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The Impact of Artificial Intelligence on the Efficiency of Higher Education Resource Allocation

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The Impact of Artificial Intelligence on the Efficiency of Higher Education Resource Allocation

Abstract The rapid development of artificial intelligence (AI) is driving a systematic transformation of higher education paradigms and has gradually become a key force in optimizing higher education resource allocation. Based on panel data from 30 Chinese provinces during 2014–2023, this study employs Data Envelopment Analysis (DEA) to measure higher education resource allocation efficiency and uses two-way fixed effects models, mediation models, and threshold regression models to systematically examine the impact of AI on this efficiency. The findings are as follows. First, China's higher education resource allocation efficiency has improved overall, but significant regional heterogeneity persists—the eastern and central regions exhibit higher efficiency, while the western region remains generally low with declining trends in some provinces. Second, AI has a significantly positive effect on allocation efficiency, with the strongest impact in the western region and an insignificant effect in the central region. Third, AI improves higher education resource allocation efficiency by promoting regional economic development. Fourth, population density and regional innovation level each exhibit a single threshold effect: AI's positive effect diminishes when population density exceeds the threshold, and its impact shifts from negative to positive when regional innovation level crosses the threshold. These findings provide empirical evidence for leveraging AI to enhance higher education resource allocation efficiency and offer policy implications for the digital transformation of higher education in China.

Keywords: Artificial intelligence; Higher education resource allocation; Efficiency improvement; Mechanism of action

Introduction

In recent years, driven by a new wave of technological revolution and industrial transformation, higher education has played an increasingly prominent role in cultivating scientific and technological talent and producing knowledge. The expansion and optimization of higher education systems are widely regarded as a strategic priority for achieving knowledge economy goals and addressing global competition (Chen and Shih, 2025). As a complex system involving substantial inputs of human, material, and financial resources and carrying the multiple missions of talent cultivation, scientific research, and social service (Ye, Khanal, and Cao, 2025), the high-quality development of higher education fundamentally depends on its resource allocation efficiency (Liefner, 2003). In this context, resource allocation efficiency has become an important area of higher education research (Yan, Sun, and Tian, 2024), and the Chinese government has identified it as a core issue and persistent practical challenge throughout the development of China's higher education system (Zhang et al., 2022). Currently, China's higher education system has achieved leapfrog development under substantial government investment. However, as the system transitions from quantitative expansion to high-quality development, insufficient systemic coordination and the mismatch between scale expansion and quality improvement have exacerbated the imbalance in higher education resource allocation (Li and Sun, 2025). If these problems remain unresolved, they will seriously impede the improvement of resource allocation efficiency. The emergence of AI has driven the digital transformation of higher education and offers new possibilities for improving allocation efficiency. Therefore, this study aims to examine the role of AI development in promoting the efficiency of higher education resource allocation.

In recent years, as AI technologies have matured—particularly with the emergence of generative AI tools such as ChatGPT—higher education has undergone a significant shift in its absorption and adoption of AI, profoundly affecting teaching, learning, and social engagement within universities (Cotton and Shipway, 2023). Some scholars have found that AI technologies significantly improve university operational efficiency by streamlining teaching and administrative processes, enabling university

staff to redirect their time and effort toward more strategic and creative endeavors (Han et al., 2025; George and Wooden, 2023). However, AI development in economically underdeveloped and remote regions lags behind, potentially creating digital technology divides (Capraro et al., 2024) that could further exacerbate inter-regional imbalances in higher education resource allocation and reduce allocation efficiency. Therefore, this study introduces regional economic development level and regional innovation level to analyze the underlying mechanisms through which AI affects higher education resource allocation efficiency, which is of considerable practical significance.

To better analyze the impact mechanism of AI on higher education resource allocation efficiency, this study uses DEA to measure China's higher education resource allocation efficiency from 2014 to 2023 and employs two-way fixed effects models, mediation models, and threshold regression models to empirically examine the impact mechanisms. This study aims to achieve the following objectives: first, to describe the overall status of China's higher education resource allocation efficiency during the observation period; second, to analyze the positive effect of AI on allocation efficiency and verify the process mechanisms through which this effect is realized; and third, to provide policy recommendations for improving China's higher education resource allocation efficiency and promoting the digital transformation of higher education.

The remainder of this paper is organized as follows. Section 2 presents the literature review and research hypotheses. Section 3 describes the data, variables, and empirical methods employed. Section 4 reports the main empirical results, verifies the potential mechanisms, and presents robustness test results. Section 5 provides the discussion and conclusion. Section 6 offers the conclusions and policy recommendations.

Literature review

Existing research on higher education resource allocation efficiency has provided valuable insights and experience. In terms of methodology, scholars have primarily employed Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) models to accurately assess higher education resource allocation efficiency (Lamb and

Tee, 2024). For instance, an analysis of U.S. public research universities from 2005 to 2015 using the SFA model found that cost inefficiency in these institutions had increased (McClure et al., 2023). Most scholars have used DEA models to measure the efficiency level of higher education resource allocation in China (Wu et al., 2020; Bai et al., 2020). As research has deepened, researchers have frequently combined the Malmquist index with DEA to overcome the limitations of single models in describing the dynamic evolution of higher education resource allocation efficiency. Some scholars have used the DEA-Malmquist model to measure the efficiency levels and trends of resource allocation in China's "double first-class" universities, finding that overall efficiency has improved year by year but with significant regional heterogeneity (Chen et al., 2024; Wang et al., 2024).

