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Analysis of the Impact of Artificial Intelligence on the Data Value Transformation Path in the Era of Digital Economy

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SUMMARY: *In recent times, the digital economy has witnessed a rapid expansion. This growth has significantly spurred the advancement of artificial intelligence technology and, simultaneously, can offer momentum for the development of the data value transformation pathway. Considering the current state of artificial intelligence and data value transformation within the digital economy context, this paper employs the entropy value approach and principal component analysis to fulfill the task of gauging the pathway of artificial intelligence and data value transformation. Subsequently, the explanatory variables, interpreted variables, mediating variables and control variables are set in turn, and the data sources of the research variables are also given explicitly, and the baseline regression model and mediating effect model are constructed. Ultimately, guided by the theoretical framework of this paper's research content, an exploration into the mechanism of artificial intelligence's role and the data value transformation pathway commences. The findings indicate that in the absence of control variables, the influence coefficient of artificial intelligence on the data value transformation pathway stands at 2.7126. When control variables are incorporated, this coefficient drops to 1.4022. This outcome not only showcases the moderating impact of control variables on the relationship between artificial intelligence's influence and the data value transformation pathway but also reveals a positive correlation between artificial intelligence and the data value transformation pathway. The research presented in this paper comprehensively elucidates the mechanism underlying the role of artificial intelligence and the data value transformation pathway, in order to make the development level of data value transformation path further improved.*

KEYWORDS: *entropy value method; principal component analysis method; benchmark regression model; mediation effect model; artificial intelligence; digital economy; data value transformation path*

1 Introduction

The rapid growth of the digital economy not only spurs the digitalization of industries but also drives the digitization of the industrial sector. Leveraging the benefits of the digital economy, enterprises have established cross - border application scenarios for enterprise data via the industrial collaboration platform. This platform serves as a vehicle for the transformation and upgrading of the enterprise assessment model, shifting it from a static and one - sided approach to a dynamic and comprehensive one.Moreover, it not only facilitates the interactive cycle between the enterprise's high - quality data and the efficiency of data utilization but also offers a new impetus for the conversion of the value of the enterprise's data assets [1-4]. As the mobile

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Internet, big data, cloud computing, artificial intelligence (AI), and other technological advancements progress, Internet giants have launched new business models and upgraded industrial service forms around the new consumer behavior of customers in the Internet era, grasping the massive amount of customer data and related market data, and improving customer stickiness [5-7]. Among them, the core function of AI is to efficiently complete task execution, logical inference, and accurate identification by virtue of its powerful data analysis capability, Infusing fundamental kinetic energy into the conversion of data value within the digital economy [8].

The digital economy is marked by data - led operations and a high degree of innovation, cross-border integration and strong permeability, and wide coverage, which effectively solves the problems of difficult data collection, low data sharing capacity and insufficient data analysis capacity in the traditional mode [9, 10]. And AI technology is able to process and mine data to realize data value. There are multiple paths of data value transformation relying on AI technology. Zia et al [11] elaborated text mining tools based on AI techniques for data based task analysis by processing large scale unstructured data from which hidden data features and correlations between data are mined. Xu et al [12] used a traditional neural network approach to construct a hybrid streaming big data analysis model combined with a decision-making algorithm, which is used to avoid redundancy of big data in data centers and to improve data processing efficiency and data quality. Zhu et al [13] stated that AI techniques of deep learning and machine learning perform relational data cleansing with the help of neural network and non-neural network methods, such as erroneous data identification and repair and vacant data filling. Ravichandran and colleagues [14]presented the utilization of generative artificial intelligence for automated data cleansing and pre - processing. , which can be used for anomaly identification and noise processing of data by learning fixed patterns in the data, in addition to having data detection, repair and filling.

AI technologies mine and process event-related data relationally for data-based application tasks. Cortez et al [15] developed an emergency forecasting framework founded on long - and short - term memory recurrent neural networks, which was able to predict emergencies more accurately by evaluating and temporal feature mining of historical emergency data. Xiang et al [16] put forward a data assimilation framework founded on artificial intelligence for handling complex linear algebra and large-scale data computations as well as high-dimensional data processing to generate high-quality kilometer-scale analyses for improving numerical weather prediction forecasting capabilities. EMMANUEL et al [17] used AI techniques for low-latency and real-time processing of multi-source and multi-modal surveillance data for optimizing the efficiency and accuracy of detection of threat elements associated with surveillance systems. Wasilewski and Wasilewska [18] constructed an integrated model based on AI and machine learning to personalize the e-commerce user interface by analyzing customer behavioral data, such as personalized recommendations, customer segmentation, and automated content generation. Zhou et al [19] feature extraction of such data as medical images with the help of AI technology for classification, segmentation, recognition and fusion can effectively improve the accuracy of diagnosis of clinical conditions such as aneurysms and reduce the probability of leakage and misdiagnosis. Huang and colleagues [20] employed machine learning for data - driven soil analysis in the context of precision agriculture. This analysis relied on real - time satellite data and remote - sensing data that pertained to climate conditions, soil composition and quote status, and fertilization. However, Hossain et al [21] pointed out that the application of AI techniques is constrained by the caliber of data, the necessity for extensive labeled data sets, the danger of model over - adaptation, and the absence of model transparency, which leads to inadequate interpretation of remotely sensed data. And according to Wan [22], AI technology is subject to the risk of leakage and misuse of data transmission during data collection, processing, and application, Consequently, they fall under the purview of privacy and security statutes and regulations.further restricting the depth of AI application.

