enabling agile knowledge recombination for sustained renewal [27]. Enhanced innovation quality and accelerated knowledge integration ultimately contribute to sustained improvements in TFP.

Hypothesis 3b. AI adoption promotes firm TFP through enhancing innovation capability.

2.2.3 Operational Efficiency Optimization

Operational efficiency, optimizing production through resource integration and reallocation, is substantially enhanced by AI-driven automation [28]. Two mechanisms dominate: (1) task substitution, as AI automates routine work, freeing human labor for strategic roles [29]; and (2) productivity augmentation, as AI analyzes large datasets to improve predictive decision-making and reduce uncertainty [25].

AI adoption shifts labor from repetitive to cognitive functions, raising efficiency across professional services and manufacturing [25]. It optimizes data flows, preempts bottlenecks, and strengthens reliability in supply chains and smart grids [30]. Such automation-driven efficiency gains reduce operational frictions and increase TFP.

Hypothesis 3c. AI adoption promotes firm TFP through enhancing automation and operational efficiency.

2.2.4 Managerial Decision-Making Enhancement

Agency Theory posits that information asymmetry between principals and agents undermines governance efficiency [31]. AI mitigates these frictions through: (1) real-time monitoring, as continuous analytics enhance oversight and reduce opportunism [32]; (2) decision quality enhancement, as AI synthesizes multi-source data into actionable insights, reducing bias and uncertainty [33]; and (3) managerial AI literacy, as AI-proficient executives execute faster strategic pivots and allocate resources more effectively, aligning governance with market dynamics [34].

AI reduces agency costs by alleviating information asymmetry [31], particularly benefiting mature firms (Cluster 1 in Section 4.2) via real-time governance analytics [32]. However, in hypercompetitive settings (Cluster 2; Herfindahl-Hirschman Index (HHI) > 0.35), short-term pressures weaken these benefits. Improved governance quality and reduced information asymmetry strengthen resource allocation and thereby elevate TFP.

Hypothesis 3d. AI adoption promotes firm TFP through enhancing corporate managerial capability.

These pathways collectively reveal an inverted U-shaped relationship between AI adoption and TFP, mediated by firms' baseline capabilities and competitive contexts. For instance, while resource-constrained firms exploit AI to bridge capability gaps, technologically advanced firms confront diminishing returns due to saturation effects, a finding empirically validated through hierarchical clustering (Supplementary Tab.1). This duality challenges linear assumptions of universal productivity gains, emphasizing the criticality of strategic alignment between AI deployment and firm-specific resource portfolios [7]. The relationships investigated in this study are presented in Fig. 1.

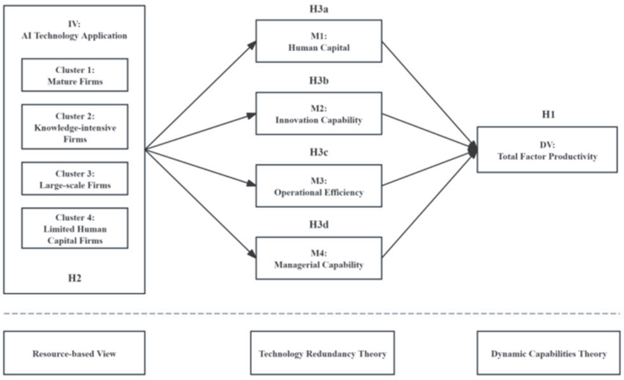

Figure 1 A theoretical framework for the effect of AI technology application on TFP

3 DATA AND METHODS
3.1 Sample

This study constructs a panel dataset of all Chinese A-share firms listed on the Shanghai and Shenzhen Stock Exchanges from 2015 to 2023. Firm-level financial and operational variables (TFP, profitability, size, age, leverage, R&D) are sourced from CSMAR. AI adoption and mediating variables are extracted from annual reports disclosed via the China Information website of the CSRC. Employee demographics and managerial backgrounds come from WIND, while patent data are obtained from CNIPA. Industrial robot usage is taken from the International Federation of Robotics.

To ensure reliability, firms under Special Treatment (ST), with major irregularities, or with missing data are excluded. Continuous variables are winsorized at the 1% tails, and skewed variables are log-transformed. After these procedures, the final sample comprises 3366 listed firms and 44569 firm-year observations, providing a robust empirical foundation for hypothesis testing.

3.2 Variables
3.2.1 Independent variable

The independent variable examined in this study is the firm-level adoption of AI. This paper follows Yao et al. [35], adopting a text-analysis methodology based on annual reports to construct a firm-specific AI adoption indicator using machine learning technology. Specifically, we collected and processed textual data from the annual reports of Chinese listed firms, applied machine learning algorithms to recognize and extract AI-related keywords, such as "machine learning", "natural language processing", "computer vision", and counted and aggregated the occurrence frequency of these keywords within each enterprise's annual reports at the firm-year level. A frequency threshold was established based on manual calibration of typical AI-related disclosures to ensure that only substantive AI adoption statements were included in the measurement. Lastly, the frequency of AI-related keywords was transformed into the firm-level AI adoption indicator by taking the natural logarithm of the keyword frequency plus one. Existing literature utilizes data on industrial robots or corporate surveys to measure enterprises' AI adoption, yet such approaches fail to fully capture the comprehensive application scenarios and technological characteristics of AI. Textual analysis can overcome these limitations.

