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Promoting the transformation of digital economy structure based on artificial intelligence in the low carbon economy environment

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Abstract: This study investigates the impact of artificial intelligence (AI) on economic structure (ES) transformation within a low-carbon economy. Focusing on ES advancement and rationalisation, an empirical model is established incorporating control variables such as policy, openness, informatisation, and population density. Using dynamic panel analysis, results show that AI significantly promotes both ES advancement and rationalisation at the 1% level in the first lagged period. The findings indicate that AI enhances industrial efficiency and supports green development, playing a crucial role in driving sustainable, high-quality economic growth. This research provides valuable insights for policymakers seeking to integrate AI into low-carbon economic strategies.

Keywords: economic restructuring; artificial intelligence; low-carbon economic environment; economic model analysis; expert system.

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1 Introduction

Artificial intelligence (AI) technology mainly refers to computer vision, machine learning, speech recognition, and natural language processing programs based on data. Its basic support is mainly composed of two parts: information data and computing power support, which together provide essential elements for the development of AI technology and its industrial development. Application integration, specifically, refers to various subsectors, including intelligent education, smart healthcare, intelligent finance, and robotics. The increasingly widespread application of AI technology will inevitably bring about further adjustments in the economic structure (ES) and changes in the employment structure. The employment structure's adjustment requires observation and guidance to adapt to technological progress. The extensive application of AI technology will replace some repetitive and low-skilled jobs while simultaneously creating new employment opportunities related to emerging technologies and business models, resulting in the transfer of labour force from traditional industries to emerging industries and changes in the employment structure across industries, occupations, and skill demands. Therefore, combined with the current low-carbon economy construction environment, analysing AI in promoting ES transformation is essential.

The ES determines the trend of economic development. Many scholars have investigated ES transformation. Herrendorf and Schoellman (2018) examined poverty through the perspective of a multisector model. Timmer's (2017) study revealed that food price instability slows economic growth and structural transformation, which offered a pathway out of rural poverty. Ke and Lin (2017) investigated the investment-driven economic growth model and assessed the effect of ES rationalisation and upgrading on green productivity in 30 provinces in China from 1997 to 2010. Yassin and Aralas (2019) examined the effect of structural transformation in some Asian countries on environmental pollution from 1990 to 2016 (Fu et al., 2024). They found that urbanisation and demographic changes would lead to changes in ES. Erwidodo et al.'s (2021) experiments indicated that rural and structural transformation in Indonesia varies from province to province in terms of the depth and pace of change (Erwidodo et al., 2021). However, the transformations examined by these studies are all based on economic benefits, and they do not integrate the broader contemporary context or the overall economic situation.

The promotion of a low-carbon lifestyle has brought the low-carbon economy into public discourse. Numerous scholars have also conducted research on the low-carbon economy. Koning et al. (2018) posited that low-carbon energy systems are more metal-intensive than conventional energy systems. Sagastume Gutierrez et al. (2018) assessed the potential to transition Cuba toward a low-carbon economy by replacing its current electricity mix, which is dominated by fossil fuel generation, with biomass generation. On the basis of a low-carbon economy, Lou et al. (2017) proposed an EV and system cooperative operation model aimed at minimising power generation cost, CO_2 emission cost, and V2G service subsidy. Dou (2017) constructed a cone model focusing on the basic factors of low-carbon technological innovation, carbon emissions trading, carbon finance, and low-carbon policies (Dou, 2017). However, their considerations of the low-carbon economy are entirely based on local carbon emissions and the total economic output. Few scholars have analysed the low-carbon economy in conjunction with the ES of AI. After analysis, the value of the explained variable, which is a qualitative index to measure the advancement of the ES, ranges between 3.477 and 25.012, indicating considerable differences among Chinese provinces regarding the quality of ES upgrading (Xia et al., 2024).

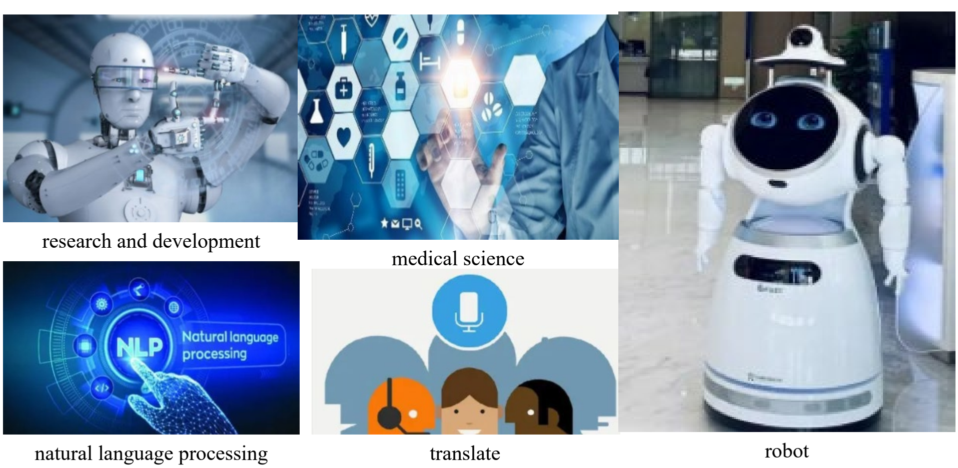
The innovation of this paper lies not only in integrating the low-carbon economy with the AI industry but also in its deep analysis of the pivotal role of AI in facilitating the low-carbon transformation of enterprises. By constructing economic models and conducting empirical analyses, this paper highlights the positive effect of AI on the upgrade of expert systems and ES transformation, offering practical guidance to policymakers and businesses. This enriches the theoretical framework and practical pathways for the integration and development of the low-carbon economy and AI (Wang et al., 2024).

2 AI economy in a low-carbon economy

2.1 AI industry and economic situation

AI, also known as machine intelligence, usually refers to technology that enables computers to emulate human intelligence. AI has a wide range of applications, mainly the extension of human intelligence in a certain aspect, giving full play to its own technical advantages and helping people's development. At the same time, the specific development of AI mainly depends on advancements in computer technology. On the eve of AI's inception, continuous advancement of industrial technology fuelled the desire to create human-like machines that can respond to different instructions. The involvement of scientists then gradually fostered the integration of intelligence and robotics. However, AI's early progress was limited because of the extensive theoretical scope involved in its development. In recent years, AI has made achievements in many fields and has subtly provided numerous conveniences in daily lives. Finally, the abovementioned definition of AI emphasises its development as a simulation and expansion of human intelligence, with detailed explanations for the differences between the two. A key difference is that human intelligence and ideas are generated by the brain, whereas AI is generated by computers (Sarker et al., 2018; Chen, 2018). The application of AI in daily life is shown in Figure 1.

