AI and Digital Economy Integration and Industrial Upgrading in China

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Abstract: Based on the integration of artificial intelligence (AI) and the development of the digital economy as well as industrial upgrading across all provinces in China during the period from 2012 to 2022 using provincial-level panel data. Using a two-way fixed-effect model combined with causal mediation analysis and quasi-experimental design to identify the three pathways through which AI-digital economy integration affects industrial structure transformation, namely, technological innovation expansion, optimisation of the workforce composition, and improvement in resource allocation efficiency. Empirical estimation shows that, on average, a one-standard deviation rise in the composite AI-Digital Economy Integration Index (ADEI) leads to an ISA score increase of 0.048 points; this effect is more pronounced in the east and after 2017 when China launched its new-generation AI development plan. Heterogeneity analysis also shows that the positive impact is significantly enhanced for provinces with national-level big data comprehensive pilot zones to demonstrate the institutional-policy synergy mechanism. The above results provide strong support for the comprehensive promotion of China's quality-driven development path. Integrated artificial intelligence digital policies show better upgrading effects than single-use technology intervention or infrastructure construction.

Keywords: Artificial Intelligence; Digital Economy; Industrial Upgrading; Total Factor Productivity; Panel Data

1. Introduction

As one of the world's major economic transformations, shifting towards a more knowledge-intensive and innovative model has been China's economy as a whole over recent years. At the core of this process is the acceleration of the merger between artificial intelligence and the digital economy to reshape manufacturing systems, optimise resource utilisation patterns and launch new modes of industrial value-creation paths. Therefore, understanding how these technological powers work together to drive industrial upgrades is currently a core research agenda for development economists and government departments that aim for high-quality development in line with their country's new five-year plan guidelines and national strategy documents related to the new generation of artificial intelligence since 2017.

Industrial Upgrade is divided into two parts: Adjustment of Industrial Structure, that is to say, promoting an optimised composition of high-tech industries in the economy; Adjustment of Allocation of Production Factors among Different Industries according to Competitiveness due to Unbalance at Present. Both will be influential factors driving China's persistent enhancement of its overall labour productivity to date, and they have an independent effect under this pattern [1]. Based on the general-purpose technology (GPT) characteristic of AI and digital infrastructure, which includes their broad application fields and potential for producing productivity-enhancing collaborative inventions, it possesses a structural transformation effect that will manifest as an adjustment cost over time after being absorbed by this change.

Although there has been numerous research on individuals, some deficiencies remain in their analyses so far. Generally speaking, most existing research on AI and the digital economy does not consider that they work together to affect industrial outcomes jointly. Furthermore, there is an incomplete understanding at the macro level of how technologies are integrated into structural transitions through transmission mechanisms. In addition, institutional contexts have not been sufficiently considered when explaining how this distribution affects these effects. There are three major issues in the current literature: firstly, is there a statistical significance of an impact on industrial structure improvement based on the comprehensive application level of artificial intelligence technology combined with the digital economy? Secondly, what mediate mechanism exists between them? Thirdly, how does spatial difference affect it after taking into account institutional policy activation?

The remainder of the paper proceeds as follows. Section 2: Summary of related theoretical and empirical studies. Theoretical Framework Section 3 builds out. Section four is the research design, data acquisition and estimation strategies. Section five presents and analyses the empirical results. Section 6 presents the policies' implications and further research directions.

2. Literature Review

Since the middle of the 2010s, scholars have been paying more attention to the interaction between AI and industrial upgrades; among these studies, many rigorous empirical researches appeared after 2020. Zou and Xiong (2023) present one of the most thorough investigations into this relationship; using panel data for 285 Chinese cities, it shows that AI development, measured by multiple indicators such as algorithm patents, resource allocation and application fields, significantly drives industrial upgrading and rationalisation. Two-way fixed-effect models using instrumental variables demonstrate that technology adoption serves as a key causal mechanism; marketisation levels and internet penetration rates serve moderating roles in increasing the effect of AI on industrial structure transformation positively.

