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A Study on the Mechanisms and Processes of Artificial Intelligence's Impact on Economic Resilience

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Abstract. The widespread adoption of artificial intelligence (AI), driven by rapid computer technology and data processing developments, has accelerated economic transformation. AI systems, powered by sophisticated algorithms and significant computational resources, have substantially contributed to improvements in food security, ecological sustainability, and overall economic development. This paper presents an empirical analysis examining how AI influences economic resilience using data from 30 provincial-level regions in China from 2011 to 2022. Results indicate that rapid AI advancements have reinforced economic resilience by boosting productivity, enhancing resource allocation, stabilizing markets, and promoting sustainability. Structural integration emerges as a key mediator, which is essential for leveraging AI's full potential, while industrial structure upgrading moderates these benefits, amplifying the positive link between AI and resilience. Nonetheless, regional disparities persist, with AI's impact more pronounced in central regions, areas with robust technological and market infrastructure, and regions still developing data ecosystems. From an AI-oriented perspective, the study offers theoretical insights and policy recommendations to tackle modernization challenges. As the digital age evolves, computers and computational power will be increasingly decisive in shaping AI's influence on economic development, fostering sustainable practices, and strengthening long-term economic resilience.

Keywords: artificial intelligence, economic resilience, structural integration, industrial structure upgrading

1 Introduction

With continuous development in computer technology, especially in data processing, algorithm optimization, and computational power, AI's capabilities have significantly grown. Amid global economic advancement, industries face challenges such as climate change, population growth, and scarce resources [1]. Meanwhile, the Fourth Industrial Revolution drives extensive AI adoption, transforming industries by enhancing operational efficiency, decision-making precision, and supply chain optimization [2]. These AI-driven gains derive from progress in high-performance computing (HPC), machine learning, and big data processing [3, 4], which enable widespread implementation. In particular, HPC systems accelerate complex computations, machine learning improves predictive accuracy, and big data infrastructures support large-scale analytics. Although AI significantly boosts productivity and risk resilience, economic resilience depends on institutional and structural factors. Accordingly, industrial modernization is pivotal for resource allocation, efficiency, and long-term sustainability [5].

As computer technology evolves, AI's potential to revolutionize economic systems becomes evident. Although AI's transformative power in fields such as healthcare, finance, and manufacturing is widely recognized, its specific impact on economic resilience remains underexamined. Previous research on technological progress and economic development reveals limited attention to how emerging technologies, particularly AI, enhance resilience through data-driven strategies. AI's capabilities in big data analytics and advanced machine learning can significantly improve risk management, resource allocation, and decision-making processes. For instance, Zhang

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et al. (2023) [6] examined technology's role in productivity but did not address AI's influence on resilience. This study investigates AI's impact on economic resilience across China's diverse provincial landscapes, offering a more nuanced view of how AI integration shapes economic outcomes.

Secondly, how technological progress and structural integration interact remains underexplored. Existing research focuses on how structural integration affects economies of scale and productivity without examining AI implementation. For instance, Gong et al. (2024) [7] highlighted structural integration's importance for economic development but omitted AI. This study examines structural integration as a mediating factor, clarifying how it facilitates AI implementation and shapes economic resilience. The role of computer technology in data management, resource optimization, and automation is crucial in this context.

Finally, the moderating effect of industrial structure upgrading on AI's impact is insufficiently examined. Although upgrading drives economic resilience [8], few studies investigate how it moderates AI's influence on financial resilience. Dong et al. (2023) [9] discussed technological progress in restructuring industries but did not explore structural changes' impact on technological outcomes. This study addresses computer technology's role in enabling industrial transformation, focusing on efficient processes and automation.

This study addresses three key questions: (1) How does provincial-level AI implementation affect economic resilience in China? (2) Does structural integration, supported by advanced computer technologies, mediate AI's influence on economic resilience? (3) How does industrial structure upgrading, facilitated by computer-based technologies, shape AI's impact on economic resilience, and what are the underlying mechanisms?

The main contributions are: (1) From a computer science perspective, demonstrating how AI algorithms, computational techniques, and data processing enhance economic resilience, highlight computer technology's practical value. (2) Broadening AI and economic resilience research by emphasizing AI's role in improving efficiency, resource allocation, and risk management, which contribute to the theoretical framework of economic resilience. (3) Introducing the mediating role of structural integration and exploring how it shapes AI's effect on economic resilience while providing novel insights into its interaction with AI. (4) Conducting a heterogeneity analysis across regions while considering infrastructure, market support, and data environments, and offering empirical evidence for region-specific policies. This study also highlights how variations in digital infrastructure, educational investment, and industrial priorities can lead to divergent outcomes when implementing AI solutions. By examining these regional differences, policymakers can craft targeted interventions that leverage computer technology to address unique developmental needs, ensuring a more balanced, sustainable economic landscape.

The structure of this paper is as follows: Section 2 reviews the literature. Section 3 outlines the theoretical framework and hypotheses. Section 4 details sample selection criteria, data sources, variable measurements, and model design. Section 5 presents empirical results, including robustness checks, endogeneity solutions, and heterogeneity analysis. Section 6 examines the mediating role of industrial structure upgrading. Section 7 provides conclusions and policy recommendations.

2 Literature Review

Artificial intelligence (AI) has seen rapid growth and widespread adoption, becoming an increasingly essential tool for enhancing productivity across various sectors. The gradual implementation of AI technologies in precision systems, intelligent management, forecasting, and market analysis has optimized resource allocation [10, 11]. Moreover, AI strengthens resilience by mitigating the adverse effects of external shocks, such as climate change and market fluctuations, supporting the steady growth of the economy [12]. These studies demonstrate that AI plays a significant role in improving economic sustainability. However, research on how AI impacts economic resilience, particularly at the provincial level in China, remains relatively limited. Therefore, this study will focus on provincial-level data to explore how AI enhances economic resilience.