Figure 1 AI application (see online version for colours)

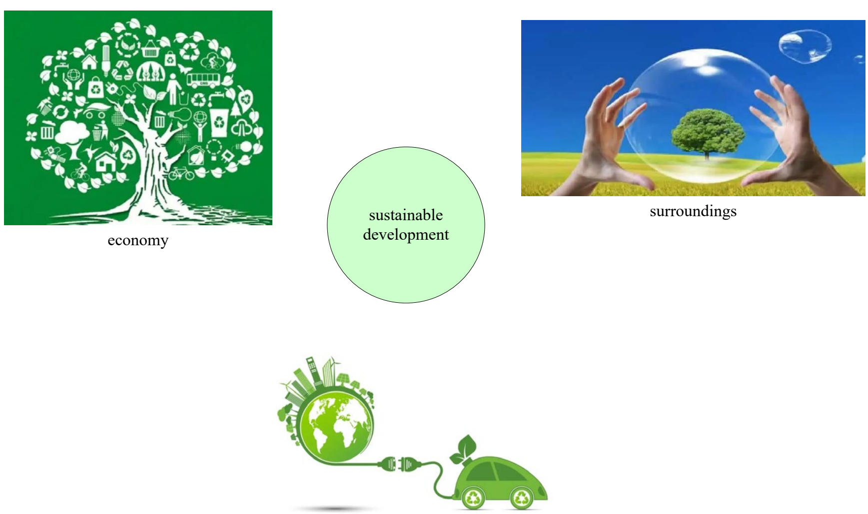


The implementation and development of AI-related technologies in different industries can improve their intelligence levels. This optimisation leads to the improved input of various elements, lower production cost, improved labour efficiency, and increased investment in product research and development, ultimately enhancing enterprise quality and realising the optimisation and upgrading of various ESs. The application of AI in the primary and secondary industries can reduce labour redundancy, improve the quality and efficiency of industrial work, liberate productivity. Furthermore, it promotes the transfer of labour to the tertiary industry (THI) under the background of intelligence and promote the rapid reform, development, and progress of the THI (Liang, 2021; Nemtinova et al., 2022).

2.2 Low-carbon economy

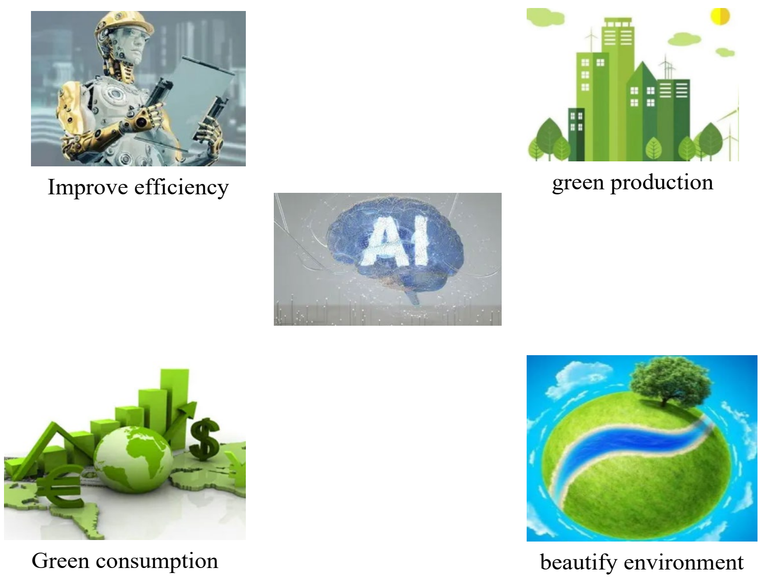
Low-carbon energy is a new type of energy that enhances energy use while maximising CO_2 emission reduction, thereby enhancing environmental protection goals. Low-carbon industries are those that adopt new technologies and reduce fossil energy consumption to meet requirements for low energy consumption and carbon emissions. A low-carbon city is an urban model that fully realises low-carbon emissions in production, construction, and consumption activities. Low-carbon management involves implementing management approaches conducive to low-carbon economic development, ensuring a low-carbon orientation by formulating relevant policies and regulations (Heffron, 2020). As shown in Figure 2, a low-carbon economy integrates society, environment, and economy, all emphasising greenness and sustainability.

Figure 2 Green development (see online version for colours)



The AI industry improves industrial production efficiency and achieves green efficiency. Grounded in intelligent technology, the AI industry ensures coordinated processes from product production to consumption, thereby becoming an important element of green production and injecting new momentum into high-quality economic development. Specifically, AI's role in green production is mainly reflected in two aspects: production methods, and products and services. From the perspective of production methods, the prominent aspect of AI in the industrial field is intelligent manufacturing. In the process from product production to sales, intelligent manufacturing, building on original production factors, leverages an intelligent production system to collect and analyse information from all aspects of product production according to consumers' individual needs, sorting, and transaction data. Consequently, resource allocation is optimised to the greatest extent; energy consumption is reduced; unnecessary input of elements is minimised; and energy conservation, emission reduction, and green development are promoted (Faerber et al., 2018). The information of each link, as shown in Figure 3, specifically refers to data involved in the whole process of product production, including production schedules, quality test results, inventory status, and logistics trajectories, from raw material procurement to production processing, quality testing, and logistics distribution.

Figure 3 AI and the green economy (see online version for colours)



The AI industry builds environmental supervision systems through intelligent technology to reduce environmental pollution. With the development of ecological civilisation, the environmental protection philosophy of "gold and silver mountains are not as good as lucid waters and lush mountains" has been continuously strengthened. The rapid development of AI technology plays an important role in environmental protection, supervision, and governance. At present, many local governments and relevant regulatory departments have built ecological environment information supervision systems leveraging intelligent technology. Many local governments and relevant regulatory authorities use intelligent technologies, such as big data, cloud computing, and the Internet of Things, to integrate environmental monitoring data, pollution source information, and geospatial data, thereby building ecological environment information supervision systems. These systems can analyse environmental data in real time, issue warnings of pollution events, and assist in decision making, realising intelligent and efficient environmental supervision. This realisation has facilitated the integration of environmental supervision data and information, enhanced the ecological environment supervision system, and resolved the problem of unreasonable allocation of information and data resources caused by traditional environmental supervision information barriers. Information technologies, such as AI technology, big data, and the internet, are important technological engines for innovative environmental protection. The intelligent technology platform is used to implement comprehensive and precise monitoring of the ecological environment and analyse the future development trend of the ecological environment (Mara et al., 2018; Duarte et al., 2018).