As assessment methods for higher education resource allocation efficiency have become more refined, current research has begun to focus on its influencing factors and spillover effects. The analysis of factors affecting higher education resource allocation mainly considers government support, social recognition of university development, and technological innovation (Wang and Yang, 2025). Some research has found that the transformation of research outputs and the input of research personnel have significant positive effects on higher education innovation efficiency, while economic development level has a certain negative effect (Guo et al., 2023). Other scholars have demonstrated that educational funding, human capital, and the regional economy are important factors influencing higher education resource allocation efficiency (Yu, 2023). Meanwhile, as higher education serves as an important driving force for talent cultivation and regional economic development, many scholars have introduced spatial econometric models to analyze the spillover effects of higher education resource allocation (Fowles and Tandberg, 2017). Research using spatial econometric models has found that higher education expenditure significantly promotes regional economic growth, with long-term effects exceeding short-term effects (Ma et al., 2023). Other scholars have focused on the effects of higher education on global ecological sustainability. Using a Spatial Durbin Model, they found that in regions outside Europe, improvements in the

comprehensive level of higher education substantially enhance regional ecological sustainability, though significant siphon effects exist (Li et al., 2025).

Although existing research on higher education resource allocation is already relatively extensive and AI has been integrated into the development process of higher education systems (Crawford et al., 2024), most current studies examine the academic costs and benefits of AI in higher education from the micro-level perspective of learners and academic achievement (Bond et al., 2024; Perkins, 2023). Few studies have empirically analyzed the causal relationship and impact mechanisms between the two from a macro-level perspective. To date, only a limited number of scholars have used the Tobit regression model to briefly verify the positive effect of AI on higher education resource allocation efficiency, without conducting a deeper analysis of the underlying mechanisms (Sun and Xu, 2025).

In summary, compared with previous research, this study makes several potential incremental contributions. First, by examining the impact of AI on higher education resource allocation efficiency, this study complements the existing literature on the factors influencing allocation efficiency. Previous studies have primarily explored the effects of socioeconomic factors such as regional economic development and government fiscal support. Our research supplements this literature by providing evidence of AI's positive impact on higher education resource allocation efficiency. Second, we combine mediation models and threshold regression models to analyze the mechanism through which AI affects allocation efficiency. In recent years, given the limitations of mediation analysis in examining nonlinear relationships, an increasing number of studies have combined mediation models with threshold models for analysis. This study is the first to introduce threshold regression models into the analysis of higher education resource allocation efficiency, providing more precise and consistent estimates. Third, we select regional economic development level as a mediating variable and use a mediation model to examine whether AI indirectly affects higher education resource allocation efficiency through its impact on regional economic development. In doing so, we clarify the impact mechanism of AI on higher education resource allocation efficiency, moving beyond the traditional focus in the

literature on identifying influencing factors or describing spatiotemporal evolution characteristics.

Theoretical analysis and research hypotheses

The direct effect of AI on higher education resource allocation efficiency

Higher education resources are the foundation for the sustained and stable development of the higher education system and an important guarantee for improving the quality of higher education. With the rapid development of AI technologies, the allocation patterns and utilization efficiency of higher education resources are being continuously reshaped. On the one hand, AI technologies break the temporal and spatial constraints of traditional educational resources through digital platform construction and intelligent resource scheduling, optimizing the input-output alignment of higher education resources and improving technical efficiency. On the other hand, digital-intelligent model innovation has become a key pathway for optimizing higher education resource allocation. Through the widespread application of AI technologies such as cloud-based resource sharing platforms, high-quality educational resources can be shared, optimizing the supply of diverse digital teaching resources and effectively alleviating regional imbalances in educational development (Qian et al., 2025). Based on the above analysis, this study proposes Hypothesis 1.

H1: The development of AI can significantly improve higher education resource allocation efficiency.

The mediating role of regional economic development level

AI technologies not only cultivate new drivers for the economy but also promote the transformation of old and new economic drivers through their powerful activation effects, becoming a new engine for driving high-quality economic development (Mo and Liu, 2024). An increase in the level of regional economic development leads to greater fiscal investment in higher education, improved educational conditions, and higher utilization efficiency of educational resources. AI empowers regional industrial development and increases economic output, providing greater financial and material support for higher education resource allocation. The improvement of regional

economic development also further optimizes the input structure of higher education resources, reducing resource redundancy and misallocation. Accordingly, this study proposes Hypothesis 2.

H2: The promoting effect of AI on regional economic development can indirectly improve higher education resource allocation efficiency.

The threshold effect of population density

Population structure and distribution are important factors affecting higher education resource allocation. Population density reflects the degree of human resource agglomeration in a region, and the impact of AI technologies on higher education resource allocation efficiency requires a certain foundation of population agglomeration. Therefore, in regions with a reasonably moderate population density, the demand-scale effects generated by talent agglomeration amplify the technology-empowerment effect of AI, significantly strengthening its positive impact on higher education resource allocation efficiency (Sun and Gao, 2025). However, if population density is excessively high, it may trigger excessive competition for educational resources and congestion effects, leading to diminishing marginal returns of AI's contribution to allocation efficiency. Accordingly, this study proposes Hypothesis 3.

H3: Based on population density, the effect of AI on higher education resource allocation efficiency exhibits a single threshold characteristic.

The threshold effect of regional innovation level

Regional innovation level reflects a region's capacity for technology absorption and transformation, and the impact of AI technologies on higher education resource allocation efficiency depends on the regional innovation ecosystem (Deng, 2025). In regions with low innovation levels, insufficient innovation linkages among universities, enterprises, and research institutions prevent AI technologies from being effectively integrated into the entire process of higher education resource allocation, potentially producing a negative impact. When the regional innovation level crosses the threshold value, a well-developed innovation system can accelerate the integration of AI technologies with higher education, promoting intelligent and precise resource

allocation. At this point, the positive impact of AI on higher education resource allocation efficiency increases significantly. Accordingly, this study proposes Hypothesis 4.