This research paper delves into the current state of artificial intelligence (AI) and data value conversion within the framework of the digital economy. By doing so, it aims to comprehend the interrelationship between these two elements, offering a crucial theoretical foundation for the subsequent model - building process. Subsequently, the entropy value approach and principal component analysis are employed to carry out the task of gauging the path of AI and data value transformation.After completing the measurement task, the explanatory variables, interpreted variables, control variables and mediating variables of the study are set, Moreover, the establishment of both the benchmark regression model and the mediating effect model has also been accomplished. Finally, under the premise that the data sources of the research variables are known,The framework presented in this paper is formally employed to investigate the mechanism of artificial intelligence and the transformation pathway of data value from the vantage point of the digital economy.

2 Status of AI and Data Value Transformation in the Context of Digital Economy

2.1 Current status of artificial intelligence development

2.1.1 Market size

Artificial Intelligence is developing from technology research and development to industry application direction, forming a new practice of intelligence in various fields of macro and micro, and gradually penetrating into multiple industries, such as manufacturing, transportation, healthcare, finance, retail and finance. China's industrial robots started late and lagged behind the U.S. for a long time, Additionally, information from the International Federation of Robotics (IFR), as shown in Figure 1, showed that the scale of China's stock of industrial robots in the manufacturing industry amounted to 209,800 units surpassing that of the U.S. in 2014 and reached 1,218,700 units in 2020. The increasing inventory of robots offers a vast market scope and technological backing for the infiltration and amalgamation of artificial intelligence with numerous industries.

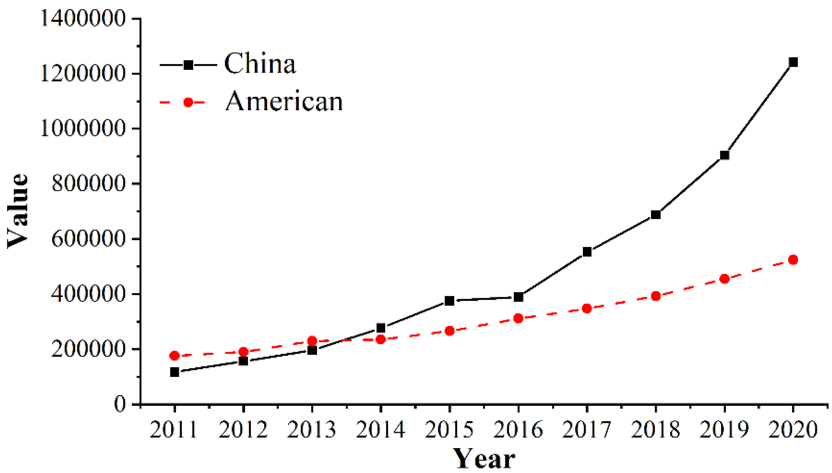

Figure 1: International Federation of Robotics (IFR) data

The market size of China's artificial intelligence is on an upward trajectory year after year. Figure 2 depicts the market size of China's real economy empowered by artificial intelligence. As per the data in Figure 2, the market size of China's AI hit 9.9 billion yuan in 2011 and is projected to reach 87.8 billion yuan in 2020. From 2011 to 2020, the size of China's core AI industry totaled 295.3 billion yuan. Core AI penetrates traditional industries, and the era of smart economy is initially formed. The extensive market scope offers a macro - environment and policy - guided backing for the advancement of China's artificial intelligence technology.

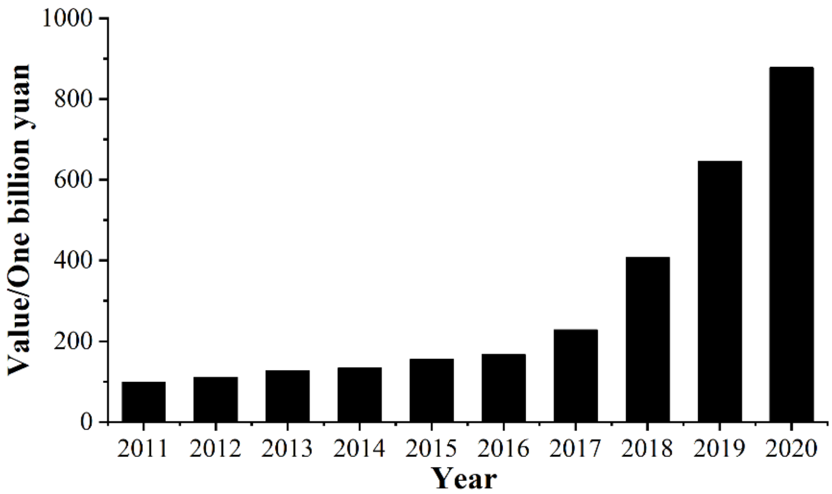

Figure 2: Artificial intelligence empowers the scale of the real economy market

2.1.2 Capital market financing

In recent years, with the promulgation and implementation of various policies, as well as the wide expansion of artificial intelligence application scenes, the application effect is gradually significant, the investment market within the domain of artificial intelligence exhibits a high level of activity as well, the investment and financing situation of the artificial intelligence industry is shown in Figure 3.2011-2018 China's artificial intelligence field has a momentum, and the amount and number of domestic investment in artificial intelligence is growing rapidly.2019 by the impact of the macro market economy, the capital market downturn, the entire investment sector is experiencing a downturn, which has impeded investments in the artificial intelligence domain. In 2020, due to the COVID - 19 pandemic, artificial intelligence was applied in anti - epidemic efforts in the medical, communication, and transportation sectors. This led to a substantial increase in capital market investments in the artificial intelligence field.By 2020, the total investment in China's artificial intelligence field reached 88.8 billion yuan, with 459 investment cases. Moreover, the majority of these investments were concentrated in high - tech areas such as big data, the Internet of Things, and computer technology.