2.3 Two-step system GMM

In practical research, the economic relationship is not static. Generally, the dynamic panel model of the first-order autoregression has the following form:

$$y_{it} = \alpha y_{it-1} + x_{it}\beta + u_i + e_{it}; i = 1,\ldots,N; t = 1,\ldots,T \tag{1}$$

The systematic GMM obtains an estimator that performs better when the true value of the autoregressive coefficient α is close to 1 or the variance is larger than that of $vr = \frac{\sigma_u^2}{\sigma_e^2}$. Specifically, the system GMM is obtained using the following $K_s = K_d + (T-2)$ moment conditions:

$$E(Z_{si}v_i) = 0 \tag{2}$$

Z_{si} is an instrumental variable matrix of $2(T-2)\times K_s$.

$$Z_{si} = \begin{pmatrix} Z_{di} & 0 \\ 0 & Z_{li}^P \end{pmatrix} \tag{3}$$

v_i is a column vector of $2(T-2)\times 1$.

$$v_i = (\Delta v_{i3}, \Delta v_{i4}, \ldots, \Delta v_{iT}, v_{i3}, v_{i4}, \ldots, v_{iT}) \tag{4}$$

The initial weight matrix of the commonly used system GMM estimator is as follows:

$$W_N^{Sys} = \sum_{i=1}^{N} Z_{si} H Z_{si} \tag{5}$$

H is a square matrix of 2(T–2), that is,

$$H = \begin{bmatrix} A & 0 \\ 0 & I_{T-2} \end{bmatrix} \tag{6}$$

I_{T-2} is an identity matrix of order (T–2), and A is the initial weight matrix commonly used for one-step difference GMM estimators (Winiewski and Kistowski, 2017; Petryk, 2017). According to the expression, the objective function of the system GMM can be expressed as follows:

$$\alpha_{Sys} = \underset{\alpha\in(-1,1)}{\arg\min} \left[\frac{1}{N}\sum_{i=1}^{N} g_i^{lew}(X_i,\alpha)\right] W_N^{Sys} \left[\frac{1}{N}\sum_{i=1}^{N} g_i^{lew}(X_i,\alpha)\right], \tag{7}$$

$$g_i^{lev} = v_i Z'_{lev,i} \tag{8}$$

Taking the one-step GMM estimator as an example, the result of the system GMM estimation can be expressed as follows:

$$\alpha_{Sys} = \frac{qz_s(z_s' z_s)^{-1} z_s' q'}{q_{-1} z_s (z_s' z_s)^{-1} z_s' q_{-1}'}, \tag{9}$$

$$Z_s' = (Z_{s,1}', \ldots, Z_{s,N}'), \tag{10}$$

$$\Delta y_i = (\Delta y_3, \Delta y_4, \ldots, \Delta y_T), \tag{11}$$

$$y_i = (y_3, y_4, \ldots, y_T), \tag{12}$$

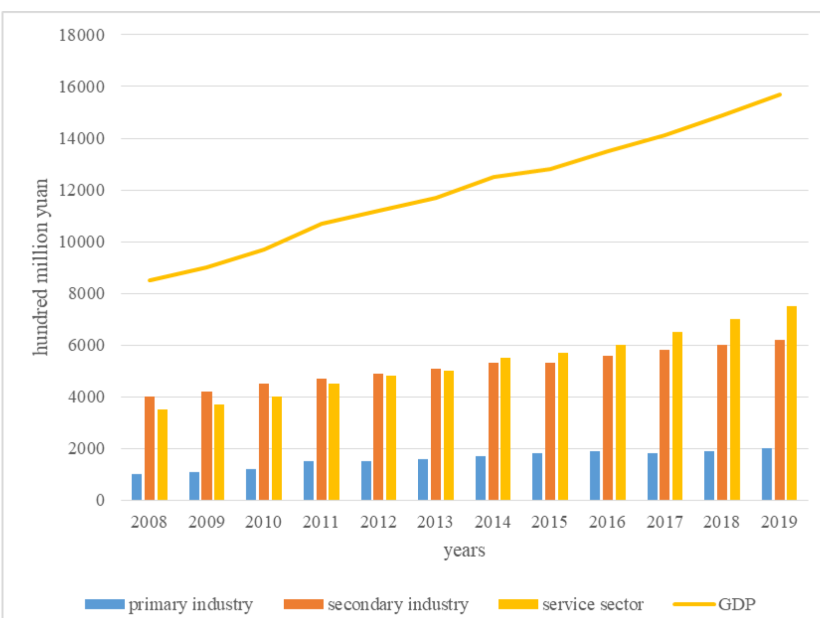
$$q_i = (\Delta y_i, y_i) \tag{13}$$

3 Impact model of AI on ES transformation

3.1 Current ES – taking the Yangtze River Delta as an example

The Yangtze River Delta region, comprising three provinces and one city, is characterised by high degree of population aggregation and strong economic development. Some data show that its population, exceeding 200 million, creates an economic aggregate of more than 20 trillion yuan. This significant economic output places the region not only among the top performers in China but also as a global standout, exceeding the total output of most other regions worldwide. It is a new force for China's economic growth and an important economic foundation. At present, the industrial links between provinces and cities have undergone great changes. As Shanghai transitions toward high-tech industries, the advantages of its traditional industries are gradually diminishing. Conversely, Jiangsu and Zhejiang Provinces hold an important position in China in terms of industrial products (Hafeznia et al., 2017).

