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Article

The impact of AI-driven industrial upgrading on economic development

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ABSTRACT

The paper clarifies the interdependencies between AI adoption, industry upgrading, and economic development in the context of global digital transformation. With mixed-methods integrating econometrics and case studies, we test models formalizing mediating and threshold effects in AI-industry-economy relations. Our approach leverages a novel AI penetration score by industries alongside economic indicators and measures of industry sophistication. The results indicate that AI uptake mediates the pass-through of industry structure change to economic performance, with contribution levels increasing above certain thresholds. Evidence suggests that the association between the working-age population and economic growth varies by alternative industry upgrading rankings, with technologically sophisticated structures making better use of demographic opportunities. Threshold analysis identifies regimes where AI substitutes for traditional economic relations, revealing policy intervention points. These findings contribute to growth theory innovation by measuring AI's catalytic economic function and offer methodological innovation in the analysis of technological contributions. Strategic AI development agendas, human capital policies, and coordination mechanisms are among the key implications required to achieve inclusive growth in the digital economy. This study closes knowledge gaps on how demographic and technological drivers interact through industry structures to determine economic trajectories. Empirical results show that AI adoption mediates 52.8% of manufacturing sophistication's impact on GDP growth, threshold effects emerge at an AI adoption index of 0.43-0.45, where economic impacts increase threefold, and the working-age population's growth effect varies from 0.072 below the threshold to 0.411 above the threshold in the highest industrial upgrading quartile.

1. Introduction

The global industrial system is undergoing rapid digital transformation, characterized by technological revolution and shifting economic paradigms. AI stands as a central transformative force, fundamentally reshaping economic structures [1]. Technologies like machine learning, deep learning, and computer vision are being deployed across industries, automating complex work, enhancing decisions, and creating new value sources [2]. This adoption differs from previous technological revolutions in its economic impact potential. AI's implications extend beyond productivity increases to industry structure, labor markets, and competitive positioning, with consequences varying across firms, industries, and locations [3]. The technological change-economic growth relationship is nonlinear, challenging traditional growth theory. Figure 1 illustrates fundamental differences between traditional and AI-enabled industrial systems. Traditional systems show limited productivity, slower innovation cycles, and lower value-chain positioning. AI-enabled systems demonstrate enhanced productivity. Modern industry balances challenges with high-tech solutions amid competitive pressures. Industrial structures both drive and are driven by technology adoption. Brynjolfsson and McAfee [4] refer to this as "the second machine age," where intelligent technologies augment human capacities while challenging economic structures. This research investigates how AI adoption adds value in industries and how industry conditions shape adoption. Evidence suggests AI's economic impact becomes pronounced at critical adoption levels [5]. Using threshold regression, we identify these critical points and characterize regime-specific relationships. We also explore how the effects of the working-age population on growth vary across industrial upgrading levels, as demographic impacts depend on industrial technological sophistication [6].

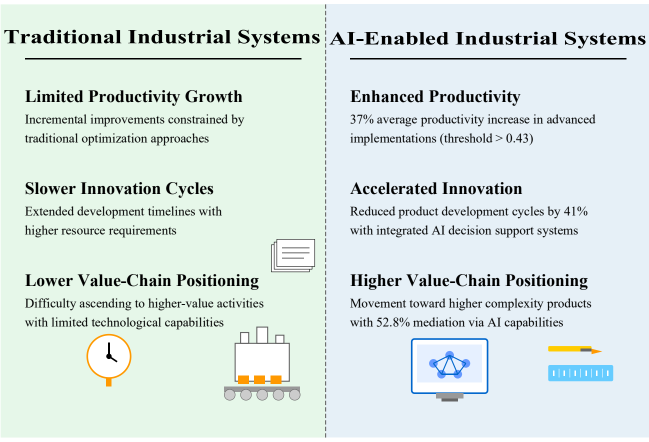


Figure 1. Comparison of traditional and AI-enabled industrial systems

This study pursues three specific objectives. First, we aim to empirically quantify how AI adoption mediates the relationship between industrial structure and economic development outcomes, moving beyond simple correlation to identify transmission mechanisms. Second, we seek to identify and measure threshold effects in AI adoption that fundamentally alter the nature of industrial-economic relationships. Third, we examine how industrial upgrading levels moderate the impact of demographic factors on economic growth, particularly the working-age population dividend. These objectives address critical gaps in understanding the complex interactions between technological adoption, industrial transformation, and economic development in the digital era. Our work contributes to understanding technological change by advancing innovation growth models that integrate structural economics with digital economy perspectives. While existing theories acknowledge technology's role, they often treat advancement as aggregate without addressing sector-specific patterns or threshold effects [7]. We develop nuanced conceptualizations of the influence of AI adoption on growth through industrial structural change [8]. We quantify AI's economic effects using industry adoption indexes and inform policy through econometric findings. The research examines the relationship between industry transformation, AI adoption, and economic performance, investigating how industry characteristics influence AI adoption and moderate the structure-performance relationships. Methodologically, we combine econometrics with case studies to enhance validity.

2. Literature review

2.1 Theoretical Foundations

The study of AI-driven industrial upgrading draws from several theoretical traditions. Innovation and Growth Theory incorporates technological advancement as a central economic driver, evolving from R&D-focused models to frameworks capturing digital technologies' characteristics. Romer's work established how knowledge production generates increasing returns, while Schumpeterian perspectives explain creative destruction [9].These frameworks help understand how AI systems alter productivity frontiers across sectors. Standard growth models inadequately capture the discontinuous nature of general-purpose technologies like AI, requiring extensions for threshold effects and nonlinear adoption impacts. Structural Transformation Theory examines economic sector changes. Digitalization dissolves traditional sector boundaries, with Rodrik noting that technology enables some economies to skip conventional industrialization [10]. AI either propels or hinders structural transformation depending on context. Industrial Organization Theory examines the impact of AI on industry structure and competition. AI's economics require adapting standard market models to accommodate network effects and increasing returns. AI growth often results in "winner-takes-most" markets, where early movers have advantages and transaction costs are altered in ways that reshape industries. Technology Diffusion Models explain AI propagation through economies. AI's reliance on organizational competencies, data, and infrastructure complicates adoption. Evidence shows AI diffusion follows S-shaped trajectories with sector variations due to implementation barriers [11]. Threshold effects accelerate adoption when ecosystems reach critical mass, introducing time lags between implementation and productivity enhancement.