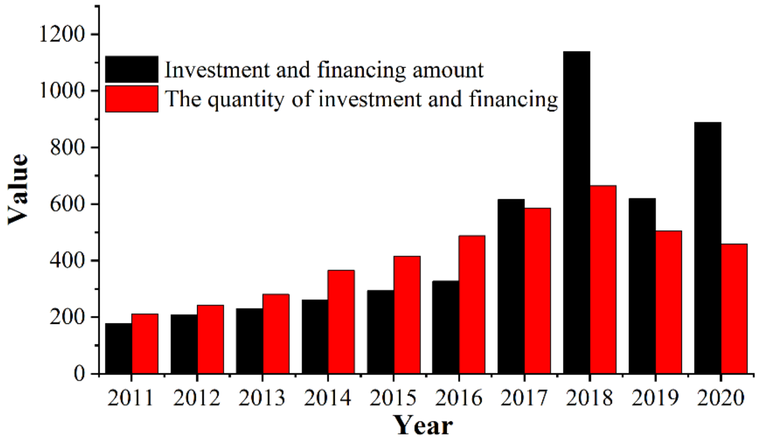

Figure 3: The investment and financing situation in the artificial intelligence industry

2.1.3 Artificial Intelligence Patents

Although China's AI technology started late, with the support of national policies and funds, it has set up a number of national laboratories and R&D team organizations, encouraged relevant scholars to research AI-related topics, and made great breakthroughs in the quantity and quality of research, with increasingly active research projects. As of 2020, the quantity of patent applications submitted by Chinese artificial intelligence (AI) enterprises held the top position globally. Technologies such as speech recognition, visual recognition, machine translation, and Chinese information processing are among the world's best. Even though China's AI takes the lead in certain technical domains, there remains a significant disparity between its overall development level and that of developed countries. China's AI industry should seize the macroeconomic advantages, introduce innovative talents, continue to research core technologies, and improve infrastructure construction to narrow the gap with the world's cutting-edge technologies.

2.2 Current status of data value transformation

2.2.1 Production value and growth rate

Since the implementation of the reform and opening - up policy, the digital economy has played a crucial role in facilitating the rapid advancement of the manufacturing sector. China has made a remarkable leap to become the world's leading manufacturing nation. Its industrial output value and volume hold the top position globally, and it is the country with the most comprehensive range of industrial categories in the world. As early as 2010, China's manufacturing output value accounted for 22.15% of the global manufacturing output value, surpassing the United States and taking the lead as the world's largest manufacturing power. The changes in the added - value situation of the manufacturing industry are presented in Figure 4.China's manufacturing added - value has been on a gradual upward trajectory. In 2010, it overtook developed countries such as the United States, Japan, and Germany. By the end of 2020, the added - value of China's manufacturing industry reached 3.899 trillion US dollars, accounting for approximately 29.79% of the global share, ranking first in the world. In fact, it is equivalent to the combined total of the United States, Japan, and Germany.Moreover, more than 100 Chinese enterprises have been included in the list of the world's top 500 companies, with over 55% of them belonging to the manufacturing sector. Alongside China's rapid economic development, the industrial system has also been continuously refined. This has guaranteed the stable growth of the manufacturing industry, elevated China's economic standing, and served as a vital driving force for employment and income generation for the people.However, the growth rate of China's manufacturing added - value experiences significant fluctuations. In 2016, it even reached a record low. The slowdown in added - value growth is the most pressing issue confronting China's manufacturing industry and also reflects the current state of China's manufacturing data value transformation.

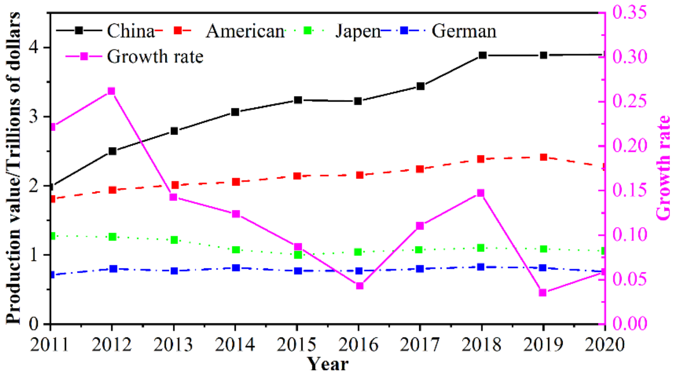

Figure 4: Alterations in the supplementary value of the manufacturing sector

2.2.2 Independent Innovation Capability and Core Competitiveness

To gain a more comprehensive understanding of the current state of China's manufacturing data value transformation, this study employs the trade value-added data from the Organization for Economic Cooperation and Development (OECD). First, the manufacturing industry is broken down into 17 sectors based on the specific categorization of GB/T4754 - 2022. Then, the global value chain status index of China's manufacturing industries is computed through forward and backward participation. Figure 5 presents the global value chain status index of China's manufacturing industries from 2011 to 2020. The value of this index ranges from 0.0653 to 0.20%. As depicted in Figure 5, the global value chain status index of China's high - tech manufacturing sectors, such as the computer, electrical, mechanical industries is lower than that of low-tech industries such as textiles, food and beverages, timber and furniture, with a value range of 0.0653~0.2093. Due to the lack of innovation capability and core competitiveness, reliance on the support of high-technology equipment from developed countries,Amid the upheaval in the global financial market following the financial crisis, the capacity for overseas investment has diminished. As a result, the position of China's manufacturing industry in the international division of labor has notably deteriorated.