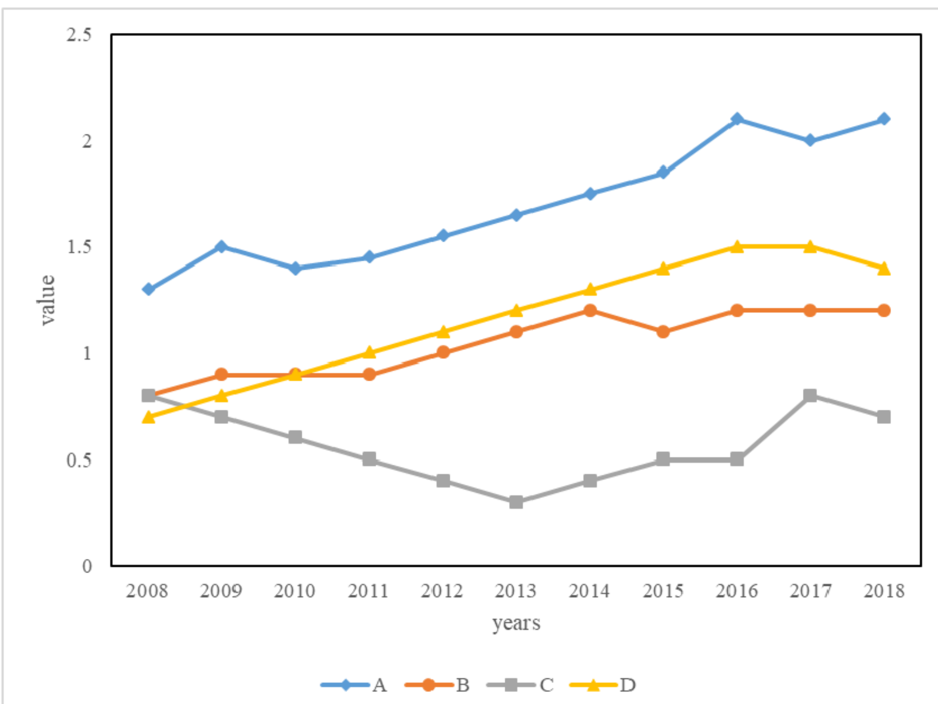
Figure 4 Composition of regional GDP (see online version for colours)



As shown in Figure 4, the total output value of the Yangtze River Delta region has shown a rapid upward trend, rising from 7.5 trillion yuan in 2008 to 23.7 trillion yuan in 2019, with expectations of maintaining a high growth rate. The three industries all showed stable growth, with the THI expanding at a faster pace. After 2015, the output value of the THI saw rapid expansion, whereas the secondary and tertiary industries consistently maintained relatively stable growth rates. This trend is attributable to the swift development of the electronic information industry, which led to the rise and prosperity of various service and financial sectors, alongside the integration of the internet with more traditional agriculture and manufacturing industries in the primary and secondary industries.

Figure 5(A) shows that from 2008 to 2018, the deviation of the overall structure of the Yangtze River Delta region was average and relatively stable, indicating that the overall structure is relatively reasonable. Particularly, Anhui's structural deviation was relatively the highest, reaching its highest in 2011, although its overall trend has been decreasing. In addition, the structural deviations of Shanghai, Zhejiang, and Jiangsu Provinces were relatively moderate, indicating that the ES rationality exhibited minimal disparities and was relatively strong.

Figure 5 ES of the Yangtze River Delta region: (A) structural deviation of the Yangtze River Delta region and (B) advanced ES (see online version for colours)



As shown in Figure 5(B), the overall advancement level of the ES in the Yangtze River Delta region is relatively high and consistently rising. Notably, Shanghai's ES advancement level has remained consistently high, significantly surpassing that of other regions. At the same time, the ES advancement level in Zhejiang and Jiangsu shifted from below 1 to above 1 between 2008 and 2018, demonstrating the rapid development and increasing proportion of the THI. Conversely, Anhui Province's structural advancement level consistently remains below 1. This finding indicates a relatively slow THI development, a persistently high proportion of the secondary industry, and a need for further improvement in its ES advancement.

3.2 Selection of variables and data description

Advancement of ES: ES advancement is an important indicator for measuring the upgrading of ES in general, and it mainly reflects the evolution process of leading industries in the domestic ES (Jakob, 2017).

a *Qualitative ES advancement* $advance\_z$: $advance\_z$ is initially the product of the output value ratio of industry *m* in the region and the labour productivity of the industry and then summed up, as shown as follows:

$$advance\_z_{i,t} = \sum_{m=1}^{3} y_{i,m,t} \times (Y_{i,m,t} / L_{i,m,t}), m = 1,2,3 , \tag{14}$$

When $advance\_z_{i,t}$ is larger, the labour productivity of the leading industry in the region is also relatively high. Therefore, a better structural ratio between industries indicates better ES advancement level.

b *Output value of ES advancement*: Given that the industrial upgrading of the country is mainly to develop the THI, the form of the THI as the leading industry is finally formed. Therefore, a higher THI output value correlates with greater ES advancement. The output value of ES advancement is shown as follows:

$$advance\_l_{i,t} = Y_{i,3,t} / Y_{i,2,t} \tag{15}$$

c *Rationalisation of ES*: ES rationalisation reflects the degree of rational distribution of production factors between ESs. This paper uses the Theil index to measure the ES rationalisation level. This index effectively reflects China's current economic development, and, to some extent, the labour employment structure across the three major industries (Liu et al., 2021). The Theil index, used to measure inequality, is selected in this paper to assess the rationalisation of the expert system. By calculating the differences in labour employment structures across various industries or regions, this index clearly reflects China's current economic development stage and the rationality of the labour employment structure in the three major industries. It also offers a quantitative basis for evaluating the effectiveness of expert system upgrading. The calculation formula is shown as follows:

$$rational_{i,t} = \sum_{m=1}^{3} y_{i,m,t} \times \ln(y_{i,m,t} / l_{i,m,t}), m = 1,2,3 \tag{16}$$

In formula (16), the variable represents the regional industry's proportion of total employment within the region during the specified period. Analysis of the formula reveals that a value approaching 0 signifies a rational ES for the region, whereas a greater deviation from 0 indicates increased ES irrationality (Han and Huo, 2021).

Control variables: ES upgrading is affected by various factors. In this paper, the government influence, the degree of opening to the outside world, population density, and informatisation construction are considered control variables. Particularly, the central and local governments can exert their influence by formulating various industrial policies, such as government spending and tax incentives, enabling them to promote regional ES upgrading from a macro level. This paper considers the use of government fiscal expenditures to measure the influence of local governments. The higher the degree of openness of provinces, cities, and regions, the more beneficial it is for local absorption of advanced knowledge and technology, and the greater the attraction to talents. A higher degree of openness at the provincial, municipal, and regional levels facilitates more frequent exchanges and cooperation with the international market and other regions. This increased interaction provides more opportunities for local areas to engage with and learn advanced knowledge and technology. An open environment also attracts more foreign investment and top talent, further promoting knowledge dissemination and technology introduction, thereby enhancing local innovation capabilities and competitiveness.

