OPPORTUNITIES AND CHALLENGES OF INTELLIGENT GREEN TRANSITION BASED ON STATISTICAL DYNAMICAL ANALYSIS

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The study employs statistical dynamics and structural equation modeling to analyze the impact of economic policies on industrial intelligent green transition, focusing on technology fusion development as a key mediating mechanism. Using stratified sampling of 100 enterprises across steel, chemical, and high-tech sectors, we construct a structural equation modeling framework to examine causal pathways from exogenous factors (policy, market environment, technological innovation) to endogenous outcomes (industrial structure optimization, performance, sustainability, and green development). Empirical results reveal that policy support significantly enhances technology fusion, which in turn drives industrial upgrading and sustainable performance, with notable regional and industrial disparities. These findings provide empirical evidence for optimizing policy design to accelerate China's industrial green transformation.

Keywords: *statistical analysis, green transition, multivariate extreme value*

Introduction

Despite the challenges posed by the domestic and international context, China's economic operation has demonstrated stability in 2024, with indications of progress, and the advancement of high-quality development has been consistent and gradual. The concept of new quality productive forces, which emphasizes enhancing total factor productivity and focuses on innovation and high-quality development, guides economic development toward the real economy, and emerging industries. It is noteworthy that a record high grain output has been achieved. However, challenges such as the growth of productivity in certain industries and the difficulties in the development of the private economy persist. The future of policy will be characterized by an augmentation in domestic demand, the implementation of effective macro policies, and an emphasis on the investment efficiency of infrastructure and manufacturing.

The *intelligent and green* transformation is of crucial significance for China's economic development, aligning with the trends of productive forces and policies. A thorough examination of the organization policies, challenges, and opportunities is imperative to comprehend contemporary development trends and attain high-quality, sustainable growth. This transformation is not merely a reaction to prevailing global trends in environmental protection and technological innovation; it is also an imperative for China to enhance its industrial competitiveness and ensure long-term economic stability. The integration of ad-

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vanced artificial intelligence (AI) technologies into the industrial green-low-carbon development process has been identified as a key element in this transformation. This integration has the potential to optimize resource allocation, reduce energy consumption and emissions, and promote the overall upgrading of the industrial structure. Consequently, a comprehensive and exhaustive investigation of this subject is of substantial theoretical and practical value. The present study employs a structural equation model (SEM) to quantitatively analyze the transmission mechanisms through which economic policies affect industrial structure, performance, and sustainability *via* technology fusion. This analysis provides empirical evidence for policy optimization.

Research on related economic policies

In December 2023, the Central Economic Work Conference advocated for the *AI + Action* initiative, underscoring the nation's emphasis on leveraging science and technology to drive energy transformation. In contemplating the economic trajectory of China in the ensuing years, the nation's economic strategy is poised to prioritize the domains of scientific and technological innovation, green transformation, and supply-side structural reform. This strategic outlook, set to unfold in the year 2025 and beyond, underscores a commitment to a multifaceted approach to economic enhancement and sustainability. In this regard, measures such as the promotion of the national carbon market have been implemented, with the objective of establishing a robust foundation for the low-carbon economy.

In the domain of energy management, AI assumes a pivotal role. The system capabilities extend to the forecasting of energy supply and demand, the optimization of power grid load distribution, and the enhancement of the overall stability of the power system. Within the framework of the production process, the integration of big data and machine-learning algorithms facilitates the implementation of AI, thereby enabling precise process control. The system possesses the capacity to monitor the status of production in real time, issue early warnings in a timely manner, and resolve potential issues. This, in turn, has been demonstrated to enhance production efficiency and minimize waste. In the domain of carbon flow management, the integration of AI [1-3] and machine learning [4-6] facilitates the formulation of emission-reduction strategies. As demonstrated in prior research [1], AI has achieved multifaceted progress in promoting industrial green and low-carbon development, propelled by favorable policies.

