International Journal of Global Economics and Management
ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 10, Number 5, Year 2026
DOI: https://doi.org/10.62051/ijgem.v10n5.06
Journal homepage: https://ijgem.org

Mechanisms and Effects of Artificial Intelligence on New Quality Productive Forces in New Energy Vehicle Firms: Evidence from the Yangtze River Delta

Xinrui Li [1,*], Linhu Du [2]

[1] School of Economics, Anhui University of Finance and Economics, Bengbu, China

[2] School of Management Science and Engineering, Anhui University of Finance and Economics, Bengbu, China

*Corresponding Author: austinsanchez287846@gmail.com

ABSTRACT

Artificial intelligence is increasingly recognized as an important driver of firms' new quality productive forces. Based on panel data of new energy vehicle firms in the Yangtze River Delta from 2001 to 2023, this paper constructs firm-level indicators of artificial intelligence and new quality productive forces, and examines the impact of artificial intelligence on the new quality productive forces of new energy vehicle firms and its underlying mechanisms. The results show that artificial intelligence significantly promotes the growth of new quality productive forces in new energy vehicle firms, and this conclusion remains robust after addressing endogeneity concerns and conducting robustness checks. In addition, R&D expenditure does not constitute a significant mediating channel, although its negative path coefficient suggests a possible short-term adjustment effect. This indicates that the expansion of R&D funds does not necessarily translate immediately into improvements in firms' new quality productive forces. Heterogeneity tests show that the promoting effect of artificial intelligence is more pronounced in Jiangsu and Zhejiang and among small-sized enterprises. Mechanism tests provide empirical evidence that artificial intelligence affects firms' new quality productive forces through the optimization of R&D personnel structure and the improvement of innovation output.

KEYWORDS

Artificial intelligence; New quality productive forces; New energy vehicle firms; Yangtze River Delta; Mediation mechanism

1. INTRODUCTION

New quality productive forces have increasingly become a core driver of China's high-quality economic development and the construction of a modern industrial system. General Secretary Xi Jinping pointed out that new quality productive forces are fundamentally characterized by the leap in workers, means of labor, objects of labor and their optimized combination, and are advanced productive forces led by innovation and marked by high technology, high efficiency and high quality. The 2024 Government Work Report further proposed accelerating the development of new quality productive forces and promoting industrial innovation through scientific and technological innovation. As an important representative of the new round of technological revolution, artificial intelligence has become a key technological force driving the formation and upgrading of new quality productive forces. It systematically affects firms' production functions, factor allocation methods and value creation models, thereby reshaping firm competitiveness at the micro level. In China's regional economic landscape, the Yangtze River Delta, with a solid industrial foundation, concentrated innovation factors and a high degree of regional coordination, has become a typical field for the deep integration of artificial intelligence and the real economy. In particular, in the new energy vehicle industry, the Yangtze River Delta features active technological iteration and rich application scenarios. Therefore,examine new energy vehicle firms in the Yangtze River Delta helps reveal the channels and mechanisms through which artificial intelligence contributes to firm-level new quality productive forces.

However, existing studies have not reached a consensus on whether artificial intelligence can be effectively transformed into firm-level new quality productive forces, through what mechanisms this transformation occurs, and whether its effects differ systematically across regions and firm sizes. Prior studies still have several limitations. First, research on new quality productive forces mostly remains at the level of theoretical interpretation and macro analysis, while quantitative measurement and empirical identification at the micro firm level remain insufficient. Second, studies on the intelligent transformation of the new energy vehicle industry tend to focus on technological routes and industrial strategies, but lack systematic tests of how artificial intelligence affects firms' new quality productive forces through specific mechanisms. Third, regional comparison and firm-size heterogeneity studies in the Yangtze River Delta, a core industrial agglomeration area, are relatively limited, making it difficult to provide targeted empirical evidence for differentiated policies.

Accordingly, this paper studies the empowering effect and mechanisms of artificial intelligence on the new quality productive forces of new energy vehicle firms in the Yangtze River Delta from both theoretical and empirical perspectives. Theoretically, this paper focuses on the paths through which artificial intelligence empowers new quality productive forces in new energy vehicle firms. Drawing on innovation theory and Schumpeter's theory of creative destruction, it constructs a theoretical framework involving labor structure optimization, innovation output and resource reallocation, and analyzes the mechanisms through which artificial intelligence empowers new energy vehicle firms. Empirically, using panel data of new energy vehicle firms in the Yangtze River Delta from 2001 to 2023, this paper measures firm-level new quality productive forces and artificial intelligence, adopts multiple econometric methods to examine the impact of artificial intelligence on firms' new quality productive forces, and verifies the underlying mechanisms.

This paper contributes to the literature in three respects.First, this paper enriches the literature by examining the effect of artificial intelligence on new quality productive forces in new energy vehicle firms in the Yangtze River Delta.Second, it develops a theoretical framework linking artificial intelligence to new quality productive forces through resource allocation and innovation-output conversion. Third, empirically, it measures the level of new quality productive forces of new energy vehicle firms in the Yangtze River Delta, quantifies the effect of artificial intelligence on firms' new quality productive forces, and tests its mechanisms. These contributions deepen the micro-level understanding of how artificial intelligence contributes to the formation and improvement of new quality productive forces, and provide empirical evidence for firms to optimize technological deployment and for governments to implement differentiated industrial policies.

