Local Government AI Policy Attention and Urban Economic Resilience:Evidence from Chinese Prefecture-Level and Above Cities

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Abstract: This paper examines the relationship between local government AI policy attention and urban economic resilience, and further identifies the roles of urban absorptive conditions and fiscal channels. Using an unbalanced panel of Chinese prefecture-level and above cities from 2011 to 2024, we construct a local government AI policy attention indicator from government work reports and measure urban economic resilience as the deviation of city GDP growth from national GDP growth. A two-way fixed effects model is employed. Baseline estimates show that, after controlling for population size, population density, economic development level, openness, industrial structure, and human capital, local government AI policy attention is significantly and positively associated with urban economic resilience. The result is robust to alternative measures of the key explanatory variable, two-sided winsorization, and the inclusion of province-by-year fixed effects. Subgroup analysis indicates that the positive association is more pronounced in eastern cities and in cities with higher economic development. Moderation tests show that industrial structure advancement and digital financial inclusion each strengthen the positive relationship, while mechanism tests indicate that local government AI policy attention is significantly associated with lower fiscal revenue-expenditure pressure, which in turn is significantly negatively associated with urban economic resilience. The findings suggest that the resilience effect of policy attention depends on urban absorptive conditions, and that fiscal space may be an important channel through which policy attention translates into economic resilience.

Key words: local government AI policy attention; urban economic resilience; industrial structure advancement; digital financial inclusion level; fiscal revenue-expenditure pressure

JEL Classification: C23; O33; R11; R58

1 Introduction

AI is evolving from a single technological tool into a general-purpose technology [1][2] that reshapes production organization, public governance, and the allocation of urban resources. For urban economies, the significance of AI extends beyond productivity gains in a single industry [3][4] to changes in information processing [5], factor matching, organizational coordination, and risk response. Against a backdrop of fluctuating external demand, supply-chain disruptions, and rising macroeconomic uncertainty, whether a city can sustain economic activity, recover rapidly, and adjust its growth structure amid shocks has become a key dimension of local economic governance. A question of practical relevance follows: is local government attention to AI issues associated with stronger urban economic resilience?

Local government AI policy attention differs from enterprise-level AI adoption [6] and from tangible industrial investment. It is first reflected in the intensity of attention that a government assigns to AI-related content in its annual policy agenda [7][8][9]. Government work reports carry explicit agenda-setting and resource-allocation implications [10], so an increase in AI-related statements can be read as the local government raising the priority of this issue in its annual governance goals. Policy attention is not itself equivalent to policy effect, but it may shape a city's capacity to respond to shocks by releasing policy signals [11], coordinating cross-departmental resources [12], guiding industrial expectations, and advancing digital governance [13].

Existing discussions of urban economic resilience typically explain cross-city differences under shocks through industrial diversification [14], digital infrastructure [15][16], innovation capacity , financial conditions , or fiscal capacity . Relative to these outcome-based or stock-based factors, local government policy attention to a new technology issue is a more upstream governance variable. Its economic meaning lies in whether the government promptly identifies new technological opportunities and incorporates them into the policy agenda. [17][18][19]During the rapid diffusion of AI [30], cities differ markedly in the timing and intensity of their attention to this issue and in their ability to convert policy signals into actual resource allocation, which provides identifiable city-year variation for examining the relationship between policy attention and urban resilience.

Using a sample of Chinese prefecture-level and above cities from 2011 to 2024, we construct a local government AI policy attention indicator from government work reports and measure urban economic resilience as the deviation of city GDP growth from national GDP growth. [20][21]The empirical analysis employs a two-way fixed effects model that controls for population size, population density, economic development level, openness, industrial structure, and human capital. To examine whether the conclusions depend on specific measures or model specifications, we further conduct robustness checks using alternative explanatory variables, two-sided winsorization, and province-by-year fixed effects.[22][23]

Beyond the average relationship, we examine whether policy attention can actually be absorbed by the urban economic system. The application of AI requires industrial scenarios, data infrastructure, financing conditions, and organizational capacity, so the same degree of policy attention may yield different outcomes across cities. On this basis, we examine the moderating roles of industrial structure advancement and digital financial inclusion, and analyze heterogeneity along regional distribution and economic development level. [24][25]Local public finance is both an important constraint on technology policy implementation and a foundation for public services and countercyclical adjustment during shocks. We therefore further test whether fiscal revenue-expenditure pressure constitutes a potential transmission channel through which local government AI policy attention affects urban economic resilience.[26][27]