The integration of technological advancements in rural economic systems has garnered significant attention in China in recent years. These innovations enhance economic resilience by optimizing resource allocation and fostering industrial transformation [13]. Moreover, the improved efficiency of resource use and the expansion of large-scale operations facilitate AI adoption and support the dissemination of modern technologies [14]. Existing studies primarily focus on the direct impact of these structural changes on productivity, with less attention given to their mediating effect in the promotion of technologies. While some studies suggest that digital technologies, such as big data, enhance operational efficiency [15], they have not examined how these changes mediate the adoption of AI technologies. Therefore, this study addresses this gap by exploring how these factors mediate AI's impact on economic resilience and clarifies the mechanisms behind this effect.

Upgrading industrial structures is a crucial factor in promoting modernization. The optimization of industrial structures, particularly the growth of the service sector, provides essential support for advancing technologies [16]. In economic development, research has shown that industrial upgrading helps reduce economic fluctuations and enhances resilience to risks [17]. Additionally, it can attract more capital and talent, facilitating the practical application of advanced technologies and promoting economic transformation [18]. Research on how industrial structure upgrading moderates AI's impact on economic development remains scarce. Some studies indicate that industrial upgrading can boost economic resilience and innovation [19], enhancing the effectiveness of AI across sectors. Nevertheless, further analysis is needed to understand how upgrading industrial structures explicitly moderates the impact of AI on economic resilience. Therefore, this study will explore the moderating mechanism of industrial structure upgrading, clarifying its specific role in how AI influences economic resilience and how AI affects broader economic systems.

In summary, while previous studies have examined the effects of AI, technological advancements, and industrial structure upgrades on economic resilience individually, a unified framework combining these factors is still missing. This study addresses this gap by empirically analyzing how AI influences economic resilience across China's provinces, focusing on the mediating role of technological integration and the moderating effect of industrial structure upgrades.

3 Theoretical Analysis and Hypotheses Development

3.1 Artificial Intelligence and Economic Resilience

The development of artificial intelligence (AI) has triggered a global technological transformation, influencing economic resilience strategies [20]. AI applications span big data analysis, precision systems, and supply chains, relying on computer technologies such as algorithm development, computational power, and data processing. These enable vast data handling and automation of complex decision-making, making industries more resilient to uncertainties like natural disasters and market fluctuations.

Economic resilience refers to the capacity of systems to sustain development despite external shocks and swiftly recover and adapt. AI potentially enhances financial resilience by improving operational precision, resource allocation, and market stability, all supported by advanced computing architectures. This synergy of technology and intelligence strengthens overall adaptability, which is crucial for maintaining stable growth.

Firstly, AI-driven precision systems, powered by sophisticated algorithms and processing speed, optimize production stages in real time [21]. Tools such as remote sensing, drones, and smart sensors gather operational, resource, and environmental data for informed, automated decisions. Secondly, AI-enabled resource allocation minimizes waste and stabilizes incomes [22]. High computing power allows precise timing, location, and quantity control, raising yields and profits while reducing the environmental footprint [23]. This comprehensive approach addresses short-term profitability and long-term sustainability.

Thirdly, AI decreases market fluctuations by leveraging big data and cloud computing to analyze consumer preferences, price trends, and climate factors. Accurate demand forecasting helps businesses plan production, align offerings with market needs, and avoid imbalances [24]. AI facilitates "on-demand production" and "on-demand delivery," mitigating overproduction or shortages [25]. This integration with robust computer infrastructures ensures stable processes and reinforces economic resilience, creating more agile supply chains.

In light of these findings, exploring how AI can further fortify economic systems holds significant implications for sustainable development. Thus, based on this analysis, the study proposes:

Hypothesis 1. The improvement of artificial intelligence (AI) levels enhances economic resilience.

3.2 The Mediating Role of Structural Integration

Structural integration expands production scale, consolidates resources, and improves market coordination, thus offering a vital pathway through which artificial intelligence (AI) enhances economic resilience. By unifying smaller or dispersed operations, structural integration creates large-scale, efficient systems better suited for AI deployment. Centralizing management and processes under one framework makes adopting modern technologies more feasible, reducing manual intervention and production uncertainties while reinforcing economic stability.

Moreover, structural integration optimizes resource allocation, laying a solid foundation for AI-driven precision. Through consolidation, assets concentrate within enterprises that possess greater financial and technological capacities, enabling more efficient adoption of AI. These entities can leverage real-time data to conduct comprehensive analyses of resource availability and environmental conditions, delivering precise allocation of resources according to actual requirements. Consequently, resource waste is reduced, and smaller-scale participants also benefit from system-wide efficiency gains.

Lastly, large-scale, specialized production facilitated by structural integration supports AI-based forecasting and logistics, mitigating market volatility. Integrated enterprises can employ AI-driven market analysis to anticipate demand and plan production, thus avoiding oversupply or shortages. Additionally, larger-scale operations formed through structural integration possess greater flexibility to adjust production and sales channels in response to market risks. This alignment of supply with demand bolsters resilience and stability across economic systems.

Hypothesis 2. Structural integration mediates the effect of artificial intelligence on economic resilience.

3.3 The Moderating Role of Industrial Structure Upgrading

Industrial structure upgrading shifts economic systems from low-value-added to high-value-added sectors, enabling deeper AI integration and reinforcing economic resilience [20]. Environmental sustainability is also crucial, and AI supports it by optimizing resource use, reducing emissions, and managing resources efficiently. Upgrading industrial structures fosters broader AI adoption across sectors, improving productivity as industries embed technology-intensive practices in production and management processes.

In traditional low-value-added sectors, outdated methods limit productivity. However, as industries move toward higher-value-added practices, AI finds more opportunities to enhance production stages, thus reinforcing resilience. Upgrading further improves resource allocation, allowing AI-driven big data analytics and the Internet of Things (IoT) to enable real-time management [21-23]. By combining labor, capital, and infrastructure with advanced technologies, resource utilization becomes more efficient, reducing waste and promoting long-term sustainability.