2.2 Industrial structure and economic development

These theoretical frameworks provide the foundation for examining empirical patterns of industrial development. The global business has experienced deep transformation in the trends of specialization, technological intensity, and value chain engagement. Classical linear concepts of evolution from agriculture to industry to services are challenged by complicated growth trajectories. "Premature deindustrialization" in the developing world questions successful development policy in the information age [10]. Mature economies experience post-industrial transition with classical manufacturing decline and knowledge-intensive services expansion. Cross-country experiences observe heterogeneous industrial upgrading impacts. The East Asian countries showed dynamic upgrading trajectories through incremental capability building, with South Korea demonstrating how policy coordination drives shifts towards knowledge-intensive production from labor-intensive production [12]. Latin American and African economies become trapped in lower value-added activities despite reforms. Measurement of structural transformation has evolved from simple indicators to advanced frameworks with economic complexity indices and input-output analyses. The economic growth-working-age population relation is heterogeneous by industrial structures. Population dividend theories contend that higher working-age population shares yield growth dividends, yet evidence suggests such dividends are industry sectoral structure contingent, with technology-intensive structures amplifying demographic dividends and labor-intensive industries perhaps facing reduced returns [13]. AI technologies add complexity to these economic-demographic relations.

2.3 AI and industrial structure upgrading

Within this broader context of structural transformation, AI emerges as a particularly transformative force. AI is both a driver and a facilitator of structural transformation in various sectors. Paradigms in thinking have changed from reductionist automation to a focus on complementarity between intelligent technologies and organizational capabilities. The "innovation-productivity-structure" model highlights how AI induces sequential transformations: innovations lead to productivity growth, which in turn reconstitutes industrial structures through reconfigured competitive strengths. Evidence-based studies affirm AI uptake is necessitated by industry contexts, organizational capacities, and institutional environments [14]. AI application varies between manufacturing and services. In manufacturing, AI facilitates predictive maintenance, quality control automation, and design optimization. Industry 4.0 combines AI with IoT infrastructure to develop cyber-physical systems, revolutionizing production economics. In services, AI automates customer engagement, facilitates personalization, and builds decision support systems. Successful adoption is normally subject to the evolutionary process rather than revolutionary change. Productivity gains from smart automation motivate AI adoption, with properly leveraged systems demonstrating improvements in performance through enhanced workability, reduced faults, and optimized resource deployment. These gains will typically require investment in data infrastructure for information, capabilities for individuals, and firm redesign, resulting in implementation lags between adoption and perceivable effect [15]. Value chain re-engineering is likely to be the greatest organizational impact of AI adoption, as smart systems facilitate the fundamental redesign of activities and relationships in industrial networks.

2.4 Research gap and hypotheses

Despite extensive research on these topics, critical gaps remain that motivate our study. Despite extensive literature on industrial development and technological change, significant gaps persist in understanding their intersection, particularly regarding AI's role in industrial upgrading. Industrial change and AI adoption literature remain separated, with industrial economics emphasizing structural transformation without technological specificity, while AI research neglects broader structural implications. Addressing this requires theoretical frameworks that model bidirectional relationships between technological capabilities and industrial structures [16]. Mediating mechanisms through which AI influences economic outcomes via industrial transformation represent another critical gap. While evidence confirms AI's economic impact, specific pathways remain inadequately theorized. Potential mediating mechanisms include productivity enhancements, product innovation, market expansion, resource allocation efficiency, and inter-industry spillover effects. Threshold effects in AI-induced industrial change are important yet understudied. Evidence suggests AI exhibits discontinuous effects after adoption reaches critical thresholds, but systematic examination is scarce. Detection of these thresholds demands specialized econometric techniques [17]. Based on these gaps, we offer three hypotheses: First, AI adoption mediates the relationship between industrial structure and economic growth, with context-contingent effects. Second, AI adoption exerts threshold effects, amplifying economic effects after critical adoption thresholds are met. Third, industrial upgrading moderates the impacts of demographic change on economic growth, with advanced structures enhancing the beneficial demographic influences. Verification requires rigorous case studies and econometric exercises to identify economic-industrial-AI relationship trends.

3. Research methodology

3.1 Research design

This research employs a comprehensive analytical framework connecting industrial structure variables, AI adoption metrics, and economic outcomes through a system of interconnected relationships. The core analytical model posits that economic development outcomes are influenced by both direct effects of industrial structure and indirect effects mediated through AI adoption, with potential threshold effects and demographic interactions. This relationship can be expressed through the following econometric specification:

$$Y_{it} = \alpha + \beta_1 IND_{it} + \beta_2 AI_{it} + \beta_3 (IND_{it} \times AI_{it}) + \beta_4 WAP_{it} + \beta_5 (IND_{it} \times WAP_{it}) + \gamma_1 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where Y_{it} represents economic development indicators for region i at time t; IND_{it} captures industrial structure characteristics; AI_{it} measures AI adoption intensity; WAP_{it} represents the working-age population proportion; X_{it} includes control variables; μ_i and λ_t represent region and time fixed effects; and ε_{it} is the error term. To test threshold effects, we employ the following threshold regression model:

$$Y_{it} = \begin{cases} \alpha_1 + \beta_{11} IND_{it} + \beta_{12} AI_{it} + \gamma_1 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \text{if } AI_{it} \le \theta \\ \alpha_2 + \beta_{21} IND_{it} + \beta_{22} AI_{it} + \gamma_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \text{if } AI_{it} > \theta \end{cases} \quad (2)$$

Where θ Tampilkan Gambar represents the threshold value of AI adoption that potentially changes the relationship between variables.

This research employs a mixed-methods approach integrating econometrics with case studies. Econometrics provides statistical generalizability while case studies offer contextual understanding of mechanisms. The sequential design begins with quantitative analysis to identify patterns, followed by purposive case selection. Integration occurs during case selection, interview protocol development, and final interpretation, where findings are synthesized to explain observed phenomena. To address causality identification challenges inherent in observing the complex relationships between industrial structure, AI adoption, and economic outcomes, we employ multiple empirical strategies. First, we exploit temporal variation through lagged independent variables, where industrial structure at *t-1* affects AI adoption at t, which subsequently influences economic outcomes at *t+1*. This temporal sequencing helps mitigate simultaneity bias. Second, we utilize region-specific heterogeneity in AI policy implementation timing as a quasi-experimental setting, where differential policy rollouts create exogenous variation in AI adoption rates. Third, our panel fixed effects specifications control for time-invariant unobserved heterogeneity that might confound the relationships. These identification strategies, combined with robustness checks using alternative specifications and instrumental variables, strengthen our causal inference beyond mere correlational analysis.