The Chinese government is proactively fostering the synergy between intelligence and green development across strategic, market, and technological dimensions to stimulate industrial innovation. However, several challenges must be addressed, including the integration of technology, the high costs of implementation, and the reluctance of businesses to adopt new technologies. Despite these challenges, the increasing integration of AI within the industrial sector is poised to unlock the green potential in energy management, production processes, and carbon flow management. This will not only give rise to emerging industries but also create new employment opportunities and fuel economic growth, enabling China to gain a competitive edge in the global green intelligent industry landscape [7].

Theoretical analysis and research hypotheses

To formalize the hypothesized role of extreme statistical variations in policy impacts, this study employs multivariate extreme value (MEV) modeling to characterize tail dependencies in technology fusion and industrial transformation. The ensuing sections delineate key distributions and correlation structures, thereby establishing a theoretical foundation for the SEM framework in section *Model Construction*. This section elucidates the linkage between policy shocks and sequential changes in technology integration and industrial sustainability.

Suppose $(X_{i,1},\ldots, X_{i,d})$ $i = 1,\ldots$ n is a d-dimensional independent and identically distributed random vector, and the joint distribution function is F, defined:

$$M_n = \left(M_{n,1},\cdots,M_{n,d}\right) = \left(\max_{1\le i\le n} X_{i,1},\cdots,\max_{1\le i\le n} X_{i,d}\right) \tag{1}$$

For a certain i, $\{X_{i,1},\ldots, X_{i,j}\}$ is the maximum value of the j^{th} component ($j = 1, \ldots, d$), so M_n is a vector composed of the maximum values of each component. Its normalized $M_{n,j}$ must be the GEV distribution. Here it is assumed to be the Frechet distribution. Note:

$$S_d = \left\{\left(x_i,\cdots,x_n\right): \sum_{i=1}^{d} x_i = 1, \quad 0 \leqslant x_i \leqslant 1, \quad i = 1,\cdots,d\right\} \tag{2}$$

where S_d is called a d-dimensional simplex.

Under the previous conditions and notations, if there is a normalization constant $a_{n,j} > 0$, $b_{n,j}$, $j = 1, \ldots, d$ such that:

$$Pr\frac{M_{n,1}-b_{n,1}}{a_{n,1}} \le x_1,\cdots,\frac{M_{n,d}-b_{n,d}}{a_{n,d}} \le x_d =$$

$$= F^n(a_{n,1}x_1 + b_{n,1},\cdots,a_{n,d}x_d + b_{n,d}) \to H(x_1,\cdots,x_d), \quad n \to +\infty \tag{3}$$

where H is a d-dimensional distribution function with a non-degenerate edge distribution. Assuming that all marginal distributions are standard Frechet distributions, then:

$$H\left(x_1,\cdots,x_d\right) = \exp\left\{-\int\limits_{S_d \leqslant i \leqslant d} \left|\frac{\omega_i}{x_i}\right| \mathrm{d}K\left(\omega\right)\right\} \tag{4}$$

where $\omega = (\omega_1, \ldots, \omega_d)$, K/d is on S_d that satisfies:

$$\int\limits_{S_d} \omega_j \mathrm{d}K(\omega) = 1,\ j = 1,\cdots,d$$

Let H be a d-dimensional extreme value distribution, and let F be in the maximum value attraction field of H, denoted as $F \in$ MDA(H).

Therefore, $F_j \in$ MDA(H_j), $j = 1, \ldots, d$, that is:

$$F_j^n(a_{n,j}x_j + b_{n,j} + b_{n,j}) \to H_j(x_j)$$

where F_j and H_j are the j^{th} marginal distributions of F and H, respectively. Therefore, the univariate marginal distribution of the MEV distribution must be a GEV distribution.

