The Impact of the Digital Economy on Urban Industrial Structure Upgrading: An Empirical Analysis Based on Panel Data from 287 Cities Across China

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Abstract: Analyzing panel data from 287 Chinese cities (2011-2022), this study constructs a multi-dimensional digital economy index covering infrastructure, industrialization scale, and financial inclusion. Employing two-way fixed effects and mediation models, results show digital economy significantly drives industrial upgrading with regional disparities (strongest in eastern/central areas), scale heterogeneity (greater impact on small/medium cities), and dual mechanisms via direct effects and AI capability enhancement.

1. Introduction

China's economy has shifted from rapid growth to high-quality development, prioritizing efficiency, innovation, and sustainability. The 20th CPC Congress highlighted industrial-digital integration as central to green growth. Driven by IT, the digital economy—marked by scalability and sustainability—accounts for 85% of growth through industrial digitization (CAICT, 2022), transforming sectors via IoT, AI, and blockchain. While enhancing productivity and urban structures, challenges include regional disparities and innovation gaps. This study addresses underexplored aspects: (1) developing a multidimensional digital economy index (internet penetration, digital finance) to assess urban-level industrial upgrading; (2) identifying AI as a key mediator in the "digital economy-AI-upgrading" mechanism; (3) revealing stronger impacts in eastern/central China and smaller cities, informing region-specific policies. The research advances theoretical frameworks and practical strategies for sustainable economic restructuring.

2. Literature Review

2.1 Research on the Digital Economy

The digital economy, first conceptualized by Don Tapscott in the 1990s, has evolved through scholarly refinements emphasizing its foundational technologies over purely economic dimensions. Digital technology, as its cornerstone, drives industrial advancements and cost efficiencies. Lane (1999) highlighted transformative impacts of information and communication technologies (ICT) on products and services [1]. Afuah (2003) noted that ICT applications reduce transaction and production costs through "synergy" and "efficiency," contingent on firm-specific traits [2]. Dewan and Kraemer (2000) further validated ICT's positive correlation with productivity in developed nations using cross-country data [3].Collectively, these studies underscore technology, governance, and regional strategies as critical to harnessing the digital economy's transformative potential.

2.2 Research on Industrial Structure Upgrading

Industrial structure upgrading denotes the coordinated development and qualitative transformation of industries through optimized resource allocation and technological-economic adjustments, aiming to align sectoral composition, technology, and demand for enhanced macroeconomic efficiency. It involves shifts from primary/secondary to tertiary sectors and transitions from labor-intensive to capital/technology-intensive industries [4].

Humphrey categorized influencing factors into local (firm collaboration, institutional roles, innovation) and global (cross-border producer-buyer interactions) dimensions [5]. Hotopp

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associated trade structure scale (concentration) and scope (diversity) changes with upgrading patterns in CEECs [6]. Ernst emphasized technological innovation as the core driver, supported by human capital and policy frameworks [7]· Rin & Hellmann stressed financial services' catalytic role in resource allocation and regional technological convergence, while digital economy expansion broadens upgrading scopes [8]·

2.3 Research on the Impact of the Digital Economy on Industrial Structure Upgrading

The Padey-Clark theorem elucidates how technological innovation drives industrial advancement, offering a theoretical basis for the digital economy's role in industrial upgrading. Existing research focuses on three dimensions: mechanisms, nonlinear effects, and spatial spillovers.Internationally, Pradhan (2019) emphasized resource optimization and new industry creation, while Acemoglu (2018) highlighted labor structure upskilling as a driver .Collectively, these works provide multidimensional insights into the digital economy's transformative mechanisms, spatial interactions, and nonlinear characteristics in industrial development.

3. Theoretical Analysis and Research Hypotheses

3.1 The Mechanisms through which the Digital Economy Drives Industrial Structure Upgrading

The digital economy drives industrial transformation through digitalization, innovation, and integration. Technologies like big data, IoT, and AI reduce information asymmetry, lower transaction costs, and enhance resource allocation efficiency, shifting growth from efficiency-driven to innovation-driven models. Digital industrialization converts knowledge into standardized data, fostering techno-economic activities and industrial clusters, while industrial digitization enables intelligent production and operational optimization. These processes collectively support balanced industrial chain development and structural upgrading. Hypothesis 1 is proposed accordingly.

H1: The digital economy exerts a positive driving effect on industrial structure upgrading.