3.2.2 Dependent variable

The dependent variable is TFP. Referring to Lu and Lian [36] and Ren et al. [37], TFP is measured using the fixed-effect (FE) method. Specifically, enterprise total output (*Y*) is represented by annual operating revenue scaled by 10000 RMB, capital input (*K*) is proxied by net fixed assets scaled by 10000 RMB, labor input (*L*) is represented by the total number of employees, intermediate input (*M*) is defined as the sum of operating costs, sales expenses, management expenses, and financial expenses, excluding depreciation, amortization, and payments to employees, scaled by 10000 RMB. The logarithmic transformation of the above variables was performed to stabilize data variance, and all variables were winsorized at the 1% and 99% percentiles annually. The specific model for estimating firm-level TFP is:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln M_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

where μ_i represents firm fixed effects, and λ_t represents year fixed effects. Subsequently, the TFP is derived by calculating the residual from this regression:

$$\mathrm{TFP}_{it} = \ln Y_{it} - \left(\hat{\beta}_1 \ln K_{it} + \hat{\beta}_2 \ln L_{it} + \hat{\beta}_3 \ln M_{it}\right) \qquad (2)$$

3.2.3 Control Variables

Consistent with prior studies, we introduce several firm-level control variables that potentially influence TFP, including firm size, firm age, and industry classification. Firm size is measured as the logarithm of total assets; firm age is defined as the number of years since the firm's initial public offering; industry fixed effects are included as dummy variables to control for sectoral heterogeneity. Tab. 1 summarizes all variables, including their definitions and data sources.

Table 1 Variable Description

Variable Name	Abbreviation	Economic Meaning	Measurement	Data Source
Total Factor Productivity	TFP	Overall firm productivity performance	Fixed effects regression residual	CSMAR
AI Adoption Index	AI	Degree of firm-level artificial intelligence engagement	ln(1 + frequency of AI-related keywords in annual reports)	CSMAR
Firm Size	Size	Scale of firm operations	ln(total assets)	CSMAR
Firm Age	Age	Firm maturity	ln(years since IPO)	CSMAR
Industry Classification	Industry	Sectoral grouping for fixed effects	Industry dummies	CSMAR
Hardware Infrastructure	Hardware	Degree of automation readiness	Robot units per 10000 manufacturing workers	IFR
Software Investment	Software	Investment in digital systems	Capital expenditures for digital transformation	CSMAR
Human Capital Quantity	Staff number	Size of the workforce	Total number of employees	WIND
Human Capital Quality	Human capital	Employee educational attainment	Proportion of employees with bachelor's degree or above	WIND
Intangible Asset Intensity	Intangible	Share of intangible assets in total assets	Intangible assets/Total assets	CSMAR
Innovation Input	Rdspend	R&D investment effort	Total R&D expenditure	CSMAR
Innovation Output	Innovation	Patent-based measure of innovativeness	Number of patent applications	CNIPA
Market Concentration	HHI	Industry-level competition	Herfindahl-Hirschman Index	CSMAR
Market Power	Lerner	Firm-level markup power	Lerner Index = (Revenue – Costs)/Revenue	CSMAR
Human Capital Productivity	HCP	Proxy for human capital effectiveness	ln(profit per employee)	CSMAR & WIND
Innovation Ability	IA	Forward citations as proxy for patent quality	ln(1 + citations to firm's patents in year t+1)	CNIPA
Days of Inventory on Hand	DOI	Reverse proxy for operational efficiency	In(365 × Inventory/COGS)	CSMAR
Managerial Ability	MA	Corporate governance alignment	Percentage of firm shares held by management	CSMAR

Notes: All continuous variables are winsorized at the 1st and 99th percentiles and standardized using Z-score normalization prior to clustering or regression. All variables are numeric unless otherwise stated. "ln" denotes natural logarithm.

3.3 Baseline Regression

To estimate the average effect of AI adoption on firm productivity, we construct the following baseline panel regression model:

$$\mathrm{TFP}_{it} = \alpha + \alpha_0 \mathrm{AI}_{it} + \gamma C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (3)$$

Here, TFP_{it} represents the total factor productivity of firm i in year t, and AI_{it} denotes firm-level AI adoption. The term C_{it} is a vector of control variables, including firm size, firm age, and industry dummies. Firm fixed effects (μ_i) and year fixed effects (λ_t) are simultaneously controlled to account for unobserved firm-level heterogeneity and common macroeconomic shocks. Standard errors are clustered at the firm level to correct for potential serial correlation and heteroskedasticity.