If the distribution function $F \in$ MDA(H), then the correlation structure function C_0 of H is called the limit extreme correlation structure function of F, which is simply referred to as the limit correlation structure function. Therefore, for each limit correlation structure function C_0 and the distribution function H determined by the marginal distribution H_j:

$$H\left(x_1,\cdots,x_d\right)=C_0\left[H_1\left(x_1;\xi_1\right),\cdots,H_d\left(x_d;\xi_d\right)\right] \tag{5}$$

It is an extreme value distribution. Obviously, the marginal distribution F_j of F determines the marginal distribution H_j of H, and it is independent of the limit correlation structure function. The C_0 is completely determined by the correlation structure function of F.

Let $X = (X_1,\ldots, X_d)$ have a joint distribution function H, and its marginal distributions H_j, $j = 1,\ldots, d$ are continuous. After transformation:

$$Y_j=\frac{-1}{\log H_j(X_j)},\quad j=1,\cdots,d \tag{6}$$

Then, the joint distribution function of $Y = (Y_1,\ldots, Y_d)$ is:

$$H_*(y_1,\cdots,y_d)=H\left(H_1^{-1}\left(\exp\left\{-y_1^{-1}\right\}\right),\cdots,H_d^{-1}\left(\exp\left\{-y_d^{-1}\right\}\right)\right),\quad y_1\geqslant 0,\cdots,\quad y_d\geqslant 0 \tag{7}$$

That is, if the marginal distribution of H_* is the standard Frechet distribution, then H is a MEV distribution, if and only if H is also a MEV distribution [8].

In order to make full use of the extreme information contained in the data, we consider those observations X_j that exceed the threshold u, which can be described by the distribution of observations above the threshold or the distribution function of exceedances. If $F(x)$ is known, these distribution functions can be fully determined. In practical applications, $F(x)$ is often unknown, so we consider its limit distribution, just like the GEV distribution as the limit distribution of the maximum value, we can find the limit distribution of exceedances.

Definition: If the distribution function of the random variable X is:

$$G(x;\mu,\sigma,\xi)=1-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi},\quad x\geqslant\mu,\quad 1+\frac{\xi(x-\mu)}{\sigma}>0 \tag{8}$$

Then X is said to follow the Generalized Pareto Distribution, abbre*via*ted as GPD or GP distribution. Where $\mu\in\mathbb{R}$ is the location parameter, $\sigma > 0$ is the scale parameter, and $\xi\in\mathbb{R}$ is the shape parameter.

We use α to represent the shape parameter, so the generalized Pareto distribution can be specifically expressed:

$$G_1(x;\mu,\sigma)=\begin{cases}1-\mathrm{e}^{-\frac{x-\mu}{\sigma}}, & x\geq\mu\\ 0, & x<\mu\end{cases} \tag{9}$$

$$G_2(x;\mu,\sigma,\alpha)=\begin{cases}1-\left(\dfrac{x-\mu}{\sigma}\right)^{-\alpha}, & x\geq\mu+\sigma,\quad \alpha>0\\ 0, & x<\mu+\sigma\end{cases} \tag{10}$$

$$G_3\left(x;\mu,\sigma,\alpha\right)=,\begin{cases} 0, & x<\mu-\sigma \\ 1-\left(-\dfrac{x-\mu}{\sigma}\right)^{\alpha}, & \mu-\sigma\le x\le\mu, \quad \alpha>0 \\ 1, & x>\mu \end{cases} \tag{11}$$

where G_1, G_2, and G_3 are, respectively, referred to as Pareto type I, II, and III distributions. Similar to the notation of the GEV distribution, when $\mu = 0$, $\sigma = 1$, it is called the standard GPD, and the corresponding distributions are denoted as $G(x; \xi)$, or $G_1(x)$, $G_2(x; \alpha)$, and $G_3(x; \alpha)$.

Therefore, the distribution $G_1(x)$ is an exponential distribution, $G_2(x; \alpha)$ is a Pareto distribution, and $G_3(x; \alpha)$ is a Beta distribution. Specifically, when $\alpha=1$, $G_3(x; 1)$ represents a uniform distribution over the interval [–1, 0]. It can be easily verified that when $\log H_j > -1$, there is $G_j = 1 + \log H_j$.