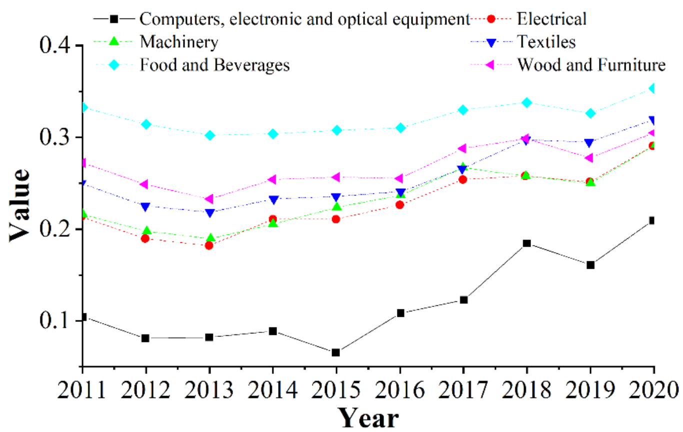

Figure 5: Index of the Position of China's Manufacturing Industry in the Value Chain from 2011 to 2020

As China's innovation-driven development strategy deepens, the R&D investment of large-scale manufacturing enterprises is presented in Figure 6. By examining the data in the figure, it's evident that the R&D investment of industrial enterprises has been steadily increasing. Moreover, from 2011 to 2020, the R&D intensity of these enterprises has advanced significantly.Based on the 2016 Global Manufacturing Competitiveness Index ranking, as early as 2016, China's manufacturing industry had already achieved a high global competitiveness level, making China the most competitive nation globally.Despite the growing R&D investment and rising competitiveness, the issue of being “large but not strong” still looms large for China's manufacturing industry. The increase in R&D investment fails to keep up with the rapid evolution of high - tech industries. The core technology remains unbreakthrough, merely maintaining parity with the industry average.

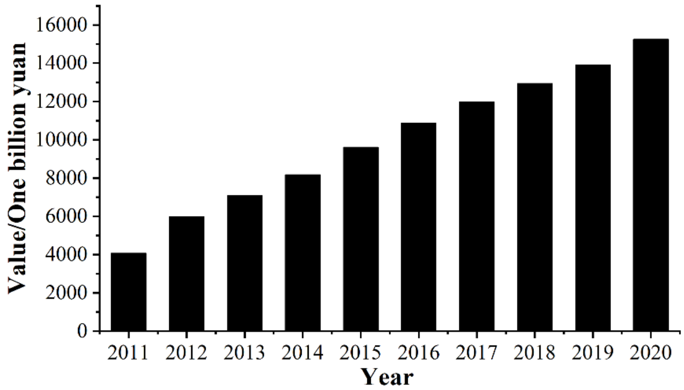

Figure 6: R&d investment of large-scale manufacturing enterprises

2.2.3 Production and operating costs and the international environment

As the population growth in China decelerates, the escalating labor costs have caused a change in China's position in the manufacturing labor - division, with the focus shifting towards Southeast Asia. where it has the advantage of low-cost labor, and slow upgrading development. In recent years, by the international trade environment turbulence, political conflicts around the world, as well as the impact of the new crown epidemic, countries around the world production capacity is blocked, the ability to reduce exports, Consequently, China's manufacturing sector exhibits a relatively high level of foreign reliance. The import of products has been significantly affected. When confronted with the downward trajectory of the international environment, the increase in foreign production costs, and the suppression and containment of China's economic development by exporting nations, the development of industries such as electromechanical, transportation, chemical, optical, and rubber and plastic is facing difficulties. This situation reveals the current state of the data - value transformation in China's manufacturing industry.

3 Study design

3.1 Artificial Intelligence and Data Value Transformation Path Measurement Methods

3.1.1 Empowerment approach using the entropy method

The entropy weighting approach is a multi - indicator decision - making technique. Its purpose is to more effectively assess and contrast the merits and demerits of various plans or decisions by computing the weights of each indicator. This approach is founded on the notion of entropy, which serves to gauge the level of uncertainty and chaos in information. As a result, the entropy weighting approach can assist us in identifying the most crucial indicators for decision - making.The fundamental concept of the entropy weighting approach is to assign weights and calculate the average of the information entropy of all indicators to derive the weight of each indicator. It is broken down into the following specific steps:

(1) Data standardization

Begin to de-quantify each indicator, given m indicators. Perform data standardization for each indicator:

When x is a positive indicator, the $$Y_{ij} = \frac{X_{ij} - \min\left(X_{ij}\right)}{\max\left(X_{ij}\right) - \min\left(X_{ij}\right)} \tag{1}$$

When x is a negative indicator, the $$Y_{ij} = \frac{\max\left(X_{ij}\right) - X_{ij}}{\max\left(X_{ij}\right) - \min\left(X_{ij}\right)} \tag{2}$$