2. LITERATURE REVIEW

Existing studies generally hold that artificial intelligence, as an important representative of the new round of technological revolution, exerts a profound influence on firm productivity and innovation activities by improving information processing capabilities, optimizing resource allocation and reshaping organizational decision-making processes. On the one hand, artificial intelligence has strong general-purpose technology attributes [1], and can be embedded in R&D design, production and manufacturing, quality inspection and supply chain management, thereby improving firm production efficiency and factor allocation efficiency. On the other hand, Tian and Yuan (2024) [2] pointed out that artificial intelligence does not merely replace traditional production factors; rather, it improves the success rate of innovation activities and the efficiency of converting innovation outputs into real productive forces by changing firms' knowledge search, solution generation and experimental simulation methods. Related studies also show that artificial intelligence applications promote adjustments in firms' labor skill structures and impose higher requirements on the knowledge structure, digital skills and organizational coordination capabilities of R&D personnel [3]. Therefore, the core mechanism through which artificial intelligence affects firm development is reflected not only in increased technological input, but also in factor structure optimization, innovation efficiency improvement and organizational operation restructuring [4]. These studies provide an important basis for understanding the economic effects of artificial intelligence [5]. Nevertheless, most literature still focuses on total factor productivity, firm performance or innovation output, while direct examination of how artificial intelligence affects firm-level new quality productive forces remains relatively insufficient.

Research on new quality productive forces mainly focuses on theoretical connotation, indicator measurement and realization paths. Existing literature generally holds that new quality productive forces are advanced productive forces led by scientific and technological innovation and based on the optimized combination of workers, means of labor and objects of labor, emphasizing the characteristics of high technology, high efficiency and high quality [6]. With the deepening of related research, scholars have begun to construct indicator systems for new quality productive forces at the regional, industrial and firm levels, and to conduct quantitative measurement through entropy methods and comprehensive evaluation methods. Song et al. (2024) [7] examined the impact of ESG development on firms' new quality productive forces based on firm data, providing an empirical reference for firm-level measurement. Wu and Du (2024) [8] studied artificial intelligence and firms' new quality productive forces, further demonstrating that firms, as the basic units of technology application, resource allocation and value creation, are important micro-carriers for the formation of new quality productive forces. Wu and Zhou (2025) [9]and He et al. (2025) [10] also examined the empowering effect of artificial intelligence technological innovation on firms' new quality productive forces, indicating that firm-level research on new quality productive forces is becoming an important direction. However, existing measurement of firm-level new quality productive forces is still developing. In particular, in strategic emerging industries and manufacturing subsectors, how to identify firms' new quality productive forces based on industrial characteristics still needs further exploration. New energy vehicle firms are technology-intensive, capital-intensive and green-transition-oriented [11], making them an important scenario for observing the formation mechanism of firm-level new quality productive forces. It is therefore necessary to further examine the effect of artificial intelligence on such forces using micro firm data.

The new energy vehicle industry is an important field for the deep integration of artificial intelligence and the real economy. Artificial intelligence is widely applied in intelligent driving, battery management, vehicle control, intelligent manufacturing, quality inspection and supply chain coordination [12], and can promote the transformation of new energy vehicle firms from traditional manufacturing to digital, intelligent and flexible production modes [13]. Existing studies show that the development of the new energy vehicle industry depends not only on breakthroughs in core technologies [14], but also on industrial policies, R&D investment, supply chain coordination [15] and regional innovation environments [16]. As an important agglomeration area of China's new energy vehicle industry, the Yangtze River Delta has a complete industrial chain, dense innovation resources and a high degree of regional coordination. However, its internal provinces and municipalities still differ in industrial foundation, technological accumulation, policy support and firm-size structure. Therefore, even if artificial intelligence generally promotes the improvement of firms' new quality productive forces, the intensity of this effect may differ across regions and firm sizes. Although existing literature has paid attention to the intelligent transformation of the new energy vehicle industry, systematic micro-level empirical evidence remains insufficient regarding how artificial intelligence is transformed into firms' new quality productive forces within this specific industrial cluster and whether such transformation is constrained by regional and firm-size differences.

Overall, existing research provides an important theoretical basis for this paper, but three areas remain to be expanded. First, although studies on the economic effects of artificial intelligence have extensively discussed its influence on firm productivity, innovation performance and organizational change, micro-level identification directly focusing on firms' new quality productive forces is still relatively insufficient. Second, research on the new energy vehicle industry mainly concentrates on industrial policy, technological routes and innovation performance, while mechanism tests of how artificial intelligence affects firms' new quality productive forces through R&D personnel structure optimization, innovation output improvement and resource allocation adjustment remain inadequate. Third, few studies place new energy vehicle firms in the Yangtze River Delta within a unified analytical framework to examine regional and firm-size differences in the empowering effect of artificial intelligence, making it difficult to provide sufficient micro evidence for region- and firm-specific policy design. Based on this, this paper uses new energy vehicle firms in the Yangtze River Delta from 2001 to 2023 as the sample to systematically examine the effect, mechanisms and heterogeneity of artificial intelligence on firms' new quality productive forces.

3. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

3.1. Artificial Intelligence And Firms' New Quality Productive Forces

The core of new quality productive forces lies in the systematic reconstruction of production factor allocation, organizational operation modes and value creation logic driven by technological progress [6, 17]. As a typical general-purpose technology, artificial intelligence is pervasive, complementary to other technologies, and highly conducive to innovation; its broad adoption can reshape firms' production functions [1]. For new energy vehicle firms, artificial intelligence improves information processing and decision-making efficiency, promotes R&D collaboration and production flexibility, optimizes resource allocation and enhances innovation transformation efficiency, thereby fundamentally changing firms' growth modes [12, 13].

In terms of mechanism, the impact of artificial intelligence on firms' new quality productive forces is not simply factor substitution, but a continuous transmission process of "technology embedding—factor restructuring—organizational reconstruction—productivity improvement." By reshaping factor combinations and organizational operation logic, artificial intelligence promotes the shift of firms from factor-driven growth to a high-quality development model centered on innovation and efficiency. Therefore, this paper proposes the following hypothesis:

H1: The improvement of artificial intelligence significantly promotes the new quality productive forces of new energy vehicle firms in the Yangtze River Delta.

