Whether, How and When Do Artificial Intelligence Technologies Improve Enterprise Total Factor Productivity?

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Abstract

The progress of artificial intelligence (AI) technology has significantly impacted economic growth. Research into the correlation between AI technology and total factor productivity (TFP) in enterprises enhances our understanding of how AI fosters economic efficiency and effectiveness. This study, based on 40,960 data points from 4,395 listed Chinese companies between 2003 and 2022, identifies the beneficial impact of AI technologies on corporate TFP, demonstrating that each additional unit of AI technology increases TFP by 0.046 units. The proposed approach using a Random Forest approach further refines these findings. The empirical results of Random Forest model include correlations of variables, trends in TFP over time, and a comparison of actual versus predicted TFP values, offering deeper insights into the factors driving productivity. Further analysis reveals that corporate innovation capabilities mediate this relationship, accounting for 22.176% of the total effect. Additionally, the infusion of youth into the top management team (TMT) positively moderates the impact of AI technology on TFP. The study's findings provide a comprehensive understanding of the mechanisms through which AI technologies enhance corporate operations and growth. This pioneering study offers valuable insights for policymaking and business management, outlining a robust framework for leveraging AI to improve enterprise productivity.

Keywords: Random forest modelling, Artificial intelligence technologies, Enterprise total factor productivity, Innovation capability, Youthfulization of top management team

1 Introduction

Artificial intelligence (AI) technology, with its robust data processing, learning capabilities, and decision support functions, is gradually transforming our work, lifestyles, and social structures. The nature of AI technology is to enable computers to possess comparable learning and decision-making capabilities as humans [1]. By simulating human intelligence, AI technology transforms traditional production methods and business models. It has been acknowledged as a key driver of corporate innovation [2], firm performance [3], and sustainable development [4-5]. AI technology is clearly becoming a crucial factor in enhancing the production efficiency and effectiveness of enterprises.

Total factor productivity (TFP) refers to the ratio of the outputs generated by a firm utilizing all input factors, such as labor, capital, technology, etc. [6-7]. Previous research has indicated that enhanced labor, capital, and land productivity [8], improved scientific and technological innovation [9], optimized resource allocation [10], and efficient supply chain management [11] are all effective strategies for enhancing corporate TFP. Although AI technology can affect corporate productivity, the investigation directly into the relationship between AI technology and corporate TFP is still in its nascent phase.

Some scholars demonstrated that AI technology can improve corporate TFP. For instance, AI technology can enhance corporate TFP via the mediating mechanism of reduced cost, and increased utilization of highly-skilled labor [12]. Additionally, AI technology can promote technological innovation, and market matching improvement to enhance corporate TFP [13]. Nevertheless, several studies propose that the impact of AI technology on corporate TFP is uncertain. Considering "Solow's paradox", the effect of AI on TFP is not significant at its early stage, significantly positive in the promotion stage, and significantly negative at the extreme stage. Accordingly, the impact of AI technology on TFP and their effect mechanisms are ambiguous, necessitating further empirical tests [14].

Against this background, this paper collects data from Chinese listed enterprises from 2003 to 2022 to conduct baseline regression analysis, mediation mechanism analysis, moderation mechanism analysis, and heterogeneity analysis. Additionally, this study introduces a Random Forest approach to further explore the relationships between AI technology, TFP, and various company characteristics. The Random Forest method is utilized to classify companies as tech or non-tech based on their AI adoption and to analyze the key company

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properties that significantly influence TFP. This approach allows for the identification of the most critical factors contributing to TFP, offering a nuanced understanding of how AI technology interacts with different organizational attributes.

The theoretical contributions of this study are threefold. Firstly, this study employs multivariate regression analysis to quantify how AI technology affects corporate TFP, finding that each additional unit of AI technology increases enterprise TFP by 0.046 units. This specific numerical value provides a clear reference point for decision-makers, aiding in the accurate assessment of the return on investment in AI technology. Secondly, the research highlights the mediating role of innovation ability in the improvement of TFP through AI technology, with the younger executive team acting as a positive moderator. The mediation effect accounted for 22.176% of the total effect, and the impact of AI technology was found to increase by 0.002 units for every 1 unit decrease in the average age of a company's executive team. Lastly, by incorporating the Random Forest approach, the study provides a robust framework for understanding the complex interactions between AI technology, company characteristics, and TFP, identifying key drivers of productivity that are critical for strategic decision-making.

This paper is the pioneering study to explore whether, how, and when AI technologies can enhance TFP within an integrated conceptual model, providing a foundation for an in-depth understanding of the relationship between AI technology and TFP. The structure of the paper is as follows. We will conduct a literature review, and then propose research hypotheses. Following that, we will present the methods, including the Random Forest approach, and results. Finally, we will discuss and provide research conclusions.

2 Literature Review and Hypothesis Development

2.1 AI Technology and Total Factor Productivity

With the rapid advancement of science and technology, AI technology has emerged as a crucial driving force in the current era, significantly boosting enterprise TFP. Firstly, AI technology is conducive to implementing intelligent decision support systems to enhance TFP. Specifically, AI technology controls the process of procuring raw materials, increases the efficiency of resource utilization, optimizes inventory management, and consequently enhances corporate TFP [15]. Secondly, AI technology can promote automation of production processes so as to improve corporate TFP [16]. In the automotive manufacturing industry, automated assembly lines demonstrate how robots and AI algorithms improve efficiency by performing repetitive tasks quickly and accurately. Finally, companies can leverage AI technology to customize marketing strategies and enhance customer service, thereby enhancing overall TFP. AI technology assists organizations in gaining a deeper comprehension of customer demands, enabling the provision of tailored products and services, which contributes to the growth of sales and market share, subsequently enhancing corporate TFP. Accordingly, we posit the following hypothesis:

H1: AI Technology positively affects TFP.

2.2 The Mediating Effect of Innovation Capability

2.2.1 AI Technology and Innovation Capability

AI technology can efficiently enhance corporate innovation capabilities. Firstly, AI technology can assist enterprises in comprehending market requirements [17], thereby facilitating the realization of product and service innovation. Through analysis of consumers' behavioral data from purchase, browsing, and clicks history, AI can accurately infer consumers' preferences and needs, providing personalized recommendations. It contributes to novel product concepts for businesses or the enhancement of existing product strategies [18]. Secondly, AI technology can promote innovation by enhanced technical capabilities. Enterprises can leverage machine learning and deep learning technologies to innovate novel products and services, such as self-driving cars, intelligent voice assistants, and other disruptive offerings [19]. Finally, AI technology enables collaboration across different industries, thereby fostering the emergence of novel business models [20]. AI technology facilitates data mining, sharing and analysis across various industries [21]. By employing big data analysis, industries can uncover potential connections and collaboration opportunities to introduce novel business models and avenues. Hence, we make the assumption that:

H2: AI Technology positively affects corporate innovation capability.

