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The Impact of Artificial Intelligence on Economic Resilience: Based on OECD Countries

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ABSTRACT: This study systematically examines the impact of artificial intelligence (AI) on national economic resilience and its underlying mechanisms, using member countries of the Organisation for Economic Co-operation and Development (OECD) as the sample. Based on cross-national panel data from 2000 to 2023, we construct a composite index to measure economic resilience and employ AI patent stock and industrial robot installations as core explanatory variables, estimated via a fixed-effects model. The baseline regression results reveal that the level of AI development exerts a significant positive effect on economic resilience. A series of robustness tests—including substituting the dependent variable with the share of industrial value-added and replacing the explanatory variable with robot installations—confirm the reliability of this core finding. Further heterogeneity analysis indicates that the enabling effect of AI exhibits distinct "institutional thresholds" and "development-level thresholds," being more pronounced in countries with higher government AI readiness and higher income levels. Mechanism tests uncover two key mediating pathways: AI not only directly enhances economic resilience but also generates significant indirect effects by driving national digital transformation and stimulating R&D investment. Theoretically and empirically, this study provides new evidence for understanding AI as a general-purpose technology in strengthening the risk-resistance and recovery capacity of macroeconomic systems, and offers policy insights for designing differentiated and inclusive AI development strategies to improve economic resilience.

KEYWORDS: Artificial Intelligence; Economic Resilience; OECD Countries

I. INTRODUCTION

In today's globalized economic landscape, countries frequently face multiple shocks, including financial crises, geopolitical conflicts, public health emergencies, and technological disruptions. Against this backdrop, "economic resilience" — the capacity of an economy to withstand, absorb, recover from, and adapt to shocks while ultimately achieving sustainable growth — has emerged as a central concern for both policymakers and academics. The Organisation for Economic Co-operation and Development (OECD), as a key platform for advanced economies, has long been committed to developing indicator systems to measure the economic resilience of its member states, aiming to identify vulnerabilities and enhance their crisis-response capabilities (Sorokina et al., 2024).

Simultaneously, the new wave of technological revolution, represented by artificial intelligence (AI), is reshaping the global economic landscape with unprecedented depth and breadth. On one hand, AI injects new momentum into economic growth by enhancing production efficiency, optimizing resource allocation, and fostering new business models. For instance, the application of industrial robots can promote employment and strengthen industrial chain resilience through output scale expansion and technological innovation effects (Wan et al., 2025). On the other hand, its potential job displacement effects, changing skill demands, and the risk of widening digital divides also pose uncertainties and challenges to economies and societies (Acemoglu et al., 2022). This "double-edged sword" effect manifests differently across OECD countries, depending on disparities in digital infrastructure, innovation ecosystems, policy frameworks, and workforce skills.

As representative advanced economies, OECD countries exhibit typical and forward-looking characteristics in their levels of AI development, policy frameworks, and economic structures. As early as 2019, they adopted the world's first intergovernmental AI standard — the OECD Recommendation on Artificial Intelligence — aimed at fostering trustworthy AI innovation (Sebastião et al., 2025). In recent years, some studies have begun to examine the specific impacts of AI within OECD contexts, such as its positive effect on youth employment (Jia et al., 2024). However, research systematically addressing how AI influences the overall economic resilience of OECD countries remains insufficient. The underlying mechanisms, heterogeneous effects, and policy implications warrant deeper investigation.

Building on this, this study takes OECD countries as its empirical sample, aiming to systematically analyze the pathways and effects through which AI influences economic resilience. Specifically, it seeks to advance academic and policy discussions in the following three aspects: (1) By combining theoretical analysis with empirical testing, it aims to systematically identify the key transmission channels through which AI affects economic resilience, thereby addressing the fragmented understanding of mechanisms in existing research; (2) It examines whether the impact of AI on economic resilience varies significantly across different OECD countries, aiming to deepen the understanding of the context-dependent nature of the "technology-resilience" relationship; and (3) Based on empirical findings, it aims to provide actionable policy recommendations and governance insights for OECD countries and similar economies to promote the synergistic advancement of AI development and enhanced economic resilience.

II. LITERATURE REVIEW

Existing research reveals a complex and dialectical relationship between artificial intelligence and economic resilience. Within the field of AI's economic effects, academic consensus holds that it shapes economic systems by enhancing total factor productivity, accelerating innovation diffusion, and optimizing resource allocation (Ding et al., 2025). However, its impact exhibits significant duality: on one hand, AI strengthens risk prediction capabilities and fosters industrial upgrading (Yan, 2025); on the other hand, technological unemployment, algorithmic bias amplifying social inequality, and risks associated with new dependencies of critical infrastructure on AI may undermine systemic stability (Liu, 2025). Nevertheless, most existing literature focuses on either micro-level firm performance or macro-level productivity, largely neglecting a systematic connection between the characteristics of AI technology and the multidimensional aspects of national-level economic resilience—namely absorptive capacity, restorative capacity, and transformative capacity (Sarker et al., 2025).