The market gains more choices regarding industry selection, and the flow of various production factors becomes more convenient. Therefore, the actual utilisation of foreign capital by local governments is used to measure the degree of opening to the outside world. In addition, human capital resources and informatisation construction are closely related to ES upgrading. Informatisation can accelerate the speed of knowledge spillover and expand the scope of dissemination, which is conducive to the research and development of innovative results. At the same time, big data can also affect local trade costs in real time. These factors collectively affect the upgrading of regional ES. Therefore, the control variables in this paper include government influence, degree of opening to the outside world, population density, and informatisation construction. The above variables are summarised in Table 1.

Table 1 Variable types

Variable type	*Variable name*	*Symbol*
Explained variable	The quality of the advanced industrial structure	*advance_z*
	The amount of advanced industrial structure	*advance_l*
	Rationalisation of industrial structure	Rational
Explanatory variables	AI	AI
Control variable	Government influence	Expend
	Degree of openness	Open
	Information construction	Digital
	Population density	Density

3.3 Model construction

Chinese provinces have different levels of economic development. As a high-precision technology that has emerged recently, AI is also widely used across provinces with different economic development levels. Therefore, this section investigates AI's effect on ES upgrading by constructing an individual fixed effects model. The explanatory variables are defined as the qualitative and quantitative ($advance\_z$) of the aspects of

ES advancement and ES rationalisation ($advance\_l$), with AI serving as the main explanatory variable. Based on the theoretical model analysis in Chapter 3, this paper constructs the following empirical regression model to test its research hypothesis, as shown in the following formulas:

$$advance - z_{i,t} = \beta_0 AI_{i,t} + \beta_1 Control_{it} + \sigma_{i,t} + \phi_{i,t}, \tag{17}$$

$$advance - l_{i,t} = \beta_0 AI_{i,t} + \beta_1 Control_{i,t} + \sigma_{1,i,t} + \phi_{i,t}, \tag{18}$$

$$rational_{i,t} = \beta_0 AI_{i,t} + \beta_1 Control_{i,t} + \sigma_{i,t} + \phi_{i,t} \tag{19}$$

3.4 Descriptive statistics

Table 2 reveals that the value of the explained variable, which serves as the qualitative index for upgrading, ranges between 3.477 and 25.012, indicating notable interprovincial disparities. This result suggests that despite significant differences in the quality of ES upgrading among Chinese provinces, variations in THI labour productivity lead to qualitative distinctions in ES advancement. Comparatively, the index measuring the quantitative aspect of ES upgrading is between 0.499 and 4.237, further highlighting substantial interprovincial differences in ES upgrading. This demonstrates that the development of the THI in each province is also extremely different from that of the secondary industry. Some THIs exhibit substantial development, whereas others lag behind the secondary industry. In addition, obvious differences are also observed among provinces regarding the indicators for measuring ES rationalisation. For some provinces, the value approaches 1, signifying a poor degree of rationalisation.

Table 2 Descriptive statistics of variables

Variable name	*advance _z*	*advance_l*	*Rational*	*AI*	*Expend*	*Open*	*Digital*	*Density*
Observations	283	283	283	283	283	283	283	283
Average value	11	1.1	0.2	128.4	0.3	0.3	0.2	2768.8
Standard deviation	4.6	0.6	0.15	112.3	0.2	0.4	0.1	1191.3
Minimum	3.5	0.5	0.02	0.6	0.1	0.05	0.06	515
Maximum value	25	4.2	0.8	662.8	1.4	3.7	0.6	5823

Regarding explanatory variables, the level of AI exhibits a wide range, with a minimum value of 0.59 and a maximum value of 662.86. This result aligns with China's national conditions, where considerable geographical and other factors exist between provinces, leading to distinct levels of economic development. Consequently, regions with more advance development tend to invest more in AI research and development. Moreover, the discrepancies in ES and AI technology application are quite pronounced, which is also reasonable.

Concerning control variables, the average value of government influence is 0.266, with a relatively large disparity between its minimum and maximum values. This finding indicates varying levels of government intervention in different regions of China. Similarly, the degree of opening to the outside world exhibits significant differences. Due to convenient transportation, the eastern and central regions of China have a relatively high degree of openness. Policies should therefore be modified to promote the degree of opening up in western China. The degree of informatisation construction is also different, attributable to factors such as geography. Population density is related to the degree of regional development; more developed areas tend to attract larger populations. Finally, human capital is also recognised as an important factor in promoting ES upgrading.

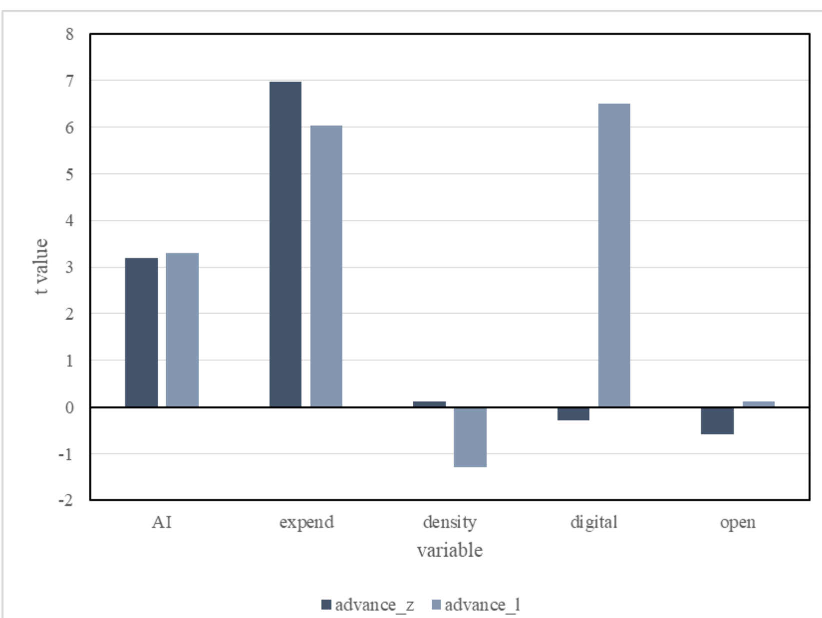
4 Empirical test of ES transformation

4.1 Empirical test of AI on ES advancement

This section empirically analyses the effect of AI on ES advancement. First, a static identification of AI's effect on ES advancement is conducted, followed by expanding the static model into a dynamic one to describe AI's effect when expectation factors are present. To ensure data stationarity, this paper takes the logarithm of the variables whose values are absolute. The measurement software used is Stata 15, and each regression formula adopts robust estimation to eliminate heteroscedasticity and avoid false regression.