Xia, Han and Yu (2024) extend the research at this level by demonstrating that industrial robot adoption can promote structural change through five mechanisms: productivity improvement due to automation; Capital Deepening of Intelligent Equipment Investment; upgrading of labour structure towards higher skills; inter-sectoral spillover effects; and demand pulls from changes in consumption patterns [2]. In addition, it has also been found through analysis that agriculture is less sensitive to industrial-innovate-shock events; changes in the service sector producers and consumers are more pronounced. The differences among regions at home suggest a structure of different sectors. Wang et al. (2023) investigated 938 A-share-listed manufacturing enterprises to provide a micro-foundation for the observed macro-patterns. They found that AI can enhance firm-level total factor productivity via three reinforcing paths – stimulation of technological innovation, improvement in human capital allocation, and enhancement in market matching efficiency [3]. Their difference-in-differences design, exploiting pilot zones for artificial intelligence innovation as quasi-experiments to strengthen causal attributions for this study's results.

At the provincial level, Luo, Lei and Hou (2024) found that the AI technology innovation effect on total factor productivity is mediated through changes in industrial structure upgrading and human capital accumulation; however, this relationship has statistical significance under conditions of high marketisation, strong financial development and a well-developed digital infrastructure [4]. The discovery of the conditionality is theoretically aligned with GPT theory's assertion that general-purpose technology can produce productivity gains if it meets a certain degree of complementarity investment in skills, organisational ability and institutional quality threshold conditions. The digital economy literature has grown along with that of AI; however, recent studies have focused more on their connection. Li, Zhang, and Li (2024) showed that digital economy development increases the total factor productivity of manufacturing firms via technology spillovers, improvements in resource allocation and technological progress pathways [5]; whereas Zhang, Hu, Guo, and Wang (2024) found crucial non-linear relationships among elements: The impact of digitalisation on technical change in China's high-tech sector displays an inverted-U-shaped curve, revealing diminishing returns at higher levels of digital penetration, indicating essential policy clues about the timing structure adjustment of investment [6].

Further documentation in relevant literature links the digital economy, environmental protection and industrial upgrading. Liu, Zhao, Liu, and Kong (2023) find that the digital economy accelerates manufacturing green development via channels of digital innovation, industrial upgrading, and human capital accumulation and has significant spatial heterogeneity after following a systematic east-to-west gradient [7]. Based on this study, Wang et al. (2024) have found that the digital economy's effect on residents' consumption depends on a medium-level intermediate change through changes in industrial structure upgrade; however, its impacts are larger for less developed regions such as rural China and western provinces than for more well-developed areas [8]. Lyu and other scholars have used the China national big-data comprehensive pilot zone project as a quasi-experiment to prove that digital economic policies can enhance green total-factor productivity through promotion of innovation, improvement of industrial structure adjustment, and reduction of resource waste dispersion; it also exhibits spatial spillover effects benefiting adjacent areas [9]. Although there is abundant material in this area, so far none has investigated simultaneously both aspects of AI's integration with the digital economy for an overall picture – precisely what our research aims to achieve.

3. Theoretical Framework

A three-fundamental-theory integration-based framework of the development theory was constructed based on endogenous growth theory, GPT, and SBT, respectively. According to the theory of endogenous growth, technological progress and an improvement in human capital are the main sources promoting persistent increases in productivity. Among these productive technologies for increasing productivity with high efficiency in knowledge production is artificial intelligence. The general-purpose technology theory explains why AI and digital infrastructure have a unique productive effect, not only on their own but also by enabling the creation of new products (complementary co-inventions) and causing widespread upgrade effects across industries through diffusion, leading to gradual accumulation. The Structural Transformation Theory offers a micro-foundational explanation of how differences in productivity among industries, driven by technology, lead to the reallocation of labour and capital into more productive sectors, ultimately resulting in an upgraded industrial structure.