3.2 The Mediating Effect of Artificial Intelligence in Promoting Industrial Structure Upgrading

In the digital economy, AI drives industrial transformation by reshaping capital-labor allocation. Industrial robots in Chinese manufacturing reconfigure capital structures and economic patterns, while AI-induced labor effects reshape industrial landscapes. Technological advances (robotics, IoT, cloud computing) enhance production intelligence, reduce uncertainties, and boost labor productivity, strengthening inter-industry synergy and structural rationalization.As key technological capital, AI integrates with manufacturing to optimize resources, elevate productivity, and accelerate high-tech sectors. Emerging AI-related industries (machine learning, smart terminals) and pervasive applications (industrial robots, cloud services) inject vitality into advanced manufacturing and modern services, promoting dual-sector sophistication and economic-structural optimization. This supports Hypothesis 2.

H2: The Digital Economy Drives Advancements in Artificial Intelligence, Subsequently Facilitating Industrial Structure Upgrading.

4. Research Design

4.1 Data Sources

This study employs 2011–2022 panel data from 287 Chinese cities, sourced from statistical yearbooks, socioeconomic databases, and PKU's Digital Finance Index. Missing values used moving averages; non-ratio variables were log-transformed. Cities lacking key variables were excluded to ensure robustness.

4.1.1 Key Explanatory Variable: Digital Economy Development Index (DEI)

This study, based on Zhao Tao et al. (2020), measures digital economy development through internet penetration and digital finance indicators, employing PCA to construct the DEI composite index.

4.1.2 Mediating Variable: Level of Artificial Intelligence (Robot)

This study examines AI development in China through industrial robots, using IFR-reported sectoral installation data. Applying the Bartik instrumental variable method, it constructs city-level industrial robot density ("Robot") as an AI proxy. By aligning national/international industry classifications and calculating sector-city weights from a benchmark year, Robot reflects AI application levels through standardized installation metrics.

$$Robot_{jt} = \sum_{s=1}^{S} \frac{E_{\ sjt}}{E_{\ jt}} \bullet \frac{Robot_{st}}{E_{\ st}} \tag{1}$$

In this context, S represents the various industries, $Robot_{jt}$ denotes the number of industrial robots installed in city j during year t, $Robot_{st}$ refers to the number of industrial robots installed in industry s during year t, $E_{\ sjt}$ indicates the number of employees in industry s in city j during year t,$E_{\ jt}$ represents the total number of employees in city j during year t, and $E_{\ st}$ denotes the total number of employees in industry s during year t.

4.1.3 Control Variables

This study employs fdi (foreign capital/GDP), gdpp (per capita GDP), gov, lnedu (ln[students/population]), tec (science expenditure ratio), and fin (loan balance) as controls. Higher gdpp drives industrial upgrading through tech demand, while lnedu enhances innovation capacity. Government intervention, human capital, technological inputs, and financial development collectively shape regional industrial transformation dynamics.

4.2 Model Specification

4.2.1 Benchmark Regression Model

To empirically analyze the impact of digital economy development on urban industrial structure upgrading, this study constructs the following two-way fixed effects model:

$$ISU_{\ it} = \alpha_0 + \alpha_1 \mathrm{DEI}_{\ it} + \alpha_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

In this model, i represents the city, t denotes the year, ISU_{it} refers to the industrial structure upgrading index, $\mathrm{DEI}_{\ it}$ represents the level of digital economy development, $Control_{it}$ denotes the control variables, μ_i indicates the individual fixed effects, δ_t represents the time fixed effects, and ε_it is the random disturbance term.

4.2.2 Mediation Effect Model

To test Hypothesis H2, this study employs a stepwise regression approach, incorporating Equation (1), to establish the following mediation effect model:

$$Robot_{\ it} = \beta_0 + \beta_1 DEI_{\ it} + \beta_{\ 2} Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

$$ISU_{\ it} = \delta_0 + \delta_1 DEI_{\ it} + \delta_2 Robot_{\ it} + \delta_3 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

Here, $Robot_{\ it}$ represents the regional artificial intelligence level of city i at time t, with other variables carrying the same meaning as those in Equation (4).