The study of economic resilience itself has undergone an evolution in paradigms. Early research focused narrowly on the speed of GDP recovery post-shock (Peng, 2025), while the triple-dimension framework proposed by Liang et al. (2025) — comprising resistance capacity, recovery capacity, and transformation capacity — has been adopted by the OECD (2020) as a policy benchmark. This framework emphasizes that the institutional environment, including labor market flexibility, the strength of social safety nets, and innovation governance systems, constitutes the core infrastructure of resilience. Notably, current resilience indicators still rely excessively on traditional economic variables and fail to incorporate key capabilities of the digital era, such as real-time data-driven policy response agility, resulting in a fragmented understanding of resilience mechanisms amid technological change (Sorokina et al., 2024).

When focusing on the intersection of AI and resilience, comparative studies of OECD countries highlight the decisive moderating role of the institutional context. Nordic countries have transformed AI-driven transitions into productivity leaps through skills retraining systems, such as Denmark's "flexicurity" model (Braun et al., 2025), whereas the market-led model of the United States has exacerbated regional disparities (Dotan, 2024). The European Union's *Artificial Intelligence Act* attempts to balance innovation and safety through risk-based regulation, yet its empirical impact on resilience remains untested (Rosskopf, 2025). An OECD (2023) cross-national analysis further confirms that data governance frameworks and the depth of public sector AI adoption significantly moderate the spillover effects of technology on societal resilience.

From this perspective, three major gaps exist in the current literature: First, a disconnection in the unit of analysis—research on AI at the firm/individual level and studies on national resilience lack integration. Second, a "black-boxing" of institutional variables—most empirical models fail to incorporate key moderating mechanisms such as labor policies and digital governance. Third, cross-national research overlooks the unique value of OECD member states—these economies share a foundation of institutional maturity yet exhibit rich diversity in their policy pathways.

III. THEORETICAL HYPOTHESES

A. The Impact of Artificial Intelligence on Economic Resilience

Economic resilience refers to an economy's capacity to withstand, absorb, and recover from external shocks. Within OECD research, this concept has been operationalized into a set of "vulnerability indicators" used for early warning and assessment. For example, the indicator system developed by Zhang (2025), which encompasses domestic imbalances and global risks, has been proven effective in predicting the risk of severe recessions in member states. This provides a foundational framework for analyzing how artificial intelligence (AI) influences these dimensions of resilience.

Existing literature indicates that AI primarily affects economic resilience through the following channels, with significant manifestations in OECD countries: First, as a general-purpose technology, AI enhances total factor productivity, thereby strengthening the foundation for long-term growth and risk resistance. For instance, studies show its significant positive impact on revenue growth for adopting firms in Italy (Deng et al., 2023). Second, AI drives industrial restructuring through automation and supply chain optimization while simultaneously exerting a dual effect on the labor market—replacing routine tasks while also creating new jobs. This makes skills retraining and social safety nets key topics in OECD policy discussions for cushioning shocks and maintaining resilience (Kyriakou et al., 2023). Third, AI technology itself can serve as a tool to enhance resilience. For example, by modeling and predicting corporate vulnerability during crises, it can help governments optimize economic stimulus policies, improving the foresight and precision of interventions. Fourth, AI can be integrated into critical infrastructure, enhancing operational efficiency and disturbance resistance through intelligent monitoring and scheduling. This is regarded by the OECD as an important direction for strengthening national economic security (Mishchuk et al., 2024).

In summary, the impact of artificial intelligence (AI) on economic resilience is first manifested through its most fundamental "foundational strengthening" effect. As a general-purpose technology, AI's core economic function lies in driving systemic productivity improvements and deep optimization of resource allocation. Such enhancement not only injects momentum into long-term economic growth but also provides economies with crucial buffer space and adjustment flexibility when facing external shocks, thereby accelerating the recovery process. Based on the above analysis, this study proposes the following hypothesis:

H1: The advancement of artificial intelligence exerts a significant enhancing effect on economic resilience.