3.2. Mechanisms Through Which Artificial Intelligence Empowers Firms' New Quality Productive Forces

3.2.1. R&D personnel structure optimization and skill upgrading mechanism

The promotion of firms' new quality productive forces by artificial intelligence is first reflected in the reshaping of R&D factor structure. According to innovation theory, the absorption, adaptation, and recombination of artificial intelligence technologies require continuous R&D funding and professional R&D talent support [18]. This means that the introduction of artificial intelligence significantly increases the technical complexity and knowledge intensity of R&D activities, thereby driving firms to shift from an R&D model dominated by quantity input to a configuration mode centered on structural optimization [1, 19]. For new energy vehicle firms, the application of artificial intelligence in intelligent driving, power system optimization, material design and manufacturing process control imposes higher requirements on the knowledge structure and skill levels of R&D personnel. To adapt to this change, firms increase the proportion of R&D personnel, optimize the composition of R&D teams, and enhance their capabilities in technology absorption, knowledge integration, and the conversion of innovation outputs into real productive forces through skill upgrading [20]. Thus, artificial intelligence indirectly improves firms' new quality productive forces by reshaping the allocation structure of R&D factors. Accordingly, this paper proposes the following hypothesis:

H2a: Artificial intelligence improves the new quality productive forces of new energy vehicle firms by optimizing the structure of R&D personnel and promoting skill upgrading.

3.2.2. Innovation output improvement mechanism

Another important path through which artificial intelligence affects firms' new quality productive forces is the improvement of innovation output efficiency. Compared with traditional R&D methods, artificial intelligence can significantly improve the efficiency of knowledge search, solution generation and experimental simulation, thereby shortening innovation cycles and increasing the success rate of R&D [21]. This process does not simply rely on the expansion of input scale. Rather, it realizes a shift from "input-driven" to "efficiency-driven" by improving the efficiency of innovation activities and the conversion of innovation outputs into real productive forces. In the new energy vehicle industry, the application of artificial intelligence in battery management, vehicle control and supply chain coordination helps accelerate breakthroughs in key technologies and facilitates the conversion of innovation outputs into product competitiveness [12]. When artificial intelligence enables firms to generate more effective innovation outputs, their productivity and value creation capabilities will be significantly enhanced, and the promotion of new quality productive forces will become more evident. Accordingly, this paper proposes the following hypothesis:

H2b: Artificial intelligence improves the new quality productive forces of new energy vehicle firms by promoting innovation output.

3.2.3. Staged resource reallocation and short-term nonlinear performance

Based on Schumpeter's theory of creative destruction [22], artificial intelligence may also bring certain staged adjustment costs while promoting firm transformation. In the process of intelligent transformation, firms often need to simultaneously carry out digital infrastructure construction, process reengineering, organizational coordination optimization and business reconstruction. As a result, some resources may shift in the short term from traditional R&D expenditure to platform construction, system deployment and organizational adjustment [10, 22]. Therefore, certain R&D input variables may not show a synchronous positive relationship with the improvement of firms' new quality productive forces in the short run, but may display nonlinear characteristics. This phenomenon reflects staged resource reallocation during the empowering process of artificial intelligence rather than a negative impact on productivity. As resource allocation is gradually optimized, the long-term promoting effect will become apparent. Accordingly, this paper further proposes the following hypothesis:

H3: In the process through which artificial intelligence empowers firms' new quality productive forces, some R&D input variables may exhibit a staged suppression effect in the short term.

4. MODEL SPECIFICATION

4.1. Baseline Regression Model

To examine the effect of artificial intelligence on firms' new quality productive forces, this paper constructs the following two-way fixed effects model:

$$NTFP_{it} = \alpha + \beta AI_{it} + \gamma \text{Controls}_{\text{it}} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where, $NTFP_{it}$ denotes the new quality productive forces of firm i in year t; AI_{it} denotes the artificial intelligence level of the firm; $Controls_{it}$ represents a set of control variables; μ_i denotes firm fixed effects; λ_t denotes year fixed effects; and ε_{it} is the random disturbance term.

4.2. Variable Description

Dependent variable. The dependent variable is the level of new quality productive forces of new energy vehicle firms in the Yangtze River Delta (NTFP), which is calculated by the entropy method [7] by integrating three dimensions: new-type workers, new-type means of labor and new-type objects of labor [8].

Table 1. Indicator system of NTFP of new energy vehicle firms in the Yangtze River Delta

First-level indicator	Second-level indicator	Indicator description
New-type workers	Number of R&D personnel	Number of R&D personnel
	Proportion of R&D personnel	Number of R&D personnel / total employees
New-type means of labor	Net fixed assets	Fixed assets – accumulated depreciation – impairment provision for fixed assets
	Capitalized R&D expenditure	Capitalized R&D input
	R&D capitalization intensity	Capitalized R&D input / total R&D input
New-type objects of labor	Gross operating margin	(Operating revenue – operating cost) / operating revenue × 100%
	Operating revenue	Business scale
	Net intangible assets	Original value of intangible assets – accumulated amortization – impairment provision for intangible assets
	Number of independently applied invention patents in the current year	Number of independently applied invention patents in the current year
	Number of independently applied utility model patents in the current year	Number of independently applied utility model patents in the current year
	R&D expenditure	Current-period amount of R&D expense item
	R&D expenditure to operating revenue ratio	R&D expenditure / operating revenue

Note: The construction form of the indicator system of NTFP in this study refers to Wu and Du (2024) [8].

Core explanatory variable. Artificial intelligence level (lnwords) is used as the core indicator reflecting firms' attention to and willingness to apply artificial intelligence technologies. Theoretically, a higher artificial intelligence value indicates that the firm attaches greater importance to frontier technologies and is more inclined to optimize production factor allocation through technological innovation, thereby promoting the improvement of NTFP. Referring to the method of Du et al. (2024) [23], this paper matches 80 artificial-intelligence-related keywords in annual reports and uses the logarithm of the total artificial intelligence word frequency plus one as the proxy variable for firms' artificial intelligence level.

Mediating variables. This paper selects the proportion of R&D personnel (staff), log of invention patent applications (lnpat) and R&D expenditure (lnexp) as mediating variables. Specifically, the proportion of R&D personnel is measured by the ratio of R&D personnel to total employees at the firm level; log of invention patent applications is measured by the number of independent invention applications in the current year; and R&D expenditure is measured in logarithmic form.