3.4 Heterogeneity Analysis Approach

While the baseline regression captures the average effect of AI adoption on productivity, firms differ in structural characteristics, technological foundations, and market contexts. As a result, the productivity gains from AI adoption are unlikely to be homogeneous across all enterprises. Cluster analysis provides an effective method for identifying groups of firms sharing similar attributes [38], thereby helping explain systematic variations in the impact of AI on TFP. To formally examine this heterogeneity, we adopt a two-step strategy. First, we conduct hierarchical clustering to classify firms into internally consistent groups based on their structural and technological attributes. Second, we re-estimate the baseline model separately for each group to assess cluster-specific effects.

3.4.1 Firm Clustering Procedure

Hierarchical clustering is implemented using firm-level data from 2014 to reflect conditions prior to large-scale AI adoption in 2015 [39]. The selection of clustering variables follows Syverson's framework [16], which attributes firm-level TFP variation to internal resource endowments and external conditions. Consistent with RBV and DCT, firms' ability to benefit from AI depends on valuable internal assets and the adaptive reconfiguration of those resources under environmental change [6, 7]. Therefore, variables capturing both internal resources and market conditions are included.

Firm size (log assets) and firm age (log years since establishment) represent organizational characteristics. Market competitiveness, which reflects contextual pressures shaping strategic behavior [20, 40], is measured by the HHI [41] and the Lerner index [42]. Three internal resource dimensions directly related to firms' AI absorptive capacity are included: human capital quality, hardware infrastructure, and foundational innovation capability [17, 43].

Hardware foundations are measured by industrial robot penetration, defined as the number of industrial robots per 10000 manufacturing employees, obtained from the International Federation of Robotics (IFR) [39]. Software foundations are extracted from annual reports, capturing digital transformation–related asset investments [44]. Human resource foundations are proxied by the total number of employees and the proportion with a bachelor's degree or higher, drawn from corporate databases. Basic innovation capability is evaluated using three indicators: patent applications, the ratio of intangible to total assets, and total R&D investment from annual reports.

To test H2b, a Technological Redundancy Index (TRI) is constructed ex post by synthesizing education level, R&D, intangibles, patent quality, and robotics penetration [5, 45, 46]. TRI is excluded from clustering inputs to avoid collinearity.

All variables are winsorized at the 1st and 99th percentiles and standardized (Z-scores). Given the moderate sample size and need for interpretability, agglomerative hierarchical clustering with Ward linkage and Euclidean distance is used. This method requires no pre-specified cluster number or centroids and produces a dendrogram that visually represents nested structures [47]. Cluster validity is evaluated with the silhouette method, a widely accepted diagnostic in clustering research. The optimal cluster number is selected by maximizing the average silhouette score, subject to sufficient sample size for inference.

3.4.2 Subgroup Regression Design

Based on the clusters derived above, we re-estimate the baseline regression model separately within each group to examine whether the effects of AI adoption differ across firm types. All control variables and fixed effects are held constant across subsamples to ensure comparability. Standard errors are clustered at the firm level within each subgroup. This approach allows us to assess the conditional productivity returns to AI adoption under internally homogeneous conditions and provides a direct empirical test of the theoretical heterogeneity posited in Hypotheses 2a and 2b.

4 RESULTS

4.1 Baseline Regression Results

The descriptive statistics for our key variables are reported in Tab. 2. Tab. 3 reports baseline regressions of AI adoption on TFP. Across alternative specifications with control variables, year fixed effects, and firm fixed effects, the estimated coefficient on AI adoption remains robustly positive, indicating that AI adoption generates productivity gains. Consequently, these results support Hypothesis 1.

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Table 2 Descriptive statistics for the variables

Variables	Mean	SD	Min	Max	Obs
TFP	11.509	1.347	7.168	15.751	22895
AI Adoption	0.5952	0.575	0	1.772	22895
Firm Size	22.430	1.371	17.261	28.697	22895
Firm Age	2.294	0.842	0	3.526	22895

Table 3 Results of fixed effects models examining the relationship between AI adoption and TFP

	(1)	(2)	(3)
	TFP	TFP	TFP
AI	0.086^{***}	0.076^{***}	0.035^{***}
	(0.016)	(0.016)	(0.009)
Control Variables	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
Firm Fixed Effects	No	No	Yes
N	22895	22895	22582
R^2 adjusted	0.807	0.808	0.971

Notes: Robust standard errors are reported in parentheses; $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4.2 Heterogeneity Regression Results

4.2.1 Clustering-Based Identification of Firm Archetypes

To investigate the heterogeneous effects of AI adoption across different types of firms, we first employed hierarchical clustering to classify firms into distinct archetypes based on their structural and technological characteristics. This grouping provides the empirical foundation for examining systematic differences in AI's productivity effects. The analysis used indicators of size, age, technological infrastructure, innovation input, human capital, and market environment. Five clusters emerged, each representing a coherent archetype with differentiated resource configurations and external conditions. Fig. 2 depicts their descriptive positioning.