Upgraded structures also help stabilize markets by making AI-based forecasting and supply chain management more effective [24, 25]. Traditional markets often suffer from supply-demand imbalances caused by information asymmetry. With industrial structure upgrading, accurate AI-driven market predictions and real-time production adjustments lessen the risks of overproduction or shortages, reducing volatility and strengthening economic stability.

Hence, the study posits:

Hypothesis 3a. Industrial structure upgrading positively moderates the relationship between AI and economic resilience. Upgrading moderates how AI drives structural integration; low-upgrade regions lack capacity for large-scale AI use, while high-upgrade regions adopt AI more effectively.

Hypothesis 3b. In AI's influence on economic resilience via structural integration, upgrading positively moderates AI's impact on structural integration. Upgrading also moderates how structural integration affects resilience, creating synergy among technology, capital, and diversified industries.

Hypothesis 3c. In AI's effect on economic resilience through structural integration, upgrading positively moderates the impact of structural integration on economic resilience.

The research model of this study is shown in Fig. 1.

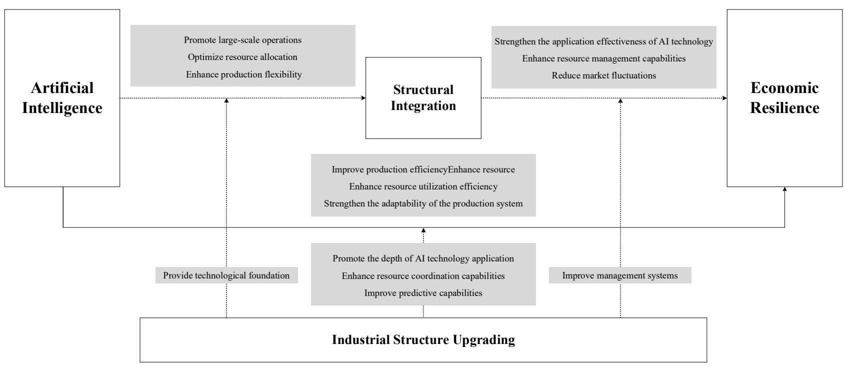

Fig. 1. Research model

4 Research Methods

4.1 Sample Selection and Data Source

This study draws from official statistical data from authoritative institutions, including the National Intellectual Property Administration's annual reports, the China Rural Statistical Yearbook, the China Statistical Yearbook, and provincial statistical yearbooks. These data sources are subject to rigorous review and validation processes over time, ensuring high reliability and widespread acceptance within academic circles. The China Statistical Yearbook and provincial statistical yearbooks, which offer detailed economic and social indicators for all provincial-level administrative regions, are among China's most commonly used sources in financial research and policy analysis. This guarantees accuracy and completeness of the data used in this study.

This research comprehensively covers most of China's economic, social, and industrial conditions, with a sample size of 360 observations, by selecting data from 30 provincial-level regions. Despite the exclusion of Tibet, Hong Kong, Macau, and Taiwan, the remaining provinces adequately represent the major economic regions of China. Through a comprehensive analysis of data from the various areas, the study further ensures the broad applicability and integrity of the findings.

For handling missing data, the study employed linear interpolation, a widely used method in time series analysis, which is especially effective when missing values are distributed evenly across time. This method ensures consistency and rationality in data processing, reducing the impact of missing data on the research results. Moreover, it helps avoid the potential sample bias that could arise from simply deleting missing values.

4.2 Variable Measurement

Independent Variable: Artificial Intelligence. Artificial Intelligence (AI) is the independent variable, measured by each province's number of AI patent applications, a commonly accepted proxy for technological innovation and research capacity. AI patent counts reflect research intensity, R&D investment, and technological reserves in areas like machine learning, natural language processing, and computer vision. Patent data from the National Intellectual Property Administration (NIPA) provide reliability, objectivity, and comparability.

A higher AI patent output signals broader adoption of AI technologies and stronger technological foundations, ultimately fostering economic growth and modernization. The specific process for measuring the AI level in each province involves identifying patents using International Patent Classification (IPC) codes relevant to AI, as specified in the Reference Table for Strategic Emerging Industry Classification and International Patent Classification (2021) (Trial Version) published by NIPA. Patent data are then retrieved from NIPA's patent search and analysis database, ensuring that only those directly related to AI are included.

Finally, the raw patent counts undergo a logarithmic transformation to address potential skewness, allowing comparability across provinces with differing patent outputs. This approach provides a robust, standardized indicator of AI capabilities, reflecting each province's commitment to research, development, and the practical implementation of emerging AI technologies.

Dependent Variable: Economic Resilience. Economic Resilience (ER) serves as the dependent variable. Following previous research [26], this paper constructs an ER evaluation framework based on three dimensions: risk resistance capability, adaptive capability, and transformational innovation capability. The framework includes three primary and 19 secondary indicators, as shown in Table 1. Risk resistance capability assesses the extent to which a system can mitigate losses and shocks in the face of unexpected events. Adaptive capability evaluates whether a system can recover to its original state after experiencing disruptions, such as natural disasters or market fluctuations. Transformational innovation capability examines whether the system can undergo self-reform and adjustments to adapt to new environments after external impacts. Subsequently, the entropy method is applied to determine indicator weights, producing an economic resilience index for each province.