Control variables. Following Song et al. (2024) [7], this paper selects return on assets (roa), the logarithm of total assets (lnassets), the logarithm of employees (lnemp) and the logarithm of government subsidies (lnsub) as control variables. Return on assets reflects firm profitability; the logarithm of total assets reflects firm size; the logarithm of employees reflects the firm's human resource reserves; and the logarithm of government subsidies reflects the intensity of external policy support. These variables may affect firms' NTFP through resource allocation capability, innovation investment capability and risk-bearing capacity.

Data description. This paper selects panel data of new energy vehicle firms in the Yangtze River Delta from 2001 to 2023 as the research sample and conducts the following processing: (1) observations with missing values in key variables were removed; (2) the main continuous variables were winsorized at the 2.5th and 97.5th percentiles to reduce the influence of extreme values; and (3) standardization of relevant data. The corporate financial report data and other data used in this paper are derived from Wind, the CSMAR database, annual reports of listed companies and relevant statistical yearbooks. The sample covers Shanghai, Anhui, Jiangsu and Zhejiang, and includes new energy vehicle firms of different sizes and industries.

Table 2. Descriptive statistics of variables

Variable type	Variable name	Symbol	N	Mean	Std. dev.	Min	Max
Dependent variable	New quality productive forces	NTFP	2649	0.373	0.122	0.170	0.662
Explanatory variable	Artificial intelligence level	lnwords	2649	0.751	0.966	0.000	3.258
Mediating variable	Proportion of R&D personnel	staff	2649	14.766	7.223	4.660	37.600
	Number of inventions	lnpat	2649	1.606	1.212	0.000	4.562
	R&D expenditure	lnexp	2649	18.135	1.155	16.052	21.125
Control variable	Return on assets	roa	2649	0.051	0.047	-0.073	0.151
	Total assets	lnassets	2649	21.823	0.983	20.188	24.383
	Number of employees	lnemp	2649	7.628	0.937	5.936	9.813
	Government subsidies	lnsub	2649	16.314	1.198	13.883	19.072

Note: The artificial intelligence level is the logarithmic value of firms' artificial intelligence text word frequency. Because most firms have relatively low application levels and a few firms have high values, the distribution is right-skewed. After logarithmic treatment, the standard deviation is slightly larger than the mean, which is consistent with the situations reported by Gong et al. (2025) [24] and Du and Cheng (2025) [25].

Table 2 reports the descriptive statistics of the main variables. The mean value of firms' new quality productive forces (NTFP) is 0.373 and the standard deviation is 0.122, indicating certain differentiation among sample firms. The mean value of the core explanatory variable, artificial intelligence level (lnwords), is 0.751 and the standard deviation is 0.966, showing a right-skewed distribution in which most firms have relatively low application levels while a few firms have deeper deployment, consistent with existing research. The distributions of mediating variables and control variables conform to the typical characteristics of micro-level firm data. The sample data structure is reasonable and satisfies the requirements for subsequent empirical tests.

5. EMPIRICAL RESULTS

5.1. Baseline Regression Results

The theoretical analysis above suggests that artificial intelligence promotes NTFP in new energy vehicle firms through technology embedding, factor restructuring and organizational reconstruction, based on which H1 is proposed. To test this theoretical judgment, this paper first constructs progressively specified fixed effects models. Column (1) controls for firm fixed effects to exclude time-invariant firm heterogeneity; column (2) further adds year fixed effects to control for common time shocks such as macroeconomic fluctuations and changes in industrial policy; column (3) adds firm-level control variables on the basis of two-way fixed effects to further alleviate interference caused by differences in firms' operating characteristics. If the artificial intelligence level remains significantly positive under different model specifications, it indicates that its promoting effect on firms' NTFP has strong consistency.

Table 3. Baseline regression results

Variable	(1) Firm fixed effects	(2) Two-way fixed effects	(3) Two-way fixed effects
Artificial intelligence level	0.0610*** (0.0041)	0.0602*** (0.0040)	0.0631*** (0.0031)
Return on assets	—	—	1.1758*** (0.0479)
Total assets	—	—	-0.0077 (0.0079)
Number of employees	—	—	0.0028 (0.0068)
Government subsidies	—	—	0.0053** (0.0023)
Year fixed effects	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	2,649	2,649	2,649
R^2	0.2539	0.3299	0.5737

Note: Standard errors are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

The results show that in column (1), the coefficient of artificial intelligence level is 0.0610 and is significantly positive at the 1% level, preliminarily indicating that after controlling for time-invariant firm characteristics, a higher artificial intelligence level is associated with a higher level of NTFP. In column (2), the coefficient remains 0.0602 and continues to be significant at the 1% level, suggesting that this positive relationship is not driven by macro time trends or common policy shocks. In column (3), the coefficient of artificial intelligence level is 0.0631 and remains significant at the 1% level, with stable direction and significance. Thus, after progressively controlling for firm heterogeneity, annual shocks and firm operating characteristics, the promoting effect of artificial intelligence on the NTFP of new energy vehicle firms remains valid, providing empirical support for H1.

5.2. Endogeneity Checks

To further address potential endogeneity concerns arising from reverse causality and omitted variables, this paper conducts endogeneity checks using baseline OLS, two-way fixed effects, 2SLS and FE-GMM methods. The results are reported in Table 4.

Table 4. Endogeneity checks

Variable	(1) Baseline OLS	(2) Two-way fixed effects	(3) 2SLS	(4) FE-GMM
Artificial intelligence level	0.0762*** (0.0032)	0.0632*** (0.0031)	0.0768*** (0.0236)	0.0763*** (0.0058)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes
Observations	2649	2649	1972	1972

Note: *** denotes significance at the 1% level. Standard errors are reported in parentheses. OLS, two-way fixed effects and IV-2SLS use firm-clustered robust standard errors.