The empirical results are broadly consistent. In the baseline regression, the coefficient on local government AI policy attention is positive and significant at the 1% level; the core result remains positive under alternative measures, outlier treatment, and controls for province-level common shocks over time. Subgroup regressions show that the positive association is more pronounced in eastern cities and in cities with higher economic development. [28][29]Moderation tests further indicate that industrial structure advancement and digital financial inclusion each significantly strengthen the positive relationship between local government AI policy attention and urban economic resilience. Mechanism results show that local government AI policy attention is significantly negatively associated with fiscal revenue-expenditure pressure, while fiscal revenue-expenditure pressure is significantly negatively associated with urban economic resilience, consistent with a fiscal-pressure-relief transmission mechanism.

The contributions are threefold. First, we examine the urban economic implications of AI from the perspective of local government policy attention rather than pure technology adoption, placing government agenda-setting and urban economic resilience within a single empirical framework. Second, we use government work report text to construct a city-year-level local government AI policy attention indicator and match it with urban macroeconomic performance, offering an operational measure that captures the intensity of local government attention to a new technology. Third, rather than treating policy attention as uniformly effective across cities, we identify the roles of industrial structure advancement, digital financial inclusion, and fiscal revenue-expenditure pressure, showing that whether policy attention translates into resilience depends on a city's absorptive conditions and fiscal space.

It should be emphasized that the baseline identification relies on city and year two-way fixed effects and a set of observable control variables, and primarily identifies the conditional correlation between within-city changes in local government AI policy attention and urban economic resilience. We maintain this identification boundary throughout and do not equate the fixed-effects estimates with strict causal effects.

2 Theoretical Mechanisms and Hypotheses

2.1 Local Government AI Policy Attention and Urban Economic Resilience

Policy attention reflects the outcome of local governments ranking different issues under finite governance resources [10]. When the frequency of AI in government work reports rises, it typically signals an increase in the visibility and priority of this issue in the annual governance agenda. Higher policy attention first generates a clear signaling effect: on one hand, it transmits priorities within the government and lowers cross-departmental coordination costs [12]; on the other, it conveys to firms, financial institutions, and other market actors the local government's supportive expectations regarding the relevant technologies and industries, thereby shaping the allocation of investment, talent, and innovation resources.

From the perspective of urban economic resilience, AI policy attention may enhance shock-coping capacity by improving information processing and resource-matching efficiency [31]. AI-related policies are often linked to digital governance [13], data-factor utilization, intelligent manufacturing, and modern service applications. Even if policy attention is not itself equivalent to actual technology adoption, raising the priority of the issue may still push local governments to organize digital infrastructure [15][16], public data, and application scenarios more rapidly, thereby reducing information search and transaction frictions. When external shocks occur, higher information-processing efficiency and stronger organizational coordination help a city identify risks, adjust resource allocation, and sustain key economic activities more quickly.

Policy attention may also raise a city's adaptive capacity through innovation and industrial adjustment [20]. AI has strong general-purpose-technology attributes [1][2], and its application can penetrate manufacturing, logistics, finance, business services, and public governance [5]. When local governments raise the policy priority of AI, they help strengthen the link between new technologies and existing industries, create new production and service scenarios, and push firms to seek alternative growth sources under demand or cost shocks. Cities may therefore exhibit stronger growth stability and recovery capacity when facing common macroeconomic shocks.

Policy attention may also entail formalistic expression, resource misallocation, or short-term crowding-out of investment, so its net effect is not a priori determined. The empirical question is whether, after controlling for city fixed characteristics, common year shocks, and major socio-economic features, a stable positive relationship exists between local government AI policy attention and urban economic resilience.

H1: Local government AI policy attention is significantly and positively associated with urban economic resilience.

2.2 The Moderating Role of Industrial Structure Advancement

Whether policy attention translates into actual economic outcomes depends on whether a city possesses industrial absorptive conditions matched to AI. Industrial structure advancement reflects the degree to which an urban economy evolves from traditional production toward service-oriented, high-value-added, and knowledge-intensive activities [32]. Compared with cities whose industrial structures are more single-track or low-value-added, cities with higher industrial structure advancement typically have richer digital-technology application scenarios, denser producer services, and stronger specialized division of labor.