Table 1. Indicator system of economic resilience

Primary indicators	Secondary indicators	Measurement method
Risk Resistance Capability	Proportion of Primary Industry	Share of primary industry value-added in regional GDP
	Fertilizer Usage	Quantity of fertilizer used for agricultural production during the year
	Pesticide Usage	Quantity of pesticides used for agricultural production during the year
	Total Crop Disaster Severity	Total affected crop area (mu)
	Soil Erosion Control	Soil erosion control area (mu)
	Effective Irrigated Area	Effective irrigated area
	Grain Yield per Unit Area	Grain output per unit of sown area
	Total Agricultural Machinery Power	Total power of agricultural machinery
	Total Water Resources	Total volume of surface and groundwater resources from local precipitation
Adaptive Capability	Per Capita Disposable Income of Rural Residents	–
	Rural Resident Consumption Expenditure	Rural residents' total consumption expenditure
	Total Output Value Index of Agriculture, Forestry, Animal Husbandry, and Fishery	Calculated at comparable prices (previous year = 100)
	Producer Price Index for Agricultural Products	Calculated at comparable prices (previous year = 100)
	Agricultural Value-Added	–
Transformational Innovation Capability	Local Government Expenditure on Science and Technology	–
	Rural Electricity Consumption	Rural electricity consumption for production and daily life
	Crop Planting Structure	Grain sown area as a share of the total crop area
	Illiteracy Rate in Rural Population	Percentage of illiterate population aged 15 and above
	Growth Rate of Fixed Asset Investment by Rural Households	–
	Rural Electricity Consumption	Electricity use for rural production and daily life

Mediating Variable: Structural Integration. Structural Integration (SI) serves as the mediating variable. This paper uses the ratio of integrated operational areas to total contracted areas as a proxy for structural integration. A higher ratio indicates a greater degree of operational integration. This method effectively captures resource allocation efficiency and the integration of technologies in each province.

Moderating Variable: Industrial Structure Upgrading. Industrial Structure Upgrading (ISU) serves as the moderating variable. Building on previous studies [27], this paper measures industrial upgrading with the industrial structure hierarchy coefficient. The specific measurement model is shown in Model (1), where y_i,m,t represents the share of industry (m) in the GDP of the province (i) at the time (t), reflecting the progressive evolution of the industrial structure from lower-value sectors to higher-value, more technology-intensive sectors. Thus, the industrial structure upgrading indicator calculated from Model (1) captures the process of industrial development from a basic level to a more advanced stage, facilitating the deeper integration and application of AI technologies across sectors.

$$ISU_{i,t} = \sum_{m=1}^{3} y_{i,m,t} \times m \quad (m = 1,\ 2,\ 3) \tag{1}$$

Control Variables. This study incorporates multiple control variables to isolate AI's effect on economic resilience at the provincial level. Controlling for these variables minimizes confounding factors and clarifies the specific contribution of AI. The chosen controls reflect diverse economic, infrastructural, social, technological, and policy dimensions that potentially influence both resilience and AI adoption.

Economic Development (Economic) is measured by the log of per capita GDP, capturing a region's overall economic performance and readiness for AI technologies. Transportation Infrastructure (Transportation) uses the log of highway mileage, indicating the extent to which transport networks facilitate economic activities and AI-based logistics. Informatization (Informatization) is the ratio of postal and telecommunication services to GDP, highlighting access to critical information and communication technologies. Technology Market (Technology) is proxied by technology market transactions relative to GDP, reflecting innovation and commercialization capacity that underpins AI-driven development. Social Consumption (Consumption), measured by retail sales of consumer goods to GDP, gauges a region's consumer demand for AI-enabled products and services. Tax Burden (Tax), the ratio of tax revenue to GDP, influences fiscal policies affecting investment decisions and AI-supported growth. R&D Intensity (R&D) is the ratio of internal R&D expenditure to GDP, capturing core innovation capabilities essential for AI integration. Government Intervention (Government), or fiscal expenditure to GDP, shows public-sector support and stabilizing functions that can foster AI-based initiatives. External Openness (Openness), measured by total imports and exports to GDP, indicates the degree of global integration and potential technology spillovers. Human Capital (Human) is the ratio of higher education enrollment to population, representing a workforce's skill level crucial for AI adoption. Environmental Regulation (Regulation) is the frequency of ecological terms in government reports, influencing how industries and AI solutions align with sustainability goals. Technology Innovation (Technology) uses the log of technology patents, reflecting a region's technological capacity for AI-related advances. Additionally, region and year fixed effects are included to control for unobserved heterogeneity across provinces and temporal trends, ensuring a more accurate assessment of AI's impact on economic resilience.

This study also controls for regional (Region) and year (Year) fixed effects. All variable definitions are listed in Table 2.

Table 2. Definition of research variables

Types	Variables	Definition
Dependent Variable	ER	Calculated from the economic resilience indicator system
Independent Variable	AI	The logarithm of the number of provincial AI patent applications
Mediating Variable	SI	The ratio of integrated operational area to total contracted area
Moderating Variable	ISU	Calculated from Model (1)
Control Variables	Economic	The logarithm of per capita GDP
	Transportation	The logarithm of highway mileage
	Informatization	The ratio of postal and telecommunication services to regional GDP
	Technology	The ratio of technology market transactions to regional GDP
	Consumption	The ratio of retail sales of consumer goods to regional GDP
	Tax	The ratio of tax revenue to regional GDP
	R&D	The ratio of internal R&D expenditures to regional GDP
	Government	The ratio of fiscal expenditures to regional GDP
	Openness	The ratio of total imports and exports (adjusted by the USD-RMB exchange rate) to regional GDP
	Human	The ratio of higher education enrollment to the total population
	Regulation	Frequency of environmental terms relative to total word count in provincial government reports
	Agriculture	Logarithm of technology patents

Table 3 presents the statistical descriptions of the main variables. The mean of ER is 0.2550, with a standard deviation (Std) of 0.1038, minimum (Min) of 0.0689, median of 0.2404, and maximum (Max) of 0.5051. These results indicate that economic resilience varies significantly across provinces, with most provinces having relatively low resilience, suggesting room for improvement. The mean of AI is 6.4118, with a standard deviation of 1.9228, minimum of 0.6931, median of 6.5758, and maximum of 10.5669. The findings show that AI levels in most provinces are still low and in the early development stages. Additionally, there are significant inter-provincial differences in AI development, with some provinces having established mature AI ecosystems while others lag behind and need to catch up. The mean of SI is 0.3267, with a standard deviation of 0.1685, minimum of 0.0335, median of 0.3048, and maximum of 0.9111. These results suggest considerable variation in operational integration rates among provinces, with most provinces still having relatively low rates, indicating potential for further improvement in the future. The mean of ISU is 2.3991, with a standard deviation of 0.1231, minimum of 2.1323, median of 2.3887, and maximum of 2.8359. The findings suggest that while provinces differ in industrial upgrading, most have gradually shifted from low-value to higher-value-added industries like manufacturing and services. Provinces with slower industrial upgrading must accelerate their shift to advanced economic structures.