B. The Role of Digital Transformation between Artificial Intelligence and Economic Resilience

Artificial intelligence technology serves as a core technical foundation for the digital transformation of enterprises and industries. By enabling process automation, optimizing decision-making procedures, and catalyzing innovative products and services, it directly drives the digitization of economic activities (Datti et al., 2023). Within OECD countries, the penetration rate of AI and related investments have become key indicators for measuring their overall level of digitalization. Concurrently, digital transformation is widely regarded as a significant channel for enhancing economic resilience—the ability of an economy to withstand, adapt to external shocks, and recover (Copestake et al., 2024). Research indicates that more digitally advanced industries and firms often exhibit greater resilience during economic downturns, such as experiencing smaller declines in sales and faster recovery speeds (Chowdhury, 2025). Specifically, digital transformation strengthens resilience through several mechanisms: it enhances operational flexibility, allowing firms to rely on digital infrastructure like cloud computing and remote collaboration to respond to external shocks and maintain business continuity (Sorokina et al., 2024); it optimizes resource allocation, as AI-driven data analytics enable more precise risk prediction, supply chain adjustment, and inventory management (Adegboye et al., 2025); and it fosters innovation and diversification by spurring new business models and markets, thereby reducing the economy's over-reliance on traditional industries and enhancing structural resilience (Yapi et al., 2024).

In summary, artificial intelligence primarily shapes economic resilience indirectly by propelling and deepening digital transformation. The transmission pathway can be summarized as follows: the widespread application of AI technology across sectors becomes a core component of enterprise digital transformation; this enables firms to build capabilities in data utilization, intelligent analytics, and automated response, forming the micro-foundation of organizational resilience; as digital transformation deepens at both the firm and industry levels, the adaptability, restorative capacity, and innovative potential of the entire economy are systematically elevated, ultimately manifesting as enhanced macroeconomic resilience. Based on the above analysis, this study proposes the following hypothesis:

H2: Digital transformation plays a significant mediating role in the process through which artificial intelligence influences economic resilience.

C. The Role of R&D Investment between Artificial Intelligence and Economic Resilience

Artificial intelligence, particularly machine learning technologies, is evolving into a general "method of invention," profoundly reshaping innovation processes and R&D organizational models. This transformation stimulates continuous increases in R&D investment by firms and nations in AI-related technologies, data infrastructure, and talent, aiming to secure a leading position at the technological frontier (Khot et al., 2023). Such R&D investment serves as a core channel for building long-term capabilities. It not only directly advances AI technological progress and knowledge accumulation but also fosters complementary innovations—such as new processes, products, and business models—thereby collectively strengthening a nation's knowledge base and technological diversity, which forms the fundamental underpinning of economic resilience (Wang et al., 2025).

Furthermore, AI-driven R&D activities enhance economic resilience through multiple pathways: First, technological innovations resulting from R&D improve total factor productivity and cultivate new growth drivers, providing the economy with more diversified and robust momentum for recovery following shocks (Hermann et al., 2021). Second, R&D promotes the development of emerging industries (e.g., the digital economy, green technologies), facilitating the transition of the industrial structure toward higher value-added and greater adaptability, thereby reducing dependence on traditional vulnerable sectors. Third, firms utilizing AI in their R&D activities can optimize operations, predict market fluctuations, and manage supply chain risks, thereby strengthening their own capacity to withstand crises. Firms with strong R&D capabilities thus tend to be more resilient and competitive (Ofodile et al., 2023). Fourth, the R&D process generates demand for and fosters the development of high-skilled talent, elevating the overall skill level of the labor market. This helps workers better adapt to changes in economic structure and mitigates the impact of technological unemployment (Guo et al., 2022).

In summary, by stimulating substantial increases in R&D investment at both the firm and national levels, artificial intelligence not only accelerates technological advancement and knowledge accumulation but also systematically enhances the economy's capacity to withstand, adapt, and recover. This is achieved through four specific pathways: total factor productivity improvement, industrial structure optimization, enterprise resilience strengthening, and human capital upgrading. Based on the above analysis, this study proposes the following hypothesis:

H3: R&D investment plays a significant mediating role in the process through which artificial intelligence influences economic resilience.

IV. DATA SOURCES AND VARIABLE MEASUREMENT

A. Estimation Model

$$Resil_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Control_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (1)$$

In Equation (1), i denotes the country and t denotes the time period. The dependent variable, $Resil_{it}$ represents the economic resilience of OECD countries, measured using GDP as the output to calculate economic resilience. The explanatory variable, AI_{it} represents the level of artificial intelligence in OECD countries, measured by the natural logarithm of AI patents. $Control_{it}$ denotes a set of control variables. δ_i represents country fixed effects, μ_t represents year fixed effects, and ε_{it} is the stochastic error term.