As shown in Figure 1, the integrated framework outlines three basic paths by which AI-Digital Economy Integration supports industrial upgrading, respectively. Firstly, there is a technological innovation channel; AI and digital infrastructure together reduce the cost of R&D activities to enable more efficient knowledge acquisition, experiments and product design so as to promote innovative output as the driving force for inter-industry productivity differences and enhance access to high value-added sectors. Secondly, there is a human capital optimisation channel through which AI-digital integration changes the composition of labour demand toward people with greater cognitive ability. It also motivates households to invest in the formation of human resources, thereby promoting reallocations of labour between simple tasks and complex, task-oriented high-technology industries. The third way improves resource utilisation efficiency through digital platforms and AI-based information systems to break down the informational barrier, enabling factors to flow freely among various industrial sectors across provinces and promoting the adjustment of excess capacity products and their transfers towards more efficient application routes.

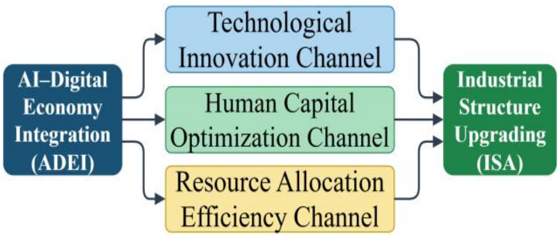

Figure 1. Digital Economy Integration and Industrial Upgrading in China

Based on this theory of the relationship among innovation activities, human resources and their quality, and efficiency in resource allocation, it can be concluded that they form an integrated development process for enterprises with innovative capabilities. AI-digital integration has a synergistic effect on economic development, which is the combination of enhancing productivity with digitalisation; therefore, its impact in terms of predicting industrial upgrading outcome performance will be higher than those of other indicators used separately to measure it. The prediction of super-additivity should be tested experimentally; therefore, it falls within the category of empirical facts in this research.

4. Research Design and Methodology

4.1 Data and Variables

Empirical research uses a balanced provincial-level panel with the range of 30 Chinese provinces from 2012 to 2022 and selects 330 province-year data points. Because of continuous missing data in critical indicators, Tibet will be omitted. Between 2012 and 2022, China consistently implemented its Eleventh to Fourteenth Five-Year Plans, propelling advanced intelligent manufacturing and artificial intelligence into a rapid growth phase. By 2025, the second digitalisation strategy (digital economy construction) was launched, and infrastructure investment continued to expand, which is expected to significantly enhance the overall economic growth and technological capabilities of the region. The provincial-level data originates from the China Statistical Yearbook, the China Science & Technology Statistical Yearbook, the National Bureau of Statistics' province-wide database, and Peking University's digital financial inclusion index data. The Industrial Structure Advancement Index (ISA) serves as the dependent variable here; it is obtained by adding up the weighted outputs of the three major industries—heavy manufacturing, light industry, and hightech—the weight factors for which are adjusted according to technological and skills-intensive ratios among these sectors. The main independent variable in this study is the Integrated Development of Artificial Intelligence and Digital Economy (hereinafter referred to as "Integrated Development"), which consists of three sub-indices based on three aspects of data: The level of innovation capability of artificial intelligence; Degree of application implementation for digital infrastructure construction; Additionally, the degree to which industrial integration is promoted is considered. Normalised subdivisions are aggregated through an entropic-weighting approach to reduce bias from subjective judgements. Controls for the following: Log per capita GDP; Capital intensity, human capital stock, foreign direct investment inflow, and government expenditure share. Table 1 shows the summaries of all variables. The significant differences in ISA and ADEI across provinces and under various times (presented in Table 1) can be seen, which provides an empirical basis for identifying it.

Table 1. Summary Statistics of Primary Variables (n=330; 30 provinces from 2012 to 2022)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	Description
ISA	330	0.681	0.124	0.421	0.947	Industrial Structure Advancement Index
ADEI	330	0.487	0.178	0.142	0.893	AI–Digital Economy Integration Index
lnGDP	330	10.847	0.612	9.231	12.104	Log per-capita GDP (CNY)
Capital	330	8.234	2.109	3.147	14.382	Capital intensity (CNY 10,000/worker)
HumanCap	330	9.413	1.247	6.820	12.540	Avg. years of schooling
FDI	330	2.341	1.873	0.124	9.217	FDI inflows (% of GDP)
GovExp	330	22.470	8.340	10.210	48.320	Government expenditure (% of GDP)