Table 3. Descriptive statistics of variables

Variables	N	Mean	Std	Min	Median	Max
ER	360	0.2550	0.1038	0.0689	0.2404	0.5051
AI	360	6.4118	1.9228	0.6931	6.5758	10.5669
SI	360	0.3267	0.1685	0.0335	0.3048	0.9111
ISU	360	2.3991	0.1231	2.1323	2.3887	2.8359
Economic	360	10.8678	0.4610	9.6818	10.8325	12.1547
Transportation	360	11.7019	0.8528	9.3996	11.9708	12.9126
Informatization	360	0.0669	0.1401	0.0151	0.0367	2.5204
Technology	360	0.0182	0.0295	0.0002	0.0080	0.1913
Consumption	360	0.3866	0.0585	0.1796	0.3916	0.5044
Tax	360	0.0836	0.0286	0.0355	0.0764	0.1882
R&D	360	0.0212	0.0151	0.0023	0.0169	0.0704
Government	360	0.2589	0.1114	0.1050	0.2313	0.7583
Openness	360	0.2715	0.2807	0.0076	0.1462	1.4638
Human	360	0.0210	0.0058	0.0080	0.0205	0.0436
Regulation	360	0.0095	0.0027	0.0037	0.0092	0.0192
Agriculture	360	7.4970	1.0896	3.6636	7.5794	9.7202

4.3 Models Construction

This paper constructs Research Model (2) to test the direct impact of artificial intelligence on improving economic resilience.

$$\mathrm{ER}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(2)}$$

This paper develops Research Models (3) and (4) to examine the mediating role of structural integration.

$$\mathrm{SI}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(3)}$$

$$\mathrm{ER}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \varphi \mathrm{SI}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(4)}$$

This paper builds Research Model (5) to assess how industrial structure upgrading moderates the relationship between artificial intelligence and economic resilience.

$$\mathrm{ER}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \gamma \mathrm{ISU}_{i,t} + \eta \mathrm{AI}_{i,t} \times \mathrm{ISU}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(5)}$$

This paper develops Research Models (6) and (7) to test the moderating effect of industrial structure upgrading in the former stage of the mediating process.

$$\mathrm{SI}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \gamma \mathrm{ISU}_{i,t} + \eta \mathrm{AI}_{i,t} \times \mathrm{ISU}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(6)}$$

$$\mathrm{ER}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \gamma \mathrm{ISU}_{i,t} + \eta \mathrm{AI}_{i,t} \times \mathrm{ISU}_{i,t} + \varphi \mathrm{SI}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi \mathrm{Year}_{t} + \varepsilon_{i,t} \quad \mathbf{(7)}$$

This paper builds Research Models (8) and (9) to assess the moderating effect of industrial structure upgrading in the latter stage of the mediation process.

$$\mathrm{SI}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \gamma \mathrm{ISU}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(8)}$$

$$\mathrm{ER}_{i,t} = \alpha + \beta \mathrm{AI}_{i,t} + \gamma \mathrm{ISU}_{i,t} + \eta \mathrm{AI}_{i,t} \times \mathrm{ISU}_{i,t} + \varphi \mathrm{SI}_{i,t} + \iota \mathrm{SI}_{i,t} \times \mathrm{ISU}_{i,t} + \chi \mathrm{Controls}_{i,t} + \delta \mathrm{Region}_{i} + \phi Year_{t} + \varepsilon_{i,t} \quad \mathbf{(9)}$$

5 The Regression Results and Analysis

5.1 Baseline Regression

Table 4 shows the impact of provincial artificial intelligence development on economic resilience. Column (1) shows that without control variables, the AI coefficient on ER is 0.0354 ($p < 0.01$) with an R-squared of 0.3543. Column (2) indicates that with control variables, the AI coefficient on ER is 0.0193 ($p < 0.01$), and the R-squared is 0.8410. The comparison suggests a significant improvement in the R-squared in Column (2) compared to Column (1), suggesting that incorporating the series of control variables makes the model specification more reasonable. Column (2) presents the regression results of Model (2). In economic terms, an increase of one standard deviation in AI level promotes economic resilience by 14.5530% ($0.0193 \times 1.9228 / 0.2550 \times 100\%$). This empirical evidence supports Hypothesis H1, indicating that improving AI levels strengthens economic resilience.

Table 4. Baseline regression analysis

Variables	(1)	(2)
	ER	ER
AI	0.0354***	0.0193***
	(10.3557)	(4.3600)
Economic	\	0.0129
	\	(0.9121)
Transportation	\	0.0646***
	\	(10.7019)
Informatization	\	-0.0073
	\	(-1.2045)
Technology	\	-0.1102
	\	(-0.9132)
Consumption	\	-0.3564***
	\	(-7.5217)
Tax	\	-0.3209
	\	(-1.5669)
R&D	\	-0.5874***
	\	(-3.1926)
Government	\	-0.0135
	\	(-0.3140)
Openness	\	0.0120
	\	(0.6424)
Human	\	-3.1917***
	\	(-5.1428)
Regulation	\	-3.6051***
	\	(-3.6510)
Agriculture	\	0.0270***
	\	(4.8617)
Region FE	YES	YES
Year FE	YES	YES
Constant	0.0358	-0.6459***
	(1.5698)	(-3.6163)
N	360	360
R-squared	0.3543	0.8410

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

5.2 Robustness Tests

Lagged Explanatory Variable. To address endogeneity from reverse causality, all explanatory variables are lagged by one and two periods before regression with the dependent variable. Table 5, Column (1), reports a coefficient of 0.0182 ($p < 0.01$) for L.AI on ER. Table 5, Column (2), shows a coefficient of 0.0171 ($p < 0.01$) for L2.AI on ER. These results show that even after addressing endogeneity from temporal causality ambiguity, improvements in AI still significantly enhance economic resilience, supporting the reliability of the proposed hypotheses.