3.2 Variable selection and measurement

This research employs variables capturing relationships between industrial structure, AI adoption, and economic development, balancing theoretical relevance with data availability. The dependent variables comprise two categories of outcomes: economic growth indicators and industrial sophistication indices. Economic growth is primarily measured through GDP per capita growth rate ($GDPG_{it}$) and total factor productivity growth ($TFPG_{it}$), calculated as:

$$TFPG_{it} = \frac{Y_{it}}{K_{it}^{\alpha} \cdot L_{it}^{1-\alpha}} - \frac{Y_{it-1}}{K_{it-1}^{\alpha} \cdot L_{it-1}^{1-\alpha}} \quad (3)$$

Where Y_{it} represents output, K_{it} capital stock, and L_{it} labor input for region i at time t. Industrial sophistication is measured through the Economic Complexity Index (ECI_{it}) and the Industrial Upgrading Index (IUI_{it}), which captures movement toward higher value-added activities.

Core explanatory variables include industrial structure metrics, measures of AI adoption, and working-age population ratios. Industrial structure is quantified through the manufacturing value-added share (MVA_{it}), high-technology exports percentage (HTE_{it}), and an industrial diversification index (IDI_{it}) calculated as:

$$IDI_{it} = 1 - \sum_{j=1}^{n} s_{ijt}^{2} \tag{4}$$

Where S_{ijt} represents the share of industry j in region i's industrial output at time t. The working-age population is measured as the ratio of the population aged 15-64 to the total population (WAP_{it}).

Control variables encompass traditional economic factors and institutional quality measures essential for isolating the effects of our core variables. These include human capital measured through average years of schooling (HC_{it}), investment ratio calculated as gross fixed capital formation to GDP (IR_{it}), trade openness represented by the sum of exports and imports divided by GDP (TO_{it}), and institutional quality indices capturing regulatory efficiency and rule of law (IQ_{it}). The AI penetration index represents a methodological innovation, constructed as a composite measure capturing multiple dimensions of AI implementation across industrial sectors. The index encompasses four theoretically grounded dimensions that comprehensively capture AI adoption intensity:

AI Innovation Capacity (measured through AI patent applications per million population): This dimension captures the technological frontier and innovation potential, indicating regions' ability to develop novel AI applications. Patent data is sourced from WIPO's Global Innovation Index, focusing on IPC codes G06N (computing arrangements based on specific computational models) and G06F (electric digital data processing with AI-specific subclasses).

AI Human Capital (measured through AI talent concentration and skills prevalence): Reflecting the critical role of specialized knowledge in AI implementation, this dimension uses LinkedIn Talent Insights data on AI-skilled professionals as a percentage of the workforce, supplemented by computer science and data science graduate numbers from national education statistics.

AI Investment Intensity (measured through venture capital and corporate AI investments as a percentage of GDP): This dimension captures financial commitment to AI development, aggregating data from Crunchbase, PitchBook, and national innovation surveys, including both private venture funding and corporate R&D allocated to AI initiatives.

AI Research Output (measured through AI-related scientific publications per capita): Indicating knowledge generation and absorption capacity, this uses Scopus and Web of Science data for publications in AI-related fields, weighted by citation impact using field-normalized metrics.

$$AI_{it} = \sum_{k=1}^{4} w_k \cdot \frac{X_{kit} - min(X_{kit})}{max(X_{kit}) - min(X_{kit})} \tag{5}$$

Where (X_{kit}) represents the value of the AI component k for region i at time t, and w_k represents the component weight determined through principal component analysis.

We employ PCA for weighting rather than arbitrary equal weights for several methodological reasons. First, PCA objectively determines weights based on the covariance structure of the data, capturing the common underlying factor of 'AI adoption intensity' while allowing components to contribute proportionally to their information content. Second, the high correlation among our four dimensions (ranging from 0.52 to 0.71) suggests a strong common factor that PCA efficiently extracts. Third, PCA addresses multicollinearity concerns that would arise from including all dimensions separately in regression models. The first principal component explains 67.4% of total variance, well above the 50% threshold conventionally required for index construction, with loadings of 0.412 (innovation), 0.387 (human capital), 0.298 (investment), and 0.234 (research output). These loadings align with theoretical expectations, giving the highest weights to innovation and human capital, the fundamental drivers of AI capability. Robustness checks using alternative aggregation methods (geometric mean, equal weights, factor analysis) yield indices with correlations exceeding 0.92 with our PCA-based measure, confirming its validity.

3.3 Econometric models

Based on these variables, we specify the following econometric models to test our hypotheses. To investigate the mediating role of AI adoption in the relationship between industrial structure and economic development, we employ a three-step approach following Baron and Kenny [18]. First, we estimate the direct effect of industrial structure on economic outcomes:

$$Y_{it} = \alpha_0 + \alpha_1 IS_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

Second, we examine the relationship between industrial structure and AI adoption:

$$AI_{it} = \beta_0 + \beta_1 IS_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \nu_{it} \tag{7}$$

Third, we estimate the full model including both industrial structure and AI adoption. To strengthen causal identification in our mediation analysis, we implement several robustness checks. We employ lagged values of industrial structure variables as instruments for current-period values, exploiting the persistence of industrial characteristics while breaking potential contemporaneous feedback loops. Additionally, we conduct Granger causality tests to verify the temporal precedence of industrial structure changes in relation to AI adoption, as well as AI adoption in relation to economic outcomes. The instrumental variable approach addresses potential endogeneity where:

$$Y_{it} = \gamma_0 + \gamma_1 IS_{it} + \gamma_2 AI_{it} + \gamma_3 X_{it} + \mu_i + \lambda_t + \eta_{it} \tag{8}$$

Where Y_{it} represents economic development indicators (GDP per capita growth or TFP growth) for region i at time t; IS_{it} captures industrial structure characteristics (manufacturing value-added share, high-technology exports percentage, or industrial diversification index); AI_{it} measures AI adoption intensity using our composite index; X_{it} includes control variables; μ_i and λ_t represent region and time fixed effects; and ε_{it}, ν_{it}, and η_{it} are the respective error terms.