4.2 Estimation Strategy

The baseline estimator uses a two-way fixed-effect model to control for unobservable time-invariant factors at the provincial level and common macroeconomic shocks; in this case, $ISA_{it} = \alpha + \beta \cdot ADEI_{it} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$ where X_{it} denotes the set of provincial-control variables; μ_i stands for provincial-fixed effect, while λ_t represents year-fixed effect. To tackle possible endogeneity due to reverse causality in the relationship between industrialization upgrade and AI-Digital Economy Development, two identification methods were used: A first-order lag of the instrumental-variable approach and a Bartik shift-share instrument created by combining national levels of AI-DEGDs growth with base-level provincial exposure indices. Mediation analysis breaks down the total effect into direct effects and mediated ones by using three theories, based on Baron and Kenny's original work for current causal mediation models applied to panel data setting with bootstrap confidence intervals. Heterogeneity analysis explores variations in the relationship between the ADEI-ISA index and different regions and times over a period of 5 years. In addition, there is an additional quasi-experimental design based on the staggered implementation of the national big data comprehensive pilot zone in various provinces at the same time, which provides a feasible way to evaluate whether industrial upgrading paths influence policies via difference-in-differences methods proposed by Lyu, Xiao and Zhang (2024) [9].

5. Empirical Results and Discussion

5.1 Baseline Estimates

The base two-way fixed-effect estimate shows that there is a statistically significant and economically relevant positive correlation among the ADEI and ISA at different specifications. The chosen specifications have a coefficient estimate of 0.342 (standard error: 0.067, $p < 0.001$), showing that for each additional unit of growth in the AI-digital economy integration index, there is an increase by 0.342 points in the industrial structural optimisation index. In terms of standard deviations, for every one-standard-deviation rise in ADEI, there is an estimated gain of 0.048 points in ISA; that is, compared with provinces within China during this period, it improves by about 39%. The IV estimator using the Bartik shift-share instrument is approximately 0.391 ($p < 0.001$) and shows a certain degree of downward attenuation bias in the traditional OLS estimations. The composite ADEI index is also better than the combination of separate AI and digital economy sub-indexes in predicting ISA, providing empirical evidence for the super-additive hypothesis proposed by theory construction and demonstrating that the synergy effect brought about by integrating artificial intelligence and the digital economy has generated industrial upgrade outcomes surpassing what each contributes alone could achieve.

5.2 Mediation Analysis

Based on a causal-mediation analysis, it can be seen that the total effect of ADEI on ISA was transmittable through all three hypotheses but in varying degrees. The technological innovation channel, represented by the ratio of provincial R&D investment to GDP and patent authorisation rate, accounted for about 41% in total impacts, as shown below. Based on this argument, it also holds for the micro level in Wang et al.'s research, which demonstrates that innovation motivation leads, through driving technological progress, to enhancing corporate productivity comprehensively [3]. The human capital optimisation path is shown as the percentage of university graduates in the province's population; it increases by an additional 28%. The resource allocation efficiency channel, which is indicated by a labour misallocation index based on marginal revenue products in different industries, accounts for the rest of 31%; the relatively smaller proportion among all channels reflects the longer lagged institution-building adjustment caused by restructuring factors in markets. Near equal impact distributions for all three pathways demonstrate support for the multi-pathway theory, indicating that policies targeting any one pathway's improvement alone are likely to achieve a significant proportion of the overall enhancement effect of artificial intelligence-integrated digitalisation.

5.3 Heterogeneity and Policy Complementarity

Several substantive findings are derived from the heterogeneity test results shown in Figure 2; ADEI has a much greater impact on ISA in the eastern regions (coefficient = 0.471) compared with those of the central and western provinces (0.298, 0.187), indicating the complementarities among AI-digital integration, pre-existing innovation infrastructure, human capital endowments, and institutional quality, which are more developed in eastern China. However, the statistically significant positive effect of AI-digital integration on industrial upgrading is still a hopeful indicator for policies; it has been proved empirically that AI's productivity impacts can cover less developed areas by way of particular drivers such as scale benefits and demand-side structure adjustments.