5. Empirical Results Analysis

5.1 Analysis of Baseline Regression Results and Robustness Checks

5.1.1 Analysis of the Benchmark Regression Results

This study employs panel data analysis using OLS, FE, and RE models. The Hausman test ($p<0.05$) favored the fixed effects approach. A two-way FE model addresses time-invariant individual heterogeneity in examining the digital economy's impact on industrial upgrading. Results confirm Hypothesis 1: digital economy significantly promotes urban industrial restructuring. Government intervention shows negative correlation with upgrading due to resource misallocation, reduced innovation incentives, and policy-market misalignment. Conversely, economic development level, human capital, technological progress, and financial development positively drive structural upgrading. The two-way FE model demonstrates improved goodness-of-fit when controlling for time and individual effects. Findings emphasize the need to balance government intervention with market-driven resource allocation while leveraging digital transformation as a catalyst for industrial advancement.

5.1.2 Robustness Test

(1) Substitution of the Key Explanatory Variables

To address endogeneity, we use one-period lagged digital economy indicators. Results show the lagged coefficient remains significantly positive (5% level) with comparable magnitude to baseline, confirming effect persistence while mitigating reverse causality. Slightly weaker significance suggests moderate time decay in digital economy's upgrading effects.

(2) Substitution of the Dependent Variable

Replacing dependent variables with lagged industrial upgrading indicators maintains the digital economy's strong positive impact (coefficient=0.1009, $p<0.01$), verifying stable temporal relationships and baseline reliability through endogeneity control. Parameter consistency reinforces result robustness.

(3) Exclusion of year and municipalities directly under the central government

Excluding 2020-2022 data (COVID-19) and four centrally-administered municipalities preserves digital economy's significant positive effect (90% confidence level), with coefficients matching baseline. Dual robustness checks confirm conclusion stability.

The results from the three models indicate that the robustness checks are consistent with the baseline regression results, confirming the robustness and reliability of the findings.

5.2 Mediation Effect Analysis

This study examines how the digital economy promotes urban industrial upgrading via artificial intelligence (AI), using robotics adoption as an AI proxy in a mediation model. Results show the digital economy's total effect on industrial upgrading is 0.101** ($p<0.01$). Each unit increase in digital economy development boosts AI by 1.716** ($p<0.01$). When controlling for AI, the digital economy's direct effect remains significant (0.110, $t=3.59$), while AI's marginal effect is 0.033 ($p<0.01$). Sobel test ($p=0.048$) and Bootstrap resampling (1,000 iterations) confirm significant mediation (95% CI). Findings validate AI's stable mediating role, demonstrating digital economy development enhances industrial upgrading through AI advancement, supporting Hypothesis 2.

5.3 Analysis of Regional Heterogeneity

5.3.1 Urban Regional Heterogeneity

The study divided China into Eastern, Central, and Western regions for reanalysis. In the East, digital economy development showed a 0.0755 coefficient (1% significance), driving industrial upgrading through advanced infrastructure and market mechanisms. The Central region exhibited a stronger effect (0.1268, 5% significance) due to industrialization-stage efficiency gains from technology spillovers. Conversely, the West reported a negative coefficient (-0.1077, 10% significance), attributed to digital infrastructure gaps and resource competition with traditional industries. Regional heterogeneity extended to control variables: government intervention ("gov") positively impacted Eastern industrial innovation but suppressed market vitality in Central/Western regions through excessive administrative measures.

5.3.2 Heterogeneity in Urban Scale

This study examines how the digital economy affects industrial upgrading across cities categorized by population (≥1 million: large; others: small/medium). Regression coefficients for digital economy development are significantly positive in both groups (large: 0.0933; small/medium: 0.1471, both 1% significance), but stronger in smaller cities. Large cities' mature industrial systems limit upgrading potential, with digitalization mainly optimizing existing structures, supported by technology (tec) and finance (fin). Smaller cities benefit more from digital-driven efficiency gains during early-stage transformation, amplified by FDI's technology spillovers. Notably, government intervention (gov) negatively impacts small cities, underscoring market mechanism preservation needs. The findings highlight context-dependent pathways for digital economy-enabled industrial upgrading.

6. Conclusion

This study analyzes China's urban digital economy (2011-2022) using panel data from 287 cities. Through fixed-effects and mediation models, we find: (1) The digital economy significantly drives industrial upgrading, validated by robustness checks; (2) AI mediates 21.8% of this effect through technological diffusion; (3) Regional disparities emerge: eastern cities optimize existing structures, central cities benefit from late-industrialization advantages, while western cities face short-term suppression due to infrastructure gaps; (4) Smaller cities show higher marginal benefits from digital transformation than larger cities, with government intervention disproportionately hindering their upgrading. Market-oriented mechanisms prove crucial for structural optimization.

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