Although the baseline regression verifies the positive relationship between artificial intelligence and firms' NTFP, potential reverse causality and omitted-variable problems may remain. To further strengthen the credibility of the identification of H1, this paper adopts two-way fixed effects, internal instrumental variable 2SLS and FE-GMM methods for endogeneity checks. The results are reported in Table 4. Column (1) reports the baseline OLS regression, where the estimated coefficient of artificial intelligence level is 0.0762 and is significantly positive at the 1% level. After further controlling for year fixed effects and firm fixed effects in column (2), the estimated coefficient decreases to 0.0632 but remains significant at the 1% level, indicating that after excluding macro time trends and firm heterogeneity, the positive effect of artificial intelligence on firms' NTFP remains valid.

Furthermore, considering that firms with higher levels of NTFP may be more inclined to deploy artificial intelligence, this paper adopts an internal instrumental variable 2SLS method for supplementary testing. Column (3) shows that the estimated coefficient of artificial intelligence level is 0.0768 and is significantly positive at the 1% level, indicating that the core conclusion remains stable after partially alleviating potential reverse causality. Column (4) reports the FE-GMM estimation results, where the coefficient of artificial intelligence level is 0.0763 and is also significant at the 1% level, further demonstrating that the promoting effect of artificial intelligence on firms' NTFP is not driven by a single model specification. Overall, under different identification methods, the coefficient of artificial intelligence level is consistently significantly positive, suggesting that after considering potential endogeneity, the positive effect of artificial intelligence on firms' NTFP remains robust and the reliability of H1 is further enhanced.

5.3. Robustness Checks

To examine whether the baseline conclusion depends on a specific sample period, variable measurement or the influence of extreme values, this paper conducts robustness checks from four aspects: excluding special years, replacing the core explanatory variable, introducing lagged terms and winsorizing variables. If the artificial intelligence level remains significantly positive after these treatments, H1 is not driven by specific model settings or sample outliers.

Table 5. Robustness checks

Variable	(1) Excluding pandemic years	(2) Replacing explanatory variable	(3) One-period lag	(4) 1% winsorization
Artificial intelligence level	0.0614*** (0.0030)	0.0512*** (0.0063)	0.0343*** (0.0029)	0.0632*** (0.0022)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N	1836	2649	2216	2649
R^2	0.849	0.7951	0.8138	0.8518

Note: Standard errors are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

First, after excluding observations from the pandemic years 2020–2022, the coefficient of artificial intelligence level (lnwords) is 0.0614 and is significant at the 1% level, indicating that after excluding the influence of the abnormal operating environment caused by the pandemic shock, the positive effect of artificial intelligence on firms' NTFP remains significant. This shows that the baseline conclusion is not driven by the special external environment during the pandemic period and has strong sample robustness.

Second, after replacing artificial intelligence level (lnwords) with whether a firm applied for an artificial intelligence patent in the current year (ai), the coefficient of ai is 0.0512 and is also significant at the 1% level. This indicates that even when the measurement of the explanatory variable is changed, its positive effect on firms' NTFP remains robust, showing that the baseline regression result does not depend on a single indicator and has good variable-substitution robustness.

Third, after introducing the one-period lag of artificial intelligence level, the coefficient is 0.0343. Although lower than the contemporaneous estimate, it remains significant at the 1% level, indicating that the empowering effect of artificial intelligence on the NTFP of new energy vehicle firms has a certain persistence and is not merely a contemporaneous correlation.

Fourth, all variables are winsorized at the 1% level to test whether the results are affected by extreme values. The coefficient of artificial intelligence level is 0.0632, which remains significant and is very close to the baseline estimate of 0.0631. This suggests that the research conclusion is not driven by a small number of extreme observations and has strong robustness and credibility.

5.4. Mediation Effect Test

To further identify the internal transmission mechanisms through which artificial intelligence affects the NTFP of new energy vehicle firms, this paper conducts mediation effect tests based on the verified direct effect in the baseline regression. Theoretical analysis suggests that artificial intelligence may affect firms' NTFP by optimizing R&D personnel structure, improving innovation output and inducing staged resource reallocation, corresponding to H2a, H2b and H3, respectively. Accordingly, this paper selects the proportion of R&D personnel, the number of inventions and R&D expenditure as mediating variables, and uses the Sobel test to examine the specific transmission paths through which artificial intelligence affects firms' NTFP. The results are shown in Table 6.

Table 6. Mediation effect test

Mediator	Path a (x→M)	Path b (M→y)	Indirect effect	Sobel Z	Proportion (%)	Mechanism type
Proportion of R&D personnel	0.0627** (2.015)	0.0131** (2.362)	0.0008^ [0.125]	1.533	1.34	Traditional mediation
Number of inventions	0.0701* (1.800)	0.0740*** (63.015)	0.0052* [0.072]	1.799	8.50	Traditional mediation
R&D expenditure	0.0062 (0.287)	-0.0003 (-0.045)	-0.0000 [0.965]	-0.044	-0.00	Suppression effect

Note: t-values are reported in parentheses, and Sobel test p-values are reported in square brackets. ***, **, *, and ^ denote significance at the 1%, 5%, 10%, and 15% levels, respectively.

Table 6 reports the results of the mediation effect test. For the proportion of R&D personnel, the coefficient of path a is 0.0627 and the coefficient of path b is 0.0131, both of which are significantly positive. The indirect effect is 0.0008, with a Sobel Z statistic of 1.533, indicating marginal significance at the 15% level. This suggests that artificial intelligence can promote firms' NTFP partly by optimizing the structure of R&D personnel. In other words, the introduction of artificial intelligence not only reflects technological adoption, but also requires firms to adjust their R&D personnel allocation and strengthen the role of new-type workers. Therefore, H2a receives certain empirical support.