When local governments raise AI policy attention, a higher level of industrial structure advancement can shorten the transmission chain from policy signals to firm adoption [33]. AI-related algorithms, data processing, and intelligent decision-making are more easily embedded in finance, logistics, R&D, business services, and high-end manufacturing, raising the matching efficiency between technology supply and industrial demand. Moreover, the more advanced the industrial structure, the more likely a city is to diversify risk through cross-industry resource reallocation and service-oriented transition when a particular industry is hit. The positive relationship between AI policy attention and economic resilience may therefore be stronger.

H2a: Industrial structure advancement positively moderates the relationship between local government AI policy attention and urban economic resilience.

2.3 The Moderating Role of Digital Financial Inclusion Level

AI-related activities feature high upfront investment, technological uncertainty, and data-capital requirements [4][34], and their diffusion is vulnerable to financing constraints. Higher digital financial inclusion can broaden financial service coverage, reduce information asymmetry, and improve financing access for small and medium enterprises and innovation entities [22][24][25][26][35]. For local governments, the industrial and technological signals released by policy attention translate into firm investment, technology adoption, and organizational adjustment only when combined with accessible financial resources [23].

During shocks, digital financial inclusion may also provide faster fund allocation and risk-buffering channels [21]. The liquidity needs of firms and residents typically rise amid economic fluctuations, and digital financial services can accelerate fund matching and expand service reach. In cities with higher digital financial inclusion, the resource mobilization and technology-application effects brought by local government AI policy attention are more easily absorbed by market actors, manifesting as stronger urban economic resilience. The core argument is not that digital financial inclusion necessarily raises resilience on its own, but that as a financial absorptive condition it changes the strength of the relationship between local government AI policy attention and resilience.

H2b: Digital financial inclusion level positively moderates the relationship between local government AI policy attention and urban economic resilience.

2.4 The Transmission Role of Fiscal Revenue-Expenditure Pressure

Local fiscal conditions directly affect a city's policy space for responding to economic shocks [28][29][14]. When the fiscal revenue-expenditure gap is large, local governments face stronger constraints on public services, employment stabilization, infrastructure maintenance, and countercyclical spending, and external shocks are more easily translated into sustained economic downturns. Fiscal revenue-expenditure pressure is therefore both an important constraint on urban governance capacity and a potential link between new-technology policy and urban macroeconomic resilience.

After local governments raise AI policy attention, fiscal revenue-expenditure pressure may change through two channels. First, AI-related policy attention may promote digital governance and improve the efficiency of public resource allocation [36], lowering part of the administrative and transaction costs. Second, if policy attention fosters new industrial activity, enterprise digital transformation, and new growth points, it may improve local economic activity and fiscal space. Conversely, AI infrastructure and industrial support may also raise fiscal spending in the short run [37][38], so this channel requires empirical testing rather than being judged on theory alone.

If local government AI policy attention is significantly associated with lower fiscal revenue-expenditure pressure, while higher fiscal revenue-expenditure pressure corresponds to weaker urban economic resilience, this provides evidence for a "policy attention-fiscal space-economic resilience" transmission path. Given that we do not employ an exogenous-shock-based mediation identification, we interpret this result as an empirical association consistent with a fiscal-pressure-relief mechanism.

H3: Fiscal revenue-expenditure pressure is a potential transmission channel through which local government AI policy attention affects urban economic resilience; higher AI policy attention is associated with lower fiscal revenue-expenditure pressure, and lower fiscal revenue-expenditure pressure is associated with higher urban economic resilience.

3 Data, Variables, and Research Design

3.1 Data Sources

The sample covers Chinese prefecture-level and above cities from 2011 to 2024. Data come from four sources: first, the text of prefecture-level government work reports, used to construct the local government AI policy attention indicator; second, city and national macroeconomic data, used to measure urban economic resilience; third, prefecture-level socio-economic statistics on population, industry, openness, and human capital, used to construct control variables; and fourth, the Peking University Digital Financial Inclusion Index, used to characterize the level of urban digital financial inclusion.

The government work report text is uniformly denoised, cleaned, and structured, after which AI-related statements are identified using an AI-related word list and standardized by text length. Data on city gross domestic product, population, industrial structure, imports and exports, and higher education come mainly from the China City Statistical Yearbook, regional statistical yearbooks, and statistical bulletins, while national data come from the national statistics authority. The data are matched by city code and year, and after removing observations missing key variables, an unbalanced city panel is formed.