H4: Based on regional innovation level, the effect of AI on higher education resource allocation efficiency exhibits a single threshold characteristic. When the regional innovation level is below the threshold value, AI has a negative impact on higher education resource allocation efficiency; when it exceeds the threshold value, the negative impact transforms into a positive one.

Research design

Sample and Data sources

Considering the limitation of data availability, this study takes 30 provinces in China from 2014 to 2023 as the research object. The data used in this study are derived from the ' China Statistical Yearbook ', ' China Education Statistical Yearbook ', ' China Science and Technology Statistical Yearbook ', and provincial statistical yearbooks and related development statistical bulletins. In view of the incomplete data, the linear interpolation method is used to ensure the comprehensiveness and continuity of the data set.

Model construction

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is an evaluation method and tool for studying the relative efficiency of homogeneous decision-making units (DMUs) with multiple inputs and multiple outputs. This method includes two classical models—CCR and BCC—which assume constant returns to scale and variable returns to scale, respectively, when measuring efficiency. This study adopts an input-oriented approach under the variable returns to scale assumption to measure the relative efficiency of China's higher education resource allocation. Under the variable returns to scale condition, Scale Efficiency (SE) = Technical Efficiency (TE) / Pure Technical Efficiency (PTE). DEA efficiency calculations in this study are performed using DEAP 2.1.

Baseline regression model

To identify the impact of artificial intelligence (AI) on higher education resource allocation efficiency (Efedu), this study constructs the following two-way fixed effects model for empirical testing:

$$Efedu_{i,t}=a_0+a_1AI_{i,t}+a_2X_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t}(1)$$

In Equation (1), i denotes the province and t denotes the year. $Efedu_{i,t}$ represents the higher education resource allocation efficiency of province i in year t; AI represents artificial intelligence. To avoid estimation bias, a set of control variables $X_{i,t}$ is included; μ_i denotes individual fixed effects, δ_t denotes time fixed effects, and $\varepsilon_{i,t}$ is the random error term.

Mediation model

To further test the mediating effect of regional economic development level as hypothesized, this study constructs a mediation model for mechanism testing. The specific models are as follows:

$$M_{i,t}=\beta_0+\beta_1AI_{i,t}+\beta_2X_{i,t}+\mu_{i,t}+\delta_t+\varepsilon_{i,t}(2)$$

$$Efuedu_{i,t}=\beta_0+\beta_1M_{i,t}+\beta_2AI_{i,t}+\beta_3X_{i,t}+\mu_{i,t}+\varepsilon_{i,t}(3)$$

where M represents the mediating variable. Other variable definitions are the same as in Equation (1).

Panel threshold regression model

To further examine the heterogeneous impact of AI on higher education resource allocation efficiency across different intervals of population density and technological innovation level, the following panel threshold model is constructed:

$$\begin{aligned}Efedu_{i,t}= \quad & a_0+a_1AI_{i,t}I(x\leqslant r_1)+a_2AI_{i,t}I(r_1<x\leqslant r_2)+\cdots+a_nAI_{i,t}I(r_{n-1}<x\leqslant r_n)+\\ & a_{n+1}AI_{i,t}I(x>r_n)+a_\phi control_{i,t}+\mu_i+\varepsilon_{i,t}\ (4)\end{aligned}$$

In Equation (4), $I(\cdot)$ is the indicator function; $\gamma1,\gamma2,\ ...,\gamma n$ are threshold values; $\beta1,\beta2,\ldots,\beta n+1$ are the impact coefficients of AI on higher education resource allocation efficiency under different threshold intervals; AI is defined as in Equation (1); x represents the threshold variable; control represents the control variables; and $\varepsilon_{i,t}$ the random error term.

Variable selection

Evaluation indicator system for higher education resource allocation efficiency

Input indicators

University educational resources generally refer to various types of resources that constitute, maintain, and serve the university education system. In selecting input indicators, mainstream international research primarily selects indicators from three dimensions: human, financial, and material resources (Nazarko and Šaparauskas, 2014; Guo, 2023). This study follows the principles of scientific validity, feasibility, and rationality in mainstream international research indicator selection, focusing on human resources, financial resources, and material resources as input indicators, and selects them according to the actual conditions of China's higher education (Ramírez-Gutiérrez, Barrachina-Palanca et al., 2020). Specifically, the number of full-time university teachers represents human resource input; educational expenditure and university research expenditure reflect financial resource input; and the total value of university fixed assets reflects material resource input.

Output indicators

In terms of higher education functions, the output indicators for higher education resource allocation efficiency should encompass talent cultivation, scientific research, and social service (Wang, 2019). Considering both the scale and quality of outputs, this study selects student enrollment, the number of academic publications, the total number of research projects, and patent licensing income as output indicators for measuring higher education resource allocation efficiency (Gralka et al., 2020; Guo et al., 2025).The detailed indicator system is shown in Table 1.

Table 1. Evaluation indicator system for higher education resource allocation efficiency

Core explanatory variable

Artificial intelligence (AI): Following related research (Han et al., 2025), based on the AI patent classification codes in the Reference Table for the Relationship between Strategic Emerging Industry Classification and International Patent Classification (2021), the number of AI patent applications for each province is retrieved from the

China National Intellectual Property Administration and used as the measurement indicator for AI.

Mediating variable

Regional economic development level (lnagdp): Following related research (Tong and Li, 2026), the natural logarithm of per capita GDP is used to reflect the level of regional economic development.

4. Threshold variables

Regional innovation level (Innov): A substantial body of research has demonstrated that using patent counts to represent innovation is reliable (Wei and Xia, 2026). Therefore, to reduce endogeneity, this study uses the number of provincial invention patent grants to represent regional innovation level (Zhao et al., 2026). Data are sourced from the patent database of the China National Intellectual Property Administration, from which invention patent application data for 30 Chinese provinces from 2014 to 2023 are extracted for calculation.