2.2.2 Innovation Capability and Total Factor Productivity

Furthermore, enterprise innovation capability can significantly promote TFP. Firstly, innovation capacity enhances corporate TFP by effective cost management [22]. Generally, the enhancement of innovation capability is frequently linked to technological innovation and process enhancement. Novel technologies contribute to decreased raw material usage and energy consumption, resulting in a direct reduction in production costs and improvement in TFP [22]. Secondly, innovation capacity can improve production and operation efficiency [23]. For instance, the creative implementation of automated machinery contributes to a reduction in the need for manual labor, decreased operating durations, lower error rates, ultimately resulting in a substantial enhancement of corporate TFP. Finally, innovation capacity enhances corporate TFP by leveraging the economies of scale effect [24]. This phenomenon enhances the rate at which innovation contributes to output without altering the input of capital and labor, thereby enhancing the overall TFP of enterprises. As a result, this paper posits the following hypothesis:

H3: Corporate innovation capability positively affects TFP.

Combined with H1, H2 and H3, we further propose:

H4: Corporate innovation capability mediates the impact of AI Technology on TFP.

2.3 The Moderating Effect of Top Management Team (TMT) Age

The youth of the senior management team is reflected in the age structure of the members. By introducing a younger generation of leaders, the average age of the senior management team is reduced, and more vitality and innovative thinking are injected [25]. First of all, the younger executive team is conducive to the renewal of corporate knowledge and skills. Young executives often have different growth backgrounds and educational experiences, usually have updated knowledge and skills, and they are easier to accept and master new technologies and new ideas [26]. It is easier for young executive teams to understand and master AI technology, so that they can apply it more effectively in enterprise production and management, and strengthen the role of AI technology in improving enterprise TFP. Secondly, the younger executive team means that the executive team has stronger learning ability and adaptability. The application of AI technology in the enterprise faces numerous challenges, including data privacy and security, lack of technical talent, inconsistent technical standards, high costs, data quality issues, and ethical and bias issues [27]. Young executives, with their higher acceptance of new technologies and faster learning ability, are better equipped to handle challenges posed by AI technology, which leads to a comprehensive improvement in enterprises TFP. Finally, a younger executive team can also help drive a more open, inclusive and innovative corporate culture [28]. An open, inclusive and innovative corporate culture provides an environmental foundation for the effective application of AI technology, and can strengthen the positive role of AI technology in the improvement of enterprise TFP. Based on this, we further propose the following hypothesis:

H5: TMT age moderates the impact of AI Technology on TFP.

The conceptual model of our research is shown in Figure 1.

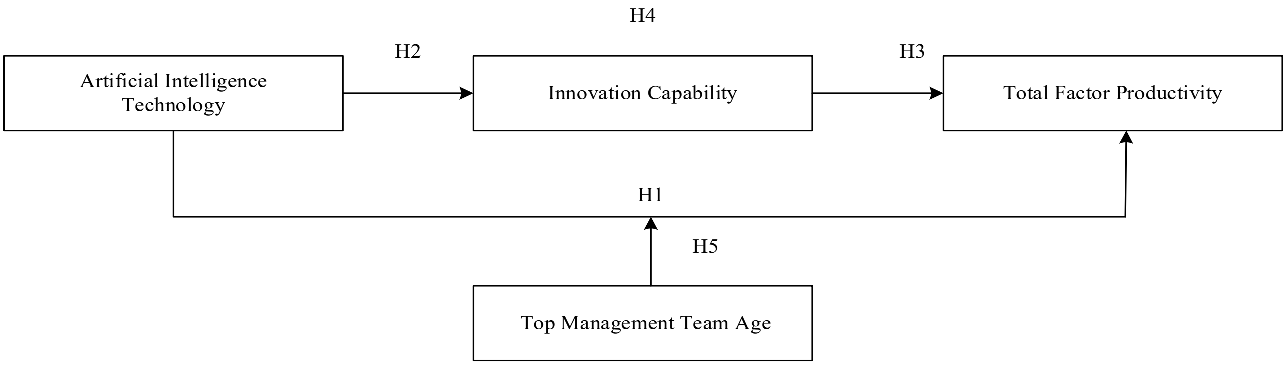


Figure 1. Conceptual model

3 Methodology

3.1 Conceptual Model

The conceptual model depicted in the Figure 1 integrates the core components of the study to analyze the influence of Artificial Intelligence (AI) technology on Total Factor Productivity (TFP) in enterprises. The model posits that AI technology directly impacts TFP, with corporate Innovation Capability serving as a mediating factor that enhances the effect of AI on productivity. Additionally, the model introduces the "Youthfulization of the Top Management Team" (TMT) as a moderating variable, suggesting that a younger TMT can amplify the positive effects of AI technology on both Innovation Capability and TFP. This conceptual framework is crucial in understanding the mechanisms through which AI technologies drive productivity improvements and the conditions under which these effects are maximized.

This model is employed in conjunction with two primary algorithms: the first, a Random Forest-based approach, classifies companies and analyzes the key properties contributing to TFP; the second algorithm conducts an empirical analysis of the AI-TFP relationship, addressing endogeneity and robustness through various statistical techniques. The combination of these elements offers a comprehensive and nuanced understanding of how AI technologies affect enterprise productivity, emphasizing the roles of innovation and leadership dynamics.

3.2 Random Forest Modelling

The first algorithm applies the Random Forest technique to classify companies and identify key factors that contribute to Total Factor Productivity (TFP). The process begins with data preparation, including handling missing values, encoding categorical variables, and normalizing data. The dataset consists of company information, properties, and TFP metrics. The algorithm first classifies companies as tech or non-tech based on features like AI, Innovation Capability (IC), and technological indicators. The classification model is trained and evaluated using Random Forest, which provides a robust and interpretable model by aggregating the results of multiple decision trees. The algorithm then shifts to regression analysis, predicting TFP using company properties as features. The importance of each feature is extracted, ranking the factors that most significantly influence TFP. This step is critical for understanding which aspects of a company's structure and strategy are most impactful in driving productivity gains through AI technologies.

3.3 Empirical Analysis

The second algorithm focuses on empirically analyzing the relationship between AI technologies and TFP, incorporating various econometric methods to ensure robust results. It starts by measuring AI technologies through word frequency statistics in corporate reports, using this as the independent variable. TFP is measured using the Levinsohn-Petrin (LP) method. The algorithm tests the direct impact of AI on TFP through Ordinary Least Squares (OLS) regression, addressing potential endogeneity using Instrumental Variable (IV) techniques and Propensity Score Matching (PSM) to control for sample selection bias. Robustness checks include re-estimating TFP using alternative methods and introducing lagged variables. The algorithm further explores the mediation effect of Innovation Capability and the moderation effect of TMTAge, providing a comprehensive view of how AI technologies influence productivity across different enterprise contexts.

4 Research Approach

4.1 Data Sources and Sample Selection

Our research collects samples from Chinese listed firms from 2003 to 2022. The text data for measuring AI technologies are extracted from listed firms' annual reports, obtained from the CNINFO website. We use Chinese Research Data Services (CRNDS) database to collect innovation capability data. The rest of data is collected from the China Stock Market and Accounting Research (CSMAR) database. STATA 16.0 is utilized in the analysis. Samples are chosen through the exclusion of ST, *ST (special treatment), and delisted companies. Moreover, financial data within the financial sector may demonstrate increased levels of volatility and uncertainty. This study omits financial industry data in order to mitigate potential analysis errors stemming from data quality issues. Finally, we apply winsorization to all continuous variables at the 1% level in both tails to mitigate the impact of extreme values.