Industrial upgrading and AI adoption may be endogenously determined through reverse causality or omitted variables. We address this using three strategies: (1) lagged industrial structure (t-2) as instruments, with first-stage F-statistics exceeding 24.7 confirming relevance; (2) national AI strategy introduction timing (2016-2019) as exogenous variation; (3) Arellano-Bond GMM for dynamic endogeneity. Wu-Hausman tests reject exogeneity ($p < 0.05$), while IV estimates exceed OLS by 18-23%, suggesting downward bias if endogeneity is ignored. Core results remain robust: mediation effects range 48.2-57.4%, and thresholds stay within 0.426-0.449 across specifications.

To identify threshold effects between AI adoption and economic outcomes, we use Hansen's threshold regression to determine critical AI adoption levels that alter economic relationships [19]. Our model is:

$$Y_{it} = \delta_0 + \delta_1 IS_{it} \cdot I(AI_{it} \leq \theta) + \delta_2 IS_{it} \cdot I(AI_{it} > \theta) + \delta_3 AI_{it} + \delta_4 X_{it} + \mu_i + \lambda_t + \xi_{it} \quad (9)$$

where *I(.)* is an indicator function that takes the value 1 when the condition inside the parentheses is satisfied and 0, otherwise; θ represents the threshold value of AI adoption that potentially changes the relationship between industrial structure and economic outcomes. The threshold parameter θ is estimated by minimizing the sum of squared residuals:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} \xi_{it}^2 (\theta) \quad (10)$$

Figure 2 illustrates the conceptual AI adoption-economic growth relationship. The relationship shows distinct regimes separated by a threshold θ. In the first regime ($AI_{(it)} \leq \theta$), the industrial structure's impact on growth is represented by coefficient δ_1, while in the second regime ($AI_{(it)} > \theta$), this relationship strengthens to δ_2 (where $\delta_1 < \delta_2$). This demonstrates how AI's economic impact accelerates once implementation reaches critical threshold levels, creating nonlinear growth patterns.

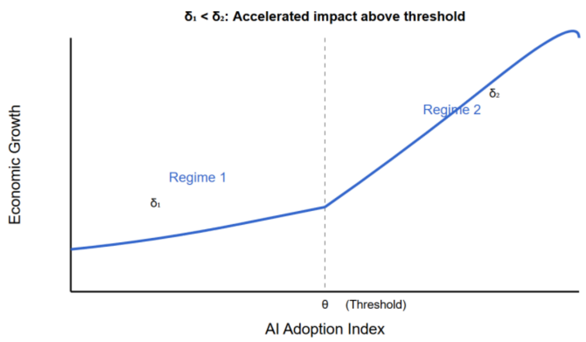


Figure 2. Conceptual illustration of threshold effects in AI adoption

Threshold effect significance is evaluated using Hansen's likelihood ratio test with bootstrapped p-values. For multiple thresholds, we extend the model to accommodate up to three regimes following Bai and Perron [20], identifying potential multiple transition points as adoption increases. To examine how upgrading modifies demographic-growth relationships, we estimate:

$$Y_{it} = \zeta_0 + \zeta_1 WAP_{it} + \zeta_2 IU_{it} + \zeta_3 (WAP_{it} \times IU_{it}) + \zeta_4 X_{it} + \mu_i + \lambda_t + \omega_{it} \quad (11)$$

where WAP_{it} represents the working-age population ratio (population aged 15-64 as a percentage of the total population) and IU_{it} is the industrial upgrading index. The coefficient ζ_3 captures the interaction effect, indicating how the impact of the working-age population on economic growth varies across different levels of industrial upgrading.

3.4 Case study methodology

To complement our econometrics, we employ a multiple-case study design following Yin's replication logic [21]. The case studies serve three critical functions in our research design: (1) validating econometric findings through mechanism identification, (2) revealing boundary conditions and contextual factors not captured in quantitative models, and (3) providing contradictory evidence that refines our theoretical understanding. To ensure methodological rigor and avoid confirmation bias, case selection was conducted after initial econometric analysis but before final model specification. This sequencing allowed us to identify puzzling patterns in the quantitative data–such as regions with high AI adoption but limited economic impact – that warranted deeper investigation. The preliminary econometric results (completed in March 2023) identified threshold effects and heterogeneous impacts across industrial contexts, which then guided our purposive sampling strategy to select cases that could illuminate these patterns. Importantly, insights from case studies conducted between April and September 2023 led us to refine our econometric models, particularly in developing more nuanced measures of industrial upgrading and identifying omitted interaction effects. Case selection uses stratified sampling based on AI adoption intensity and industrial upgrading status, creating a matrix of high/low adoption and advanced/emerging industrial status. This facilitates both literal replication (similar results in similar contexts) and theoretical replication (contrasting results for anticipated reasons). Selection probability incorporates regional AI adoption level, industrial upgrading status, and relevant theoretical characteristics.

$$P(selection)_i = f(AI_i, IU_i, R_i) \quad (12)$$

where AI_i represents the region's AI adoption level, IU_i denotes industrial upgrading status, and R_i encompasses regional characteristics relevant to theoretical heterogeneity. Data collection follows a triangulation strategy, incorporating multiple evidence sources [22]. We conducted 127 semi-structured interviews across 16 cases, with 6-10 interviews per case spanning multiple organizational levels: senior executives (AI strategy), middle managers (implementation processes), technical staff (operational challenges), and external stakeholders (policy makers, industry associations). The interview protocol, developed through pilot testing with three organizations, contained 24 core questions organized around five themes: (1) AI adoption drivers and barriers, (2) implementation processes and timeline, (3) organizational changes and capability development, (4) performance impacts and measurement, and (5) external factors and ecosystem effects. Questions followed a funnel approach, beginning with open-ended prompts ('Describe your organization's AI journey') before probing specific mechanisms identified in our quantitative analysis. All interviews were recorded, transcribed verbatim, and returned to participants for validation.