Population density (PD): Urban population density reflects the degree of population concentration within a city or a specific area and is an important indicator of population scale (Rao et al., 2026). This study uses the number of people per square kilometer to reflect population density.

Control variables

Based on Burton Clark's "triangle of coordination" theory and the actual conditions of China's higher education development, and to address endogeneity issues arising from the omission of important variables, this study draws on a systematic review of the relevant literature (Yu et al., 2024; Hoang et al., 2026) to comprehensively select control variables from six dimensions: government support intensity, digital infrastructure development level, technology market development, social recognition of universities, urbanization level, and labor force level. Details are shown in Table 2. The data used in this study are sourced from the China Statistical Yearbook, the China Education Statistical Yearbook, the China Science and Technology Statistical Yearbook, and provincial statistical yearbooks and related development statistical bulletins.

Table 2. Control variables

Empirical results

Characteristics of China's higher education resource allocation efficiency

Using 30 Chinese provinces (municipalities and autonomous regions) as DMUs, the raw data are imported into DEAP 2.1 to calculate the higher education resource allocation efficiency from 2014 to 2023. For a more intuitive presentation, this study selects four time points—2014, 2017, 2020, and 2023—to illustrate the overall characteristics of higher education resource allocation efficiency, as detailed in Table 3. Overall, from 2014 to 2023, the higher education resource allocation efficiency of most Chinese provinces (municipalities and autonomous regions) has improved or approached the efficiency frontier, indicating that China's higher education resource allocation efficiency has been effectively improved and maintained at a relatively high level. The spatial distribution characteristics reveal significant regional heterogeneity, generally exhibiting a pattern of higher efficiency in the eastern and central regions and lower efficiency in the northeast and western regions. Specifically, the economically developed eastern coastal areas, such as Beijing, Shanghai, and Jiangsu, are mostly traditional educational powerhouses with relatively high levels of economic development that can provide strong support for higher education resource investment. Although the northeast region has a lower overall efficiency level, it shows an upward trend during the observation period; for example, Jilin Province's efficiency increased from 0.879 in 2014 to 1 in 2023, which is related to its historical industrial base, relatively concentrated educational resources, and regional policy orientation. In contrast, the western region has a generally low overall efficiency level, and regions such as Gansu, Guizhou, Ningxia, Qinghai, and Chongqing show a clear declining trend in efficiency values, with decreases exceeding 10%. This is mainly related to the complex geographical conditions, weak economic foundations, and uneven distribution of educational resources in the western region. In summary, China's higher education resource allocation efficiency is at a relatively high overall level, but significant regional imbalances persist.

Table 3. Distribution characteristics of China's higher education resource allocation efficiency

Baseline regression

Table 4 presents the baseline regression results, where columns (1) and (2) show OLS regression results and columns (3) and (4) show two-way fixed effects regression results. The coefficients of the core explanatory variable are all significantly positive at the 5% level, indicating that AI has a significantly positive impact on higher education resource allocation efficiency, thus verifying Hypothesis 1. This suggests that as AI deeply penetrates the higher education sector, it has become a key driving force for transforming higher education development from "extensive" quantitative expansion to "intensive" quality improvement.

Table 4. Baseline regression results

Robustness tests

To ensure the reliability of the research conclusions, this study conducts the following robustness tests.

Replacing the core explanatory variable. As shown in the previous regression results, AI has a significantly positive effect on higher education resource allocation efficiency. Currently, most domestic and international studies use the number of industrial robots to reflect the level of AI (Zhang et al., 2024). Therefore, this study replaces the number of AI patent applications with the provincial industrial robot penetration rate (AI2) to test the robustness of the results. The specific results are shown in column (1) of Table 5. The coefficient of AI remains significantly positive, confirming the robustness of the above results.

Excluding municipality samples. Considering that municipalities are generally at a higher overall level in terms of AI and higher education development, and that national policies implemented in these areas differ somewhat from other regions, this study excludes the data from the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing. The regression results are shown in column (2) of Table 5. After excluding the influence of municipality samples, the coefficient of AI remains significantly positive, verifying the robustness of the baseline regression results.

Table 5. Robustness test regression results

Endogeneity test

Given the potential bidirectional mechanism between AI and higher education resource allocation efficiency, to avoid the resulting estimation bias and address endogeneity issues, this study follows related literature (Cheng and Xu, 2025) and uses the first-order lag of AI (L.AI) as an instrumental variable for AI in a two-stage least squares regression. The specific results are shown in Table 6. The regression results show that the significance level of AI's impact coefficient on higher education resource allocation efficiency is consistent with the conclusions from the baseline regression, indicating that AI can still promote the improvement of higher education resource allocation efficiency after accounting for endogeneity.

Table 6. Endogeneity test results

Heterogeneity analysis

Considering that different regions of China exhibit significant differences in geographical location, economic development level, climate conditions, and land resource endowments, this study divides the research regions into four major areas—eastern, central, western, and northeast—based on geographical characteristics. Regression is then performed on each sub-sample, with results shown in Table 7.

Table 7 reveals that AI's contribution to improving higher education resource allocation efficiency exhibits distinct regional heterogeneity. Specifically, the eastern, northeast, and western regions show a significantly positive impact, with the western region having the largest impact coefficient of 3.78. This is primarily because AI development in the western region is largely driven by national policy support, which provides unconventional support for AI to optimize higher education resource allocation efficiency in the west. In contrast, the eastern region relies more on market-driven forces, and the incremental support from policy is relatively limited. Meanwhile, AI development in the central region has a non-significant negative impact on higher education resource allocation efficiency. This result is similar to other related research findings (Zhang et al., 2025), indicating that the "central collapse" phenomenon in higher education resource allocation efficiency persists and

that the level of higher education governance in the central region still needs improvement.