B. Data Sources

This study selects member countries of the Organisation for Economic Co-operation and Development (OECD) as the research sample, with the data covering the period from 2000 to 2023. Core macroeconomic data were primarily sourced from the OECD official statistical database, supplemented by indicators extracted from authoritative datasets such as the World Bank's World Development Indicators, the International Patent Classification (IPC), and the International Federation of Robotics (IFR). To ensure the rigor of the empirical analysis and the robustness of the results, systematic pre-processing was applied to the raw data, involving the following specific steps: First, for individual missing values in key variables, linear interpolation was employed to ensure the continuity of the time series. Second, to mitigate potential bias in parameter estimation caused by extreme outliers, all continuous variables in the model were winsorized at the 1st and 99th percentiles.

C. Variable Definition

a. Dependent Variable

This study focuses on economic resilience at the national level, aiming to examine—from a macro-system perspective—the mechanisms through which artificial intelligence technology influences the overall risk-resistance capacity and dynamic adaptability of an economy. However, given the difficulty in systematically obtaining direct data linking national-level AI development and economic resilience, this paper draws on the innovative approach proposed by Arbabi et al. (2023) to construct a regional composite economic resilience index applicable to member countries of the Organisation for Economic Co-operation and Development (OECD). The core formula for calculating this index is as follows:

$$Resilience_r^T = \frac{\frac{Y_r^T - Y_r^t}{Y_r^t} - \frac{Y_{\text{OECD}}^T - Y_{\text{OECD}}^t}{Y_{\text{OECD}}^t}}{\left|\frac{Y_{\text{OECD}}^T - Y_{\text{OECD}}^t}{Y_{\text{OECD}}^t}\right|} \quad (2)$$

In Equation (2), Y_r^t and Y_r^T represent the real economic output of region r (i.e., the member country) in the base year t and the final assessment year T respectively. Correspondingly, Y_{OECD}^t and Y_{OECD}^T denote the real GDP of the entire OECD economy in the same base year t and final year T. Output Y is measured by real Gross Domestic Product (GDP).

The index constructed through this calculation method captures a composite signal of the adaptability, restorative capacity, and transformative capability of a national economic system over the long-term dynamic process. Specifically, a positive value indicates that the country's economic system possesses stronger inherent robustness and dynamic adjustment efficacy, enabling it to better withstand risks and seize opportunities amid the waves of globalization and digitalization, thereby achieving relatively superior long-term performance. Conversely, a negative value suggests that the country may exhibit systematic vulnerabilities in its economic structure, institutional flexibility, or technological adaptability.

In the subsequent analysis, drawing on the research approaches of Martin (2011) and Ma et al. (2024), this study selects the share of industrial value-added in GDP (Industry Value Added / GDP) as an important structural indicator for measuring regional economic resilience. This ratio can intuitively reflect the scale and importance of the industrial sector relative to the overall economy in a specific region, thereby revealing the fundamental characteristics of its industrial structure and its potential capacity to buffer against risks. Specifically, a higher share of industry typically indicates that the region possesses a relatively complete industrial system and supply chain foundation. When facing external shocks, such a region may demonstrate stronger short-term resistance and production recovery elasticity through capacity adjustment, technological substitution, and endogenous production cycles. Conversely, a lower share may suggest that the regional economy relies more on the service sector or other forms of economic activity, and its resilience mechanisms may depend more on different pathways, such as demand adaptation, innovative flexibility, or digital connectivity.

b. Independent Variable

Drawing on the methodology of Bordot (2022), this study utilizes the OECD database on "AI-related inventions." This database systematically identifies patent inventions related to core AI technologies—such as machine learning, computer vision, and natural language processing—based on International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes, thereby constructing a country-year level indicator of AI patent stock. This metric effectively reflects a country's foundational innovation capacity, depth of technological accumulation, and pre-existing knowledge base for future industrial applications in the field of artificial intelligence. It provides a reliable and transparent quantitative foundation for measuring the technological supply and development level of AI from a macroeconomic perspective.