3.2 Variable Construction

3.2.1 Dependent Variable

Urban economic resilience (resilience) captures the capacity of an urban economic system to maintain relative stability, recover, and adjust adaptively under external shocks. Given that composite indicator systems may introduce substantial subjectivity in indicator selection and weighting, we adopt a core-variable proxy approach: using city gross domestic product as the core variable and national GDP growth as the benchmark reference under a common macroeconomic shock, we examine the deviation of a city's actual growth performance from the national benchmark.

Specifically, under a one-year period setting, urban economic resilience is expressed as the ratio of the difference between city GDP growth and national GDP growth to the absolute value of national GDP growth:

$$Resilience\_it = (cg\_it - ng\_t) / |ng\_t| \qquad (1)$$

where cg_it denotes the GDP growth rate of city i in year t, and ng_t denotes the national GDP growth rate in year t. When resilience_it > 0, the city's actual growth performance exceeds the national average; a larger value indicates stronger resistance and recovery capacity under the common shock.

3.2.2 Independent Variable

The key explanatory variable is local government AI policy attention (ai). We sum the frequencies of AI-related word items in prefecture-level government work reports and standardize by the report text length to eliminate the influence of differences in report length across cities and years. The calculation is:

$$AI\_it = (AIWords\_it / TextLength\_it) \times 10{,}000 \qquad (2)$$

where AIWords_it denotes the total number of occurrences of AI-related word items in the government work report of city i in year t, and TextLength_it denotes the total length of the corresponding report. A larger value of ai indicates a higher degree of local government attention to the AI issue in the annual governance agenda. In robustness checks, we further replace the key explanatory variable with two alternative measures: "frequency per ten thousand words based only on Chinese-English text" and "the ratio of AI word frequency to total word frequency."

3.2.3 Control Variables

To reduce omitted-variable bias arising from differences in city-level socio-economic characteristics, we select the following control variables. Population size (population) is measured by the natural logarithm of the permanent population; population density (pd) is measured by the natural logarithm of the ratio of permanent population to administrative land area.

Economic development level (development) is measured by the natural logarithm of per capita gross regional product; openness (openness) is measured by the share of total imports and exports in gross regional product.

Industrial structure (structure) is measured by the share of tertiary industry value-added in gross regional product; human capital (hc) is measured by the share of students enrolled in regular higher education institutions in the year-end total population.

3.2.4 Moderator and Mediator Variables

We further select industrial structure advancement and digital financial inclusion level as moderators, and fiscal revenue-expenditure pressure as a mediator. Industrial structure advancement (isa) is measured by the ratio of tertiary industry value-added to secondary industry value-added; a higher value indicates a higher degree of evolution toward service-oriented and high-value-added activities. Digital financial inclusion level (dif) is measured by the Peking University Digital Financial Inclusion Index, reflecting the comprehensive development of urban digital financial services. Fiscal revenue-expenditure pressure (fp) is measured by the share of the gap between local general budget expenditure and general budget revenue in gross regional product; a larger value indicates a larger fiscal gap and stronger fiscal constraints. The calculation of the main variables is shown in Table 1.

Table 1 Definition of main variables

Variable type	**Variable**	**Calculation**
Dependent variable	Urban economic resilience (resilience)	(City GDP growth − National GDP growth) / |National GDP growth|
Independent variable	Local government AI policy attention (ai)	Total frequency of AI-related words in government work report / Total report text length × 10,000
Control variable	Population size (population)	Natural logarithm of permanent population
Control variable	Population density (pd)	Permanent population / Administrative land area, natural logarithm
Control variable	Economic development level (development)	Natural logarithm of per capita gross regional product
Control variable	Openness (openness)	Total imports and exports / Gross regional product
Control variable	Industrial structure (structure)	Tertiary industry value-added / Gross regional product
Control variable	Human capital (hc)	Students enrolled in regular higher education institutions / Year-end total population
Moderator	Industrial structure advancement (isa)	Tertiary industry value-added / Secondary industry value-added
Moderator	Digital financial inclusion level (dif)	Peking University Digital Financial Inclusion Index
Mediator	Fiscal revenue-expenditure pressure (fp)	(Local general budget expenditure − Local general budget revenue) / Gross regional product

3.3 Model Specification

To examine the relationship between local government AI policy attention and urban economic resilience, we specify a city and year two-way fixed effects model:

$$Resilience\_it = \alpha + \beta\, AI\_it + \gamma\, Controls\_it + \mu\_i + \lambda\_t + \varepsilon\_it \qquad (3)$$

where resilience_it denotes urban economic resilience of city i in year t, ai_it denotes local government AI policy attention, Controls_it is the set of control variables, and μ_i and λ_t denote city fixed effects and year fixed effects, respectively; ε_it is the random disturbance. The parameter β captures the direction and magnitude of the relationship between local government AI policy attention and urban economic resilience. Standard errors of all regressions are clustered at the city level.