Table 7. Regional heterogeneity test results

Mechanism test

To further investigate the mechanism through which AI affects higher education resource allocation efficiency, this study uses the two-step mediation approach to test the mediating effect of regional economic development level. The specific results are shown in Table 8. Models (1) and (2) reflect the mediating role of regional economic development level. The results show that AI's impact coefficient on regional economic development level is significantly positive, and regional economic development has a significantly positive impact on higher education resource allocation efficiency. This indicates that AI indirectly improves higher education resource allocation efficiency by promoting regional economic development, verifying Hypothesis 2. In fact, regional economic development provides the material foundation and demand orientation for higher education resource allocation, while the improvement of higher education resource allocation efficiency contributes to regional economic growth through talent supply and research commercialization pathways. Therefore, particular attention should be paid to regional economic development when promoting the high-quality development of higher education.

Table 8. Mediation mechanism results of AI's impact on higher education resource allocation efficiency

Threshold effect test

Based on the baseline regression results and mediation mechanism test, this study further uses the threshold model to verify whether AI indirectly affects higher education resource allocation efficiency through population density and regional innovation level. First, the existence of threshold effects for population density and regional innovation level is tested, with each self-test repeated 500 times. The test results are shown in Table 9. As can be seen from Table 9, both population density and regional innovation level exhibit significant single threshold effects on AI's impact on higher education resource allocation efficiency. Therefore, this study

adopts the single threshold regression model for analysis, with the specific estimation results shown in Table 10.

Table 9. Threshold effect test results

Table 10. Threshold regression estimation results

Corresponding to Table 10, Figure 1 presents the likelihood ratio function graph for the threshold estimate of population density at the 95% confidence interval, while Figure 2 presents the likelihood ratio function graph for the threshold estimate of regional innovation level. The true threshold values represented by the lowest points of the LR statistics are all below the critical values indicated by the dashed lines, confirming that the threshold values are valid and reliable.

Figure 1. Threshold estimate for population density

Figure 2. Threshold estimate for regional innovation level

As shown in Table 10, when population density is below the threshold value, AI has a significantly positive impact on higher education resource allocation efficiency, with a coefficient of 6.14. When population density exceeds the threshold value, the impact coefficient of AI on efficiency is 2.52, which is still significant at the 5% level, but the promoting effect has diminished. This indicates that as population density increases, AI's impact on higher education resource allocation efficiency exhibits a significantly positive effect, but excessively high population density may trigger excessive competition for educational resources and congestion effects, consistent with the nonlinear characteristic of diminishing marginal returns. This verifies Hypothesis 3.

Regional innovation level reflects the current status of technological innovation development in different regions. As shown in Table 10, when the innovation level is below the threshold value, AI has a significantly negative impact on higher education resource allocation efficiency. When it exceeds the threshold value, the direction of impact changes, becoming a positive influence that is significant at the 5% level, verifying Hypothesis 4. This is primarily because when the overall regional innovation level is low, insufficient momentum for industrial upgrading and weak demand from emerging industries force university resources to concentrate on

traditional saturated disciplines, creating a resource misallocation pattern characterized by the coexistence of "resource redundancy and demand gaps," which directly reduces higher education resource allocation efficiency. As regional innovation capacity improves, cutting-edge technologies such as AI and big data develop rapidly, not only promoting a fundamental reshaping of teaching models but also directly forming a technological support system for improving higher education resource allocation efficiency. Therefore, particular attention should be paid to using technological innovation to lead the high-quality development of higher education.

Conclusions and implications

Conclusions

Based on the analysis of panel data from 30 Chinese provinces during 2014–2023, this study examines the mechanism through which AI affects the efficiency of higher education resource allocation in China. The specific empirical conclusions are as follows.

The DEA results show that China's higher education resource allocation efficiency has improved overall, but regional heterogeneity remains significant. The eastern and central regions exhibit higher efficiency, the western region remains generally low with declining trends in some provinces, and the northeast shows an upward trajectory. This spatial divergence reflects the uneven geographic distribution of economic development, infrastructure, and historical educational investment across China.

AI has a significantly positive effect on higher education resource allocation efficiency. The baseline regression results confirm that AI technology development has a significant enhancing effect on higher education resource allocation efficiency. The heterogeneity test further demonstrates that the positive effect of AI varies significantly across regions, with the most pronounced effect in the western region and a non-significant negative effect in the central region. This indicates that in regions with lower technology baselines, policy-driven AI investment generates higher marginal returns, while in regions where AI technologies have not yet been effectively integrated with governance structures, the expected efficiency gains remain unrealized.

The mediation analysis results indicate that the primary impact mechanism operates through the pathway of regional economic development. Specifically, AI promotes regional economic growth, expanding the fiscal base for government investment in higher education, enhancing universities' capacity to attract high-quality faculty and upgrade research facilities, and broadening channels for social cooperation.

The threshold regression analysis further reveals single threshold effects for population density and regional innovation level. When population density is below the threshold value, AI's positive effect is more pronounced; once it exceeds the threshold, the effect diminishes notably, indicating that congestion effects and intensified resource competition in high-density areas reduce the marginal returns of AI-enabled optimization. When regional innovation level is below the threshold, AI has a significantly negative effect on allocation efficiency; once it exceeds the threshold, the effect shifts from negative to positive. This indicates that a minimum level of regional innovation capacity is a necessary precondition for AI to effectively improve resource allocation efficiency, and that premature introduction of AI technologies in regions lacking adequate innovation ecosystems may lead to a technology trap that exacerbates rather than alleviates resource misallocation.