Table 1. Artificial intelligence dictionary

Keywords related to AI technologies				
AI	AI Products	AI Chips	Machine Translation	Machine Learning
Computer Vision	Human-Computer Interaction	Deep Learning	Neural Network	Biometrics Identification
Image Recognition	Data Mining	Feature Extraction	Voice Synthesis	Speech Recognition
Knowledge Graph	Intelligent Banking	Intelligent Insurance	Human-machine Cooperation	Intelligent Supervision
Intelligent Education	Intelligent Customer Service	Intelligent Retail	Intelligent Agriculture	Robo-adviser
Augmented Reality	Virtual Reality	Intelligent Medicine	Smart Speaker	Intelligent TTS
Smart Government Service	Autonomous Driving	Intelligent Transportation	Convolutional Neural Network	Voiceprint Recognition
Feature Extraction	Driving-less technology	Intelligent Home	Q&A System	Face Recognition
Business Intelligence	Smart Finance	Recurrent Neural Network	Reinforcement Learning	Agent
Intelligent Elderly Care	Big Data Marketing	Big Data Risk Control	Big Data Analysis	Big Data Processing
Support Vector Machine (SVM)	Long Short-term Memory (LSTM)	Robotic Process Automation	Natural Language Processing	Distributed Computing
Knowledge Representation	Smart Chips	Wearable Products	Big Data Management	Intelligent Sensor
Pattern Recognition	Edge Computing	Big Data Platform	Intelligent Computation	Intelligent Search
Internet of Things	Cloud Computing	Augmented Intelligence	Voice Interaction	Intelligent-Environmental Protection
Human-computer Dialogue	Deep Neural Network	Big Data Operation		

4.2 Measurements of Variables

4.2.1 AI Technologies(AI)

Aligned with [29], this study evaluates artificial intelligence (AI) technologies by employing word frequency statistics and text analysis of annual reports from various listed companies. As depicted in Table 1, a total of 73 keywords related to artificial intelligence (AI) technologies were chosen for the purpose of performing word frequency analyses. Finally, 1 is added to the total word frequency data, and logarithmic processing is performed.

4.2.2 Total Factor Productivity (TFP)

Referring to the studies by [11], the production function of a firm is defined as follows (Formula 1):

$$Y_{i,t} = A_{i,t}K_{i,t}^{\alpha}L_{i,t}^{\beta}M_{i,t}^{\gamma} \quad \textbf{(1)}$$

Where $Y_{i,t}$ represents the output of enterprise, i, $K_{i,t}$, $L_{i,t}$ and $M_{i,t}$ represent the quantities of capital, labor, and intermediate inputs, respectively, $A_{i,t}$ represents TFP. Based on this premise, by applying the logarithm to both sides of equation (1) and accounting for the random interference factors, equation (2) can be derived as follows (Formula 2):

$$Y_{i,t} = a_{i,t} + \alpha k_{i,t+}\beta l_{i,t} + \gamma m_{i,t} + \varepsilon_{i,t} \quad \textbf{(2)}$$

Where $y_{i,t}$, $a_{i,t}$, $k_{i,t}$, $l_{i,t}$ and $m_{i,t}$ are the logarithmic forms of $Y_{i,t}$, $A_{i,t}$, $K_{i,t}$, $L_{i,t}$, and $M_{i,t}$ respectively, and $\varepsilon_{i,t}$ is the random disturbance term. Considering that $a_{i,t}$ cannot be directly observed, and the Ordinary Least Squares (OLS) estimation may lead to deviations. To address this issue, we employ the semi-parametric method introduced by [30] (LP) for estimating TFP. Moreover, as outlined by [31], the primary business revenue of an organization serves as the output indicator, while its net fixed assets, employee salaries, cash allocated for procurement of goods, and payment for services form the input indicators. To prevent estimation bias, a corresponding price index is applied for adjustments.

4.2.3 Innovation Capability (IC)

According to [32], patents are commonly utilized as a quantified measure of innovation capability. According to Chinese patent laws, patents can be classified into three categories: invention patents, utility model patents, and design patents. Consistently, the patent data in the CNRDS database is categorized into three types. Innovation capability can be assessed by the total number of patent applications submitted by a company within a specific year.

4.2.4 Top Management Team Age (TMTAge)

The age of the executive team refers to the age of the board of directors, board of supervisors, and senior management personnel in a listed company. This paper uses average age of directors, supervisors, and senior management to measure top management team age.

4.2.5 Control Variables

Our research controls company scale (Size), years of establishment of the company (FirmAge), asset-liability ratio (Lev), net profit margin on total assets (ROA), number of directors (Board), liquidity ratio (Liquid), state-owned enterprise or not (SOE), and operating revenue growth rate (Growth). Additionally, time and industry dummy variables are incorporated to control for fixed effects. The control variable measurements are shown in Table 2.

Table 2. Control variable measurements

	Variables	Variable name	Measurements
Control variables	Company scale	Size	Natural logarithm of total assets
	Years of establishment of the company	FirmAge	The natural logarithm of the difference between the current year and the established year plus 1
	Asset-liability ratio	Lev	Total liabilities/ total assets
	Net profit margin on total assets	ROA	Net profit margin on total assets
	Number of directors	Board	Natural logarithm of the number of board members
	Liquidity ratio	Liquid	Current assets/ Current liabilities
	State-owned enterprise or not	SOE	1 for state-owned enterprises and 0 for others
	Operating revenue growth rate	Growth	Current year operating income/ Previous year operating income -1

4.3 Regression Model Construction

To investigate the mechanism of the effect, the paper establishes the baseline regression model (Formula 3).

$$TFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \quad \textbf{(3)}$$

Subsequently, the mediation models are estimated using Formulas 4-5.

$$IC_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \quad \textbf{(4)}$$

$$TFP_{i,t} = \beta_0 + \beta_1 IC_{i,t} + \beta_2 AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \quad \textbf{(5)}$$

Finally, the models of moderating effects are formulated as follows (Formulas 6):

$$TFP_{i,t} = \beta_0 + \beta_1 TMTAge_{i,t} + \beta_2 AI_{i,t} + \beta_3 TMTAge_{i,t} \times AI_{i,t} + \beta_n C_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \quad \textbf{(6)}$$

In the model, i and t represent the firm and year, while β denotes the parameters to be estimated. C stands for the control variables, *Year* and *Industry* respectively indicate the year and industry fixed effects. Additionally, *TFP* represents total factor productivity, *AI* stands for AI technology, *IC* represents innovation capability, *TMTAge* denotes the average age of TMT, and ε signifies the error term.

4.4 Random Forest Modelling Test

4.4.1 Correlation of Variables

The correlation analysis in Figure 2 conducted on the dataset provided valuable in-sights into the relationships between various company properties and total factor productivity (TFP_LP) in Figure 2. The correlation coefficients, which range from -1 to 1, indicate the strength and direction of linear relationships between the variables.