(2) Determine the ratio of each indicator within each program, as well as the weight of the -th indicator in the -th program for that particular indicator:

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}}, i = 1, 2, 3, \ldots n; \ j = 1, 2, 3, \ldots m \tag{3}$$

(3) Determine the information entropy of each indicator based on the definition of information entropy within information theory:

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} P_{ij} \ln P_{ij}, \text{ where } E_j \geq 0; \text{ If } P_{ij} = 0, \text{ then define } E_{j=0} \tag{4}$$

(4) Ascertain the weights of each indicator and compute the weights by calculating the redundancy of information:

$$D_j = 1 - E_j \tag{5}$$

The indicator weights are then calculated:

$$W_l = \frac{D_l}{\sum_{j=1}^{m} D_l} \tag{6}$$

Finally, a composite score was calculated for each program:

$$S_i = \sum_{j=1}^{m} W_i \cdot X_{ij} \tag{7}$$

One of the benefits of the entropy weighting approach is that it has the capacity to consider the interrelationships and significance among the indicators,thus more accurately assessing and comparing the advantages and disadvantages of different options. In addition, the method does not require prior assumptions about the relationship between indicators and can therefore be applied to a variety of different types of decision-making problems.

3.1.2 Analysis of principal components

Principal Component Analysis (PCA) boosts the effectiveness of data visualization and analysis. It achieves this by condensing high - dimensional data sets into lower dimensions, thus diminishing redundancy and noise within the data. The fundamental concept behind Principal Component Analysis is to minimize the inter - dimensional correlation. This way, a fresh set of independent variables, known as principal components, can be obtained. These principal components are employed to depict the maximum variance of the data with minimal loss. The specific procedures of the principal component analysis method are as follows:

(1) Data standardization: Initially, the raw data undergoes standardization. The reason for this is that the principal component analysis approach computes based on the covariance matrix. If the data is not standardized, it will be affected by the unit of the variable and the scale, resulting in inaccurate results.

(2) Computation of the covariance matrix: The covariance matrix is computed using the standardized data. This matrix serves to depict the inter - variable correlations. By computing the covariance, the relationships between the variables are analyzed.

(3) Calculation of eigenvalues and eigenvectors: By calculating the eigenvalues and the eigenvectors, the degree of importance between the variables to the evaluation index is analyzed.

(4) Choose principal components: Based on the magnitude of the eigenvalues, pick the initial k principal components. This selection is made to ensure that these components can account for the majority of the data's variance. Additionally, choose the indicators with eigenvalues exceeding 1 for the construction process.

(5) Compute principal component scores: project the initial data onto the chosen principal components to get scores for every data point on the principal components. These scores can be employed to depict the maximum variance and minimal loss of the data.

(6) Analyze the principal components: Based on the eigenvectors of the principal components, we can analyze the connection and significance among the variables that each principal component represents. This analysis can assist us in comprehending the structure and features of the data.

3.2 Simulation Crucial:

3.2.1 Simulation

(1) Benchmark regression model

To conduct a detailed investigation into the mechanism of artificial intelligence (AI) regarding the transformation pathway of data value (TPDV) within the digital economy context, this paper formulates the following benchmark regression model:

$$Tpdv_{it} = a_0 + a_1 Ai + \sum a_n control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{8}$$

Among these, $Tpdv_{it}$ symbolizes the measurement of the data value transformation pathway, Ai represents the measurement of the AI development level, $control$ stands for a set of control variables, and μ and δ signify the individual effect and the time effect respectively.

(2) Mediating effect model

Beyond the direct impacts mentioned earlier, the mechanism by which artificial intelligence (AI) operates on the data value transformation pathway (Tpdv) within the digital economy context might exert an indirect influence on this pathway via intermediary variables. According to the analysis above, artificial intelligence (Ai) can affect the data value transformation path by influencing the level of independent innovation (Lin), production efficiency (Tfp) and production cost (Pdc). Therefore, a model is constructed to test its influence mechanism:

$$M_{it} = \beta_0 + \beta_1 Ai_{it} + \sum \beta_n contral_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{9}$$

$$Tpdv_{it} = \gamma_0 + \gamma_1 Ai_{it} + \gamma_2 M_{it} + \sum \gamma_n contral_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{10}$$

Among them, M represents the mediating variables, which are the level of independent innovation (Lin), production efficiency (Tfp) and production cost (Pdc), and the other variables are defined in the same way as in equation (8), and whether there is a mediating effect or not is judged by the regression coefficients β, γ.

If β_1 is significant when considering γ_2 and γ_1 is not significant, a full mediation effect exists. If β_1 is significant when considering γ_2 and γ_1 is also significant, a partial mediation effect is present. In other cases, there will be no mediation effect.

3.2.2 Setting variables

(1) Explained variables

Referring to the relevant studies of scholars, the data value transformation path is set as the explanatory variable.Subsequently, the entropy power approach is employed to derive the quantitative value of the data value transformation route.

(2) Explanatory variables

Referring to relevant literature and data, artificial intelligence is set as the explanatory variable.Additionally, the entropy weight approach is employed to derive the quantitative measure of artificial intelligence. Moreover, principal component analysis is utilized to compute the value for the robustness assessment.

(3) Mediating variable

Artificial intelligence can have an indirect impact on the data value transformation path through the level of independent innovation (Lin), production efficiency (Tfp) and production cost (Pdc), considering the availability of data.