Main contributions

First, this study introduces AI as a key explanatory variable into the study of factors influencing higher education resource allocation efficiency, extending the analytical framework that previously focused on socioeconomic factors such as fiscal investment and economic development. In the current context where AI technologies are rapidly penetrating various industries, examining their impact on higher education resource allocation has important theoretical value and practical urgency. The empirical results of this study confirm the significant impact of AI as a new productive force element on higher education resource allocation efficiency, enriching the research horizons of education economics and education management.

Second, by combining mediation models and threshold regression models, this study simultaneously reveals both the transmission channels and boundary conditions of AI's impact on allocation efficiency, constructing a systematic analytical framework

that accounts for both impact mechanisms and boundary conditions. Previous studies have mostly remained at the level of identifying influencing factors, with little in-depth exploration of the intermediate links in impact mechanisms and the boundary conditions for effect realization. This study fills this gap, providing a more complete theoretical picture for understanding the internal logic of AI-empowered higher education resource allocation.

Third, introducing the threshold regression method into the analysis of higher education resource allocation efficiency represents a methodological innovation. Traditional linear models assume that the impact of independent variables on dependent variables is uniform and constant, and cannot capture the nonlinear characteristics in which impact effects undergo qualitative changes as conditioning variables vary. The introduction of the threshold regression model enables this study to identify critical points at which AI's effects change significantly, revealing important information overlooked by standard linear analysis and providing a methodological reference for subsequent related research.

Policy implications

Based on the empirical findings, this study proposes the following policy recommendations.

First, regionally differentiated AI-empowerment measures for higher education should be formulated. For western and northeast provinces, governments at all levels should increase investment in AI infrastructure construction and provide dedicated fiscal support, with a focus on deploying intelligent teaching platforms and digital management systems in universities to narrow the digital divide with eastern regions. For central provinces, the priority should be placed on removing institutional barriers between AI technology deployment and higher education governance, advancing university management reform, and improving the coordination mechanisms between technology adoption and organizational change so that AI can be effectively translated into efficiency gains. For eastern provinces, the focus should shift from infrastructure expansion to deepening the integration of AI with teaching, learning,

and research management, encouraging universities to develop innovative demonstrations of AI-empowered education, and avoiding redundant investment.

Second, higher education resource allocation should be incorporated into the overall planning of regional economic development. A performance-oriented fiscal funding mechanism for higher education should be established, linking budget allocation to key indicators such as management efficiency and digital resource utilization, thereby guiding universities to actively improve resource use effectiveness. Local government expenditure structures should be optimized to ensure that fiscal increments generated by economic growth are appropriately directed toward the higher education sector. In addition, diversified funding channels for higher education should be broadened, and social capital should be encouraged to participate in university digitalization, providing sustained and stable economic support for AI-empowered higher education resource allocation.

Third, a classified policy mechanism that adapts to differences in population density and innovation capacity should be established. In high-population-density areas, provincial or cross-regional intelligent resource scheduling platforms should be built. Big data technologies should be employed to dynamically monitor enrollment scales, program offerings, and resource utilization across universities, facilitating resource sharing and complementarity within regions and preventing excessive competition and resource waste caused by the homogeneous expansion of higher education institutions. In regions with lower innovation levels, priority should be given to building collaborative innovation platforms that connect universities, enterprises, and research institutions, strengthening regional capacity for technology absorption and transfer. AI-powered databases for industry-university-research collaboration could be established to match corporate technology demands with university research outputs, promoting collaborative innovation and creating the necessary innovation ecosystem conditions for AI to positively affect higher education resource allocation.

Limitations and future directions

This study has several limitations that should be acknowledged. First, the AI indicator used reflects the development level of AI technology at the provincial level but may

not fully capture the extent to which AI is actually adopted and applied within higher education institutions. Future research could incorporate more direct measures of AI adoption in universities, such as the deployment rate of intelligent teaching platforms or the coverage of smart administrative systems. Second, the province-level unit of analysis may mask within-province heterogeneity. University-level data would enable more fine-grained analysis. Third, the ten-year observation period coincides with a phase of rapid AI development. As technologies mature and diffuse more broadly, the long-term effects of AI on higher education resource allocation may differ. Future studies could extend the time window for verification. Fourth, although this study identifies regional economic development as a mediating variable, other potential mechanisms—such as digital literacy, institutional governance quality, and inter-university collaboration networks—warrant further investigation in future research.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

Authors certify that the data, figures, and images presented in this manuscript are original or have been authorized and licensed legally. The authors guarantee that ethical standards have been followed and informed consent has been obtained.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data supporting the findings of this study are openly available. All data files have been shared and are provided as supplementary materials accompanying this article.

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Table 1. Evaluation indicator system for higher education resource allocation efficiency

Primary indicator	Secondary indicator	Tertiary indicator	Unit
Input indicators	Human resources	Number of full-time university teachers	Persons
	Financial resources	Educational expenditure	10,000 yuan
		University research expenditure	10,000 yuan
	Material resources	Total value of university fixed assets	10,000 yuan
Output indicators	Talent cultivation	Student enrollment in higher education institutions	Persons
	Technological innovation	Number of academic publications	Papers

		Total number of research projects	Projects
	Social service	Patent licensing income	1,000 yuan

Table 2. Control variables

Dimension	Indicator name	Specific content	Unit
Government	Government fiscal support (GFS)	Public budget education expenditure / General budget expenditure	%
	Digital infrastructure development level (Digfra)	Word frequency extraction	%
Market	Technology market development level (Tmdl)	Technology market turnover / GDP	%
University	Social recognition (USR)	University research funding from enterprises and public institutions	Yuan
Society	Urbanization level (UL)	Urbanization rate	%
	Labor force level (LF)	Number of employed persons / Geographic area	%

Table 3. Distribution characteristics of China's higher education resource allocation efficiency