We can see that there is a very close relationship between the generalized extreme value distribution and the generalized Pareto distribution. When $\xi > 0$, the support of $G(x; \mu, \sigma, \xi)$ is $[\mu, +\infty]$, and if we take $\alpha = 1/\xi$, then:

$$G(x;\mu,\sigma,\xi)=1-\left(\frac{x-\dfrac{\mu-\sigma}{\xi}}{\dfrac{\sigma}{\xi}}\right)^{-1/\xi}=G_2\left(x;\frac{\mu-\sigma}{\xi},\frac{\sigma}{\xi},\alpha\right) \tag{12}$$

When $\xi < 0$, the support of $G(x; \mu, \sigma, \xi)$ is $|\mu, \mu - \sigma/\xi|$. If we take $\alpha = -1/\xi$, then:

$$G(x;\mu,\sigma,\xi)=1-\left(-\frac{x-\dfrac{\mu-\sigma}{\xi}}{-\dfrac{\sigma}{\xi}}\right)^{-1/\xi}=G_3\left(x;\frac{\mu-\sigma}{\xi},-\frac{\sigma}{\xi},\alpha\right) \tag{13}$$

Obviously, when $\xi = 0$, that is:

$$\lim_{\xi\to 0}G(x;\mu,\sigma,\xi)=G_1(x;\mu,\sigma)$$

the support is $[\mu, +\infty]$. It can be seen that the type of the GP distribution is completely determined by the sign of ξ.

When $\mu = 0$, $\sigma > 0$, the distribution function $G(x; \mu, \sigma, \xi)$ plays an important role, which is called the two-parameter generalized Pareto distribution. For the sake of simplicity of notation, we sometimes write $G(x; \sigma, \xi)$ as $G(x; 0, \sigma, \xi)$.

It is not hard to find that the density function of GPD is:

$$g(x;\mu,\sigma,\xi)=\frac{1}{\sigma}\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi-1}, \quad x\ge\mu, \quad 1+\frac{\xi(x-\mu)}{\sigma}>0 \tag{14}$$

Moreover, we give the relationship between the survival function $\bar{F}(t)$, the average excess function $e(t)$, and the hazard rate function $q(t)$:

$$\bar{F}(t) = \exp\left\{-\int_{x_*}^{t} q(x)\mathrm{d}x\right\}, \quad x_* < t < x^* \tag{15}$$

$$e(t) = \frac{\int_t^{\infty} \bar{F}(x)\,\mathrm{d}x}{\bar{F}(u)}, \quad x_* < t < x^* \tag{16}$$

$$q(t) = \frac{1+e'(t)}{e(t)}, \quad x_* < t < x^* \tag{17}$$

As can be seen, as long as we give one of $\bar{F}(t), e(t)$, and $q(t)$, , the other two formulas can be obtained from the previous equation [8].

Benchmark model setting and variable definition

It is hypothesized that in the context of the *intelligent and green* transformation, China's economic policies have a positive impact on the integrated development of AI and green and low-carbon technologies in the industrial sector. This, in turn, promotes the optimization of the industrial structure, the improvement of industrial performance, and the enhancement of industrial sustainability. Ultimately, this will realize the overall improvement of the level of industrial green and low-carbon development. Furthermore, the impact of industrial policy varies among different industrial types and regions. It is also subject to regulation by factors such as the market environment and technological innovation ability [9].