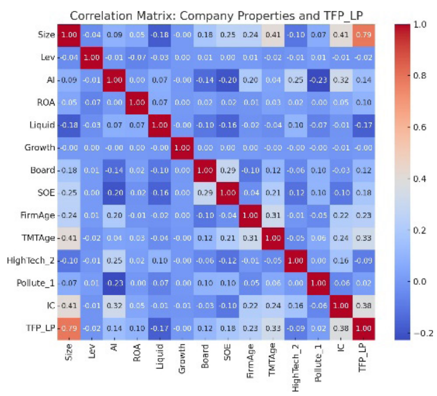


Figure 2. Correlation matrix

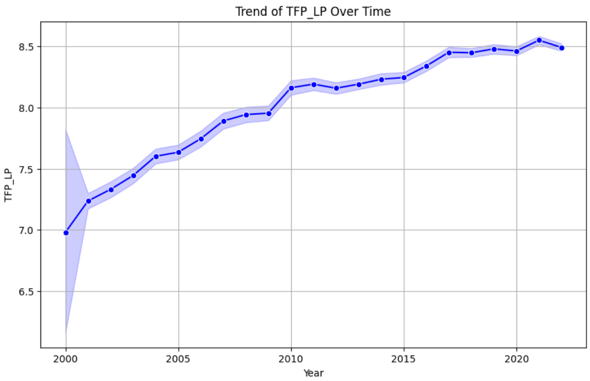
Variables such as Size, IC (Innovation Capability) and the age of the firm (*FirmAge*) and its management team (*TMTAge*) and AI technology (*AI*) also showed positive correlations with TFP_LP. This implies that companies with higher innovation capabilities and higher application level of AI technology and those that are more established tend to exhibit better productivity. The comprehensive correlation matrix provided further insights, offering a more detailed understanding of how these variables interact with each other.

4.4.2 Trend of TFP

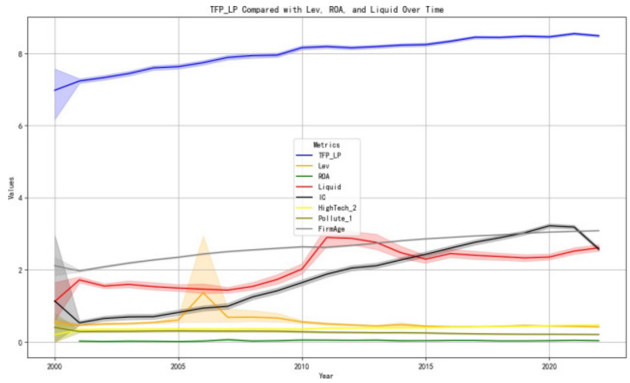
The trend analysis of TFP_LP provides valuable insights into how total factor productivity has evolved over time across the companies in the dataset. By comparing the actual and predicted values of TFP_LP, we can assess the accuracy of the model and understand the broader trends influencing productivity. The trend analysis of TFP_LP across different industries provides critical insights into how productivity has evolved not only over time but also within specific sectors. This analysis helps to identify which industries are driving overall productivity and how different sectors are responding to economic and technological changes.

In Figure 3(a), the overall trend of TFP_LP over time reflects the aggregate productivity performance of companies in the dataset. This analysis revealed periods of both growth and decline, suggesting that external factors such as economic conditions, technological innovations, and industry-specific developments significantly influence productivity. For instance, periods of marked increases in TFP_LP may correspond to economic booms or the adoption of new technologies, whereas declines could be associated with economic downturns or increased competition.

In Figure 3(b), when examining TFP_LP trends across different industries, significant variability is observed. Some industries consistently outperform others in terms productivity, reflecting the unique characteristics and competitive dynamics of those sectors. For example, figure industries may show steady increases in TFP_LP, suggesting that companies in these sectors are effectively leveraging technological advancements and scaling operations to improve productivity. In contrast, other industries may exhibit more volatile trends, possibly due to cyclical demand, regulatory changes, or shifts in consumer preferences. The industry-specific analysis of TFP_LP highlights that different sectors experience varying productivity trajectories. Companies in high-performing industries can gain insights into the factors driving productivity in their sector, such as the adoption of new technologies, efficient supply chain management, or regulatory advantages. These firms should continue to innovate and refine their processes to sustain their competitive edge. On the other hand, companies in industries with more volatile or declining TFP_LP trends need to identify the underlying challenges—whether they are structural, competitive, or related to external pressures—and develop strategies to address them. This could involve investing in new technologies, exploring new markets, or restructuring operations efficiency.



(a) TFP_LP across industries

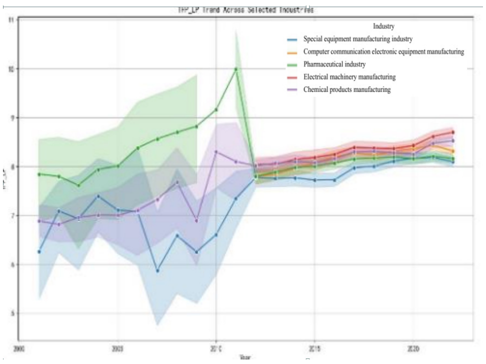


(b) Actual vs Predicted TFP_LP

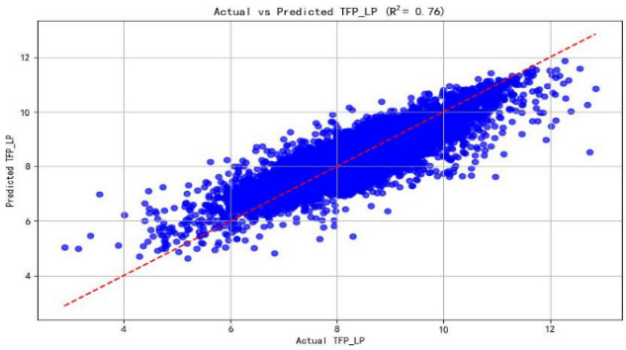
Figure 3. Trend analysis

4.4.3 Actual vs Predicted TFP

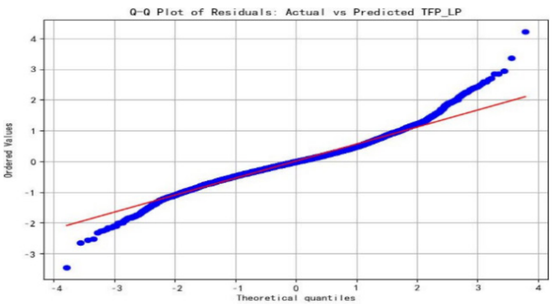
The comparison between actual and predicted TFP_LP values provide critical insights into the performance of the predictive model and highlights areas where the model excels or may require further refinement. Several key analyses were conducted to evaluate the model, including the R-squared value, Q-Q plot, distribution comparison, and summary statistics