Cluster 1: Mature firms with constrained intangible assets

Firms in Cluster 1 exhibit advanced firm age (mean = 3.020 vs. 2.809 in pooled other clusters, $p < 0.001$), signaling extensive operational experience yet limited intangible asset intensity (mean = 0.118 vs. 0.160, $p < 0.001$). This pattern aligns with lifecycle theory predictions, where mature firms prioritize risk mitigation over innovation-driven strategies [48]. Their low Herfindahl-Hirschman Index (HHI = 0.125 vs. 0.141, $p < 0.001$) reflects participation in less dynamic markets, reducing incentives for disruptive AI adoption [49]. Compared to other clusters, this cluster companies' conservative intangible investment strategy may reflect strategic caution or resource constraints (TRI = −0.060 vs. 0.015, $p < 0.001$), consistent with the description of resource-constrained entities.

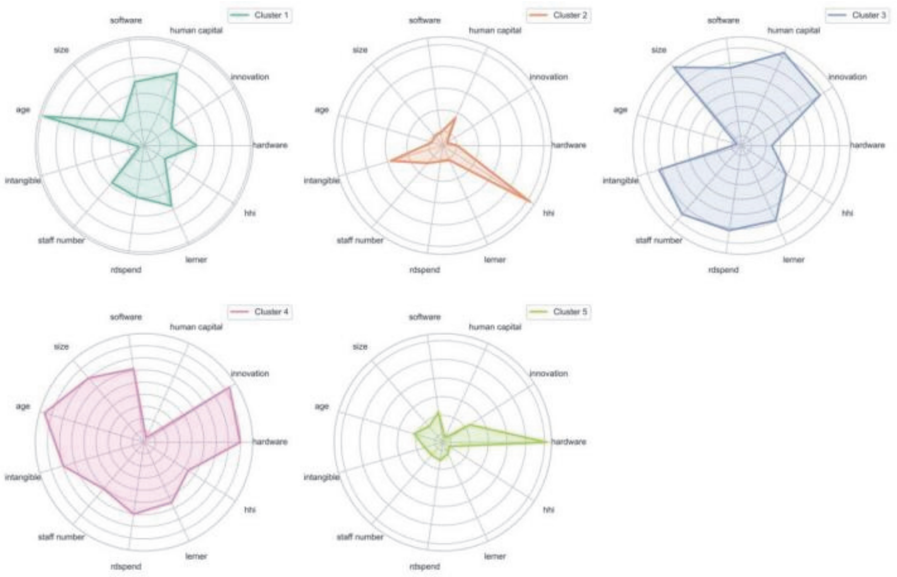

Figure 2a Feature Distributions by Cluster

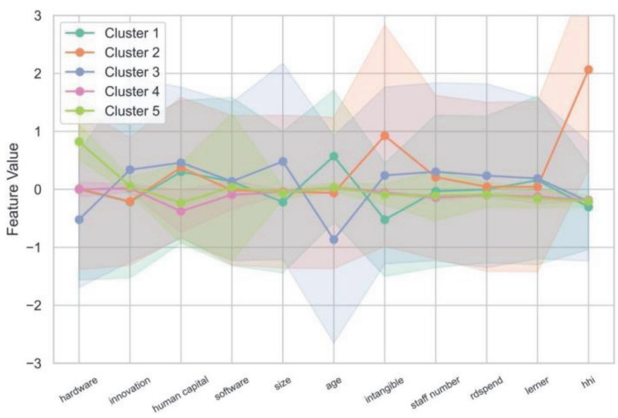

Figure 2b Comparative Cluster Profile (Notes: Hardware, innovation, human capital and software indicate each capability accordingly; intangible is the proportion of intangible assets to total assets; rdspend means total R&D investment; lerner and hhi indicate Lerner and HHI index)

Cluster 2: Knowledge-intensive firms facing intense competition

Cluster 2 firms are marked by large number of highly educated employees (mean = 5.737 vs. 3.603, $p < 0.001$) and substantial intangible asset holdings (mean = 0.210 vs. 0.144, $p < 0.001$), reflecting strong internal investments in human capital and knowledge-based capabilities. Simultaneously, these firms operate in highly competitive environments (HHI = 0.218 vs. 0.128, $p < 0.001$). This combination of resource abundance and competitive pressure indicates firms having reached a saturation point in technological deployment (TRI = 0.248 vs. −0.029, $p < 0.001$). These firms may exhibit diminished marginal returns from additional AI investment due to overlapping capabilities, path dependence, and constrained strategic flexibility.

Cluster 3: Dynamic capable Firms with Structural Hardware Deficits

Enterprises in this cluster are defined by their large scale (mean = 22.867 vs. 22.138, $p < 0.001$) and relatively young organizational age (mean age = 2.596 vs. 2.896, $p < 0.001$), suggesting rapid expansion and strong growth potential. Despite this structural advantage, these firms exhibit limited investment in core hardware infrastructure such as robotics and smart automation (robotic penetration rate = 5.356 vs. 6.225, $p < 0.001$), aligning with RBV predictions, where scale-driven firms prioritize asset accumulation over capability building [6]. However, this constraint is partially offset by relatively high levels of intangible asset accumulation (mean = 0.167 vs. 0.149, $p < 0.001$), indicating investments in innovation capability, brand equity, or knowledge systems. The resulting configuration reflects a hybrid state: the lack of physical digital infrastructure aligns with the resource deficiency type, and their age and intangible investments signal organizational flexibility and reconfiguration potential, which is a typical example of dynamic capable companies (TRI = 0.181 vs. -0.030, $p < 0.001$).