In subsequent analysis, this study draws on the approach of Acemoglu et al. (2019) by employing annual data on new industrial robot installations in OECD countries, sourced from the International Federation of Robotics (IFR), as a measure of artificial intelligence. This indicator effectively captures the real-world intensity of AI and automation technology adoption within the physical economy, as well as the pace of capital deepening. A higher value signifies more active investment in intelligent production equipment within a country's manufacturing sector and broader economy for that specific year, indicating a faster process of converting cutting-edge technologies into tangible productive capacity. This serves as a complementary physical indicator to the patent-based measure.

c. Control Variables

Drawing on the methodology established by Liang et al. (2022) and Zhang et al. (2024), this study incorporates a set of control variables to account for other factors potentially influencing economic resilience in OECD countries, including: GDP, real GDP per capita based on purchasing power parity (PPP); Trade, the sum of exports and imports of goods and services as a percentage of GDP; Infra, a composite infrastructure index synthesizing indicators from transportation, telecommunications, and energy; FDI, net inflows of foreign direct investment as a percentage of GDP; Unempl, the unemployment rate as a percentage of the total labor force; Findev, the total stock market capitalization as a percentage of GDP; and Edu, government expenditure on education as a percentage of GDP.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Resil	912	1.469	7.038	-4.833	55.53
AI	912	2.516	2.061	0.467	8.474
Gdp	912	1.048	0.839	-4.874	3.196
Trade	912	22.93	1.863	14.25	27.11
Infra	912	16.35	1.506	12.69	19.59
Fdi	912	23.04	1.736	14.50	27.32
Unempl	912	6.047	1.552	1.629	9.079
Findev	912	4.504	0.060	4.409	4.621
Edu	912	78.67	7.979	7.944	94.86

V. RESULT AND ANALAYSIS

A. Benchmark Regression

The baseline regression results are presented in Table 2. Column (1) reports the estimates from a parsimonious model including only the core explanatory variable, Artificial Intelligence (AI), while controlling for year and entity fixed effects. The regression coefficient for AI is 0.388, which is positive and statistically significant at the 1% level. This preliminary finding suggests that the level of AI development has a significant positive impact on economic resilience. Column (2) further incorporates a set of macroeconomic control variables while maintaining the year and entity fixed effects. Under this more comprehensive model specification, the estimated coefficient for AI increases to 0.427 and remains highly significant at the 1% level. This result indicates that, after controlling for a series of macroeconomic factors that may influence economic resilience, as well as unobserved heterogeneity across entities and time, the positive promoting effect of AI on economic resilience remains robust, and its magnitude even strengthens. In other words, the application and development of artificial intelligence technology can significantly enhance a nation's capacity to respond to external shocks, maintain stability, and achieve recovery. This finding provides strong empirical support for Hypothesis 1 of this study.

Table 2 Baseline Regression

	Resil	
VARIABLES	**(1)**	**(2)**
AI	0.388***	0.427***
	(0.124)	(0.124)
Gdp		0.328*
		(0.177)
Trade		-0.087
		(0.141)
Infra		-0.180
		(0.358)
Fdi		-0.080
		(0.146)
Unempl		-1.623***
		(0.455)
Findev		9.234***
		(2.330)
Edu		0.018
		(0.024)
Constant	0.494	56.79***
	(0.339)	(12.25)
Fix Effect	Yes	Yes
Observations	912	912
R-squared	0.011	0.044
Number of ID	38	38

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

B. Robustness Test

a. Replace the dependent variable

In the previous analysis, the composite economic resilience index (Resilience), measured by calculating relative regional recovery differentials, primarily captures a country's relative economic performance in terms of recovery compared to the OECD average following shocks. This index comprehensively reflects its adaptability, restorative capacity, and transformative capability. However, the calculation of this indicator is highly dependent on the selection of the base and evaluation periods. Its value may, to some extent, be influenced by specific macroeconomic fluctuations, common global shocks, or synchronized regional cycles within the chosen time window, introducing potential measurement bias and endogeneity concerns. Therefore, to address these potential limitations and verify the robustness of the baseline regression findings, this study draws on the research of Martin (2011) and Ma et al. (2024) by introducing the share of industrial value-added in GDP (Industry Value Added / GDP) as a structural proxy variable for economic resilience (Resil_2). This indicator more directly reflects the scale and depth of the tangible productive sector within a country's economic system, as well as the resulting supply chain completeness, production capacity buffer, and potential for short-term adjustment and endogenous recovery in the face of external shocks. The robustness check results are presented in Table 3. Column (1) shows that the regression coefficient of Artificial Intelligence (AI) on economic resilience measured by the industrial share (Resil_2) is 0.266, which is positive and statistically significant at the 5% level. This indicates that even when the measurement of economic resilience is changed—from a comprehensive relative performance indicator to a specific structural characteristic of the industrial sector—artificial intelligence still exerts a significant positive effect on it. The core conclusion remains consistent with the baseline regression, verifying the reliability of the research findings.