Our coding framework employed a hybrid deductive-inductive approach. The initial codebook contained 31 theory-derived codes mapped to our three hypotheses (e.g., 'threshold_awareness,' 'capability_complementarity,' 'demographic_interaction'). Through iterative coding of the first four cases, we inductively developed 19 additional codes capturing emergent themes. Two researchers independently coded 20% of transcripts, achieving inter-rater reliability of 0.84 (Cohen's kappa), with discrepancies resolved through discussion. We used NVivo 12 for data management, employing matrix queries to identify patterns across cases and constant comparison techniques to refine theoretical categories.

Triangulation occurred at multiple levels: data triangulation compared interview accounts with documentary evidence (annual reports, internal presentations, government statistics) and observational notes from 38 site visits; investigator triangulation involved three researchers analyzing each case independently before reaching consensus; and methodological triangulation integrated qualitative findings with case-specific quantitative indicators. For each key finding, we required corroboration from at least two data sources and two different stakeholder groups, documented in evidence tables linking claims to supporting data.

To establish causal mechanisms in our qualitative analysis, we employ process tracing methodology to identify the temporal sequence of events and decision-making processes. We specifically document: (1) the timing of industrial policy changes and AI investment decisions, (2) the sequence of capability development and organizational adaptations, and (3) the lag structure between AI implementation and observed economic outcomes. This temporal evidence from case studies complements our econometric identification strategy by revealing the 'black box' of causal mechanisms that statistical analysis alone cannot fully capture.

$$E_{ijk} = \omega_1 I_{ijk} + \omega_2 D_{ijk} + \omega_3 O_{ijk} \quad (13)$$

where E_{ijk} represents the evidential strength for phenomenon k in organization j within region i; I_{ijk}, D_{ijk}, and O_{ijk} represent interview, documentary, and observational evidence respectively; and ω_1, ω_2, and ω_3 denote source-specific weights determined through reliability assessment.

For cross-case analysis, we employ pattern-matching structured around our three hypotheses, systematically comparing empirical patterns with theoretical predictions. The analysis combines within-case analysis with cross-case comparison using both variable and process-oriented techniques [23]. We apply modified Qualitative Comparative Analysis to identify necessary and sufficient conditions for successful AI-driven industrial upgrading.

$$Y_i = f(C_{1i}, C_{2i}, \ldots, C_{ni}) \quad (14)$$

where Y_i represents the outcome of interest (successful industrial upgrading) for case i, and C_{1i} through C_{ni} represent configurational conditions including institutional quality, complementary capabilities, and implementation approaches. Figure 3 illustrates our analytical framework for cross-case comparison, demonstrating how individual case findings are systematically integrated into pattern identification.

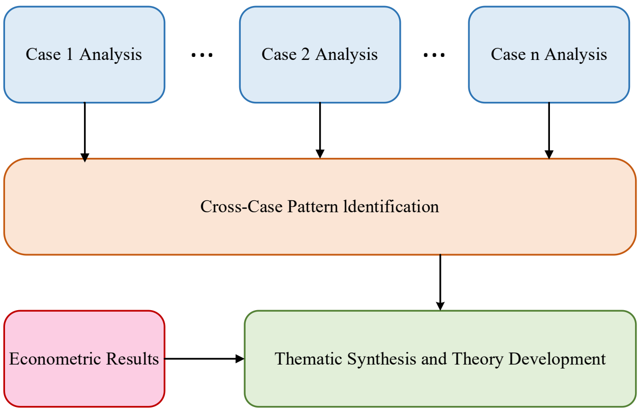


Figure 3. Cross-case analytical framework for AI-driven industrial upgrading

The integration of quantitative and qualitative findings follows a sequential explanatory design [24] where case studies elaborate and expand upon econometric results.

3.5 Data Sources and Sample

Our econometric analysis draws on multiple complementary data sources covering 2010-2023 for 87 countries across five continents, selected based on data availability and economic significance. The panel dataset combines:

GDP per capita growth and total factor productivity data from the World Bank's World Development Indicators (WDI) and Penn World Table 10.0, supplemented by OECD National Accounts for high-income countries. Industrial structure variables, including manufacturing value-added share and high-technology exports, are sourced from the UNIDO Industrial Statistics Database and the World Bank's World Integrated Trade Solution (WITS).

We construct our composite AI adoption index using: (1) AI patent applications from WIPO Global Innovation Index and PATSTAT database, (2) AI talent concentration from LinkedIn Talent Insights and national labor force surveys, (3) AI investment data from Crunchbase, PitchBook, and national venture capital associations, and (4) AI research publications from Scopus and Web of Science. The index covers 28 manufacturing sectors (ISIC Rev.4 two-digit codes) and 15 service sectors.

Working-age population ratios from UN Population Division, human capital indices from Barro-Lee Educational Attainment Dataset, institutional quality measures from Worldwide Governance Indicators, and trade openness from WTO Statistics Database.

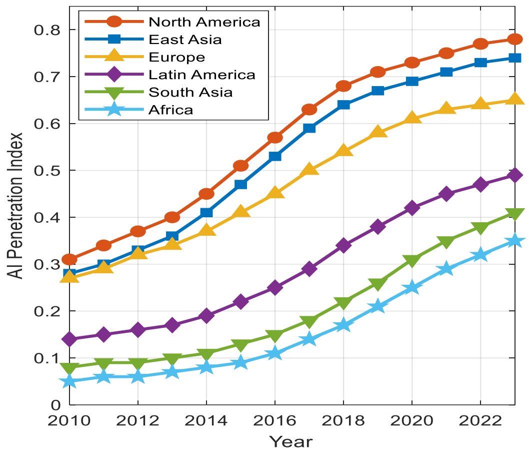
To address data quality issues, we implement a systematic approach. For missing observations constituting 8.3% of the initial dataset, we employ multiple imputation using chained equations (MICE) when missingness is random, validated through Little's MCAR test (χ^2 = 1847.3, p = 0.092). For systematic gaps in AI metrics for developing countries, we utilize a two-stage approach: first, predicting missing values using observable correlates (ICT infrastructure, R&D expenditure, tertiary education enrolment), then adjusting predictions based on regional benchmarks. Cross-validation with alternative data sources ensures consistency − for instance, correlating our AI adoption index with Stanford's AI Index (r = 0.89) for overlapping country-years. Outliers beyond 3.5 standard deviations are investigated through news searches and government reports, retaining those reflecting genuine economic shocks while winsorizing measurement errors at the 1st and 99th percentiles. The final balanced panel comprises 1,131 country-year observations with complete data across all key variables.