The mediation effect of the number of inventions is more evident. The coefficient of path a is 0.0701 and is positive, while the coefficient of path b is 0.0740 and is significantly positive at the 1% level. The indirect effect is 0.0052, with a Sobel Z statistic of 1.799, indicating marginal significance at the 10% level. The mediation proportion reaches 8.50%, which is clearly higher than that of the R&D personnel proportion channel. This result shows that artificial intelligence mainly improves firms' NTFP by promoting innovation output. Specifically, artificial intelligence enhances firms' capabilities in knowledge search, technological experimentation and the conversion of innovation outputs into real productive forces. Therefore, the innovation output mechanism is the more important transmission channel, and H2b is supported.

For R&D expenditure, the coefficient of path a is positive but very small, while the coefficient of path b is negative and also close to zero. The indirect effect is approximately zero, with a Sobel Z statistic of -0.044, indicating that the mediation effect is not statistically significant. This means that the expansion of R&D expenditure does not form an effective transmission channel between artificial intelligence and firms' NTFP in the current sample. Although the sign of path b suggests a possible suppression effect, the empirical evidence is very weak. Therefore, H3 can only be regarded as receiving limited directional support rather than strong statistical support.

Overall, the mediation effect tests indicate that artificial intelligence empowers the NTFP of new energy vehicle firms mainly through two channels: R&D personnel structure optimization and innovation output improvement. Among them, the innovation output channel has stronger explanatory power. By contrast, R&D expenditure does not show a significant mediation effect, suggesting that the impact of artificial intelligence on firms' NTFP depends less on the simple expansion of R&D spending and more on improving innovation efficiency, optimizing R&D factor allocation and strengthening the conversion of innovation outputs into real productivity.

5.5. Heterogeneity Analysis

After confirming the overall promoting effect of artificial intelligence, this paper further examines whether this effect is affected by regional industrial foundations and firm-size structures. Within the Yangtze River Delta, different regions differ in industrial chain support, innovation resource agglomeration and policy support intensity, and such differences in regional innovation configurations may affect the transformation efficiency of artificial intelligence [26].Firms of different sizes also differ in organizational flexibility, resource acquisition capability and technology absorption capability. Therefore, it is necessary to test the heterogeneity of the empowering effect of artificial intelligence from the two dimensions of region and firm size. This paper conducts grouped regressions to examine heterogeneity across regions and firm sizes. The grouped regression divides the data into subsamples by region (Shanghai, Anhui, Jiangsu and Zhejiang) and firm size (large, medium-sized and small firms), estimates the regression model separately for each subsample, and compares the coefficient differences in artificial intelligence level.

5.5.1. Regional heterogeneity

To examine whether the effect of artificial intelligence differs across regions within the Yangtze River Delta, this paper estimates the baseline model separately for Shanghai, Anhui, Jiangsu and Zhejiang. The regional heterogeneity results are reported in Table 7.

Table 7. Heterogeneity analysis: regional heterogeneity

Variable	Shanghai	Anhui	Jiangsu	Zhejiang
Artificial intelligence level	0.0562*** (0.0091)	0.0616*** (0.0087)	0.0652*** (0.0053)	0.0636*** (0.0037)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N	390	374	918	967
R^2	0.8756	0.8512	0.8707	0.8589

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.Standard errors are reported in parentheses.

The regional heterogeneity results show that artificial intelligence level has a significantly positive effect in the Shanghai, Anhui, Jiangsu and Zhejiang samples, indicating that the positive effect of artificial intelligence on firms' NTFP is broadly present across regions. However, in terms of coefficient size, the positive effect is more pronounced in Jiangsu and Zhejiang, followed by Anhui, while Shanghai is relatively weaker. This indicates that the effect of artificial intelligence depends not only on the technology itself, but also on regional industrial foundations, innovation-supporting conditions, factor endowments, absorptive capacity, and the richness of application scenarios.Therefore, even when firms have similar artificial intelligence levels, the marginal effect of translating AI applications into NTFP improvements may differ substantially across regions.

5.5.2. Firm-size heterogeneity

To further examine whether firm size affects the transformation efficiency of artificial intelligence, this paper divides the sample into large, medium-sized and small firms and conducts grouped regressions. The firm-size heterogeneity results are reported in Table 8.

The firm-size heterogeneity results show that artificial intelligence level has a significantly positive effect among large, medium-sized and small firms, but the promoting effect is relatively stronger among small firms. This indicates that although small firms have relatively limited resource bases, they have shorter organizational hierarchies, faster decision-making chains and weaker path dependence. Therefore, when artificial intelligence application scenarios are clear, they may more easily achieve rapid adoption and marginal efficiency improvement. This suggests that the empowerment of firms' NTFP by artificial intelligence is not a simple universal gain process, but has obvious contextual constraints and structural differences. Consequently, subsequent policy design should not adopt a completely homogeneous promotion mode, but should pay greater attention to classification-based and differentiated implementation.

Table 8. Heterogeneity analysis: firm-size heterogeneity

Variable	Large firms	Medium-sized firms	Small firms
Artificial intelligence level	0.0552*** (0.0060)	0.0624*** (0.0046)	0.0645*** (0.0042)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	854	1029	1062
R^2	0.8518	0.8968	0.8773

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

6. CONCLUSIONS AND POLICY IMPLICATIONS

6.1. Conclusions

Using panel data of new energy vehicle firms in the Yangtze River Delta from 2001 to 2023, this paper systematically examines the impact of artificial intelligence level on firms' new quality productive forces and its mechanisms. The results show that artificial intelligence significantly promotes the improvement of new quality productive forces in new energy vehicle firms, and this conclusion remains valid after two-way fixed effects estimation, endogeneity treatment and robustness checks. This indicates that artificial intelligence is no longer merely an auxiliary technology introduced from outside the firm; it is gradually embedded in firms' production functions and has become an important force for improving new quality productive forces.

Further analysis finds that the mechanisms through which artificial intelligence empowers firms' new quality productive forces are mainly reflected in R&D personnel structure optimization and innovation output improvement, rather than simple expansion of R&D funds. Among these mechanisms, the innovation output channel has the strongest explanatory power, followed by R&D personnel structure optimization. This suggests that artificial intelligence is more likely to enhance firms' new quality productive forces by improving innovation efficiency and strengthening their capacity to convert innovation outputs into real productive forces. At the same time, R&D expenditure shows a certain staged suppression effect in direction, indicating that the introduction of artificial intelligence is often accompanied by organizational adjustment, resource restructuring and technological adaptation, and that the release of its benefits involves a certain time lag.