(4) Control variables

In the context of the digital economy, to comprehensively examine the extent of the influence of artificial intelligence (AI) on the data value transformation path (Tpdv), it is essential to manage the factors that impact this path, and the specific selection of the tertiary industry coordination (Cti), direct investment (Di), gross domestic product (Gdp), the degree of openness of trade (Open), and the degree of fiscal decentralization (Dfd).

3.2.3 Data sources

A balanced panel dataset spanning from 2011 to 2020 was gathered for 30 provinces in China, excluding Tibet, the Hong Kong Special Administrative Region, the Macao Special Administrative Region, and Taiwan Province. The primary data sources encompass the Wind database, the National Bureau of Statistics, the China Statistical Yearbook, the China Energy Yearbook, local statistical yearbooks, local customs, and the National Economic and Social

Development Statistical Bulletins of each province. Missing data were filled using linear interpolation. To guarantee the data's smoothness, logarithmic transformation was applied to certain variables.

4 Analysis of empirical studies

4.1 Descriptive statistics and correlation tests

4.1.1 Descriptive statistics

With the support of relevant analysis software, a descriptive statistical analysis has been conducted on the set of research variables mentioned earlier. The results of this descriptive statistical analysis are presented in Table 1. By examining the data in the table, it becomes evident that the average values of Artificial Intelligence (AI) , Data Value Transformation Path (Tpdv), Level of Independent Innovation (Lin), Production Efficiency (Tfp), Production Costs (Pdc), Coordination of the Tertiary Industry (Cti), Direct Investment (Di), Gross Domestic Product (Gdp), Openness to Trade (Open), and Degree of Fiscal Decentralization (Dfd) were 5.188, 8.772, 6.016, 8.163, 7.186, 8.403, 8.539, 5.148, 8.252, 6.945, and the corresponding standard deviations are 0.922, 1.247, 1.207, 1.249, 1.219, 0.914, 0.915, 1.12, 1.04, 1.218, providing a comprehensive overview of the characterization of the distribution of the study values.

Table 1: Analytical overview of descriptive statistics

Variable	Mean	SD	Min	Max
Tpdv	5.188	0.922	0.119	9.535
Ai	8.772	1.247	0.103	9.531
Lin	6.016	1.207	0.13	9.534
Tfp	8.163	1.249	0.136	9.53
Pdc	7.186	1.219	0.12	9.539
Cti	8.403	0.914	0.134	9.53
Di	8.539	0.915	0.147	9.525
Gdp	5.148	1.12	0.126	9.514
Open	8.252	1.04	0.108	9.546
Dfd	6.945	1.218	0.129	9.501

4.1.2 Correlation test

Based on the descriptive statistical examination of the research variables presented in the table above, the Pearson correlation coefficient, a tool within the statistical analysis approach, is employed to conduct a correlation test on the research variables. The outcomes of this correlation test analysis are presented in Table 2. By examining the data in the table, it becomes evident that the Pearson's correlation coefficients of artificial intelligence (AI), level of independent innovation (Lin), production efficiency (Tfp), production cost (Pdc), tertiary industry coordination (Cti), direct investment (Di), gross domestic product (Gdp), trade openness (Open), and degree of fiscal decentralization (Dfd) and the transformation path of the data value (Tpdv) are 0.739, 0.739, 0.739, 0.739, 0.739, 0.739, 0.739 and 0.739 respectively. The correlation coefficients are 0.739, 0.655, 0.503, 0.612, 0.759, 0.595, 0.661, 0.759, 0.585, and the corresponding Sig values are 0.008, 0.001, 0.003, 0.008, 0.006, 0.005, 0.006, 0.008, 0.003, respectively, and the Sig< 0.05 condition holds, i.e., it proves that artificial intelligence

(Ai), the level of independent innovation (Lin), production efficiency (Tfp), production cost (Pdc), tertiary industry coordination (Cti), direct investment (Di), gross domestic product (Gdp), trade openness (Open), and degree of fiscal decentralization (Dfd) and the path of transforming the value of the data (Tpdv) are significantly correlation.