The time sub-period analysis shows that the average impact factor of ADEI on ISA in recent years has nearly doubled compared to earlier periods. The acceleration aligns with crossing the threshold of critical digital investment for reaching a non-linear increase in productivity, according to Wu et al.'s research on digital transformation and manufacturing company output levels [10]. The step change in effect scale after 2017 is confirmed to be an effective indicator of national policy activation as a key factor promoting industrial upgrades of artificial intelligence-digital integration; it works through direct technological investment channels and additional institutions and governance transformations at the provincial level, which have been essential in facilitating the adoption of AI technologies in various sectors.

There is not only a statistical but also an economic policy-specification impact in the quasi-experimental evidence from the National Big Data Comprehensive Pilot Area. Provinces that have hosted pilot zones show an additional 0.126-point amplification of the ADEI-ISA coefficient after designation relative to other non-hosting provinces in this period, and the parallel trend assumption is verified by pre-event-stated tests. As shown by Lyu et al. (2024), this phenomenon also holds true for the activation of institutional policies enhancing production capacity through technological innovation: [9] It is implied from this result that the governance and incentive mechanisms embedded in the regional pilot zone framework constitute an important institutional supplement enabling technology-endowment-induced industrial structure adjustment within China, which may lead to increased competitiveness and sustainability in the industrial sector.

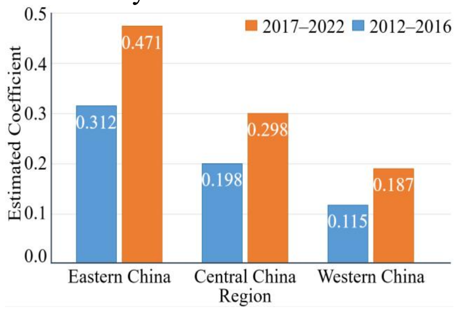

Figure 2. Regional Heterogeneity in the Effect of ADEI on Industrial Structure Advancement

6. Conclusion

Developed and tested a unified analysis framework to study how both the joint promotion of artificial intelligence and the digital economy promote industrial upgrading among Chinese provinces at once. Based on a balanced, province-level panel from 2012 to 2022, employing two-way fixed effects plus quasi-experimental design identification, and conducting causality-mediated analysis to obtain four key empirical findings.

The composite AI-Digital Economy Integration Index shows that there is a statistically rigorous and economically relevant positive effect on the upgrade of provincial industrial structure; all specifications have obtained similar estimations. It was found through this study that the combined ADEI index performs better compared to an additive combination of its individual components; therefore, it validates the superadditive property of artificial intelligence and the digital economy as a driving force for industrial restructuring. Secondly, there are three complements of mediating effects: technological innovation promotion, optimisation of human capital, and resource allocation. Efficiency Improvement Through Enhancing The Contribution Of The Innovation Channel Is The Largest. The nearly even impact on each channel suggests that policies need to work together in all three ways for AI-digital integration industrial upgrades to be fully realised. Third, there is a spatial difference in effect. The three eastern provinces have obtained the most benefits. However, Western Provinces still receive statistically significant positive effects and belong to none. Chinese provinces fall below the threshold required for extracting an industrial upgrade dividend at least through AI-digital integration.

Four, institutional policy activation through National Big Data Comprehensive Pilot Areas substantially strengthens the base combination-effect-impacting-upgrade chain, proving that governance capacity and technology endowment complement each other rather than substitute for one another in producing industrial structure adjustments. The former's results provide support for linking AI and digital policies to undermine the fragmented theory from a central government perspective. Provincial governments' space-specific outcomes suggest a need for tailored policies based on different scenarios of AI-digital integration with region-specific factor endowments rather than adopting uniform national schemes. Future research should extend this framework to incorporate the rapidly changing environment of generative AI, explore within-provincial variation using city-level data, and develop dynamic panel methods that can capture full temporal dynamics of AI-integrated digital transformation with higher accuracy.

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