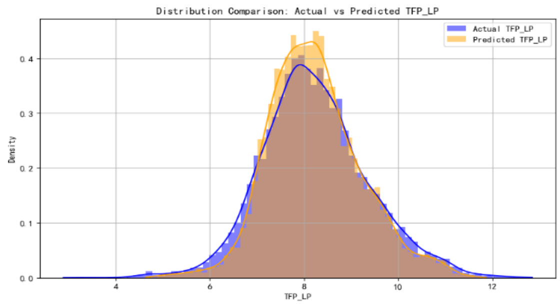
(a) TFP_LP across industries



(b) Actual vs Predicted TFP_LP



(c) Quantile–Quantile plot residuals



(d) Distribution comparison of Actual vs Predicted TFP_LP

Figure 4. Distribution comparison

Figure 4 is a combination of visualization of the result. The model's R-squared value, approximately 0.76, indicates that around 76% of the variance in TFP_LP can be explained by the selected company properties. This relatively high R-squared suggests that the model is fairly effective at capturing the factors that influence productivity. However, the remaining 24% of the variance, which is not explained by the model, suggests there may be additional factors or non-linear relationships that the model does not account for. The Q-Q plot, which compares the residuals of the model's predictions to a normal distribution, provides insights into the distribution of the errors. Ideally, if the residuals are normally distributed, the points on the Q-Q plot should lie along the reference line. In this analysis, while many of the residuals align with the reference line, deviations at the tails indicate that the model struggles with extreme values of TFP_LP. This suggests that the model may perform well for predicting typical values but may not capture outliers or extreme cases accurately, which could be due to factors like unmodeled complexity or rare events in the data. The distribution comparison between actual and predicted TFP_LP values, visualized using histograms, further evaluates how well the model captures the overall distribution of productivity. The histograms show that while the predicted values generally follow the distribution of the actual values, the predicted distribution is somewhat narrower, with a lower standard deviation. This indicates that the model tends to predict values closer to the mean, potentially underestimating the variability in TFP_LP. This limitation suggests that while the model is effective at capturing central tendencies, it may not fully account for the range of productivity outcomes observed in the actual data.

5 Empirical Result

5.1 Descriptive Statistics Analysis

Table 3 presents the results of the descriptive statistics analysis.

Table 3. Summary statistics

Variables	Observation	Mean	SD	Min	Median	Max
AI	40960	0.664	1.103	0.000	0.000	4.407
IC	40960	2.352	1.794	0.000	2.485	6.717
TFP_LP	40960	8.306	1.060	5.996	8.213	11.146
TMTAge	40960	48.933	3.271	40.950	49.000	56.540
Size	40960	22.108	1.277	19.777	21.922	26.105
FirmAge	40960	2.821	0.390	1.609	2.890	3.526
Lev	40960	0.440	0.202	0.059	0.438	0.896
ROA	40960	0.039	0.064	-0.224	0.037	0.221
Board	40960	2.141	0.204	1.609	2.197	2.708
Liquid	40960	2.241	2.181	0.302	1.555	14.114
SOE	40960	0.427	0.495	0.000	0.000	1.000
Growth	40960	0.177	0.407	-0.579	0.114	2.505

5.2 Benchmark Regression Analysis

Table 4 presents the findings of the benchmark regression analysis. Columns (1) to (3) represent three regression models. Column (1) presents the fundamental regression model without any supplementary variables. Columns (2) incorporates industry and year fixed effects, and column (3) complements control variables. In the comprehensive model presented in Column (3), the estimated coefficient for AI technology on TFP is 0.046, demonstrating statistical significance at the 1% level, representing the expected change in the TFP for a one-unit increase in AI, holding all other variables constant. These findings support H1.

The Column label (such as AI, Size, FirmAge, Lev…) represents the independent variables of the regression, and the three Row label in Column (1) to (3) (such as TFP_LP) represents the dependent variables of the regression. The important coefficients are shown in bold. The above rules apply to all the following tables.

Table 4. Benchmark regression results

Variables	Model (1) TFP_LP	Model (2) TFP_LP	Model (3) TFP_LP
AI	0.099***	0.073***	**0.046*** **
	(21.014)	(12.898)	**(14.997)**
Size			0.595***
			(197.704)
FirmAge			0.003
			(0.301)
Lev			0.788***
			(30.034)
ROA			2.817***
			(44.837)
1Board			-0.071***
			(-4.731)
Liquid			-0.004**
			(-2.345)
SOE			0.065***
			(9.263)
Growth			0.140***
			(14.990)
_cons	8.240***	8.258***	-5.240***
	(1354.644)	(1375.573)	(-74.917)
Year / Industry FE	No	Yes	Yes
N	40960	40960	40960
adj. R^2	0.011	0.146	0.716

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

5.3 Endogeneity Test

5.3.1 Instrumental Variable (IV) Method

This paper uses the IV method to tackle endogeneity caused by omitted variables and reverse causation. The instrumental variable (IV) used is the average AI technology level among firms in the same industry and year, meeting the relevance and exogeneity criteria. The average digital transformation level of other firms in the same industry and year influences the AI level of a specific firm but does not directly impact the TFP of that company. In Column (2) of Table 5, there is a significant positive effect of AI technology on TFP, with a coefficient of 0.878, significant at 1%. H1 is further supported.

5.3.2 Propensity Score Matching (PSM) Method

This paper utilizes the PSM approach to address endogeneity resulting from sample self-selection bias. The study uses the industry-year median as a benchmark to create a categorizing variable for AI technology. *Size*, *FirmAge*, *Lev*, *ROA*, *Board*, *Liquid*, *SOE*, *Growth, Industry*, and *Year* are considered concomitant variables. We use the radius matching principle to identify closely aligned control cohorts. As indicated in Column (3) of Table 5, the average treatment effect on the treated (ATT) in the treatment group is positive and statistically significant at the 1% level. The post-matching estimation outcomes in Table 5 are 0.046, significant, confirming the research conclusions' robustness after addressing sample self-selection bias. H1 is further supported.

Table 5. Endogeneity test results

	Model (1)	Model (2)	Model (3)
Variables	AI	TFP_LP	TFP_LP
AI		0.092***	**0.046*** **
		(4.998)	**(15.058)**
Size	0.059***	0.593***	0.596***
	(13.110)	(191.771)	(197.160)
FirmAge	-0.148***	0.010	0.006
	(-9.840)	(1.024)	(0.583)
Lev	-0.011	0.792***	0.791***
	(-0.320)	(35.106)	(30.066)
ROA	-0.281***	2.842***	2.825***
	(-3.490)	(54.098)	(45.012)
Board	-0.163***	-0.063***	-0.073***
	(-7.060)	(-4.112)	(-4.835)
Liquid	0.007***	-0.004**	-0.004**
	(2.620)	(-2.432)	(-2.311)
SOE	-0.134***	0.071***	0.065***
	(-12.940)	(9.884)	(9.266)
Growth	0.043***	0.138***	0.139***
	(3.770)	(18.514)	(14.869)
IV	**0.878*** **		
	(35.340)		
_cons	-0.490***	-5.700***	-5.251***
	(-4.500)	(-79.796)	(-75.002)
N	40947	40947	40773
adj. R^2	0.372	0.715	0.716

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

5.4 Robustness Test

5.4.1 Substitute the Explained Variable

Table 6 presents the findings of the robustness tests. The impact of AI technology on TFP could be affected by the measurement error associated with the dependent variable. We employ Ordinary Least Squares (OLS), Fixed Effects (FE), and Generalized Method of Moments (GMM) techniques to re-calibrate TFP. The model is subsequently re-estimated. Columns (1), (2), and (3) demonstrate that the coefficient of AI technology on TFP remains significantly positive.