Table 3 Roboustness Test

VARIABLES	**Resil_2** **(1)**	**Resil** **(2)**
AI	0.266**	
	(0.120)	
AI_2		0.188**
		(0.088)
Constant	54.34***	55.13***
	(11.87)	(12.29)
Control Var	Yes	Yes
Fix Effect	Yes	Yes
Observations	912	912
R-squared	0.037	0.036
Number of ID	38	38

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

b. Replace the independent variable

The previous analysis primarily relied on the OECD "AI-related inventions" database, utilizing country-year level AI patent stock to measure the level of artificial intelligence development. This indicator mainly captures a country's knowledge creation capacity, foundational innovation accumulation, and future technological application potential in core AI technology fields. However, as a patent-based measure, this indicator may be influenced to some extent by factors such as variations in patent application quality, delays in patent examination, the length of commercialization cycles, and strategic "patent bubble" behaviors. It emphasizes the "innovation capacity" on the technology supply side, which does not fully equate to the actual "penetration and application intensity" of technology in real economic production, thus presenting potential measurement bias and limitations.

Therefore, to further test the robustness of the core findings from the perspective of technology application, this study draws on the approach of Acemoglu et al. (2019) by introducing a new proxy variable for artificial intelligence (AI_2): the annual number of new industrial robot installations in each country, as reported by the International Federation of Robotics (IFR). This indicator more directly reflects the actual capital investment intensity of AI and automation technologies in real economic sectors like manufacturing, the pace of intelligent transformation in production processes, and the immediate progress of translating cutting-edge technologies into tangible productive forces.

The results of this robustness check are presented in Table 3. Column (2) shows that when the core explanatory variable is replaced with industrial robot installations (AI_2), its regression coefficient on economic resilience (Resil) is 0.188, which is positive and statistically significant at the 5% level. This further confirms that whether measured from the perspective of innovative knowledge stock (patent stock) or physical technology application (robot installations), artificial intelligence exerts a significant positive promoting effect on economic resilience. The core conclusion of the baseline regression remains robust under different measurement approaches.

C. Heterogeneity Test

a. AI Readiness

Drawing on the methodological approach of Sioumalas-Christodoulou et al. (2025), this study uses the Government AI Readiness Index—an authoritative annual index published by Oxford Insights that assesses a government's preparedness to utilize AI for public service delivery across three pillars: government strategy, the technology sector, and data & infrastructure—as the basis for sample stratification. The sample is divided into a high AI-readiness country group and a low AI-readiness country group.

The heterogeneity test results in Columns (1) and (2) of Table 4 reveal significant inter-group differences in the impact of Artificial Intelligence (AI) on economic resilience. In the high AI-readiness country group, the regression coefficient for AI is 0.615, which is positive and highly statistically significant at the 1% level. In contrast, in the low AI-readiness country group, the coefficient for AI is only 0.216 and lacks statistical significance.

This indicates a clear "institutional threshold effect" in the empowering role of AI on economic resilience, with its positive impact fully manifesting only in countries with higher government AI readiness. The likely reason is that a high level of government AI readiness typically signifies more forward-looking national digital strategies, more robust digital infrastructure, better-regulated public data governance frameworks, and more efficient cross-departmental coordination mechanisms. These institutional conditions collectively create an "enabling environment." This environment not only effectively reduces the systemic costs and uncertainties associated with the diffusion and application of AI technology at the firm and industry levels but also channels AI investment and innovation more precisely towards key areas that enhance economic system stability, such as improving supply chain resilience and optimizing public crisis response. Consequently, it facilitates the translation of technological potential into tangible macro-level risk resistance.

In contrast, in countries with low government AI readiness, despite the potential existence of isolated technological applications, the depth of penetration and breadth of application of AI technologies are constrained by the lack of top-level strategic guidance, coordinated supportive policies, and inclusive infrastructure. As a result, the systemic benefits of AI for enhancing economic resilience fail to fully materialize, leading to an insignificant marginal contribution to macroeconomic resilience.

Table 4 Heterogeniety Test

VARIABLES	High AI Readiness (1)	Low AI Readiness (2)	High Income (3)	Low-Middle Income (4)
AI	0.615***	0.216	0.633***	0.190
	(0.212)	(0.134)	(0.218)	(0.135)
Constant	92.52***	11.104	101.8***	12.26
	(21.08)	(14.12)	(27.59)	(11.59)
Control Var	Yes	Yes	Yes	Yes
Fix Effect	Yes	Yes	Yes	Yes
Fisher’s Test	0.047		0.054	
Observations	336	576	480	432
R-squared	0.085	0.025	0.057	0.050
Number of ID	14	24	20	18

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

b. National Income Level

Drawing on the methodological approach of Marchand (2025), this study stratifies the sample into a high-income country group and a middle-to-low-income country group based on the World Bank income classification. The heterogeneity test results in Columns (3) and (4) of Table 5 reveal significant differences in the impact of Artificial Intelligence (AI) on economic resilience across countries with different income levels. In the high-income country group, the regression coefficient for AI is 0.633, which is positive and highly statistically significant at the 1% level. Conversely, in the middle-to-low-income country group, the coefficient for AI is 0.190 and does not achieve statistical significance.