– Technology fusion development function *TFD* = *f* (Policy, *ME*, *TIC*)

The degree of integrated development of AI and green and low-carbon technologies in the industrial sector is expressed as a function of economic policies, market environment and technological innovation capabilities:

$$TFD = \alpha_1 \text{Policy} + \alpha_2 ME + \alpha_3 TIC + \sum_{i=1}^{n} \delta_{1i} \text{IndustryType}_i + \sum_{j=1}^{m} \gamma_{1j} \text{Region}_j + \epsilon_1 \tag{18}$$

where α_1, α_2, and α_3 are the influence coefficients of Policy, *ME*, and *TIC* on *TFD*, respectively, δ_{1i} – the influence coefficient of different industrial types on *TFD*, γ_{1j} – the influence coefficient of different regions on *TFD*, and ϵ_1 – the error term.

– The optimization of industrial structure depends on the degree of technological fusion development, economic policies and industrial types. Assume the functional form is:

$$ISO = \beta_1 TFD + \beta_2 \text{Policy} + \sum_{i=1}^{n} \theta_{1i} \text{IndustryType}_i + \epsilon_2 \tag{19}$$

where β_1 and β_2 are coefficients, θ_{1j} – the influence coefficient of different industrial types on *ISO*, and ϵ_2 – the random error term.

– The optimization of industrial structure depends on the degree of technological fusion development, economic policies and industrial types. Assume the functional form is:

$$IPE = \lambda_1 TFD + \lambda_2 ME + \sum_{i=1}^{n} \varphi_{1i} \text{IndustryType}_i + \epsilon_3 \tag{20}$$

where λ_1 and λ_2 are coefficients, φ_{1j} – the influence coefficient of different industrial types on *IPE*, and ϵ_3 – the random error term.

– The enhancement of industrial sustainability is the comprehensive result of the improvement of industrial performance, the optimization of industrial structure, economic policies and technological innovation capabilities. Assume the function is:

$$ISS = \mu_1 IPE + \mu_2 ISO + \mu_3 \text{Policy} + \mu_4 TIC + \sum_{j=1}^{m} \omega_{1j} \text{Region}_j + \epsilon_4 \tag{21}$$

where μ_1, μ_2, and μ_3 are the coefficients, ω_{1j} – the influence coefficient of different regions on *ISS*, and ϵ_4 – the random error term.

– Industrial green and low-carbon development level function *IGLCD* = l(*ISS, TFD, ME,* Policy, Region).

The level of industrial green and low-carbon development is a function of the enhancement of industrial sustainability, the degree of technological fusion development, the market environment, economic policies and regional factors. Assume the function is:

$$IGLCD = \rho_1 ISS + \rho_2 TFD + \rho_3 \text{Policy} + \sum_{j=1}^{m} \kappa_{1j} \text{Region}_j + \epsilon_5 \tag{22}$$

where ρ_1, ρ_2, and ρ_3 are the coefficients, κ_{1j} – the influence coefficient of different regions on *IGLCD*, and ϵ_5 – the random error term [10].

Model construction

Structural equation model framework

The hypothesized relationships are the foundation for the construction of a SEM. This model is employed to illustrate the hierarchical influence of exogenous variables on industrial green development, as depicted in fig. 1.

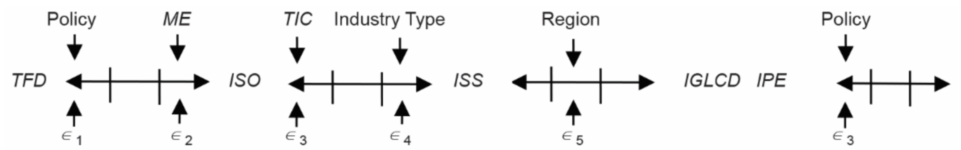

Figure 1. Model 1 for SEM

The model offers a comprehensive reflection of the influence relationship from exogenous variables (Policy, *ME*, *TIC*, Industry Type, Region) to endogenous variables (*IGLCD*), including the transmission mechanism and error terms of each intermediate variable (*TFD, ISO, IPE, ISS*). Within the model, Policy, *ME, TIC*, Industry Type, and Region are designated as exogenous variables, while *TFD, ISO, IPE, ISS*, and *IGLCD* are classified as endogenous variables. The error term, ϵ, is also incorporated into the model. The utilization of SEM software, such as AMOS and LISREL, facilitates the estimation and testing of the model, the analysis of the path coefficients and goodness-of-fit between variables, and the verification of the validity of the research hypotheses.