To examine the influence of urban absorptive conditions on the resilience effect of local government AI policy attention, we introduce industrial structure advancement and digital financial inclusion for moderation tests. After mean-centering the key explanatory variable and the moderators, we specify:

$$Resilience\_it = \alpha + \beta_1\, AI\_it + \beta_2\, M\_it + \beta_3(AI\_it \times M\_it) + \gamma\, Controls\_it + \mu\_i + \lambda\_t + \varepsilon\_it \qquad (4)$$

where M_it denotes industrial structure advancement (isa) and digital financial inclusion level (dif), respectively, and β3 is the interaction coefficient. If β3 is significantly positive, the corresponding absorptive condition strengthens the positive relationship between local government AI policy attention and urban economic resilience.

In addition, to test the transmission role of fiscal revenue-expenditure pressure, we estimate the following mediation model:

$$FP\_it = \alpha + \theta\, AI\_it + \gamma\, Controls\_it + \mu\_i + \lambda\_t + \varepsilon\_it \qquad (5)$$

$$Resilience\_it = \alpha + \beta_1\, AI\_it + \beta_2\, FP\_it + \gamma\, Controls\_it + \mu\_i + \lambda\_t + \varepsilon\_it \qquad (6)$$

If local government AI policy attention significantly affects fiscal revenue-expenditure pressure, and fiscal revenue-expenditure pressure is significant in the urban economic resilience equation, then fiscal conditions may be an important transmission channel through which local government AI policy attention affects urban economic resilience.

4 Empirical Results

4.1 Descriptive Statistics

Table 2 reports the descriptive statistics of the main variables. Urban economic resilience (resilience) has a mean of -0.0386, a standard deviation of 0.9476, a minimum of -12.7235, and a maximum of 8.8124, indicating substantial variation across cities and years relative to the national growth benchmark. Local government AI policy attention (ai) has a mean of 0.8653, a standard deviation of 1.1973, and a range of 0–22.0566, indicating noticeable regional and temporal variation in local government attention to the AI issue.

For the moderators and mediator, industrial structure advancement (isa) has a mean of 1.2403, digital financial inclusion level (dif) has a mean of 209.7108, and fiscal revenue-expenditure pressure (fp) has a mean of 0.1463; all three display a certain degree of dispersion. The control variables also differ markedly across population size, population density, economic development level, openness, industrial structure, and human capital, providing the sample variation needed to identify the relationship between local government AI policy attention and urban economic resilience. Sample sizes differ slightly across variables, mainly due to missing values from different data sources.

Table 2 Descriptive statistics

Variables	N	Mean	Std. Dev.	Min	Max
resilience	3978	-0.0386	0.9476	-12.7235	8.8124
ai	3902	0.8653	1.1973	0.0000	22.0566
isa	3970	1.2403	0.6624	0.1602	6.2430
dif	4103	209.7108	82.8404	17.0200	403.0792
fp	4124	0.1463	0.1471	-0.0104	1.5990
population	3928	5.8470	0.7627	2.9977	8.0751
pd	3928	5.6493	1.1824	0.1507	9.1059
development	3928	10.8146	0.5526	8.8068	12.5567
openness	3970	0.1853	0.2930	0.0000	2.7123
structure	3970	0.4573	0.0941	0.1331	0.8527
hc	3928	0.0206	0.0224	0.0001	0.1666

4.2 Baseline Regression

Table 3 reports the baseline regression results. Column (1) controls only for city and year fixed effects; the estimated coefficient on ai is 0.0319 and significant at the 5% level, indicating that higher local government attention to AI is significantly associated with stronger urban economic resilience. Column (2) further adds population size, population density, economic development level, openness, industrial structure, and human capital; the coefficient on ai rises to 0.0409 and is significant at the 1% level. The core coefficient remains positive and significant after adding controls, suggesting that the result is not driven by the included observable city characteristics.

Among the control variables, the coefficient on economic development level (development) is 1.0651 and significant at the 1% level; the coefficient on industrial structure (structure) is -3.9926 and significant at the 1% level. The remaining controls do not reach conventional significance levels under this specification. As the focus is local government AI policy attention, we do not offer structural interpretations of the control coefficients. Overall, the baseline results support H1.