Table 5. Robustness test results: Lagged explanatory variables

Variables	(1)	(2)
	ER	ER
L.AI	0.0182***	\
	(4.2472)	\
L2.AI	\	0.0171***
	\	(4.0541)
L. Controls	YES	\
L2. Controls	\	YES
Region FE	YES	YES
Year FE	YES	YES
Constant	-0.6436***	-0.6585***
	(-3.5044)	(-3.4932)
N	330	300
R-squared	0.8466	0.8521

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Instrumental Variable Method. This paper uses the instrumental variable (IV) method to address endogeneity in AI's impact on economic resilience. The instruments are "labor quality" (logarithm of higher education graduates, IV1) and "labor quantity" (logarithm of the employed population, IV2). IV1 is closely correlated with AI development, reflecting how labor quality fosters AI adoption but does not directly affect economic resilience. Taking the logarithm smooths nonlinear relationships and mitigates scale effects. IV2 captures the effect of labor supply on AI adoption without directly influencing economic resilience. Results from the 2SLS model confirm both IV1 and IV2 as valid instruments, indicated by a large first-stage F-statistic (exceeding the threshold of 10), high Shea's partial R-squared, and surpassing the Stock–Yogo critical values. In Table 6, Columns (1) and (3) present the first-stage regressions, where IV1's coefficient on AI is 1.2374 ($p < 0.01$) and IV2's coefficient is 1.1642 ($p < 0.01$). Columns (2) and (4) show the second-stage results, indicating that AI's coefficients on economic resilience are 0.0692 ($p < 0.01$) and 0.0908 ($p < 0.01$), respectively. These findings underscore the robustness of the IV approach and affirm that AI significantly enhances economic resilience once endogeneity is addressed. In summary, after resolving endogeneity with the instrumental variable method, improvements in AI still significantly enhance economic resilience, validating the proposed hypotheses.

Table 6. Robustness test results: Instrumental variable method

Variables	(1)	(2)	(3)	(4)
	AI (IV1_Stage1)	ER (IV1_Stage2)	AI (IV2_Stage1)	ER (IV2_Stage2)
IV1	1.2374***	\	\	\
	(10.1896)	\	\	\
IV2	\	\	1.1642***	\
	\	\	(8.1046)	\
AI	\	0.0692***	\	0.0908***
	\	(6.7233)	\	(6.3681)
Controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Constant	-21.8562***	-0.0463	-29.5989***	0.2130
	(-8.8164)	(-0.2045)	(-8.6114)	(0.7710)
N	360	360	360	360
R-squared	0.9565	0.7891	0.9528	0.7344
First-stage regression summary statistics	F=103.827***		F=65.6846***	

Shea's partial R-squared	0.2839				0.2229			
Minimum eigenvalue statistic	132.0490				95.5191			
	10%	15%	20%	25%	10%	15%	20%	25%
	16.3800	8.9600	6.6600	5.5300	16.3800	8.9600	6.6600	5.5300

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Winsorization. This study applies winsorization at the 1% and 5% levels to continuous variables to reduce the influence of outliers before performing the regression analysis. Outliers can disproportionately affect the regression results, leading to biased estimates. The study minimizes their interference by winsorizing extreme values while preserving the data structure and sample consistency. Unlike simply removing outliers, winsorization avoids sample loss and potential sample bias.

According to Column (1) of Table 7, after applying 1% winsorization, the coefficient of AI on economic resilience (ER) is 0.0197 ($p < 0.01$). In Column (2), after 5% winsorization, the coefficient becomes 0.0192 ($p < 0.01$). These results show that the regression coefficients remain stable under different levels of winsorization, demonstrating the robustness of the empirical tests and indicating that the regression results are not significantly affected by extreme values.

Table 7. Robustness test results: Instrumental variable method

Variables	(1)	(2)
	ER	ER
AI	0.0197***	0.0192***
	(4.4405)	(3.5589)
Controls	YES	YES
Region FE	YES	YES
Year FE	YES	YES
Constant	-0.5749***	-0.6169***
	(-3.1941)	(-3.0168)
N	360	360
R-squared	0.8417	0.8456

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Adjust the Sample Period. In December 2014, the Central Economic Work Conference stated that China's economic development had entered a new normal. Accordingly, the study period was adjusted from 2011–2022 to 2016–2022. Column (1) of Table 8 shows that, after changing the sample period, the coefficient of AI on economic resilience (ER) is 0.0396 ($p < 0.01$), suggesting that higher AI levels continue to enhance financial resilience significantly. This verifies the robustness of the primary empirical test in this study.

Table 8. Robustness test results: Adjust the sample period

Variables	(1)
	ER
AI	0.0396***
	(4.7660)
Controls	YES
Region FE	YES
Year FE	YES
Constant	-0.3870
	(-1.5258)
N	210
R-squared	0.8633

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

5.3 Heterogeneity Tests

Geographical Region. The impact of artificial intelligence (AI) on economic resilience varies across China's eastern, central, and western regions. In the east, where the economy is highly modernized, AI contributes relatively little to enhancing resilience. Advanced automation and intelligence technologies already dominate, resulting in minimal incremental benefits and diminishing marginal returns. Additionally, the focus on service-oriented industries reduces AI's relevance to traditional sectors.