Variable classification and path specification

The Model 2 delineates five structural equations to quantify direct and indirect effects. To illustrate, the *TFD* model is formulated as a function of Policy, *ME*, *TIC*, industrial types, and regions, with coefficients denoting the magnitude of each influence. The following mind map offers a visual representation of the SEM architecture, emphasizing the role of *TFD* as a central mediator between exogenous drivers and endogenous outcomes, fig. 2.

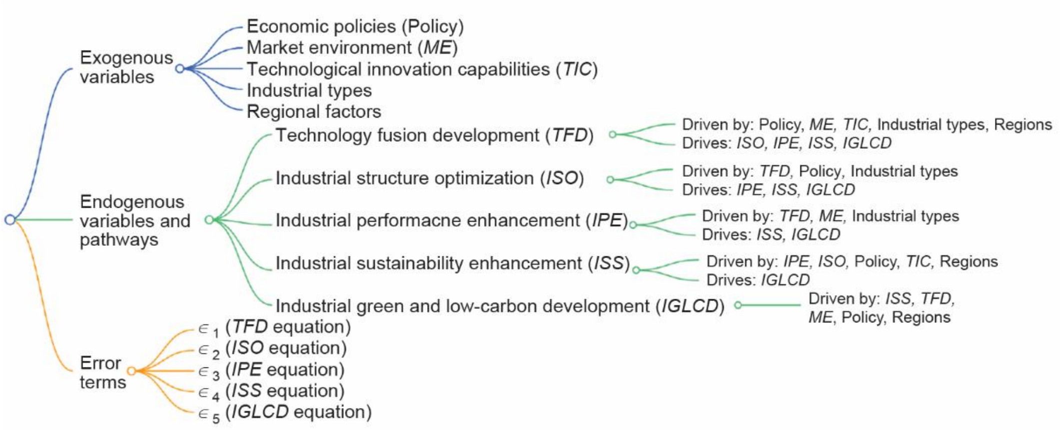

Figure 2. Model 2 for SEM for industrial intelligent green transition

Variables and sample selection

Variable setting

Independent variables encompass economic policies (quantified by enterprise subsidies, tax exemptions, and policy intensity), market environment (measured by market research to assess demand, competition, and price), technological innovation capabilities (judged based on the proportion of scientific research investment, the number of patents, and the proportion of R & D personnel), industrial types (distinguished by dummy variables such as traditional manufacturing, high-tech, and energy industries), and regions (assigned corresponding values for the eastern, central, western, and northeastern regions).

The mediating variables encompass the degree of technology integration (*e.g.*, R & D investment), industrial structure optimization (as indicated by the proportion of green and low-carbon industries, the upgrading proportion of traditional industries, and changes in industrial concentration), industrial performance (assessed by indicators such as profit margins), and industrial sustainability (evaluated from aspects such as resource utilization, pollutant emission reduction, and social responsibility fulfillment).

The dependent variable of this study is the level of industrial green and low-carbon development. The hierarchical or principal component analysis method is employed to synthesize indicators such as energy consumption, carbon emission intensity, and the market share of green products and services to construct a comprehensive evaluation index [11].

Sample selection

Industries concentrate on representative sectors, such as steel and chemical industries, to underscore industrial disparities.

Enterprises are selected according to stratified sampling, including those of different scales and natures. Large enterprises play a leading role, medium-sized enterprises are flexible, and small enterprises are innovative, which helps analyze the policy effects.

The regions encompass the conventional provinces in the eastern, central, western, and northeastern regions of China, with a consideration of numerous factors to augment the generalizability of the results. The regions encompass the conventional provinces in the eastern, central, western, and northeastern regions of China, with a consideration of numerous factors to augment the generalizability of the results.