Region	Province	2014	2017	2020	2023
Eastern	Beijing	1	1	0.986	1
	Fujian	0.973	0.88	0.947	0.9
	Guangdong	0.936	0.94	0.989	0.88
	Hainan	1	0.947	0.852	0.876
	Hebei	1	0.891	0.882	0.841
	Jiangsu	0.992	0.993	0.965	0.972
	Shandong	0.928	0.884	0.871	0.853
	Shanghai	1	0.944	0.983	1
	Tianjin	1	0.947	0.912	0.892
	Zhejiang	0.914	1	0.985	0.957

Western	Gansu	1	0.862	0.867	0.848
	Guangxi	1	0.98	1	0.998
	Guizhou	1	0.836	0.961	0.844
	Inner Mongolia	0.912	0.961	0.847	0.992
	Ningxia	1	0.821	0.777	0.854
	Qinghai	0.939	0.757	0.995	0.867
	Shaanxi	0.925	1	1	0.995
	Sichuan	0.916	0.941	1	0.97
	Xinjiang	1	0.943	0.989	0.937
	Yunnan	0.899	0.839	0.95	1
	Chongqing	0.985	0.866	0.896	0.872
Central	Anhui	1	1	0.978	1
	Hebei	1	0.891	0.882	0.841
	Henan	1	1	0.953	0.957
	Hubei	1	0.989	0.958	0.938
	Hunan	1	0.998	0.982	1
	Shanxi	1	0.972	0.923	0.943
Northeast	Heilongjiang	0.926	0.855	0.883	0.955
	Jilin	0.879	0.93	0.966	1
	Liaoning	0.881	0.896	0.957	0.892

Table 4. Baseline regression results

	Efedu			
Variables	(1)	(2)	(3)	(4)
AI	0.001**	0.002***	0.003***	0.002***
	(2.05)	(5.84)	(3.28)	(3.33)
GFS	-0.146**		-0.167	
	(-2.30)		(-1.37)	
Digfra	0.059		0.019	
	(1.53)		(0.53)	

Tmdl	0.365**		-0.467*	
	(2.31)		(-1.86)	
UL	-0.078		-0.403	
	(-1.13)		(-1.52)	
LF	0.005		-0.170**	
	(0.41)		(-2.57)	
lnURS	-0.000		-0.008	
	(-0.07)		(-1.15)	
Constat	0.992***	0.962***	2.630***	0.961***
	(9.05)	(96.18)	(5.01)	(122.21)
R-squared	0.265	0.182	0.205	0.160
N	300	300	300	300
id	NO	NO	YES	YES
year	NO	NO	YES	YES

t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 5. Robustness test regression results

	Efedu	
Variables	(1)	(2)
AI	0.040**	
	(2.45)	
AI2		0.010**
		(2.56)
GFS	-0.245*	-0.210
	(-1.92)	(-1.49)
Digfra	0.056	0.057
	(1.52)	(1.50)
Tmdl	-0.578	-0.391
	(-1.50)	(-1.29)
UL	-0.352	-0.546

	(-1.24)	(-1.31)
LF	-0.109	-0.163**
	(-1.62)	(-2.36)
lnURS	-0.005	-0.013
	(-0.70)	(-1.54)
Constant	2.104***	2.713***
	(3.80)	(4.74)
N	300	260
R-squared	0.174	0.192
id	YES	YES
Year	YES	YES

t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 6. Endogeneity test results

Variable	First stage: AI	Second stage: Efedu
	AI	Efedu
AI		0.002***
		(2.68)
L.AI	0.001**	
	(2.57)	
Constant	1.059***	2.046*
	(32.38)	(1.83)
Control	YES	YES
N	251	231
R-squared	0.191	0.263
id	YES	YES
Year	YES	YES

t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 7. Regional heterogeneity test results

Variable	**Eastern**	**Western**	**Central**	**Northeast**

AI	0.0025**	0.053***	-0.0012	0.127*
	(2.60)	(3.78)	(-0.02)	(2.11)
GFS	-0.562**	-0.408	-0.784***	0.001
	(-2.18)	(-1.48)	(-3.32)	(0.00)
Digfra	-0.041	0.003	0.047	0.069
	(-0.88)	(0.05)	(1.24)	(0.63)
Tmdl	0.789	-0.468	0.020	0.047
	(1.65)	(-0.75)	(0.06)	(0.05)
UL	-0.009	-1.767	0.047	3.103
	(-0.03)	(-1.66)	(0.07)	(0.71)
LF	0.081	-0.378	-0.016	0.276
	(0.57)	(-1.31)	(-0.23)	(1.03)
lnURS	-0.016	0.021	0.010	0.039
	(-1.53)	(1.21)	(0.91)	(1.29)
Constant	0.669	4.450**	1.114	-3.689
	(0.60)	(2.23)	(1.47)	(-1.08)
N	120	110	60	30
R-squared	0.503	0.312	0.682	0.701
id	YES	YES	YES	YES
Year	YES	YES	YES	YES

t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 8. Mediation mechanism results of AI's impact on higher education resource allocation efficiency

Variable	(3) Efedu	(4) lnPD
AI	0.000**	0.000***
	(2.07)	(2.84)
Stru		

lnPD	0.087*	
	(1.74)	
GFS	0.042	-2.155***
	(0.26)	(-14.20)
Digfra	0.026	0.025
	(0.75)	(0.57)
Tmdl	-0.312	-0.691**
	(-1.24)	(-2.18)
UL	-0.413	0.613*
	(-1.62)	(1.90)
LF	-0.144**	-0.049
	(-2.23)	(-0.60)
lnURS	-0.011	0.004
	(-1.46)	(0.45)
Constant	1.619**	9.802***
	(2.28)	(14.90)
N	300	300
R-squared	0.185	0.615
id	YES	YES
Year	YES	YES

t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 9. Threshold effect test results