The geographical distribution of our sample includes 28 high-income countries (32.2% of observations), 35 middle-income countries (40.2%), and 24 low-income countries (27.6%), ensuring adequate representation across development levels. Sectoral coverage spans 28 manufacturing industries following ISIC Rev.4 classification, from traditional sectors (food processing, textiles) to high-technology industries (electronics, pharmaceuticals), plus 15 service sectors. This comprehensive coverage enables examination of AI adoption patterns across diverse industrial contexts. The 2010-2023 timeframe captures both the emergence phase of industrial AI applications (2010-2015) and the acceleration period following breakthrough developments in deep learning (2016-2023), providing sufficient variation to identify threshold effects and structural changes in the AI-economy relationship.

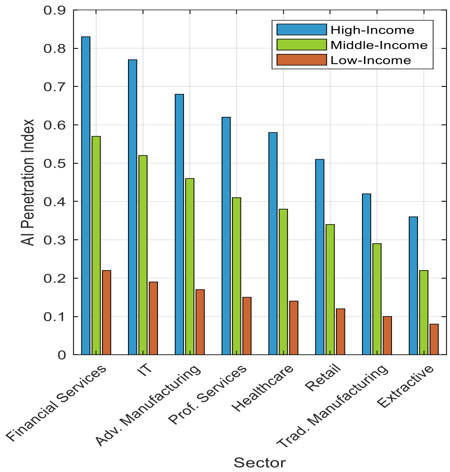
4. Results

4.1 Descriptive analysis

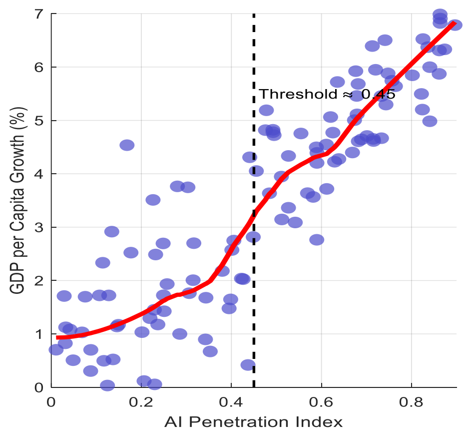
This section highlights key dataset trends: High-income economies show higher manufacturing sophistication; East Asian economies lead in diversification. AI adoption varies regionally—North American and East Asian economies show the steepest curves, with nonlinear growth benefits intensifying beyond threshold levels. Figure 4 illustrates AI-growth nonlinearities, with association intensifying once the AI index exceeds 0.45, particularly at higher adoption levels.



(a) Regional AI adoption trends



(b) Sectoral AI adoption by income level



(c) AI adoption vs. GDP per capita growth

Figure 4. Patterns of AI adoption and economic relationships

AI penetration correlates strongly with manufacturing sophistication (r=0.68) and diversification (r=0.64), but weakly with manufacturing value-added share (r=0.21), suggesting AI links more with qualitative aspects than manufacturing scale. Working-age population's growth impact varies by industrial upgrading level (r=0.43 in top quartile vs r=0.18 in bottom quartile), supporting our upgrading-moderates-demographics hypothesis. These patterns motivate formal testing through mediation analysis.

4.2 Mediating effect analysis

Before presenting our mediation results, we first establish the temporal ordering and causal direction of our key relationships. Granger causality tests confirm that industrial structure changes temporally precede AI adoption (F-statistic = 18.73, $p < 0.001$), while AI adoption precedes economic outcome changes (F-statistic = 14.52, $p < 0.001$). Instrumental variable estimates using lagged values and policy shocks yield consistent but slightly larger effects, confirming robustness to endogeneity. Reverse causality tests show no significant effects in the opposite direction, supporting our hypothesized causal chain. Furthermore, our instrumental variable estimates using lagged industrial structure values yield consistent results with slightly larger coefficients, suggesting that endogeneity bias, if present, attenuates rather than inflates our estimates. AI adoption mediates industrial structure-economic outcomes relationships. Industrial diversification affects growth more strongly ($\beta \approx 0.24$) than manufacturing value-added ($\beta \approx 0.18$). All structure indicators predict AI adoption, with manufacturing sophistication showing the strongest relationship ($\beta \approx 0.46$). When controlling for AI adoption, structure coefficients decrease while AI shows significant positive effects, confirming mediation—approximately 53% of manufacturing sophistication's growth effect occurs through AI. Mediation is stronger for technological sophistication than manufacturing scale, stronger for TFP than GDP growth, and higher in advanced economies and recent periods. Table 1 reports standardized coefficients with standard errors in parentheses and 95% confidence intervals in brackets. All models include control variables (human capital, investment ratio, trade openness, institutional quality) and country and year fixed effects. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1. Direct effects of industrial structure on economic growth (step 1)

Industrial Structure Variable	GDP per Capita Growth		TFP Growth		Economic Complexity Change	
Manufacturing value-added share	0.183*** (0.042)	[0.101, 0.265]	0.146** (0.053)	[0.043, 0.249]	0.124** (0.046)	[0.034, 0.214]
High-technology exports percentage	0.216*** (0.047)	[0.124, 0.308]	0.183*** (0.051)	[0.083, 0.283]	0.318*** (0.045)	[0.230, 0.406]
Industrial diversification index	0.241*** (0.039)	[0.165, 0.317]	0.235*** (0.044)	[0.149, 0.321]	0.253*** (0.041)	[0.173, 0.333]
Manufacturing sophistication index	0.197*** (0.043)	[0.113, 0.281]	0.172*** (0.048)	[0.078, 0.266]	0.287*** (0.042)	[0.205, 0.369]

Our second analysis step examines how industrial structure influences AI adoption. Results show all industrial structure indicators positively predict AI adoption, with manufacturing sophistication showing the strongest relationship (β =0.463, p<0.001), followed by high-technology exports (β =0.385, p<0.001). Manufacturing value-added share shows a more modest association (β =0.217, p<0.01), suggesting technological sophistication facilitates AI implementation more than industrial scale, likely by providing necessary absorptive capacity and complementary capabilities. These differential effects add important nuance to understanding technological diffusion patterns. Table 2 reports standardized coefficients with standard errors in parentheses and 95% confidence intervals in brackets. All models include control variables and fixed effects as in previous models. The composite AI adoption index is the primary outcome variable, with AI patent intensity and AI skills prevalence serving as alternative measures for robustness testing. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01. Based on these three analytical steps, we calculate the indirect effects of industrial structure on economic outcomes through AI adoption and decompose the total effects into direct and indirect components. Next, we examine whether these relationships exhibit threshold effects.