Table 3 Baseline regression

Variables	(1)	(2)
ai	0.0319**	0.0409***
	(0.0136)	(0.0139)
population		0.5216
		(0.3656)
pd		-0.4722
		(0.3783)
development		1.0651***
		(0.1995)
openness		-0.0516
		(0.1478)
structure		-3.9926***
		(0.5482)

hc		-0.5146
		(3.6194)
Constants	-0.0832***	-10.1434***
	(0.0117)	(3.5283)
Controls	NO	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	3825	3674
Adjusted R-squared	0.1408	0.1942

Note: Standard errors clustered at the city level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Robustness Checks

To test the sensitivity of the baseline results to measure, outliers, and fixed-effects specification, we conduct robustness checks in three respects. First, columns (1) and (2) of Table 4 replace the baseline explanatory variable with "AI word frequency standardized only by Chinese-English text length" and "the ratio of AI word frequency to total word frequency," respectively; the core coefficients are 0.0352 and 195.0802, both positive and significant at the 1% level. Because the two alternative measures have different units, the coefficient magnitudes are not directly comparable, but the direction and significance are consistent with the baseline.

Second, column (3) applies two-sided winsorization at the 1% and 99% percentiles to the main continuous variables; the estimated coefficient on ai is 0.0330 and significant at the 5% level. Finally, column (4) further absorbs province-by-year fixed effects to control for province-level common shocks varying over time; the coefficient on ai remains 0.0207 and significant at the 10% level. Compared with the baseline, the coefficient narrows under the stricter fixed-effects specification but remains positive. These results indicate that the positive relationship between local government AI policy attention and urban economic resilience does not depend on a particular measure, extreme sample, or single fixed-effects specification.

Table 4 Robustness checks

Variables	(1)	(2)	(3)	(4)
ai	0.0352***	195.0802***	0.0330**	0.0207*
	(0.0118)	(65.6807)	(0.0142)	(0.0119)
Constants	-10.1309***	-10.1511***	-6.2911**	-29.1155***
	(3.5282)	(3.5284)	(2.8314)	(5.0467)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province × Year FE	No	No	No	Yes
Observations	3674	3674	3674	3605
Adjusted R-squared	0.1942	0.1942	0.2085	0.4785

Note: Columns (1) and (2) use two alternative measures of local government AI policy attention; column (3) applies two-sided winsorization at the 1% and 99% percentiles to the main continuous variables; column (4) absorbs province-by-year fixed effects. Standard errors clustered at the city level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Heterogeneity Analysis

Given marked differences across cities in economic foundation, industrial conditions, and resource endowment, we further examine heterogeneity along regional distribution and economic development level. Columns (1)–(3) of Table 5 show that the coefficient on ai is 0.0481 and significant at the 1% level in eastern cities, 0.0367 and significant at the 10% level in central cities, and 0.0358 but insignificant in western cities. The subgroup results indicate that the positive relationship between local government AI policy attention and urban economic resilience is more pronounced in eastern cities. This is consistent with the view that eastern cities typically possess better digital infrastructure, industrial complementarity, and factor agglomeration, so policy attention is more readily translated into actual technology adoption and resource allocation in regions with stronger absorptive capacity.

Columns (4) and (5) split the sample by the median of city average economic development level over the sample period. In the low-development group, the coefficient on ai is 0.0237 and statistically insignificant; in the high-development group, the coefficient is 0.0478 and significant at the 1% level. This result again points to a clear dependence on foundational conditions: cities with higher economic development typically possess more complete industrial systems, technological foundations, and resource allocation capacity, which is more conducive to converting policy-level AI attention into real capacity to cope with shocks and recover growth.

It should be noted that one subgroup being significant while another is not does not automatically imply a statistically significant difference between the two coefficients. As the present results do not report a formal test of between-group coefficient differences, the heterogeneity findings are mainly used to describe changes in the strength and significance of the relationship under different sample conditions, and do not make between-group causal comparisons that exceed the estimates.