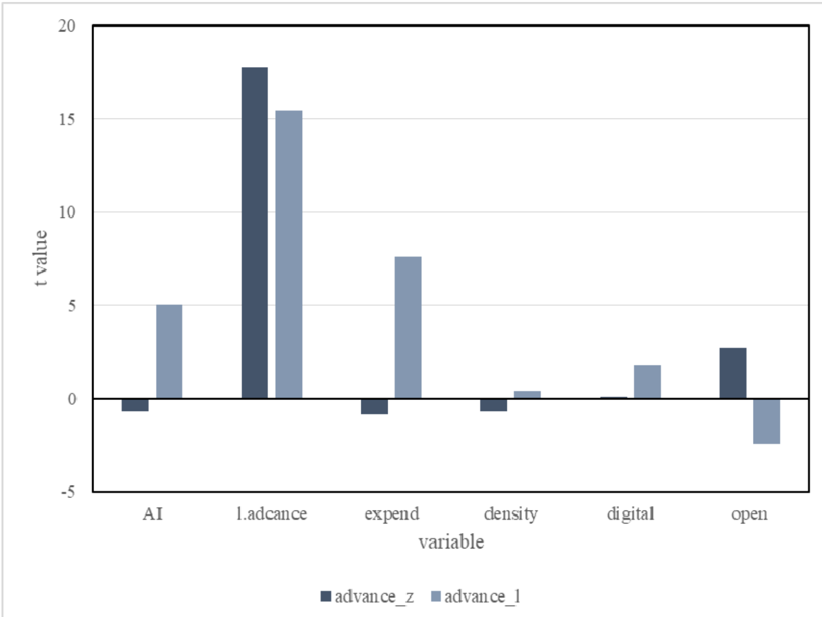
This paper divides the effect of AI on ES advancement into two parts: its influence on the quality of ES advancement (*advance_z*) and its influence on the quantity of ES advancement (*advance_l*). The estimated results of the basic model are shown in Figure 6.

Figure 6 Basic model of advanced ES: (A) static panel and (B) dynamic panel (see online version for colours)



(A)

Figure 6 Basic model of advanced ES: (A) static panel and (B) dynamic panel (see online version for colours) (continued)



(B)

In Table 3, Column (1) uses AI as a single variable for the quality of ES advancement (advance_z). Column (2) adds the corresponding control variable, which increases significantly from 24.40% to 48.1%. This result suggests that the selection of control variables in this paper is highly reasonable. From the regression results, both regression structures are significant, and the coefficients of the core explanatory variables are all positive, indicating a positive correlation between AI investment level and ES advancement.

Table 3 The impact of AI on the advanced ES

	Variable		*Number of samples*	*Adj_R²*
Advanced static panel	Advance_z	(1)	279	24.4%
		(2)	279	48.1%
	Advance_l	(3)	279	38.1%
		(4)	279	62.2%
Advanced dynamic panel	Advance_z	(5)	248	82.5%
	Advance_l	(6)	248	89.7%

In Column (2), AI's effect on the quality of ES advancement (advance_z) is significant at the 5% level. From an economic point of view, a 1% increase in AI investment corresponds to a 0.09% improvement in ES quality. Among the control variables, government influence significantly affects ES upgrading quality. The reason is that government intervention can support some industries, directly promoting ES advancement. Column (3) uses AI as a single variable for the quantity of ES advancement (advance_l), whereas Column (4) adds a control variable, R^2, which increases significantly from 38.1% to 62.2%. This result, again, indicates the appropriateness of the selected control variables. From the regression results, both regression structures are significant, coefficients of the core explanatory variables are positive, and a positive correlation exists between AI investment level and the quantity of ES advancement. In column (4), AI's effect on the quantity of ES advancement (advance_l) is significant at the 5% level, showing a 0.065% increase in structural advancement. Similarly, in terms of control variables, the influence of local governments directly affects the quantity of ES advancement. Informatisation construction can accelerate information flow, and the innovation effect brought by knowledge spillover can prompt enterprises to expedite innovation, thereby promoting ES advancement. Columns (5) and (6) present the dynamic model estimation results for AI's effect on the quality (advance_z) and quantity (advance_l) of ES advancement. The results show that AI's qualitative effect on ES advancement (advance_z) is not significant, and the correlation coefficient is negative. However, the quality of advance_z lagged by 1 period is significantly positive at the 1% level. This result might be due to a mismatch in human capital when industries initially adopt AI technology, resulting in a decline in enterprise labour productivity. Nevertheless, in the long run, AI can promote the qualitative improvement of ES advancement.

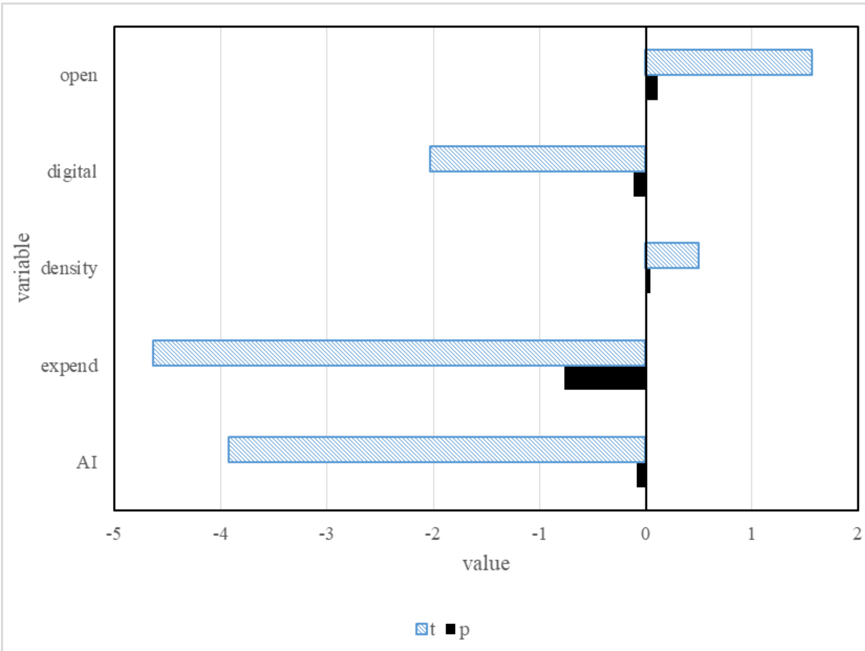
AI and advanced lag 1 are significantly positive at the 1% significance level, indicating that AI positively affects the quantity of ES upgrading. In addition, expectation factors can significantly influence the quantity of ES upgrading. This finding suggests that AI requires a certain period from investment and construction to full functionality. Consequently, local governments should increase investment in AI technology and provide targeted support to enterprises adopting AI technology.