Table 2: Outcomes of the correlation test evaluation

Variable		Tpdv	Ai	Lin	Tfp	Pdc	Cti	Di	Gdp	Open	Dfd
Tpdv	Pearson	1	0.739	0.655	0.503	0.612	0.759	0.595	0.661	0.759	0.586
	Sig.		0.008	0.001	0.003	0.008	0.006	0.005	0.006	0.008	0.003
	N	436	436	436	436	436	436	436	436	436	436
Ai	Pearson	0.739	1	0.739	0.607	0.532	0.654	0.785	0.763	0.513	0.642
	Sig.	0.008		0.007	0.005	0.004	0.003	0.007	0.007	0.007	0.007
	N	436	436	436	436	436	436	436	436	436	436
Lin	Pearson	0.655	0.739	1	0.777	0.715	0.688	0.773	0.744	0.753	0.689
	Sig.	0.001	0.007		0.005	0.004	0.003	0.004	0.003	0.002	0.007
	N	436	436	436	436	436	436	436	436	436	436
Tfp	Pearson	0.503	0.607	0.777	1	0.689	0.731	0.535	0.641	0.543	0.665
	Sig.	0.003	0.005	0.005		0.008	0.008	0.007	0.006	0.005	0.009
	N	436	436	436	436	436	436	436	436	436	436
Pdc	Pearson	0.612	0.532	0.715	0.689	1	0.679	0.613	0.719	0.773	0.601
	Sig.	0.008	0.004	0.004	0.008		0.003	0.008	0.005	0.004	0.007
	N	436	436	436	436	436	436	436	436	436	436
Cti	Pearson	0.759	0.654	0.688	0.731	0.679	1	0.543	0.646	0.624	0.759
	Sig.	0.006	0.003	0.003	0.008	0.003		0.007	0.005	0.005	0.007
	N	436	436	436	436	436	436	436	436	436	436
Di	Pearson	0.595	0.785	0.773	0.535	0.613	0.543	1	0.617	0.611	0.625
	Sig.	0.005	0.007	0.004	0.007	0.008	0.007		0.005	0.008	0.002
	N	436	436	436	436	436	436	436	436	436	436
Gdp	Pearson	0.661	0.763	0.744	0.641	0.719	0.646	0.617	1	0.576	0.597
	Sig.	0.006	0.007	0.003	0.006	0.005	0.005	0.005		0.001	0.004
	N	436	436	436	436	436	436	436	436	436	436
Open	Pearson	0.759	0.513	0.753	0.543	0.773	0.624	0.611	0.576	1	0.743
	Sig.	0.008	0.007	0.002	0.005	0.004	0.005	0.008	0.001		0.005
	N	436	436	436	436	436	436	436	436	436	436
Dfd	Pearson	0.586	0.642	0.689	0.665	0.601	0.759	0.625	0.597	0.743	1
	Sig.	0.003	0.007	0.007	0.009	0.007	0.007	0.002	0.004	0.005	
	N	436	436	436	436	436	436	436	436	436	436

4.2 Multicollinearity test

To guarantee the reliability and standardization of the outcomes and avoid the strong inter - relationship between variables from affecting the results, this study conducted a multicollinearity test. The results of this test are presented in Table 3. The presence of multicollinearity in the model was examined using the VIF (Variance Inflation Factor). Generally, it is assumed that multicollinearity exists when the VIF value exceeds 10. In this model, the average VIF is 3.229, and the VIF value of each variable is less than 10. Evidently, this model has successfully passed the multicollinearity test.

Table 3: Outcomes of the Multicollinearity Test

Variable	VIF	1/VIF
Tpdv	4.54	0.220264
Ai	2.69	0.371747
Lin	2.24	0.446429
Tfp	4.78	0.209205
Pdc	3.86	0.259067
Cti	1.94	0.515464
Di	4.14	0.241546
Gdp	2.39	0.418410
Open	1.88	0.531915
Dfd	3.83	0.261097
Mean	3.229	0.347514

4.3 Analysis of baseline regression results

Using the formula previously mentioned, a benchmark regression analysis was conducted, and the results of this analysis are presented in Table 4. In Model 1, only the core explanatory variables were included in the regression. In Models 2 through 6, control variables were added incrementally. In the model, without the inclusion of control variables, the impact coefficient of the core explanatory variables was 2.7126, and this coefficient was significant at the 1% level. As control variables were gradually added, the impact coefficients of the core explanatory variables either increased or decreased, yet they consistently remained significant at the 1% level. The impact coefficient of the core explanatory variables dropped from 2.7126 (without control variables) to 1.4022 after all control variables were added. Evidently, the core explanatory variables exhibit a significantly positive effect regardless of whether control variables are incorporated. All coefficients pass the 1% significance level, suggesting that artificial intelligence (AI) can indeed significantly enhance the data value transformation path. Regarding each control variable, the impact coefficient of tertiary industry coordination is 0.0746, and it is significant at the 1% level. This indicates that the coordination of the tertiary industry has a notable driving influence on the data value transformation path, and for every unit of tertiary industry coordination, the latter improves by 0.0746 units, which is most likely due to the fact that with the improvement of the level of tertiary industry coordination, the quality of life of the people The reason for this is likely to be that as the level of coordination of the tertiary industry increases, the quality of life of the people improves, the demand also shows a rising trend, and the degree of diversification of the demand increases, which makes the transformation of the data value increase,consequently, it facilitates the advancement of the route for the conversion of data value, and the same applies to other control variables.

Table 4: Analysis of benchmark regression results

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ai	2.7126** (0.1938)	2.3034** (0.2341)	1.8149** (0.2834)	1.2424** (0.3243)	1.2748** (0.3248)	1.4022** (0.2945)
Cti		0.1743** (0.00537)	0.1258** (0.05925)	0.0408 (0.0621)	0.0416 (0.0622)	0.0746** (0.0543)
Di			1.1712** (0.4021)	-0.2317 (0.5946)	-0.1549 (0.5604)	0.3455 (0.5536)
Gdp				0.4704** (0.1512)	0.4916** (0.1519)	0.5916** (0.1256)
Open					-0.1643** (0.0224)	-0.1631** (0.0226)
Dfd						0.0633 (0.1831)
_Cons	0.0245 (0.0344)	-1.5618** (0.5128)	-1.6905** (0.5043)	-5.0344** (1.1451)	-5.2236** (1.2094)	-6.3094** (1.1071)
N	436	436	436	436	436	436
R2	0.469	0.496	0.516	0.536	0.537	0.619

4.4 Analysis of intermediation effects

Drawing on the theory of the aforementioned mediation model, an analysis of the mediation effect is conducted. The outcomes of this mediation effect analysis are presented in Table 5. Regarding the mediation effect, Model 8 reveals that AI technology has a notable positive influence on the mediator variable. The estimated coefficient stands at 0.077, which means that for every 1 - percentage - point rise in AI, the mediator variable increases by 0.077 percentage points. In Model 9, artificial intelligence plays a more prominent role in facilitating the data value transformation path. Each 1 - percentage - point increase in AI drives the data value transformation path up by 0.468 percentage points. Additionally, the regression coefficient of the digital economy in this model is smaller than the regression results in Model 7, which indicates that artificial intelligence promotes the data value through the three mediator variables of the level of independent innovation (Lin), production efficiency (Tfp), and production cost (Pdc) to promote the data value transformation path, i.e., there is a positive mediation effect.