Cluster 4: Human Capital-Constrained Firms in Hyper-competitive Markets

This cluster includes firms notably constrained by significantly lower employee educational attainment levels (mean = 2.249 vs. 5.578, $p < 0.001$), coupled with limited research investment (1.90×10^8 vs. 2.05×10^8, $p < 0.001$) and relatively fewer staff (6363 vs. 6840, $p < 0.001$). The characteristics of these firms correspond to the category within the RBV framework in which firms lack both tangible and intangible assets necessary for sustained innovation (TRI = −0.081 vs. 0.089, $p < 0.001$). In this context, their absorptive capacity is weak, and productivity improvements depend on external technologies compensating for internal deficits.

Cluster 5: Specialized Hardware Investors with Capability Saturation

Firms in this cluster are clearly distinguished by exceptionally strong foundations in technology hardware investment (mean = 7.507 vs. 6.070, $p < 0.001$), reflecting a strategic orientation that prioritizes automation, process efficiency, and equipment-based operational improvements, rather than broad-based organizational scale (R&D investment = 1.90×10^8 vs. 1.97×10^8, $p < 0.01$). In contrast to firms with balanced or diversified resource portfolios, these enterprises exhibit a narrowly focused technological configuration centered on physical infrastructure, corresponding to firms characterized by limited dynamic capabilities. Although they demonstrate high commitment to specific technological assets, the absence of complementary capabilities, such as human capital (2.904 vs. 3.849, $p < 0.01$) or intangible assets (0.146 vs. 0.151, $p < 0.001$), suggests a constrained capacity to sense, seize, and adapt to changing environments [7]. Their technological investments appear path-dependent and asset-specific, rather than embedded within a broader capability architecture.

As shown in Supplementary Tab. 1, Kruskal-Wallis statistics confirm significant differences across clusters, validating their distinctiveness. Given non-normality, we applied nonparametric Kruskal-Wallis tests instead of ANOVA. Results were consistent across alternative algorithms (K-means, density-based methods) and quality indices (CPCC, CH, silhouette). A bootstrap procedure (1000 resamples) confirmed stability of the dendrogram and cluster separation.

4.2.2 Cluster-Specific Effects of AI on TFP

Building on the cluster typology derived above, we re-estimate the baseline model separately for each firm cluster to evaluate whether the effect of AI adoption on TFP differs by firm type. As shown in Tab. 4, the effect of AI adoption on TFP varies significantly across firm clusters. AI adoption has a significantly positive impact on TFP in Cluster 1 ($\beta = 0.042$, $p < 0.001$), Cluster 3 ($\beta = 0.030$, $p < 0.025$), and Cluster 4 ($\beta = 0.031$, $p < 0.001$). In contrast, the effect is statistically insignificant in Cluster 2 ($\beta = 0.032$, $p < 0.201$). These results support Hypothesis 2a, which posits that the productivity effects of AI adoption are moderated by firm-level heterogeneity.

Hypothesis 2b, which proposes that firms with highly developed technological foundations experience no significant productivity improvement from AI adoption, is also supported. Specifically, Clusters 1, 3, and 4, characterized by intangible, hardware, or human capital constraints, benefit more, while Cluster 2, with advanced technological foundations and intense competition, shows no further gains. This is consistent with the expectation that AI yields diminishing returns when firms already possess mature digital infrastructure and face resource saturation. The contrast between underdeveloped and advanced firms directly supports Hypothesis 2b.

Table 4 Results of heterogeneous models examining the relationship between AI adoption and TFP

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
	TFP	TFP	TFP	TFP	TFP
AI	0.042^{***}	0.032	0.030^{*}	0.031^{***}	−0.016
	(0.013)	(0.247)	(0.013)	(0.009)	(0.090)
N	6235	4212	5316	4045	54
R^2 adjusted	0.976	0.943	0.981	0.989	0.899

Notes: Standard errors are reported in parentheses; $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Prior studies often emphasize that innovation-oriented firms are particularly well-positioned to capture productivity gains from AI adoption, citing their stronger absorptive capacity, advanced digital routines, and greater organizational learning potential [12]. Yet they typically assess innovation in isolation, overlooking interactions with broader contexts. In our analysis, Cluster 2, knowledge-intensive firms under competitive pressure, exhibit no statistically significant effect of AI adoption on TFP. This result suggests that innovation alone may not be sufficient to translate AI investments into productivity gains, particularly when firms simultaneously face high external uncertainty or resource constraints. Our multidimensional clustering shows that AI's impact depends on combined organizational and market conditions, not single-attribute subgrouping.