5.4.2 Treat the Explanatory Variables with "Lag 1 Period"

AI technology involves strategic decisions that may have delayed effects. To account for potential time lags, the model is re-estimated using a 1-year lag of the AI technology variable. Columns (4) show the coefficient on the 1-year lagged AI technology remains significantly positive at the 1% level.

5.4.3 Shorten the Research Period

2012 is widely considered the seminal year for big data, marking the beginning of major digitization efforts across various countries. To address potential structural changes around the rise of big data, the model is re-estimated for a shortened sample period from 2013-2022. Column (5) shows the coefficient on AI technology remains significantly positive, even for the shortened time period. These consistent findings provide evidence of a robust relationship between AI technology and TFP.

Table 6. Robustness test results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Variables	TFP_OLS	TFP_FE	TFP_GMM	TFP_LP	TFP_LP
AI	**0.017*** **	**0.015*** **	**0.065*** **		**0.044*** **
	(5.831)	**(5.016)**	**(16.027)**		**(13.687)**
Size	0.828***	0.885***	0.142***	0.594***	0.589***
	(275.807)	(290.410)	(37.047)	(185.103)	(166.817)
FirmAge	-0.001	-0.003	0.011	0.012	0.020
	(-0.120)	(-0.295)	(0.917)	(1.150)	(1.641)
Lev	0.605***	0.572***	1.073***	0.808***	0.807***
	(22.641)	(21.118)	(32.095)	(28.528)	(25.744)
ROA	2.732***	2.747***	2.751***	2.795***	2.774***
	(43.908)	(43.692)	(35.194)	(41.551)	(37.806)
Board	-0.014	0.003	-0.212***	-0.081***	-0.106***
	(-0.979)	(0.191)	(-10.738)	(-5.015)	(-5.887)
Liquid	-0.031***	-0.038***	0.052***	-0.003	-0.006***
	(-18.110)	(-21.622)	(22.392)	(-1.435)	(-2.815)
SOE	0.088***	0.092***	0.037***	0.071***	0.047***
	(12.735)	(13.187)	(4.093)	(9.700)	(5.435)
Growth	0.129***	0.121***	0.209***	0.146***	0.131***
	(13.943)	(13.014)	(17.262)	(14.319)	(11.596)
L.AI				**0.050*** **	
				(14.650)	
_cons	-7.926***	-8.580***	-0.082	-5.233***	-5.048***
	(-114.530)	(-122.383)	(-0.933)	(-68.883)	(-59.323)
N	40960	40960	40960	35836	28396
adj. R^2	0.818	0.832	0.378	0.714	0.723

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

5.5 Mechanism Analysis Results

5.5.1 Mediating Effect Analysis

The results of the mediation analysis are presented in Table 7. In the first column, a positive association is observed between AI technology and innovation capability, with a regression coefficient of 0.345, significant at the 1% level. Upon integrating innovation capability into the model analyzing the relationship between AI technology and TFP, a significant positive coefficient of 0.030 is observed for innovation capability in Column (2). The coefficient for AI technology in this context is 0.036, which is lower than the coefficient in Column (3) of Table 4 (0.046). These results confirm the mediating role of innovation capability, confirming H2, H3 and H4.

5.5.2 Moderating Effect Analysis

The moderating effects are outlined in Table 7. In Column (3), the coefficient for the interaction term between TMT age and AI technology is -0.002, significant at the 10% level. This suggests that TMT age negatively moderates the relationship between AI technology and TFP. TMT age is identified as a negative moderator. Therefore, H5 is validated based on these results.

Table 7. Mechanism analysis results

Variables	Model (1) IC	Model (2) TFP_LP	Model (3) TFP_LP
AI	**0.345*****	**0.036*****	0.124***
	(50.374)	**(11.303)**	(2.800)
Size	0.533***	0.579***	0.593***
	(74.610)	(177.377)	(188.920)
FirmAge	-0.240***	0.010	0.002
	(-10.848)	(1.045)	(0.179)
Lev	-0.182***	0.793***	0.794***
	(-3.526)	(30.292)	(30.144)
ROA	1.165***	2.782***	2.815***
	(9.544)	(44.375)	(44.818)
Board	0.045	-0.073***	-0.075***
	(1.281)	(-4.843)	(-4.969)
Liquid	-0.031***	-0.003*	-0.004**
	(-8.068)	(-1.820)	(-2.291)
SOE	0.006	0.064***	0.060***
	(0.395)	(9.263)	(8.426)
Growth	-0.032*	0.141***	0.142***
	(-1.785)	(15.092)	(15.096)
IC		**0.030*****	
		(13.214)	
inter1			**-0.002***
			(-1.751)
TMTAge			0.004***
			(3.383)
_cons	-8.964***	-4.974***	-5.383***
	(-53.566)	(-68.005)	(-65.955)
N	40960	40960	40960
adj. R^2	0.482	0.717	0.716

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

5.6 Heterogeneity analysis

5.6.1 Based on Ownership Nature

State-owned enterprises (SOEs) often have advantages in obtaining financial and political support from governments. The impact of AI on TFP may vary depending on ownership nature. The sample is divided into SOEs and non-SOEs for re-estimation in the main effect analysis. In Columns (1) and (2) of Table 8, the regression coefficients for AI technology are significantly positive in both groups, with the coefficient in SOEs being larger.

Table 8. Robustness test results

Variables	Model (1) TFP_LP	Model (2) TFP_LP	Model (3) TFP_LP	Model (4) TFP_LP	Model (5) TFP_LP	Model (6) TFP_LP
AI	**0.033*****	**0.070*****	**0.055*****	**0.047*****	**0.054*****	**0.028*****
	(9.660)	**(10.660)**	**(10.121)**	**(12.405)**	**(16.344)**	**(2.613)**
Size	0.590***	0.606***	0.603***	0.578***	0.596***	0.594***
	(132.527)	(146.566)	(154.651)	(122.675)	(164.310)	(111.077)
FirmAge	-0.033***	0.083***	-0.062***	0.097***	-0.008	0.039**
	(-2.767)	(4.999)	(-4.661)	(7.069)	(-0.681)	(2.045)
Lev	0.792***	0.765***	0.797***	0.755***	0.963***	0.248***
	(22.149)	(19.140)	(22.472)	(19.515)	(31.110)	(5.141)
ROA	2.754***	2.976***	2.893***	2.788***	2.992***	2.170***
	(36.054)	(27.400)	(32.388)	(31.648)	(40.057)	(19.473)
Board	-0.027	-0.110***	-0.099***	-0.019	-0.101***	0.044
	(-1.364)	(-4.702)	(-4.773)	(-0.895)	(-5.721)	(1.525)
Liquid	-0.009***	0.013***	0.005*	-0.013***	-0.003	0.000
	(-4.444)	(3.433)	(1.897)	(-5.668)	(-1.431)	(0.023)
SOE	0.000	0.000	0.074***	0.053***	0.060***	0.081***
	(.)	(.)	(8.004)	(5.102)	(7.428)	(6.057)
Growth	0.122***	0.168***	0.179***	0.076***	0.147***	0.117***
	(9.872)	(11.836)	(14.758)	(5.285)	(13.750)	(6.089)
_cons	-5.043***	-5.644***	-5.209***	-5.196***	-5.248***	-5.340***
	(-51.741)	(-52.051)	(-54.973)	(-50.325)	(-63.312)	(-41.089)
N	23460	17499	24290	16670	30995	9965
adj. R^2	0.681	0.739	0.724	0.697	0.718	0.722

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

5.6.2 Based on High-tech Enterprises

When AI technology is implemented, the law of diminishing marginal effect suggests that the same technological advancements may result in relatively small productivity gains for high-tech enterprises. The sample is separated into non-high-tech and high-tech sectors. As is illustrated in Columns (3) and (4), the coefficients on AI technology are 0.055 and 0.047 respectively, both significant at 1%. The impact of AI technology on TFP is more pronounced in non-high-tech companies.