4.2 Empirical test of AI on ES rationalisation

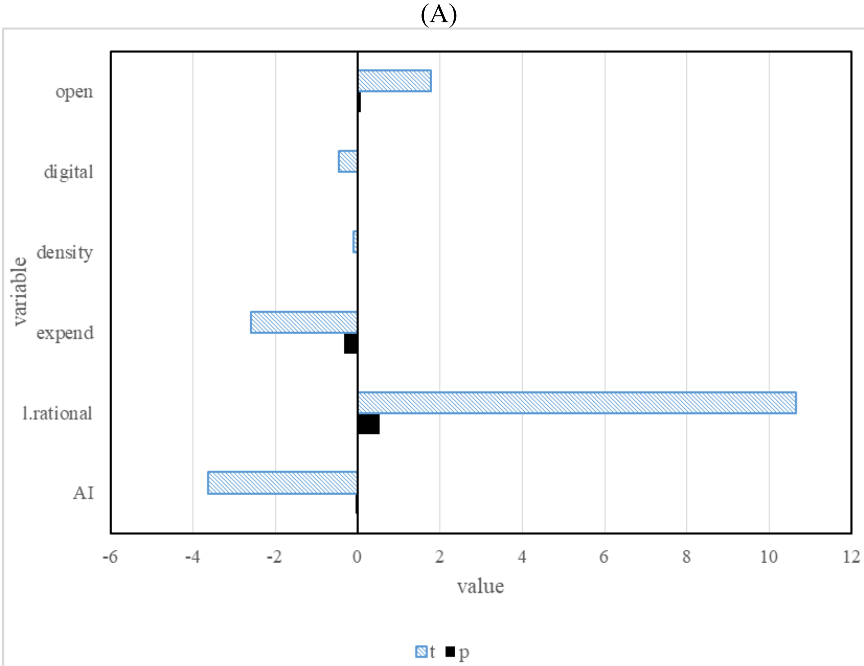
The AI rationalisation level on ES is empirically tested. The estimation results of the basic model are shown in Figure 7.

Column (19) of Table 4 uses AI as a single variable for the rationalisation level of the ES. Column (20), with includes the control variables, improves significantly from 24.4% to 48.1%. This result suggests that the control variables selected in this paper are appropriate. AI significantly affects ES rationalisation (rational) at the 1% significance level. This significant effect may stem from companies adopting AI technology to replace a workforce reduced by aging. This adoption enhances enterprise productivity while promoting the flow of labour from the primary industry to the secondary industry and THI, thereby improving workforce quality and promoting ES rationalisation. Among the control variables, government influence also significantly promotes ES rationalisation. Column (21) presents the estimation results of AI on the dynamic model of industrial integration of physics and chemistry. The results show that AI significantly affects ES rationalisation. A lag of 1 period shows a significantly positive effect on ES rationalisation at the 1% level, indicating that expectation factors can substantially affect ES rationalisation.

Figure 7 ES rationalisation model: (A) static panel estimation results and (B) dynamic panel estimation results (see online version for colours)



(A)



(B)

Table 4 The impact of AI on the rationalisation of ES

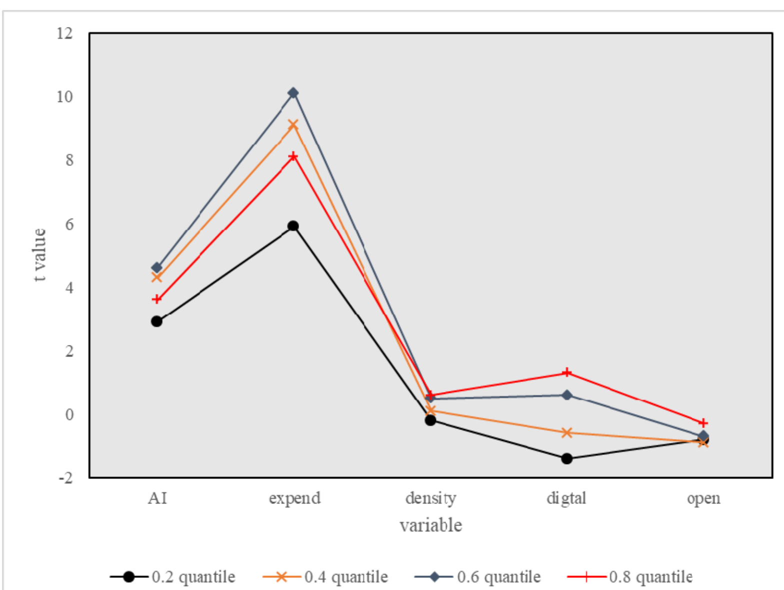
		Number of samples	*Adj_R²*
Static panel	(19)	279	24.4%
	(20)	279	48.1%
Dynamic panel	(21)	279	38.1%

4.3 Impact of AI at different levels of ES

To alleviate the effect of potential data extreme values on the results, this paper comprehensively evaluates AI's influence on ES upgrading at different ES levels. Based on existing research methods, a fixed effect panel quantile regression method is used to analyse AI's influence across various ES levels. Data related to AI and ES from 2009 to 2017 are selected at every 20th percentile. The regression results are shown in Figure 8.