This indicates a distinct "development-level threshold effect" in the ability of AI to promote economic resilience, with its positive impact being primarily concentrated in high-income economies. The likely explanation is that high-income countries generally possess more substantial material capital accumulation, more complete and complementary digital infrastructure (such as high-speed broadband and cloud computing), higher levels of R&D investment and human capital reserves. Furthermore, their market environments and regulatory frameworks are typically more conducive to the rapid iteration, large-scale commercialization, and cross-sector penetration of frontier technologies. These conditions collectively form an efficient "technology absorption and transformation ecosystem." This ecosystem facilitates the deep integration of AI's general-purpose technological potential into existing production networks, innovation systems, and governance models, thereby systematically enhancing the economy's buffer capacity against shocks and its agility in structural adjustment.

In contrast, in middle-to-low-income countries, despite the presence of isolated cases of AI technology adoption, factors such as relatively weaker foundational R&D capabilities, insufficient supportive infrastructure, shortages of skilled personnel for technology application, and potentially more pressing developmental constraints, collectively limit the efficiency of AI technology absorption, the depth of its application, and the breadth of its diffusion. Consequently, the marginal effect of AI on enhancing macroeconomic resilience is not statistically evident at the aggregate level, suggesting that the technological dividend has not yet crossed the threshold required to trigger systemic resilience strengthening.

D. Mechanism Test

In this study, to further unveil the intrinsic mechanisms through which artificial intelligence influences economic resilience, national digital transformation is introduced as a key mediating variable. Drawing on the methodology of Ji et al. (2024) and utilizing the OECD Digital Government Index (DGI) database, it is proposed that the national-level digital transformation serves as a critical channel for transmitting the technological dividends of AI and shaping economic resilience. Specifically, AI-driven digital transformation can reduce frictions and delays in economic activities caused by information asymmetry and geographical distance, enhance the dynamic allocation efficiency of production factors across sectors and regions, and improve the visibility and coordination of supply chains. Consequently, when facing external shocks, the overall economic system becomes more capable of rapidly identifying risks, reallocating resources, and adapting to changes, ultimately strengthening its comprehensive resilience in terms of resistance, recovery, and transformation. Simultaneously, effective digital governance and data security frameworks are essential for ensuring the robustness and inclusiveness of the digital transformation process. They help prevent the widening of the digital divide, safeguard fair market competition, and ensure that the benefits of digital growth are distributed across broader economic sectors.

Furthermore, to examine another pathway involving knowledge creation and absorption, this study also draws on the approach of Mishchuk et al. (2024) by adopting R&D intensity as an additional mediating variable, with data sourced from the OECD AI Policy Observatory database. Specifically, R&D investment directly facilitates the digestion, absorption, and re-innovation of frontier technologies such as AI, accelerating the capitalization of technological knowledge. It reflects a country's endogenous innovation capacity in translating the potential of general-purpose technologies into localized, specialized solutions, which constitutes an indispensable knowledge foundation for long-term economic resilience. To rigorously test the above mediating mechanisms, the following recursive equation models are constructed for stepwise examination:

$$Digital_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Control_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (3)$$

$$Resil_{it} = \emptyset_0 + \emptyset_1 AI_{it} + \emptyset_2 Digital_{it} + \emptyset_3 Control_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (4)$$

$$Rnd_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Control_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (5)$$

$$Resil_{it} = \emptyset_0 + \emptyset_1 AI_{it} + \emptyset_2 Rnd_{it} + \emptyset_3 Control_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (6)$$

In Equation (3), i and t denote the country and year, respectively. $Digital_{it}$ represents the level of digital transformation, serving as the dependent variable. In Equation (3), the variable $Digital_{it}$ is introduced into the model as a mediating variable. In Equation (4), RND_{it} denotes research and development (R&D) intensity as the dependent variable. In Equation (5), the variable RND_{it} is incorporated into the model as an additional mediating variable. $Control_{it}$ refers to a set of control variables. δ_i and μ_t represent the individual fixed effects (which are time-invariant) and the time fixed effects (which are cross-sectionally invariant), respectively. ε_{it} is the stochastic error term.