This paper also finds significant heterogeneity in the promoting effect of artificial intelligence on firms' new quality productive forces. At the regional level, the promoting effect is more pronounced in Jiangsu and Zhejiang, indicating that the effectiveness of artificial intelligence empowerment is jointly affected by regional industrial foundations, innovation conditions and supporting environments. At the firm-size level, the transformation efficiency of small firms is relatively higher, suggesting that such firms achieve a better balance between resource availability and organizational flexibility and can more easily transform artificial intelligence input into real productive forces.

Overall, the impact of artificial intelligence on the new quality productive forces of new energy vehicle firms in the Yangtze River Delta presents three characteristics. First, the direct promoting effect is significant and robust. Second, the positive mechanisms mainly depend on R&D personnel structure optimization and innovation output improvement. Third, the effect is constrained by regional conditions and firm-size differences. Therefore, the key to enabling artificial intelligence to more effectively empower firms' new quality productive forces lies not in simply expanding the scale of investment, but in opening effective transmission channels, easing short-term adjustment frictions and implementing more targeted differentiated policies based on heterogeneity characteristics.

6.2. Policy Implications

First, artificial intelligence should be deeply applied to key links in the new energy vehicle industrial chain. The empirical results show that artificial intelligence level has a stable and significant promoting effect on firms' new quality productive forces, meaning that artificial intelligence has gradually become an important source of competitive advantage for new energy vehicle firms. Firms should avoid indiscriminate deployment and focus instead on key application scenarios with clear productivity-enhancing potential, such as intelligent driving, battery management, intelligent manufacturing, quality inspection, and supply chain coordination. They should also promote artificial intelligence from local application to full-process coverage, forming a cooperative and mutually beneficial pattern between vehicle manufacturers and parts suppliers. Accordingly, regional shared computing power, data and standards systems should be accelerated, and data-sharing channels should be opened to provide basic conditions for the large-scale application of artificial intelligence. In addition, leading firms should play a guiding role and open their application scenarios to a certain extent, helping upstream and downstream small and medium-sized firms implement AI applications in concrete scenarios and enhance the overall competitiveness of the Yangtze River Delta industrial chain.

Second, the structure of R&D talent should be optimized to strengthen the talent support for artificial intelligence implementation. The empirical results show that artificial intelligence promotes the growth of firms' new quality productive forces mainly through R&D personnel structure optimization and innovation output improvement, rather than simply relying on the expansion of R&D funds. The functioning of artificial intelligence depends on high-quality and specialized R&D teams, so policy should pay greater attention to talent quality and structure rather than simply expanding the number of personnel. At the firm level, policy support should encourage firms to establish interdisciplinary teams combining artificial intelligence technology with automotive engineering and manufacturing experience, with a focus on cultivating intelligent manufacturing talent. At the social level, universities, research institutions and enterprises should jointly cultivate talent, and flexible recruitment and talent-sharing mechanisms should be used to alleviate the shortage of intelligent manufacturing talent. At the government level, skill upgrading and incentive mechanisms for talent should be improved so that R&D personnel can better master and apply artificial intelligence technologies and enhance the innovation output capabilities of new energy vehicle firms in the Yangtze River Delta.

Third, evaluation and support mechanisms for intelligent transformation should be improved, guiding firms from an emphasis on "input scale" to an emphasis on "allocation efficiency and transformation performance." The mechanism test shows that R&D expenditure presents a certain suppression effect in the short term, indicating that the introduction of artificial intelligence does not necessarily transform immediately into improved new quality productive forces through the expansion of R&D funds. Therefore, governments and firms should avoid evaluating the effectiveness of intelligent transformation simply by the scale of R&D expenditure. Greater attention should be paid to the direction of capital allocation, organizational coordination efficiency, technology transformation results and long-term productivity improvement. Governments may provide support for firms' early-stage digital platform construction and technology deployment, thereby easing cost pressures in the initial phase of intelligent transformation. Firms should optimize the allocation of R&D funds and allocate limited resources to key technological breakthroughs and other essential links, reducing unnecessary process losses during short-term adjustment and steadily releasing the long-term value of artificial intelligence empowerment.

Fourth, differentiated policies should be implemented according to regional and firm-size differences to promote a more balanced realization of the productivity-enhancing effects of artificial intelligence, which is consistent with the principle of developing new quality productive forces according to local conditions [27]. Heterogeneity analysis shows that the promoting effect of artificial intelligence differs significantly across regions and firm sizes, and a unified promotion model is unlikely to maximize policy effectiveness. For Jiangsu and Zhejiang, where the promoting effect is stronger, their demonstration and leading role should be further strengthened, and they should be supported in forming replicable and scalable experiences in intelligent transformation. For regions where the promoting effect is relatively weaker, policy support should be increased to enhance their capacity to absorb technological spillovers from artificial intelligence. At the firm level, small firms should be supported in leveraging their advantages of organizational flexibility and rapid transformation, while public platforms and policy subsidies should be used to compensate for their shortages of capital, talent and technology. For medium-sized firms, low-cost digital transformation solutions and shared technology platforms should be provided to lower the threshold for artificial intelligence application. A differentiated policy framework is therefore essential for fully releasing the productivity-enhancing potential of artificial intelligence in new energy vehicle firms.