The results also reflect that firm characteristics co-occur and jointly shape technological outcomes. Innovation capabilities often coexist with competitive intensity, and it is the interaction of attributes that conditions productivity gains. This implies that digital transformation strategies must be tailored to multidimensional firm contexts, rather than based solely on innovation intensity.

4.3 Endogeneity Analysis

To address potential endogeneity between AI adoption and firm TFP, particularly the concern that inherently more productive firms may adopt AI earlier, we employ a two-stage least squares (2SLS) strategy with two Bartik-style instrumental variables [50].

The first instrument is based on academic AI research output, measured by annual citations of seminal publications in neural networks, machine learning, and computer vision. This citation-based measure captures exogenous diffusion of AI knowledge, constructed by interacting firms' baseline AI-R&D exposure with aggregate citation growth, thus reflecting external spillovers rather than firm-specific productivity shocks. The second instrument is robotics installation density (IFR), reflecting sector-wide automation trends driven by technological progress and capital investment, independent of individual firms' productivity shocks.

Table 5 Main 2SLS estimates using bartik-style instruments

	AI	TFP
AI		0.043^{***}
		(0.010)
IV: AI Citation Bartik Index	0.030^{***}	
	(0.001)	
IV: Robot Density Bartik Index	1.836^{***}	
	(0.029)	
Kleibergen-PaaprkLM	9851.81^{***}	
Cragg-Donald Wald F	10530.47	
Hansen J. P. value		0.249
N	18501	18501

Notes: Robust standard errors are reported in parentheses; $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Diagnostic results, shown in Tab. 5, confirm instrument strength and validity. First-stage estimates (Supplementary Tab. 2 to Tab. 4) show both instruments strongly predict AI adoption. Standard diagnostics (underidentification, Cragg-Donald F., Hansen J., Stock-Wright L. M.) confirm relevance and exogeneity. Turning to the second-stage 2SLS results, the coefficient on AI adoption remains robust and positive, indicating a substantial and causal effect on TFP after purging endogenous variation, which reinforces that AI usage plays a causal role in enhancing productivity.

4.4 Robustness Checks

To ascertain the reliability of the core findings, several robustness checks are conducted by altering variable definitions, incorporating lag structures, augmenting control variables, and modifying the sample scope. Across all specifications, the coefficients remain consistent with the primary results, reinforcing the baseline conclusion of a positive AI-TFP relationship.

To start with, the AI adoption index is alternatively captured by AI keyword frequency in M&A contexts and by the ratio of AI expenditures to intangible investment. TFP is also recalculated using Olley-Pakes [51] and Doraszelski-Jaumandreu structural estimators [52], which account for simultaneity and dynamic firm behavior. Re-estimating with these alternative measures yields results that remain positive and significant. Next, lagging AI adoption by one period continues to produce robustly positive coefficients, indicating durable effects over time. Moreover, adding leverage and profitability as controls does not alter results, confirming that the AI-TFP linkage is not driven by firms' financial health. Finally, restricting the sample to the post-2017 policy era likewise confirms a strong positive effect.

These robustness tests consistently validate the main empirical findings. The positive influence of AI on productivity is stable across alternative variable definitions, lag structures, additional controls, sample scopes, and structurally estimated productivity measures.

5 MECHANISM ANALYSIS

In order to clarify the channels through which AI technology application promotes firm total factor productivity, we use a three-step mediation approach [53] augmented by Bootstrap tests [54]. Based on our framework, we examine four channels: human capital, innovation capability, automation and operational efficiency, and corporate governance.

5.1 Theoretical Basis and Empirical Strategy for Mediation

This study adopts the classical three-step method to test whether AI affects TFP through proposed mediators, using the following equations.

TFP_{it} is total factor productivity of firm i in year t; AI_{it} denotes the degree of AI technology application; $\mathrm{Mediator}_{it}$ represents one of the hypothesized mediators; and C_{it} a vector of control variables. All regressions include firm and year fixed effects and cluster standard errors at the firm level. To ensure robust identification, we apply Bootstrap tests to obtain bias-corrected confidence intervals for the indirect effect. Because earlier regressions show AI significantly increases TFP only in Clusters 1, 3, and 4, mediation analyses are confined to these clusters.

(Step 1)

$$\mathrm{TFP}_{it} = \alpha_1 + c\mathrm{AI}_{it} + \gamma_1 C_{it} + \mu_i + \lambda_t + \varepsilon_{1it} \tag{4}$$

(Step 2)

$$\mathrm{Mediator}_{it} = \alpha_2 + a\mathrm{AI}_{it} + \gamma_2 C_{it} + \mu_i + \lambda_t + \varepsilon_{2it} \tag{5}$$

(Step 3)

$$\mathrm{TFP}_{it} = \alpha_3 + b\mathrm{Mediator}_{it} + c'\mathrm{AI}_{it} + \gamma_3 C_{it} + \mu_i + \lambda_t + \varepsilon_{3it} \quad (6)$$

5.2 Measures of Mediators

5.2.1 Human Capital Productivity (Hypothesis 3a)

In accordance with the notion that AI adoption elevates workforce productivity, this study uses the natural logarithm of per-capita operating revenue to reflect human capital at the firm level. If AI-based solutions, such as automated data analytics or targeted training programs, improve the effectiveness of each worker, then the firm's output per employee should rise. Following Niu [55], the measure is computed as the natural logarithm of profit per employee, scaled by 100000:

$$\mathrm{HCP} = \ln\left(\frac{P}{NE \times 100000}\right) \quad (7)$$

P stands for profit and NE means the number of employees. A positive association with AI adoption would suggest that AI enhances labor productivity.