5.6.3 Based on Pollution Level

Non-high-polluting enterprises are typically more flexible, innovative, and adept at absorbing technology, enabling them to quickly adopt and implement new technologies for rapid productivity growth. The grouping regression results in Columns (5) and (6) show that the AI technology coefficients of non-heavy-polluting and heavy-polluting enterprises are 0.054 and 0.028 respectively, both significant at 1%. The impact of AI technology on TFP is more pronounced in non-heavy-polluting companies.

6 Discussion

6.1 Theoretical Implications

Based on an analysis of 40,960 data points obtained from 4,395 Chinese companies listed between 2003 and 2022, this study evaluates how AI technology affects corporate TFP. It is found that for each additional unit of AI technology implemented, enterprise TFP increases by 0.046 units. This specific numerical value serves as a precise reference point for decision-makers, aiding in the accurate evaluation of the return on investment in AI technology. This study explores how AI variables impact TFP in enterprises, adding to existing theories and empirical research. On the one hand, this introduces a new method to boost productivity by using smart technology to improve the efficiency and output of traditional production elements, enriching the theoretical basis of TFP growth. On the other hand, the text emphasizes the interdisciplinary application of AI technology theory, leading to a notable enhancement in production efficiency through widespread adoption across various industries and sectors.

The study highlights the role of innovation capability in improving TFP through AI technology, with a younger executive team showing a positive moderating effect. The mediating effect of corporate innovation ability is 0.010, explaining 22.176% of the total effect. For every one-unit decrease in the average age of a company’s executive team, the impact of AI technology on the company’s TFP will increase by 0.002 units. This paper introduces an integrated analytical framework that combines AI technology, innovation capabilities, executive team characteristics, and TFP. It explores how AI technology internally impacts enterprises’ TFP. This study is a pioneering effort to explore whether, how and when AI technologies can enhance TFP in enterprises. It aims to create a comprehensive framework to analyze the impact of AI technology on TFP, laying the groundwork for a deeper understanding of their relationship.

6.2 Practical Implications

AI technology can greatly improve operational efficiency and effectiveness through automation and intelligent systems. Enterprises are advised to introduce and utilize AI technology to improve organization’s market competitiveness. Besides, the study emphasizes the important role of innovation capability in enhancing TFP through AI technology. This finding provides valuable insights for enterprises looking to develop technology innovation strategies. Enterprises should prioritize developing their innovation capabilities when implementing AI technology. This will enable organizations to effectively leverage AI technology to boost productivity and gain long-term advantages.

Young executive teams typically demonstrate higher levels of innovation and rapid market responsiveness. They are inclined to adopt and incorporate AI technology seamlessly into their business operations. Young executive teams often show a strong ability to learn and adapt. They show a higher inclination for learning and mastering new technologies. Through continuous learning and practical application, individuals can improve their use of AI technology in business operations. When implementing AI technologies, more young managers could be hired.

6.3 Limitations and Future Research Direction

This paper uses the sample of listed companies for the empirical analysis, which may not provide a comprehensive representation of the overall market or industry. Moreover, using keyword frequency statistics to measure AI technologies has certain limitations. As is known, the depiction and terms of AI technology can differ across enterprises, potentially introducing bias into the word frequency statistics.

In future research, it is recommended to broaden the sample scope extensively by including representative non-listed companies. Besides, data such as macroeconomic indicators, industry statistics, and corporate announcements can be gathered as supplementary data to verify the information of the listed companies and gain a comprehensive understanding of the market and the company’s activities. Moreover, it is advisable to gather additional terms and phrases associated with AI technology to minimize potential bias and errors.

7 Conclusion

This study utilizes data from Chinese listed companies between 2003 and 2022 to demonstrate that AI technologies have a positive impact on enterprise Total Factor Productivity (TFP). The Random Forest analysis further supports these findings.

Further analysis also reveals that corporate innovation capabilities have mediating effects. AI technologies can drive product and service innovation design, technological advancements, and business model innovation, which collectively contribute to TFP. The Random Forest analysis emphasizes the importance of firm age and management experience, showing that while innovation is crucial, the experience and stability of older firms and established management teams also play a significant role in driving productivity.

Additionally, the study finds that having a younger TMT has positive moderating effects. Young senior management teams, with their receptiveness to new knowledge and adaptability, can enhance the impact of AI technology on TFP. This is supported by the feature importance analysis, which indicates that management and firm age are important factors in maximizing the benefits of AI technologies.

Moreover, the impact of AI technologies on TFP is particularly significant in Chinese state-owned enterprises that are not high-tech or high-polluting. The Random Forest results further clarify that state ownership, while less influential than other factors like size and financial health, still plays a role in determining how effectively AI technologies enhance productivity.

This paper is the first study to investigate how AI technologies can enhance enterprise TFP, combining both traditional statistical methods and advanced machine learning techniques to provide a comprehensive analysis. The findings provide valuable insights for scholars and practitioners on how AI technologies can enhance sustainable innovation capabilities and overall productivity, particularly in firms that effectively leverage their size, financial resources, and managerial experience.

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References

[1] V. Terziyan, S. Gryshko, M. Golovianko, Patented Intelligence: Cloning Human Decision Models For Industry 4.0, *Journal of Manufacturing Systems*, Vol. 48, pp. 204-217, July, 2018.

[2] I. Igna, F. Venturini, The Determinants Of AI Innovation Across European Firms, *Research Policy*, Vol. 52, No. 2, Article No. 104661, March, 2023.

[3] C. H. Chen, Influence of Employees' Intention to Adopt AI Applications and Big Data Analytical Capability on Operational Performance in the High-Tech Firms, *Journal of the Knowledge Economy*, Vol. 15, No. 1, pp. 3946-3974, March, 2024.

[4] A. N. Khan, Artificial Intelligence And Sustainable Performance: Role Of Organisational Agility And Environmental Dynamism, *Technology Analysis & Strategic Management*, pp. 1-16, December, 2023. https://doi.org/10.1080/09537325.2023.2290171

[5] F. Y. Li, G. H. Xu, Ai-Driven Customer Relationship Management For Sustainable Enterprise Performance, *Sustainable Energy Technologies and Assessments*, Vol. 52, Article No. 102103, August, 2022.

[6] G. Q. Li, F. Y. Liao, Input Digitalization And Green Total Factor Productivity Under The Constraint Of Carbon Emissions, *Journal of Cleaner Production*, Vol. 377, Article No. 134403, December, 2022.