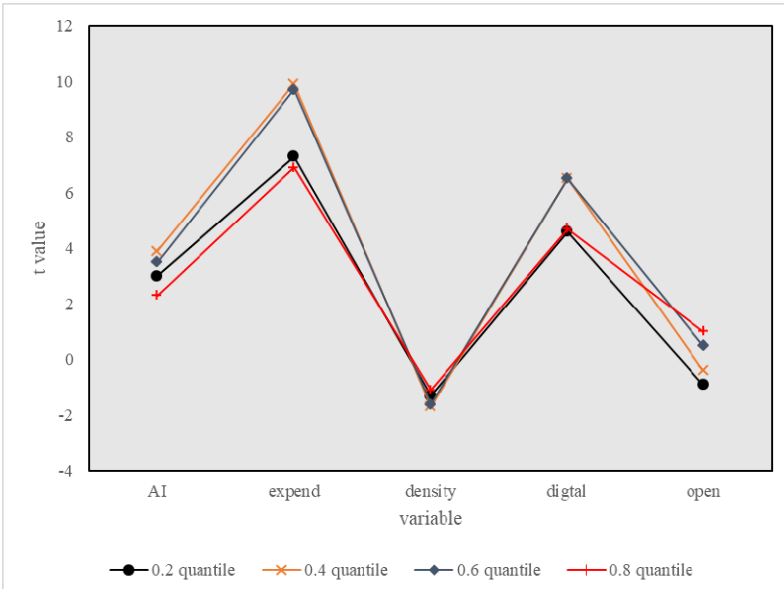
Based on the regression results from Figure 8(A), as the quantile gradually changes from 0.2 to 0.8, the coefficients for AI's influence on the quality of ES advancement (advance_z) consistently decrease, yet remain significant. The coefficient is largest at the 0.2 quantile, indicating that AI exerts its most substantial effect on advanced ES quality when the latter is at a low level. From the perspective of actual ES growth, early AI adoption can quickly improve ES quality. However, as the industry develops, new challenges emerge, necessitating continuous investment in new resources and technologies to ensure ongoing ES improvement and optimisation. Among the control variables, government influence also continuously diminishes.

Figure 8 The impact of AI on ES: (A) the qualitative quantile regression results of AI on the advanced ES; (B) quantile regression results of AI on the amount of advanced ES and (C) quantile regression results of AI on ES rationalisation (see online version for colours)

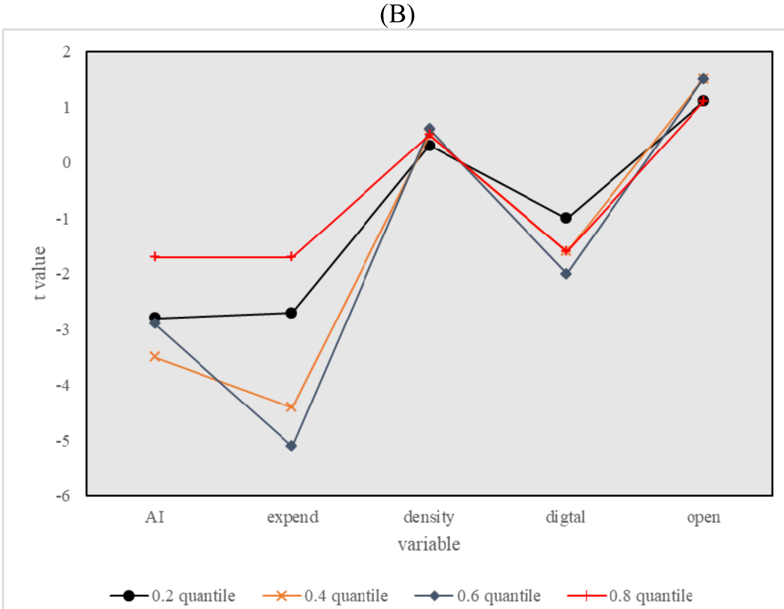


(A)

Figure 8 The impact of AI on ES: (A) the qualitative quantile regression results of AI on the advanced ES; (B) quantile regression results of AI on the amount of advanced ES and (C) quantile regression results of AI on ES rationalisation (see online version for colours) (continued)



(B)



(C)

Regarding the regression results in Figure 8(B), as the quantile gradually changes from 0.2 to 0.8, the coefficient for AI's influence on the quantity of ES advancement (advance_l) also decreases. However, the variation interval of these coefficients is limited, and all remain significant. This result shows that although the marginal effect of

AI on ES advancement progressively weakens with improvements in ES level, the overall reduction is limited, and the effect remains positive. That is, from the perspective of ES advancement, AI has a positive role in its promotion. Among the control variables, government expenditure and the degree of local informatisation continuously increase with the ES advancement level, and their influence gradually increases.

As shown in the regression results in Figure 8(C), when the quantile gradually changes from 0.2 to 0.8, the absolute value of AI's influence coefficient on ES rationalisation consistently decreases. At the same time, the significance level also shows a downward trend. These results demonstrate that AI has a greater influence on ES rationalisation when the latter is at a low or medium-low level. In other words, from the perspective of ES rationalisation level, AI's positive effect is particularly obvious in the low-level and low-medium-level stages.

5 Conclusions

The adjustment of China's ES and employment structure exhibits two primary trends. First, a clear shift exists from policy-driven development to one mainly guided by technological innovation. This phenomenon is evident in the enhanced scientific and technological content of industrial growth, propelled by new industrialisation strategies, and the improved agricultural production efficiency resulting from technological applications. Both instances underscore the increasing influence of technological innovation on the evolution of China's ES and employment structure. Second, there exists an observable emphasis on the development of the real economy. Due to the inherent instability of the virtual economy, the process of ES optimisation increasingly prioritises the real economy, which plays a fundamental role, indicating a strategic reorientation toward its development. In sum, from the perspective of different levels of ES upgrading, AI will play a positive role in promoting the ES. However, the influence of AI varies significantly across different levels and types of ES. Specifically, AI is expected to have a consistently positive effect on the quantity of ES advancement. However, its most substantial effect on the quality of ES advancement occurs when the ES is at a low level. AI's effect on ES rationalisation is more pronounced at low and medium development levels. Despite yielding numerous research findings, this paper presents several limitations. The exploration of specific implementation paths for integrating a low-carbon economy with AI lacks sufficient depth, and the number of case studies is relatively limited, primarily focusing on the Yangtze River Delta region without broader regional comparisons. Furthermore, the analysis of AI's long-term effects and potential risks in driving corporate transformation is insufficient, failing to fully illustrate the complexity and multifaceted nature of technology application.

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Conflicts of interest

The authors declare no conflict of interest.

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