5.2.2 Innovation Ability (Hypothesis 3b)

Drawing on Hall [56] and Bradley [57], this study measures innovation capability using forward citations of the firm's newly granted patents in the subsequent year. Specifically, for each firm-year observation, we sum the number of forward citations received in year $t + 1$ by all patents granted in year t. To ensure comparability and mitigate skewness, the final indicator is constructed by taking the natural logarithm of one plus the citation count:

$$\mathrm{IA} = \ln\left(1 + \sum_{p \in P_{it}} \mathrm{Citations}_{p,\, t+1}\right) \quad (8)$$

A positive link between AI adoption and this indicator supports Hypothesis 3b, implying AI enhances innovation quality and impact.

5.2.3 Operational Efficiency (Hypothesis 3c)

To assess whether AI improves operational efficiency, we use Days of Inventory on Hand (DOI) as a reverse proxy [58]:

$$\mathrm{DOI} = \ln\left(\frac{365 \cdot \mathrm{Inventory}_{it}}{\mathrm{COGS}_{it}}\right) \quad (9)$$

Higher DOI indicates lower efficiency, while reductions reflect automation-driven improvements, consistent with Hypothesis 3c.

5.2.4 Managerial Ability (Hypothesis 3d)

To capture whether managerial ability acts as a critical channel linking AI usage to enhanced total factor productivity, this study adopts the managerial ownership ratio as a proxy for managerial competence, following established methodologies in prior literature [59, 60]. Specifically, managerial ownership refers to the percentage of the firm's outstanding shares owned by its management team. A higher ownership stake aligns managerial and shareholder interests, thereby strengthening long-term value orientation, mitigating agency conflicts, and enhancing strategic responsiveness. Prior research finds that greater managerial ownership is positively associated with improved governance quality and firm performance [60, 61]. Hence, the managerial ownership ratio is adopted as a valid and interpretable indicator of managerial capability, and is calculated as follows:

$$MA = \frac{\mathrm{Shares\_Held\_by\_Management}_{it}}{\mathrm{Total\_Shares\_Held\_by\_All\_Shareholders}_{it}} \cdot 100\% \quad (10)$$

Greater ownership aligns managerial and shareholder interests, strengthens governance, and indicates higher managerial capability.

5.3 Results of Mechanism Analysis

For each of the channels, both the three-step regression method and the Bootstrap test produce consistent findings, as summarized in Tab. 6.

Drawing on prior theory, we test whether AI improves TFP through human capital (H3a), innovation (H3b), operational efficiency (H3c), and governance (H3d). Results support all four hypotheses: AI adoption significantly enhances these mediators, which in turn promote TFP.

Table 6 Mediation analysis results using three-step regressions and bootstrap tests

	Cluster 1	Cluster 3	Cluster 4
c	0.042^{***}	0.030^{*}	0.031^{***}
HCP			
a	-	0.106^{***}	-
b	-	0.080^{***}	-
c'	-	0.030^{*}	-
bootstrap coefficient	-	0.009^{*}	-
IA			
a	0.095^{*}	0.107^{*}	-
b	0.011^{*}	0.015^{***}	-
c'	0.041^{**}	0.030^{*}	-
bootstrap coefficient	0.002^{*}	0.002^{*}	-
DOI			
a	-0.005^{*}	-	-0.005^{***}
b	-2.018^{***}	-	-1.411^{***}
c'	0.034^{***}	-	0.024^{***}
bootstrap coefficient	0.011^{*}	-	0.007^{*}
MA			
a	0.830^{*}	-	-
b	0.002^{*}	-	-
c'	0.020^{*}	-	-
bootstrap coefficient	0.004^{*}	-0.001^{*}	-

Notes: Robust standard errors are reported in parentheses; $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A detailed cluster-level examination clarifies how TFP enhancement mechanisms vary across enterprise archetypes. Cluster 1, consisting of mature firms with limited intangible assets, shows the strongest mediation through managerial ability, innovation capability, and supply chain efficiency. These firms, though well established, lack intangible knowledge such as proprietary technologies and in-house R&D breakthroughs. By integrating AI tools for predictive analytics, decision support, and operational planning, top managers compensate for these gaps. AI-driven dashboards provide granular visibility into operational bottlenecks, enabling more agile resource reallocation. Once innovation is activated, through AI-enabled ideation, prototype testing, and incremental product refinement, the shortage of intangible assets becomes less binding, as employees generate new ideas based on data insights rather than tacit expertise. Supply chain efficiency further improves via real-time tracking, automated inventory control, and dynamic logistics. Together, managerial coordination, innovation renewal, and smoother supply chain operations enhance overall efficiency, translating into higher TFP.