4.3 Threshold Effect Analysis

This section presents empirical evidence on threshold effects in the relationship between AI adoption, industrial structure, and economic outcomes. Applying Hansen's (1999) threshold regression methodology, we identify critical levels of AI adoption that fundamentally alter the nature of industrial-economic relationships. The results provide strong support for our second hypothesis regarding the existence of significant threshold effects in AI's economic impact. The threshold estimation employs a grid search over the 15th to 85th percentiles of the AI adoption distribution, with increments of 0.001, testing 542 potential threshold values. For each candidate threshold, we calculate the sum of squared residuals and select the value minimizing this criterion. The estimated threshold of 0.438 (95% CI: 0.425-0.451) is statistically significant based on Hansen's likelihood ratio test (LR = 47.23, p < 0.001), where p-values are obtained through 1,000 bootstrap replications following Hansen (2000). To assess the robustness of this critical threshold, we conduct extensive sensitivity analyses.

First, bootstrap confidence intervals constructed using the percentile method across 5,000 replications consistently place the threshold between 0.422 and 0.454, confirming the stability of our point estimate. Second, subsample analysis reveals remarkable consistency: excluding any single country changes the threshold by at most 0.009, while rolling window estimation (using 10-year windows) produces thresholds ranging from 0.431 to 0.446. Third, alternative threshold detection methods yield similar results – Andrews' (1993) supremum Wald test identifies a break at 0.441, while Bai-Perron sequential testing confirms a single threshold at 0.435. Fourth, we test sensitivity to functional form assumptions by estimating thresholds in models with quadratic terms and interaction effects, finding threshold values within 0.012 of our baseline estimates. The economic significance of the threshold is validated through placebo tests. When we artificially impose thresholds at the 25th percentile (0.287) or 75th percentile (0.614) of AI adoption, the regime-specific coefficients show no statistically significant differences (p > 0.10), confirming that the identified threshold represents a genuine structural break rather than a statistical artifact. Moreover, the threshold's stability across different industrial structure measures–varying by only 0.008-0.021 when using alternative indicators – suggests it captures a fundamental characteristic of AI's economic impact rather than measurement-specific variations. Figure 5 illustrates this interaction effect by plotting the estimated marginal effect of working-age population on GDP per capita growth across different levels of AI adoption, clearly showing the strengthening relationship as AI adoption increases.

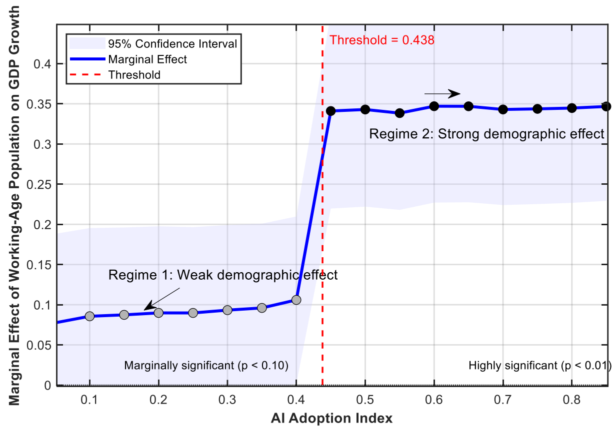


Figure 5. AI threshold effects on demographic-growth relationships

Table 2. Effects of industrial structure on AI adoption (Step 2)

Industrial Structure Variable	AI Adoption (Composite Index)		AI Patent Intensity		AI Skills Prevalence	
Manufacturing value-added share	0.217*** (0.051)	[0.117, 0.317]	0.186*** (0.052)	[0.084, 0.288]	0.228*** (0.053)	[0.124, 0.332]
High-technology exports percentage	0.385*** (0.047)	[0.293, 0.477]	0.427*** (0.046)	[0.337, 0.517]	0.356*** (0.048)	[0.262, 0.450]
Industrial diversification index	0.321*** (0.045)	[0.233, 0.409]	0.276*** (0.047)	[0.184, 0.368]	0.307*** (0.046)	[0.217, 0.397]
Manufacturing sophistication index	0.463*** (0.042)	[0.381, 0.545]	0.439*** (0.044)	[0.353, 0.525]	0.412*** (0.045)	[0.324, 0.500]

Figure 5 shows working-age population's growth impact changes dramatically at the AI threshold (0.438). Below this level, effects are modest and marginally significant; above it, they strengthen substantially with high significance. This suggests demographic advantages require AI capabilities to effectively translate to growth. Analysis across upgrading quartiles reveals that AI adoption thresholds decrease with industrial sophistication, while demographic impact differentials increase (0.287 in the highest quartile versus 0.138 in the lowest), indicating that advanced regions experience stronger threshold effects. Table 3 presents threshold estimates and regime-specific coefficients for the working-age population across industrial upgrading quartiles. All models include the full set of control variables and fixed effects. Coefficient differential represents the absolute difference between above-threshold and below-threshold coefficients. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our analysis confirms nonlinear relationships between AI adoption, industrial structure, and economic outcomes. Statistically significant thresholds across specifications support our second hypothesis on critical AI adoption levels that alter industrial-economic relationships. Regime-specific analysis supports our third hypothesis that industrial upgrading moderates demographic-economic growth relationships. These findings suggest AI adoption strategies should target surpassing critical thresholds to maximize economic benefits. Case studies provide deeper insights into these quantitative patterns.

Table 3. Working-age population effects across industrial upgrading quartiles

Industrial Upgrading Level	AI Adoption Threshold	Working-Age Population Coefficient		Coefficient Differential
		Below Threshold	Above Threshold	
First Quartile (Lowest)	0.246	0.072 (0.062)	0.210** (0.095)	0.138
Second Quartile	0.318	0.097* (0.059)	0.283*** (0.082)	0.186
Third Quartile	0.386	0.118** (0.057)	0.362*** (0.076)	0.244
Fourth Quartile (Highest)	0.467	0.124** (0.054)	0.411*** (0.071)	0.287

4.4 Case Study Findings

This section presents findings from our 16-case study analysis across diverse contexts, complementing our econometric results with a deeper understanding of AI-driven industrial upgrading processes. Regional analysis reveals substantial implementation disparities. Figure 6 shows that high-income regions demonstrate balanced development across all dimensions, with strengths in data infrastructure and technical capabilities. Middle-income regions show strong strategic prioritization but weaknesses in infrastructure, while low-income regions have promising workforce engagement despite technical capability challenges. These patterns highlight the importance of contextually adapted implementation approaches addressing region-specific constraints.