Table 6 Mechanism Test

VARIABLES	Digital (1)	Resil (2)	Rnd (3)	Resil (4)
AI	0.007***	0.414***		
	(0.002)	(0.125)		
Digital		0.599**		
		(0.233)		
AI			0.052***	0.408***
			(0.017)	(0.124)
Rnd				0.014***
				(0.004)
Constant	14.17***	65.28**	66.15***	55.87***
	(0.207)	(31.06)	(2.955)	(15.40)
Control Var	Yes	Yes	Yes	Yes
Fix Effect	Yes	Yes	Yes	Yes

Observations	912	912	912	912
R-squared	0.026	0.044	0.032	0.044
Number of ID	38	38	38	38

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 presents the results of the mechanism tests for the two mediating pathways through which artificial intelligence influences economic resilience. First, regarding the pathway of "AI → Digital Transformation → Economic Resilience," Column (1) shows that the regression coefficient of Artificial Intelligence (AI) on Digital Transformation (Digital) is 0.007, which is statistically significant at the 1% level. This indicates that the development of AI effectively drives the process of digital transformation at the national level, providing a necessary precondition for its role in enhancing economic resilience. Furthermore, the results in Column (2) reveal that, after controlling for the direct effect of AI, the coefficient of Digital Transformation (Digital) on Economic Resilience (Resil) is 0.599, which is positive and significant at the 5% level. This suggests that an increase in the level of digital transformation is itself a significant driver for strengthening the resilience of the economic system. Combining the findings from Columns (1) and (2), it is evident that AI not only directly promotes economic resilience (with a significant coefficient of 0.414, which is notably smaller than in the baseline regression) but also partially exerts its influence indirectly by fostering digital transformation. Thus, Hypothesis 2 is supported by the empirical evidence.

Second, concerning the pathway of "AI → R&D Investment → Economic Resilience," Column (3) indicates that the coefficient of Artificial Intelligence (AI) on national R&D intensity (Rnd) is 0.052, which is highly significant at the 1% level. This implies that advancements in the field of AI significantly incentivize countries to increase R&D investment, thereby stimulating broader knowledge creation and technological innovation activities. Simultaneously, the results in Column (4) show that the coefficient of R&D Investment (Rnd) on Economic Resilience (Resil) is 0.014, also positive and significant at the 1% level. This demonstrates that R&D and innovation constitute a critical knowledge foundation and capacity reserve for building long-term economic resilience. Integrating the results from Columns (3) and (4), it is clear that AI not only directly enhances economic resilience (with a significant coefficient of 0.408, which is noticeably smaller than in the baseline regression) but also partially operates indirectly through stimulating increased R&D investment. Consequently, Hypothesis 3 is empirically substantiated.

CONCLUSSION

Based on panel data from OECD member countries spanning 2000 to 2023, this study systematically investigates the impact of artificial intelligence (AI) on national economic resilience and its underlying mechanisms, yielding the following conclusions. The baseline regression and a series of robustness tests consistently demonstrate that the level of AI development—whether measured by innovation capacity (patent stock) or application intensity (industrial robot installations)—exerts a significant positive effect on national economic resilience. This validates Hypothesis 1, confirming AI's role as a general-purpose technology in enhancing an economy's capacity to buffer against and recover from external shocks through fundamental channels such as productivity gains and resource optimization. Heterogeneity analysis further reveals a significant "threshold effect," where AI's positive impact is markedly stronger in countries with higher government AI readiness and income levels, highlighting its dependence on complementary institutional environments and development conditions. The mechanism tests identify two key mediating pathways: AI not only directly enhances resilience but also does so indirectly by driving national digital transformation and stimulating R&D investment. Specifically, AI acts as a core engine for digital transformation (Pathway 1), which subsequently strengthens resilience by improving systemic transparency, allocation efficiency, and adaptive agility. Concurrently, AI advancement incentivizes greater R&D investment (Pathway 2), with the accumulated knowledge capital and innovative capacity forming a critical foundation for long-term economic adaptation, thereby supporting Hypotheses 2 and 3.

Based on these findings, integrated recommendations are proposed. Policymakers should focus on building systemic national AI strategies and strengthening digital infrastructure and governance to create a conducive "enabling environment," while implementing inclusive and differentiated policies—such as promoting digital literacy, expanding network access, and providing fiscal incentives—to bridge divides. Sustained increases in R&D investment and fostering industry-academia-research collaboration are also crucial. International organizations like the OECD should facilitate the sharing of best practices and standards among members and provide capacity-building support for lagging economies to promote inclusive development. Future research should further expand the investigation of impact mechanisms, deepen contextual analyses, and refine measurement methodologies to more comprehensively and dynamically elucidate the complex relationship between AI and economic resilience.

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