Cluster 3 represents large-scale enterprises constrained by outdated or inadequate hardware infrastructure. For these firms, human capital and innovation capability emerge as the primary mediators. Because hardware upgrades are costly, AI adoption strategically bypasses such bottlenecks by equipping existing staff with smarter tools and more flexible workflows. AI-based training modules, analytics dashboards, and cross-departmental platforms enhance skill levels and cross-unit collaboration. A more capable workforce, in turn, leverages AI-enabled R&D tools and collaborative design systems to drive both incremental and radical innovation. As employees utilize limited physical assets more efficiently and reconfigure workflows, innovation capability rises. These intangible improvements allow large firms to maintain competitiveness even under technological constraints.

Cluster 4 comprises firms facing pronounced human capital shortages. Unlike Cluster 3, where upskilling is feasible, these firms encounter fundamental labor or skill deficits that impede short-term development. For these entities, AI's principal mediation channel is supply chain efficiency. Deploying AI in demand forecasting, route optimization, and automated inventory checks reduces labor dependence and substitutes for skill-intensive tasks. In essence, AI serves as a partial substitute for scarce human capital. Negative coefficients on turnover metrics confirm that operational fluidity, driven by automation and precise logistics, directly contributes to higher TFP. Hence, AI adoption enables these firms to coordinate resources effectively despite limited skilled personnel, alleviating human capital constraints.

Comparative analysis across clusters reveals a clear pattern: AI produces the greatest TFP gains for firms facing structural weaknesses, Cluster 1 (intangible gaps), Cluster 3 (hardware deficits), and Cluster 4 (human capital shortages). Each uses AI to offset its binding constraint: supplementing intangible resources, upskilling employees, or automating labor-intensive processes. The shared mechanism is that AI mitigates structural rigidity, orchestrating complementary improvements that collectively enhance productivity. These subgroup findings reinforce the broader mechanism analysis, showing that AI leverages firm heterogeneity to generate differentiated yet convergent productivity benefits.

Unlike prior research that treats mediators as universal, our results show firm-specific pathways: Cluster 1 relies on governance and innovation, Cluster 3 on workforce productivity, Cluster 4 on automation. The effectiveness of each channel depends on how well it matches a firm's capability-constraint profile. This highlights the importance of heterogeneity in understanding how AI enhances performance and suggests that firms should tailor transformation paths to their organizational conditions and priorities.

6 CONCLUSION AND POLICY IMPLICATIONS

With the growing ubiquity and strategic importance of AI, understanding how its adoption shapes firm productivity has become a pressing issue. This study yields three core findings. First, AI adoption significantly enhances TFP by approximately 3.5%, mediated through four channels: human capital augmentation, innovation output, operational automation, and governance quality. Second, hierarchical clustering reveals substantial heterogeneity: resource-constrained young firms benefit the most, established incumbents experience moderate gains, and hypercompetitive knowledge-intensive firms exhibit limited improvement, suggesting that complementarities beyond technological adoption determine outcomes. Third, mechanism heterogeneity emerges across firm archetypes: mature firms leverage AI for governance and incremental innovation, labor-constrained firms emphasize automation, and large firms with hardware deficits employ AI for workforce upskilling.

This study advances four theoretical contributions: 1) integrating the resource-based view and dynamic capabilities theory to reveal the duality of AI efficiency potential and saturation limitations; 2) Building a multidimensional classification model for heterogeneity such as enterprise scale and digitization, breaking through the limitations of traditional single-dimensional analysis; 3) Confirming that AI may fail under the constraints of technological saturation and strong competition, disrupting the perception of the "universal technological dividend"; 4) Elucidating the mechanism by which different enterprises transform AI value through differentiated pathways, and establishing a dynamic connection between heterogeneity and productivity.

These insights carry practical implications for policymakers and managers. Rather than pursuing one-size-fits-all digitalization, organizations should design AI strategies aligned with their resource profiles. For labor-intensive firms, policymakers could combine tax incentives for AI-enabled automation (e.g., accelerated depreciation) with workforce transition programs. Establishing AI innovation hubs with shared R&D infrastructure, particularly for mature firms, through public-private partnerships can accelerate diffusion. Moreover, AI adoption subsidies should be made contingent on industry concentration, prioritizing moderately competitive sectors where productivity returns are strongest. The timing of adoption also matters: real-time AI impact dashboards that integrate firm-level TFP metrics with cluster-specific benchmarks would improve monitoring and policy calibration.

These findings underscore that AI serves as an organizational transformation catalyst, not a universal productivity booster. Its impact depends on the strategic alignment between adoption pathways and firms' structural constraints. Future research could further explore how industry-specific digital infrastructures shape heterogeneous AI productivity effects, or extend the analysis to cross-country settings to validate the generalizability of the findings.

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