In the west, inadequate infrastructure and underdeveloped economic conditions constrain AI adoption. Substantial initial investments in infrastructure, data collection, and training often exceed local financial capacities. Moreover, challenging natural conditions and limited supporting facilities hinder AI's deployment, making it difficult to achieve significant improvements in financial resilience.

By contrast, the central region's economic and infrastructural conditions occupy a middle ground. While not as advanced as the east, it surpasses the west in financial capability and infrastructure readiness, enabling a more extensive application of AI. Government support and policy incentives further encourage AI-driven improvements in productivity, risk management, and industrial upgrading, collectively strengthening economic resilience.

This study categorizes 30 provinces into eastern, central, and western groups. Table 9 indicates that AI does not significantly enhance economic resilience (ER) in the east or west. In the central region, AI's effect on ER is statistically significant, underscoring regional disparities in AI's overall impact.

Table 9. Heterogeneity test: Geographical region

Variables	(1) ER (Eastern)	(2) ER (Central)	(3) ER (Western)
AI	0.0052 (0.3570)	0.0375^{**} (2.5342)	-0.0010 (-0.1655)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.2648 (0.3458)	0.3138 (0.3674)	-0.6370^{*} (-1.7994)
N	132	96	132
R-squared	0.9080	0.9155	0.8587
Test of Intergroup Coefficient Differences		8.060^{0**}*	

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Technological and Market Support. In addition to geographical differences, AI's impact differs by industry (e.g., agriculture and manufacturing) and is shaped by the local digital economy level, which reflects technological and market support for AI. Provinces with advanced digital economies possess stronger IT infrastructures, enabling AI-based interventions and big-data-driven decisions that bolster resilience. These areas typically have more mature market mechanisms and greater access to capital, facilitating AI innovation.

This study divides provinces into groups based on the digital economy levels: DE_High (above mean) and DE_Low (at or below mean). In Table 10, AI significantly promotes economic resilience in the DE_High group, indicating low digital economy conditions limit AI's effect. The Wald test yields $F=6.3000$ ($p<0.05$). The inter-group coefficient difference test confirms heterogeneous effects across different levels of technological and market support. It highlights the importance of an advanced digital environment for AI-driven growth, as digital economy disparities shape AI's impact on economic resilience.

Table 10. Heterogeneity test: Technological and market support

Variables	(1) ER (DE_High)	(2) ER (DE_Low)
AI	0.0309*** (3.8443)	0.0033 (0.5890)
Controls	YES	YES

Region FE	YES	YES
Year FE	YES	YES
Constant	-3.0636***	-0.5983***
	(-9.3590)	(-3.0314)
N	111	249
R-squared	0.9571	0.8641
Test of Intergroup Coefficient Differences	6.3000**	

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Data Environment. The development of AI in each province is influenced by its data environment. This paper evaluates the data environment for AI development based on whether a province is designated as a National Big Data Comprehensive Pilot Zone. Firstly, the pilot zones have well-established data sharing and integration conditions. As a result, further improvements in AI levels may no longer significantly enhance economic resilience. However, in non-pilot zones, improvements in AI levels can effectively promote the collection, integration, and sharing of information within the region, strengthening the information foundation for AI applications across sectors. This enables these regions to enhance economic resilience through intelligent management and decision-making. Secondly, in non-pilot zones with weaker digital infrastructure, the advancement of AI is more likely to facilitate cross-sector data integration. As data from different fields, such as climate, finance, and markets, becomes more integrated, it can further enhance productivity and improve the ability to cope with disruptions, thereby strengthening economic resilience.

This paper divides the provinces involved in the sample into National Big Data Comprehensive Pilot Zones (Yes) and Non-Pilot Zones (No) based on China's classification standard for these pilot zones. As shown in Table 11, in the non-pilot zone group, improvements in AI levels significantly promote economic resilience. However, in the pilot zone group, this effect no longer holds. The heterogeneity analysis regarding the data environment is thus validated. Additionally, the Wald test yields an F-value of 9.2600 ($p < 0.05$). The inter-group coefficient difference test confirms that differing data environments across provinces during AI development result in varied effects of AI on economic resilience.

Table 11. Heterogeneity test: Data environment

Variables	(1)	(2)
	ER	ER
	(Yes)	(No)
AI	-0.0121	0.0119**
	(-1.4944)	(2.2667)
Controls	YES	YES
Region FE	YES	YES
Year FE	YES	YES
Constant	-1.0473***	-0.8378***
	(-2.8592)	(-3.5730)
N	120	240
R-squared	0.9434	0.8814
Test of Intergroup Coefficient Differences	9.2600**	

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

6 Mechanism Analysis

6.1 Mediating Effect

Building on the established effect of AI on enhancing economic resilience, this section further validates the mediating role of structural integration. Column (1) of Table 12 shows the regression results of Model (3), with a coefficient of AI on SI of 0.0454 ($p < 0.01$). Column (2) of Table 12 presents the regression results of Model

(4), showing a coefficient of AI on ER of 0.0141 ($p < 0.01$) and a coefficient of SI on ER of 0.1146 ($p < 0.01$). Comparing the results from Column (2) of Table 4 with those from Column (2) of Table 12, the coefficient of AI on ER in Column (2) of Table 12 (0.0141) is smaller than that in Column (2) of Table 4 (0.0193). Furthermore, the R-squared value in Column (2) of Table 12 (0.8507) is higher than that in Column (2) of Table 4 (0.8410). This suggests that incorporating the mediating variable, structural integration, significantly improves the model's explanatory power. The empirical evidence supports Hypothesis H2, confirming that the improvement in AI levels promotes more efficient integration of resources, thereby strengthening economic resilience." Further validation of structural integration's mediating role is achieved by including province-specific evidence. Robustness checks and regional case studies ensure the generalizability of findings, addressing disparities in technological and economic capacities across provinces."