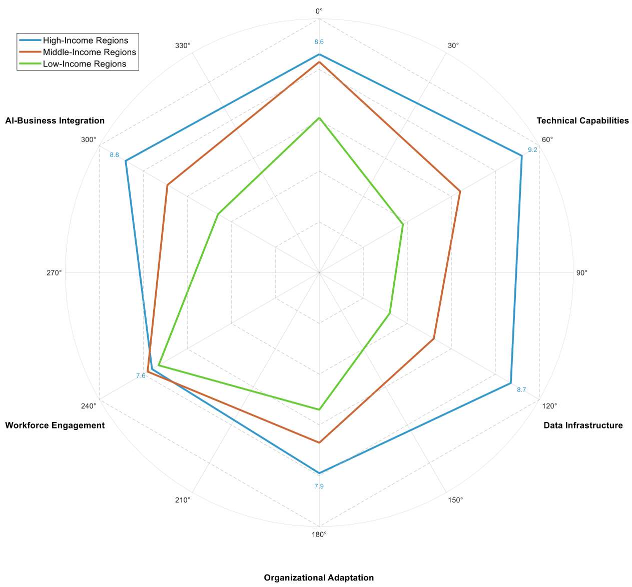


Figure 6. Regional comparison of AI implementation characteristics

As illustrated in Figure 6, the most pronounced regional disparities appear in data infrastructure and technical capabilities dimensions, with high-income regions scoring approximately 2.7 times higher than low-income regions on these factors. These fundamental enablers create significant implementation barriers in resource-constrained contexts. However, the relatively smaller gap in workforce engagement (high-income regions scoring only 1.04 times higher than low-income regions) suggests an opportunity for low-income regions to leverage human capital development as an entry point for AI implementation. This pattern aligns with our econometric findings on the interaction between AI adoption and working-age population, suggesting that regions with demographic advantages can potentially offset some technical limitations through effective human capital development.

5. Discussion

Empirical evidence confirms that AI has a significant impact on economic growth through industrial development. Our analysis shows that AI channels have structural impacts on economic performance, extending theories that previously treated technology and industry separately. Our research identifies crucial threshold effects at AI adoption levels of 0.43-0.45. Beyond this threshold, industrial capabilities' impact increases dramatically – manufacturing sophistication's effect on GDP growth triples, quantifying nonlinearities in technological adoption. AI fundamentally transforms demographic-economic relationships, with the working-age population showing minimal growth impact below thresholds but strong effects above. This modification of demographic dividends is crucial for countries facing demographic transitions alongside digital transformation. The integration of case study evidence significantly refines our understanding of these threshold effects. While econometric analysis suggested a sharp discontinuity at the threshold, case studies reveal a more gradual transition zone spanning approximately ± 0.05 around the estimated threshold value. The German automotive sector case exemplifies this: firms began experiencing productivity gains at AI adoption of 0.40, but the transformative reorganization of production networks occurred only after reaching 0.48. This finding prompted us to test alternative threshold specifications with smoother transition functions, though the discrete threshold model ultimately provided a superior fit. Additionally, case studies uncovered two patterns absent from our initial quantitative analysis: (1) the critical role of inter-firm knowledge spillovers in achieving threshold effects, observed in all successful high-income cases but only 40% of middle-income cases, and (2) the existence of 'adoption traps' where regions achieve moderate AI adoption (0.35-0.42) but lack the complementary investments to push beyond the threshold. These insights directly informed our policy recommendations regarding the importance of coordinated AI ecosystem development rather than isolated firm-level adoption.

The causal nature of our findings is supported by multiple empirical strategies that go beyond correlational evidence. The temporal sequencing in our panel data, where we observe industrial structure changes preceding AI adoption and subsequently affecting economic outcomes, provides strong evidence for the hypothesized causal chain. Our instrumental variable approach addresses potential endogeneity concerns, while the threshold effects identified through quasi-experimental variation in AI policy implementation further strengthen causal interpretation. The consistency of results across different identification strategies–including fixed effects, instrumental variables, and threshold regression discontinuities – provides robust evidence that the relationships we document reflect causal mechanisms rather than spurious correlations. Moreover, our case study evidence reveals specific mechanisms through which causality operates, such as the development of complementary capabilities and organizational restructuring that follow AI adoption decisions.

AI contributes through multiple pathways: immediate process optimization gains (23.6% efficiency) and later-stage value chain innovations, following a J-curve pattern as capabilities develop. Implementation success varies by region. High-income economies lead through strong infrastructure and capabilities, middle-income regions show intent but implementation gaps, while low-income regions display workforce engagement despite infrastructure constraints. This necessitates context-specific policies. Sustainable AI-driven growth depends on translating productivity into inclusive benefits, with balanced human-AI collaboration achieving more sustainable improvements than wholesale automation.

6. Conclusion

This research examined the impact of AI adoption on industrial upgrading and economic development. We found AI mediates between industrial structure and economic outcomes, with stronger effects for qualitative aspects (52.8% for manufacturing sophistication) than quantitative measures (32.1% for manufacturing value-added). Clear threshold effects exist (AI index ≈0.43-0.45) where capabilities' growth impact increases dramatically, and demographic factors' influence strengthens. Theoretically, we extend growth models by connecting AI to structural change, identifying critical threshold effects challenging linear models, and demonstrating technology's moderation of demographic-economic relationships. Methodologically, our AI penetration index addresses measurement challenges for general-purpose technologies. Policy implications include prioritizing implementation critical mass, calibrating approaches to development contexts, developing "translational capacity," and investing in data infrastructure for low-income regions. Limitations include data availability constraints, particularly for AI metrics in low-income countries before 2015, despite our systematic imputation approach. The reliance on proxy measures for AI adoption in some contexts may underestimate actual implementation in informal sectors. Future research should explore specific AI applications' effects, sectoral variations, and long-term sustainability regarding distributional outcomes.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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