Table 5 Heterogeneity analysis

Variables	(1) Eastern	(2) Central	(3) Western	(4) Low Dev.	(5) High Dev.
ai	0.0481***	0.0367*	0.0358	0.0237	0.0478***
	(0.0170)	(0.0220)	(0.0421)	(0.0323)	(0.0129)
Constants	-4.4674	-9.3602*	-27.7113**	-4.0320	-8.6122*
	(3.6973)	(5.6205)	(10.6485)	(5.8985)	(4.6281)
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1362	1328	984	1803	1871
Adjusted R-squared	0.2511	0.1916	0.1887	0.1933	0.2018

Note: All models control for the control variables, city fixed effects, and year fixed effects. Standard errors clustered at the city level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Moderation Effects and the Fiscal Pressure Mechanism

Columns (1) and (2) of Table 6 report the moderation effects of industrial structure advancement and digital financial inclusion, respectively. All interacting variables are mean-centered before regression. In column (1), the coefficient on the interaction between local government AI policy attention and industrial structure advancement (cai × cisa) is 0.0267 and significant at the 10% level. This implies that as industrial structure advancement rises, the positive relationship between local government AI policy attention and urban economic resilience becomes stronger, supporting H2a. Cities with more advanced industrial structures have richer digital-technology application scenarios and stronger factor-reallocation capacity, and are therefore more likely to absorb the AI policy signals released by the government.

In column (2), the coefficient on the interaction between local government AI policy attention and digital financial inclusion (cai × cdif) is 0.0005 and significant at the 1% level, indicating that digital financial inclusion significantly strengthens the positive relationship between local government AI policy attention and urban economic resilience, supporting H2b. It is worth noting that in the mean-centered conditional model, the main effect of cdif is -0.0097 and significant at the 1% level, while the main effect of cai is 0.0226 and insignificant. This implies that the core information in column (2) of Table 6 should be placed on the interaction term: the role of digital financial inclusion is to change the slope of the relationship between local government AI policy attention and urban economic resilience, rather than to be read as digital financial inclusion unconditionally raising urban economic resilience.

Columns (3) and (4) further test the transmission role of fiscal revenue-expenditure pressure. Column (3) shows that the estimated coefficient of ai on fiscal revenue-expenditure pressure (fp) is -0.0012 and significant at the 1% level, indicating that higher local government AI policy attention is significantly associated with lower fiscal revenue-expenditure pressure. Column (4) includes ai and fp jointly in the urban economic resilience equation; the coefficient on fp is -2.0868 and significant at the 5% level, while the coefficient on ai remains 0.0386 and significant at the 1% level. The two-step results are consistent with the transmission path of "local government AI policy attention — relief of fiscal revenue-expenditure pressure — higher urban economic resilience." As the direct effect of ai remains significant after including fiscal revenue-expenditure pressure, the results are consistent with a partial mediation mechanism.

In terms of the economic mechanism, raising policy attention to AI may improve fiscal space by promoting digital governance, new industrial activity, and resource allocation efficiency; lower fiscal revenue-expenditure pressure in turn provides fuller policy space for public services and countercyclical adjustment during shocks. The mediation results in Table 6, however, remain based on conditional correlations within a fixed-effects framework, so we treat fiscal revenue-expenditure pressure as an empirically supported potential channel rather than describing it as a strictly causally identified mediation mechanism.

Table 6 Moderation and mediation effects

Variables	(1) resilience	(2) resilience	(3) fp	(4) resilience
cai	0.0390***	0.0226		
	(0.0139)	(0.0141)		
cisa	-0.0323			
	(0.0820)			
cai × cisa	0.0267*			
	(0.0137)			
cdif		-0.0097***		
		(0.0026)		
cai × cdif		0.0005***		
		(0.0002)		
ai			-0.0012***	0.0386***
			(0.0004)	(0.0138)
fp				-2.0868**
				(0.8359)
Constants	-9.6300***	-13.0222***	2.1442***	-5.6132
	(3.5090)	(3.5895)	(0.1911)	(3.4875)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,674	3,674	3,750	3,674
Adjusted R-squared	0.1942	0.1980	0.9465	0.1967

Note: cai, cisa, and cdif denote mean-centered ai, isa, and dif, respectively. Standard errors clustered at the city level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusions and Policy Implications

5.1 Main Conclusions

Using an unbalanced panel of Chinese prefecture-level and above cities from 2011 to 2024, we construct a local government AI policy attention indicator from government work report text and examine its relationship with urban economic resilience. Rather than using AI industry scale or enterprise technology adoption directly, we focus on whether local governments incorporate AI into their annual governance agenda and whether this policy attention can be linked to a city's relative growth performance under common macroeconomic shocks.