[7] I. M. Sabiroglu, S. Bashirli, Input-Output Analysis In An Oil-Rich Economy: The Case Of Azerbaijan, *Resources Policy*, Vol. 37, No. 1, pp. 73-80, March, 2012.

[8] Y. Zhang, J. C. Peng, Z. Z. Ding, A Study On The Influencing Factors Of Total Factor Productivity Of Cultivated Land Resource Utilization: Evidences From Direct Influence And Spatial Spillover In China, *International Journal of Low-Carbon Technologies*, Vol. 18, pp. 228-243, 2023.

[9] Y. R. Cheng, X. R. Zhou, Y. J. Li, The effect of digital Transformation on Real Economy Enterprises' Total Factor Productivity, *International Review of Economics & Finance*, Vol. 85, pp. 488-501, May, 2023.

[10] J. F. Hu, Y. Deng, Resource Misallocation And Unbalanced Growth In Green Total Factor Productivity In Chinese Agriculture, *Journal of Environmental Planning and Management*, Vol. 68, No. 1, pp. 49-83, 2025.

[11] H. Zhang, Q. W. Zhang, How Does Digital Transformation Facilitate Enterprise Total Factor Productivity? The Multiple Mediators of Supplier Concentration and Customer Concentration, *Sustainability*, Vol. 15, No. 3, Article No. 1896, February, 2023.

[12] S. X. Zhai, Z. P. Liu, Artificial Intelligence Technology Innovation And Firm Productivity: Evidence from China, *Finance Research Letters*, Vol. 58, Article No. 104437, December, 2023.

[13] K. L. Wang, T. T. Sun, R. Y. Xu, The Impact Of Artificial Intelligence On Total Factor Productivity: Empirical Evidence From China's Manufacturing Enterprises, *Economic Change and Restructuring*, Vol. 56, No. 2, pp. 1113-1146, April, 2023.

[14] J. Huang, J. Y. Wei, Impact of Intelligent Development on the Total Factor Productivity of Firms - Based on the Evidence from Listed Chinese Manufacturing Firms, *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Vol. 26, No. 4, pp. 555-561, July, 2022.

[15] F. Qu, Q. Tang, C. M. Li, J. Liu, Exploring the impact of digital transformation on productivity: the role of artificial intelligence technology, green technology, and energy technology, *Technological and Economic Development of Economy*, pp. 1-32, February, 2025. https://doi.org/10.3846/tede.2025.23009

[16] J. H. Cavalcanti, T. Kovacs, A. D. Ko, K. Pocsarovszky, Production System Efficiency Optimization Through Application Of A Hybrid Artificial Intelligence Solution, *International Journal of Computer Integrated Manufacturing*, Vol. 37, No. 6, pp. 790-807, 2024.

[17] R. K. Behera, P. K. Bala, N. P. Rana, R. S. Algharabat, K. Kumar, Transforming customer engagement with artificial intelligence E-marketing: an E-retailer perspective in the era of retail 4.0, *Marketing Intelligence & Planning*, Vol. 42, No. 7, pp. 1141-1168. September, 2024.

[18] P. C. Johnson, C. Laurell, M. Ots, C. Sandström, Digital Innovation And The Effects Of Artificial Intelligence On Firms' Research And Development-Automation Or Augmentation, Exploration Or Exploitation?, *Technological Forecasting and Social Change*, Vol. 179, Article No. 121636, June, 2022.

[19] P. Y. Zhou, Y. G. Xie, C. Y. Liang, How To Increase Consumers' Continued Use Intention Of Artificial Intelligence Voice Assistants?, *Electronic Markets*, Vol. 33, No. 1, Article No. 60, December, 2023.

[20] M. Weber, M. Beutter, J. Weking, M. Böhm, H. Krcmar, AI Startup Business Models: Key Characteristics and Directions for Entrepreneurship Research, *Business & Information Systems Engineering*, Vol. 64, No. 1, pp. 91-109, February, 2022.
[21] Y. H. Wang, Social Network Information Security And Artificial Intelligence Privacy Protection Based On Data Mining, *International Journal of System Assurance Engineering and Management*, September, 2023. https://doi.org/10.1007/s13198-023-02155-0
[22] P. Y. Nie, Y. C. Yang, Cost-Reduction Innovation Under Mixed Economy, *Managerial and Decision Economics*, Vol. 41, No. 7, pp. 1195-1201, October, 2020.
[23] Y. N. Gao, M. C. Zhang, J. H. Zheng, Accounting And Determinants Analysis Of China's Provincial Total Factor Productivity Considering Carbon Emissions, *China Economic Review*, Vol. 65, Article No. 101576, February, 2021.
[24] B. O. S. Djibo, E. M. Horsey, S. L. Zhao, Good Innovation Capacity, Good Eco-Innovation Performance? From Firms Innovation, Learning Capacity, and Institutional Environment, *Journal of the Knowledge Economy*, Vol. 15, No. 1, pp. 1179-1209, March, 2024.
[25] W. Yoon, S. J. Kim, J. Song, Top Management Team Characteristics And Organizational Creativity, *Review of Managerial Science*, Vol. 10, No. 4, pp. 757-779, October, 2016.
[26] Y. M. Wang, Q. H. Su, W. Sun, CEO Relational Leadership and Product Innovation Performance: The Roles of TMT Behavior and Characteristics, *Frontiers in Psychology*, Vol. 13, Article No. 874105, April, 2022.
[27] R. H. Binsaeed, Z. Yousaf, A. Grigorescu, A. Samoila, R. I. Chitescu, A. A. Nassani, Knowledge Sharing Key Issue for Digital Technology and Artificial Intelligence Adoption, *Systems*, Vol. 11, No. 7, Article No. 316, July, 2023.
[28] C. Lu, Z. Y. Liu, Y. Xu, S. Q. Liao, L. H. Fu, How Tmt Diversity Influences Open Innovation: An Empirical Study On Biopharmaceutical Firms In China, *Technology Analysis & Strategic Management*, Vol. 34, No. 2, pp. 151-165, 2022.
[29] J. Q. Yao, K. P. Zhang, L. P. Guo, X. Feng, How Does Artificial Intelligence Improve Firm Productivity? Based on the Perspective of Labor Skill Structure Adjustment, *Management World*, Vol. 40, No. 2, pp. 101-122, February, 2024. DOI: 10.19744/j.cnki.11-1235/f.2024.0018
[30] J. Levinsohn, A. Petrin, Estimating Production Functions Using Inputs To Control For Unobservable, *The Review of Economic Studies*, Vol. 70, No. 2, pp. 317-341, April, 2003.
[31] Y. Chen, S. P. Yang, Q. Li, How Does The Development Of Digital Financial Inclusion Affect The Total Factor Productivity Of Listed Companies? Evidence from China, *Finance Research Letters*, Vol. 47, Article No. 102956, June, 2022.
[32] H. Zhang, X. H. Wang, M. W. Akhtar, Digital Transformation, Supplier Concentration, And CEO Financial Experience: Unveiling The Dynamics Of Innovation Performance In Chinese Firms, *Journal of Cleaner Production*, Vol. 442, Article No. 140825, February, 2024.

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