Table: Analysis results of mediating effects

Variable	Model 7	Model 8	Model 9
Ai	0.468*** (0.158)	0.077** (0.025)	0.468*** (0.156)
Lin			0.022** (0.526)
Tfp			0.287** (0.417)
Pdc			0.331** (0.085)
Cti	0.425*** (0.117)	-0.026 (0.0245)	0.426** (0.116)
Di	0.228** (0.086)	0.0635*** (0.0135)	0.227** (0.088)
Gdp	-0.129** (0.048)	-0.012 (0.012)	-0.129** (0.048)
Open	0.136** (0.066)	-0.018 (0.018)	0.168** (0.061)
Dfd	0.144 (0.121)	-0.049** (0.016)	0.176 (0.138)
_Cons	-0.909 (1.331)	0.006 (0.311)	-0.909 (1.333)
Provincial fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	436	436	436
R2	0.514	0.737	0.508

4.5 Robustness Tests

To further ascertain the dependability of the conclusion that artificial intelligence facilitates the data value transformation pathway, a robustness examination is carried out. The Tobit model and the least - squares approach are employed to eliminate heteroskedasticity and lagged impacts for the stability assessment. The outcomes of the robustness test are presented in Table 6. In this table, Model 10 showcases the regression findings of the Tobit model, Model 11 displays the results of the least - squares regression, and Model 12 reveals the regression of the lagged effects.Consequently, it is clearly observable that the core explanatory variables in Model 10, Model 11, and Model 12 have met the 1% significance threshold. Moreover, all the influence coefficients are positive. This indicates that AI exerts a positive influence on the data value transformation path, thus validating the robustness of the regression results.

Table 6: Robustness test results

Variable	Model 10	Model 11	Model 12
Ai	1.0316** (0.2511)	0.6038** (0.1442)	0.6644** (0.0424)
Cti	0.0508 (0.0347)	0.0547** (0.0254)	0.1238 (0.1105)
Di	0.1346 (0.4201)	-0.2137 (0.2619)	0.0126 (0.0146)
Gdp	0.5222** (0.1116)	0.4171** (0.0621)	0.2916 (0.2016)
Open	-0.1548** (0.0638)	-0.0516* (0.0271)	0.0128 (0.0518)
Dfd	-0.1125 (0.0226)	-0.0233 (0.0127)	-0.0207 (0.0189)
_Cons	-5.5081 (1.0028)	-4.4427** (0.6074)	-0.0744 (0.0627)
N	436	436	436
R^2	0.455	0.476	0.588

5 Conclusion

In the present era of high - quality advancement of the digital economy, artificial intelligence has steadily emerged as a significant driving force for the transformation of data value. The influence exerted by artificial intelligence is far from negligible. In response to this, a research project has been formulated to explore the impact of artificial intelligence on the data value transformation path within the digital economy context. Empirical research methods are employed to conduct an in - depth analysis of this project. The findings of this research are as follows:

(1) On the basis of the known data distribution characteristics of the research variables, the correlation verification is carried out, and it is found that the research variables set in this paper have significant correlation and satisfy the condition of Sig<0.05.

(2) In order to prevent the existence of multicollinearity in the correlation of the research variables, for this reason, the research variable multicollinearity test was carried out, and it was found that the value of VIF of the research variables was less than 10, i.e., there was no multicollinearity in the research variables.

(3) In the absence of control variables, the coefficient reflecting the impact of the explanatory variables on the explained variables stands at 2.7126, and this relationship shows a significant correlation at the 0.01 level. Once the control variables are incorporated, the

coefficient of influence drops to 1.4022. This outcome leads to the inference that artificial intelligence exerts a positive influence on the data value transformation path, regardless of whether control variables are included.

(4) The estimated coefficient of artificial intelligence technology with respect to the mediator variable is 0.077. This implies that for each unit increase in artificial intelligence, the mediator variable increases by 0.077 units, which in turn promotes the development of the data value transformation path, i.e., verifies that there is a mediating effect between artificial intelligence and the data value transformation path.

(5) Finally, with the help of Tobit model, the method of least squares eliminates the issues of heteroskedasticity and lag effect to conduct a robustness assessment of the aforementioned benchmark regression outcomes, and it is found that no matter which method is used for the test, the path of transformation of artificial intelligence and data value still has a notably positive influence at the 1% level, which serves to validate the reliability of the benchmark regression outcomes.

About the Author

Zhixiang Yan was born in Qingdao, Shandong, P.R. China, in 1993. I received my bachelor's degree from Qingdao University of Science and Technology. I am currently pursuing a master's degree in Business Administration at Shanghai Jiao Tong University. My main research focuses are the digital economy and artificial intelligence.

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