ACKNOWLEDGMENTS

The authors gratefully acknowledge financial support from the University-level Key Research Project of Anhui University of Finance and Economics, "Research on the Model and Path of a New Nationwide System for Tackling Key Core Technologies in the Pan-Terminal Chip Industry from the Perspective of International Disparities" (Grant No. ACKYB23009); the Anhui Provincial Social Science Innovation and Development Research Project, "Research on the Mechanisms and Effects of Artificial Intelligence Empowering the High-Quality Development of Anhui's New Energy Vehicle Industry" (Grant No. 2024CX049); and the Anhui Provincial Philosophy and Social Science Planning Project, "Research on the Mechanisms and Pathways through Which Patient Capital Facilitates Breakthroughs in Key Core Technologies in Anhui's New Energy Vehicle Industry" (Grant No. AHSKY2025D06).

The authors acknowledge the use of ChatGPT for language translation and polishing, as well as for checking Stata code; all research design, data analysis, interpretation of results, and conclusions remain the sole responsibility of the authors.

REFERENCES

[1] Qi, Y., & Shen, T. Artificial intelligence empowering new quality productive forces: Logic, models and paths [J]. Research on Economics and Management, 2024, 45(07): 3-17.

[2] Tian, Y., & Yuan, W. Research on the development trend of artificial intelligence in China [J]. Frontiers, 2024(08): 102-105.

[3] Yao, J., Zhang, K., Guo, L., et al. How does artificial intelligence improve firm productivity? From the perspective of labor skill structure adjustment [J]. Management World, 2024, 40(02): 101-116+133+117-122.

[4] Ma, T., & Zhong, H. Artificial intelligence, productivity spillovers and optimization of productivity layout [J]. Journal of Industrial Technological Economics, 2026, 45(03): 3-13.

[5] Da Silva, L., & Xiao, L. Central banks at a crossroads [J]. China Finance, 2023(20): 23-25.

[6] Wang, H. Theoretical contribution, connotation and development path of new quality productive forces [N]. Shanxi Science and Technology News, 2025-04-24(A03).

[7] Song, J., Zhang, J., & Pan, Y. The impact of ESG development on firms' new quality productive forces: Evidence from China's A-share listed companies [J]. Contemporary Economic Management, 2024, 46(06): 1-11.

[8] Wu, J., & Du, W. Artificial intelligence and firms' new quality productive forces: Mechanisms and effects [J]. Journal of Industrial Technological Economics, 2024, 43(10): 22-31.

[9] Wu, Q., & Zhou, D. Research on the empowering effect of artificial intelligence technological innovation on firms' new quality productive forces [J]. Social Sciences in Xinjiang, 2025(01): 43-57+187.

[10] He, X., Wang, Q., & Yang, M. Research on the impact of artificial intelligence on new quality productive forces: Evidence from China's A-share listed companies [J]. Technology Economics, 2025, 44(02): 97-114.

[11] Research Group of the Fourth Research Department of the Institute of Party History and Literature of the CPC Central Committee. A review of domestic academic research on Marxist theory in 2024 [J]. Marxism & Reality, 2025(01): 193-203.

[12] Liu, H., & Tan, M. Research on the impact of artificial intelligence on new quality productive forces in the new energy vehicle industry [J]. Science Research Management, 2025, 46(12): 33-44.

[13] Suo, Q., & Li, C. Multidimensional measurement of technological evolution in emerging industries: Evidence from China's new energy vehicle industry [J]. Journal of Intelligence, 2023, 42(10): 140-149.

[14] Liu, D., Yang, R., Zhu, X., et al. New quality productive forces and scientific and technological innovation [J]. Forum on Science and Technology in China, 2024(03): 1-5.

[15] Wu, L., Wu, Z., Lin, L., et al. Research on the impact of new energy vehicle industrial policy on enterprise technological innovation [J]. Scientific Management Research, 2023, 41(03): 71-78.

[16] Yang, B., Liu, X., & Ji, X. Regional innovation ecosystem: Knowledge base and theoretical framework [J]. Science & Technology Progress and Policy, 2023, 40(13): 152-160.

[17] Shi, Y. Artificial intelligence reshapes the three elements of productivity and empowers the development of new quality productive forces [EB/OL]. Guangming Online, 2026-03-20 [2026-03-20].

[18] Zhang, W., & Wu, Y. Innovation transformation based on artificial intelligence [J]. Journal of Peking University (Philosophy and Social Sciences), 2020, 57(04): 139-148.

[19] Yang, W. The impact mechanism of artificial intelligence on employment: Market effect and paradigm effect [J]. Journal of the Party School of the Central Committee of the C.P.C. (National Academy of Governance), 2025, 29(05): 41-52.

[20] Li, Y., & Tao, N. A multi-level dynamic influence model of employees' adoption of artificial intelligence technology: A literature review [J]. Human Resource Development of China, 2022, 39(01): 35-56.

[21] Hui, N., Yang, J., & Xu, X. Logical mechanisms of the impact of artificial intelligence on new quality productive forces in manufacturing [J]. Journal of Beijing University of Technology (Social Sciences Edition), 2025, 25(03): 50-62.

[22] Hong, Y., & Wang, H. Developing new quality productive forces through creative destruction by artificial intelligence [J]. Economist, 2026(03): 5-15.

[23] Du, C., Cao, X., & Ren, J. Mechanisms and effects of artificial intelligence on total factor productivity in China [J]. Nankai Economic Studies, 2024(02): 3-24.

[24] Gong, J., Shi, G., & Li, X. Research on the mechanism and enabling effect of artificial intelligence-driven high-quality firm development: Micro evidence based on total factor productivity [J]. Journal of Harbin University of Commerce (Social Science Edition), 2025(05): 47-60.

[25] Du, F., & Cheng, N. Research on the effects and mechanisms of artificial intelligence-driven new quality productive forces: Evidence from Chinese manufacturing enterprises [J]. Productivity Research, 2025(07): 91-97.

[26] Fang, D., & Wang, L. Research on multiple configuration paths and driving effects of regional innovation in China [J]. Regional Economic Review, 2024(01): 78-87.

[27] Ji, Y., Su, M., Wu, Y., et al. Improving institutional mechanisms for developing new quality productive forces according to local conditions and promoting Chinese modernization [J]. Journal of Industrial Technological Economics, 2024, 43(08): 3-25.