First, a stable and significant positive relationship exists between local government AI policy attention and urban economic resilience. In the baseline model, after controlling for major city characteristics, city fixed effects, and year fixed effects, the coefficient on ai is 0.0409 and significant at the 1% level. Under alternative measures, two-sided winsorization at the 1% and 99% percentiles, and the absorption of province-by-year fixed effects, the core coefficient remains positive and reaches conventional significance levels.

Second, this positive relationship exhibits a clear dependence on city conditions. In the subgroup results, the coefficient on ai is 0.0481 and significant at the 1% level in eastern cities, 0.0367 and significant at the 10% level in central cities, and 0.0358 but insignificant in western cities; in the high-development group the coefficient on ai is 0.0478 and significant at the 1% level, whereas in the low-development group it is 0.0237 and insignificant. The moderation regressions further show that the interaction coefficient of industrial structure advancement with local government AI policy attention is 0.0267 and significant at the 10% level, and that of digital financial inclusion with local government AI policy attention is 0.0005 and significant at the 1% level.

Third, fiscal revenue-expenditure pressure may be an important channel through which local government AI policy attention affects urban economic resilience. The estimated coefficient of ai on fiscal revenue-expenditure pressure is -0.0012 and significant at the 1% level; in the urban economic resilience equation, the coefficient on fiscal revenue-expenditure pressure is -2.0868 and significant at the 5% level, while the coefficient on ai remains 0.0386 and significant at the 1% level. This result is consistent with a partial mediation mechanism, suggesting that the link between local government AI policy attention and improved fiscal space deserves attention.

5.2 Policy Implications

First, local government policy attention to AI needs to be connected with executable resource allocation and application scenarios. The empirical results show a significant positive relationship between policy attention and urban economic resilience, but policy attention itself is only a front-end variable in the governance process. For local governments, the more important task is to convert AI from an issue priority in policy text into concrete arrangements for public data governance, industrial application, technical services, and organizational coordination, reducing situations in which policy expression exists without absorptive implementation.

Second, AI policy should not follow a fully homogeneous city-level logic. The heterogeneity and moderation results together indicate that industrial structure advancement and digital financial inclusion are important conditions for converting policy attention. For cities with stronger industrial and financial conditions, the integration of AI with manufacturing, logistics, finance, business services, and public governance scenarios can be further strengthened; for cities with weaker absorptive conditions, policy should focus more on improving industrial complementarity, digital foundations, and financial access, rather than simply replicating the policy intensity of highly developed regions.

Third, fiscal sustainability should be incorporated into the evaluation of AI policy implementation. The mechanism results show that local government AI policy attention is significantly associated with lower fiscal revenue-expenditure pressure, and that fiscal revenue-expenditure pressure is significantly negatively associated with urban economic resilience. This implies that the evaluation of AI-related policy should attend not only to project counts or industrial scale, but also to whether it improves the efficiency of public resource allocation, whether it fosters sustainable economic activity, and whether it preserves the fiscal adjustment space local governments need during shocks.

5.3 Research Boundaries and Future Directions

Several identification and measurement issues still require further work. First, city and year two-way fixed effects can control for time-invariant city characteristics and common year shocks, and province-by-year fixed effects can further absorb finer province-level common shocks, but these specifications cannot fully rule out reverse causality and city-year-varying omitted variables. For example, cities with stronger economic foundations and recovery capacity may also raise their policy attention to AI earlier. The results should therefore be read mainly as conditional correlation evidence with strong robustness, rather than as strict causal estimates.

Second, local government AI policy attention is a text indicator built from government work report word frequencies; it reflects issue attention intensity and cannot directly measure policy quality, enforcement, or the actual degree of AI adoption. Future research can build on the text-attention indicator by combining implementation-level indicators such as the number of policy documents, fiscal expenditure, AI enterprise activity, and computing-power or data infrastructure, to distinguish "policy attention" from "policy implementation."

Third, we measure urban economic resilience as the deviation of city GDP growth from national GDP growth. This measure has the advantages of clarity, comparability, and freedom from complex weighting, but its core remains growth performance. Urban economic resilience may also encompass employment stability, firm entry and exit, fiscal recovery, and industrial structural adjustment. Future work can introduce additional outcome variables without altering the core identification logic, to verify the resilience effect of AI policy attention along multiple dimensions.

Finally, the regional and economic-development heterogeneity analysis is based on subgroup estimates, and the present results do not report a formal statistical test of between-group coefficient differences. Subsequent research can use interaction terms, coefficient-difference tests, or finer continuous heterogeneity models to further identify the marginal changes in policy attention under different city conditions.

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