This study also employs the Sobel test and the Bootstrap method to verify the accuracy of the mediation effect results. The Sobel test yields a Z-value of 3.1940 ($p < 0.01$) with a mediation effect value of 27.0167%. The Bootstrap test shows that the results do not include zero within the 95% confidence interval. These tests further support Hypothesis H2, indicating that improved efficiency in resource integration plays a key mediating role in how AI enhances economic resilience.

Table 12. Mediating effects test

Variables	(1)	(2)
	SI	ER
AI	0.0454^{***}	0.0141^{***}
	(4.4308)	(3.3663)
SI	\	0.1146^{***}
	\	(4.5266)
Controls	YES	YES
Region FE	YES	YES
Year FE	YES	YES
Constant	-2.4228^{***}	-0.3682^{**}
	(-5.9997)	(-2.0543)
N	360	360
R-squared	0.7202	0.8507
Sobel Z	3.1940^{***}	
Mediating Effects	27.0167%	
_BS_1	[0.0025, 0.0084]	
_BS_2	[0.0065, 0.0246]	

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

6.2 Moderating Effect

Building on the established effect of AI levels in promoting economic resilience, this section further validates the moderating role of industrial structure upgrading. Column (1) of Table 13 shows the regression results of Model (5), with the coefficient of AI × ISU on ER being 0.0393 ($p < 0.01$). The empirical evidence supports Hypothesis H3a, showing that a higher level of industrial structure upgrading strengthens the positive effect of AI on economic resilience, whereas a lower level weakens this effect.

Column (2) of Table 13 displays the regression results of Model (6), indicating that the coefficient of AI × ISU on SI is 0.1224 ($p < 0.01$). Column (3) of Table 7 displays the regression results of Model (7), indicating that the coefficient of SI on ER is 0.1094 ($p < 0.01$). These results support Hypothesis H3b, suggesting that industrial structure upgrading effectively moderates the first part of the mediation process, where AI promotes resource integration, thereby enhancing economic resilience. A higher level of industrial structure upgrading amplifies the positive effect of AI on resource integration, which in turn further enhances economic resilience.

Column (4) of Table 13 shows the regression results of Model (8), indicating that the coefficient of AI on SI is 0.0454 ($p < 0.01$). Column (5) of Table 7 presents the results of Model (9), with the coefficient of SI × ISU on ER being 0.3509 ($p < 0.1$). These results support Hypothesis H3c, suggesting that industrial structure upgrading effectively moderates the second part of the mediation process, where AI promotes resource optimization, thereby enhancing economic resilience. A higher level of industrial structure upgrading strengthens the positive effect of improved resource integration efficiency, driven by AI, on financial resilience.

Table 13. Moderating effects test

Variables	(1)	(2)	(3)	(4)	(5)
	ER	SI	ER	SI	ER
AI	0.0202***	0.0484***	0.0149***	0.0454***	0.0117**
	(4.7571)	(4.8612)	(3.6199)	(4.4231)	(2.5148)
SI			0.109^{4**}*		0.0992***
			(4.3871)		(3.9441)
ISU	-0.1034**	0.0935	-0.1136**	0.0902	-0.1413***
	(-2.2329)	(0.6815)	(-2.5760)	(0.6338)	(-2.9700)
AI × ISU	0.0393***	0.1224***	0.0259*		0.0040
	(2.8539)	(3.6752)	(1.9064)		(0.2232)
SI × ISU					0.3509*
					(1.7967)
Controls	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Constant	-0.5730***	-2.8286***	-0.2637	-2.5602***	-0.3461*
	(-3.1058)	(-6.8285)	(-1.3776)	(-5.8793)	(-1.8267)
N	360	360	360	360	360
R-squared	0.8455	0.7307	0.8540	0.7207	0.8558

Note: Parentheses show robust clustered standard errors; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

7 Conclusions, Recommendations, and Outlook

This study uses data from 30 provincial-level regions in China (2011–2022, excluding Tibet, Hong Kong, Macau, and Taiwan) to examine AI's impact on economic resilience. Results show that higher AI levels enhance operational efficiency, improve resource allocation, and mitigate market fluctuations, laying a solid foundation for sustainable economic growth. Mediation analysis reveals that structural integration fosters production scale and specialization, broadening AI application and enabling AI-powered market forecasting to reduce market volatility. Moderation analysis indicates that industrial structure upgrading positively moderates AI's effect on economic resilience by combining traditional sectors with advanced technology and coordinating resources across industries, improving stability and reinforcing AI's positive impact. Heterogeneity tests reveal that AI's effects are stronger in the central region, as well as in areas with high technological and market support and under less favorable data conditions.

This study highlights advanced computer technologies, particularly AI algorithms, machine learning models, and big data analytics, as key drivers of economic resilience. Four policy recommendations follow:

First, provincial governments should strengthen AI research, focusing on precision production, resource management, and predictive analytics, supported by robust digital infrastructure and workforce training. Second, clear legal frameworks and regulations for data integration and resource optimization are essential. Incentives such as subsidies and tax benefits can encourage broader AI adoption, while transparent information platforms reduce asymmetry and improve efficiency. Third, industrial structure upgrading should integrate AI into production, processing, and distribution, enhancing value chains through innovation and intelligent operations. Fourth, policymakers must tailor strategies to local economic and technological contexts. In leading regions, prioritize AI-driven solutions for production, supply chain management, and market forecasting. Underdeveloped areas require investments in infrastructure and human capital. Strengthening risk management and market forecasting mechanisms further bolsters economic resilience.

Although this study has explored AI's impact on economic resilience in China and its mechanisms through structural integration and industrial upgrading, limitations remain. First, the data cover only 30 Chinese provincial regions, raising questions about generalizability. Technological infrastructure, market environments, and policy support differ across countries, so further validation through international comparative studies is needed.

Second, the data extend only from 2011 to 2022, omitting evolving impacts across different development stages. As AI technologies rapidly advance, new application scenarios—such as smart manufacturing, fintech, and green technologies—may yield novel effects. Future research should examine these emerging fields' dynamic influences.

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