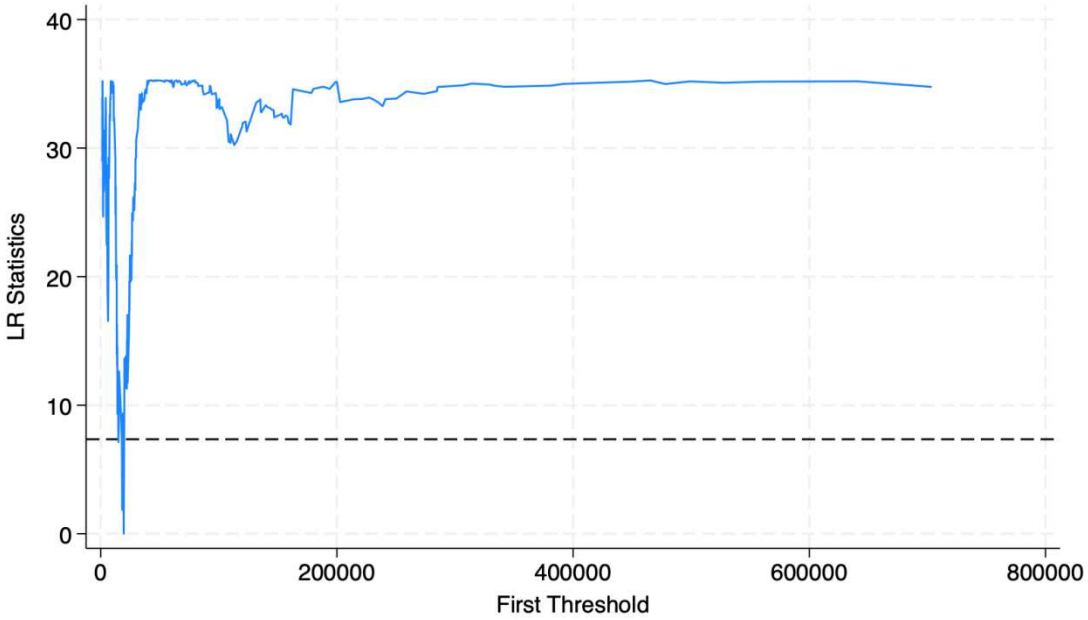
Threshold variable	Test	F-value	P-value	BS times	Critical values: 10%	5%	1%
Population density	Single	37.59	0.026	500	28.2574	33.8719	41.7047
	Double	10.65	0.682	500	27.2744	34.1957	42.6404
	Triple	9.41	0.710	500	23.9273	30.1611	39.6363
Regional	Single	36.26	0.004	500	19.9000	24.6449	33.1386

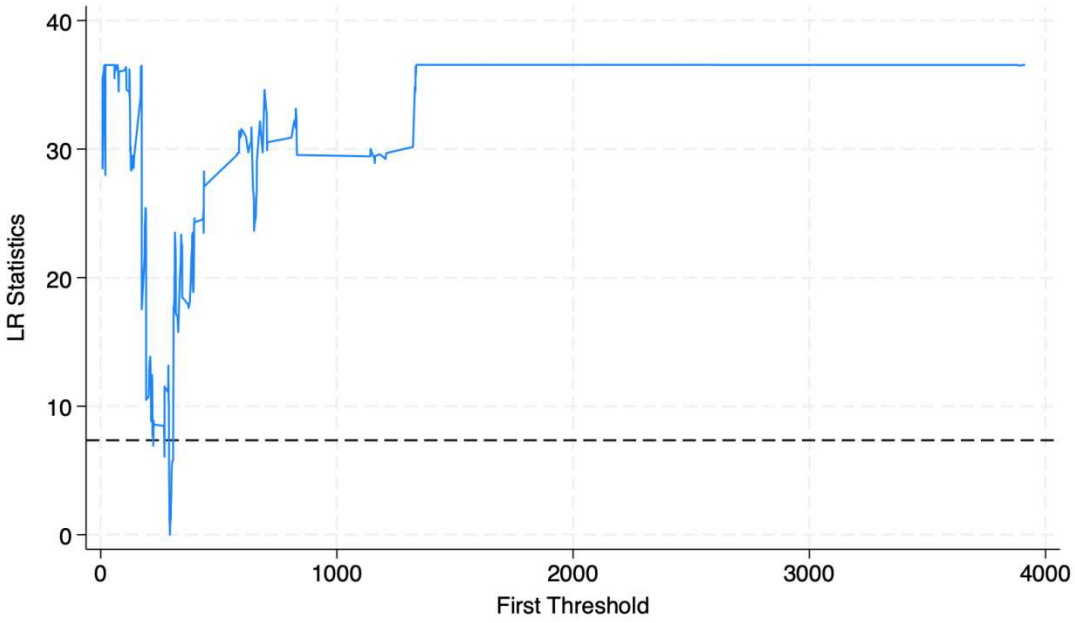
innovation level							
	Double	14.71	0.264	500	19.7110	24.2110	30.3647
	Triple	10.37	0.354	500	16.6280	20.6279	32.8064

Table 10. Threshold regression estimation results

	Population density as threshold variable	**Regional innovation level as threshold variable**
First threshold value	0.4097	0.4114
AI×I(λ≤th1)	6.14***	-5.60***
AI×I(λ>th1)	2.52**	2.16**
Control	YES	YES
Constant	2.910***	1.950***
N	300	300
R-squared	0.224	0.220
id	YES	YES
Year	YES	YES

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$


LR Statistics
40
30
20
10
0
0
200000
400000
600000
800000
First Threshold


LR Statistics
40
30
20
10
0
0
1000
2000
3000
4000
First Threshold

Supplementary Files

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