A stratified random sampling method was adopted to select 100 enterprises. The sample included 30 respondents from the traditional manufacturing industry, 40 from the high-tech industry, and 30 from the energy industry. Furthermore, a total of 25 enterprises were selected from each of the eastern, central, western, and northeastern regions. The sample size was determined according to the SEM parameter estimation rule (10 observations per parameter) to ensure statistical power (Power ≥ 0.8).

Data collection

Questionnaires are disseminated to a sample of enterprises. The integration of online and offline methodologies facilitates the aggregation of data concerning policies and technology integration, thereby ensuring the efficacy of the recovery rate.

A sample of representative enterprises is selected for in-depth interviews to explore their transformation experiences and demands, which serve to supplement the data gathered through the questionnaire.

A variety of public channels are utilized for the purpose of collecting data, with the objective of cross-validating the questionnaire and interview materials. This approach is adopted to enhance the reliability of the collected data.

In conclusion, this series of processing provides scientific support for the empirical analysis of policy impacts as well as for decision-making and management.

Empirical results and analysis

Following the estimation and testing of the SEM with the collected data, empirical results were obtained. Initially, the goodness-of-fit indicators are examined. The $\chi^2/\mathrm{d}f$ is 1.78 (less than 2), the *CFI* is 0.94 (greater than 0.9), the *RMSEA* is 0.058 (less than 0.08), and the *SRMR* is 0. The findings indicated that the model demonstrated a satisfactory fit, as evidenced by its performance within the acceptable range of 049 (0.08). This observation suggests the presence of a variable relationship that can be explained by the model structure.

The path coefficients demonstrated that the implementation of economic policies has been demonstrated to exert a substantial positive influence on the development of technological fusion. For instance, an increase of 10 units in policy support resulted in an average increase of 4.5 units in the degree of technological fusion development, thereby substantiating the promotion role of policies.

The market environment also exerted a substantial positive influence. Specifically, the growth of market demand scale notably promoted technological fusion, as it drove enterprises to invest more to meet demand.

The ability to innovate in the technological sphere has been demonstrated to exert a positive influence on the development of technological fusion. Enterprises that allocate more resources to R & D, possess a greater number of patents, and employ more personnel demonstrated stronger performance in this regard.

The development of technological fusion had a considerable positive effect on the optimization of industrial structure, the improvement of performance, and the enhancement of sustainability. This initiative has given rise to novel forms, modernized industries, enhanced performance, and bolstered sustainability.

The path coefficients among industrial structure optimization, performance improvement, sustainability enhancement, and the level of industrial green and low-carbon development were all positive. This finding corroborates the established roles of these actors in the promotion of industrial green and low-carbon development through economic policies.

In conclusion, a divergence in characteristics was observed among the various industrial types and geographical regions. In certain respects, high-tech industries and the eastern region demonstrated superior performance. However, it should be noted that these outcomes were influenced by various economic policies, market conditions, and technological innovation capabilities. The variable data of specific sample enterprises is shown in tab. 1.

Table 1. Variable data of sample enterprises in intelligent green transition research

Enterprise number	1	2	3	4	5	6	7	8	9	10
Policy (10-50 points)	40	20	50	20	40	30	50	20	40	30
ME (10-50 points)	30	40	40	10	30	20	40	10	30	20
TIC (10-50 points)	40	30	50	20	40	30	50	20	40	30
Industry Type (0-20 code)	10	0	20	0	10	0	20	0	10	0
Region (0-40 code)	20	30	10	40	20	30	40	10	30	20
TFD (10-50 points)	40	50	20	10	30	30	40	20	30	40
ISO (10-50 points)	30	20	40	20	20	50	30	10	40	30
IPE (10-50 points)	40	30	50	20	40	30	50	20	40	30
ISS (10-50 points)	30	20	40	10	30	20	40	10	30	20
IGLCD (10-50 points)	40	30	50	20	40	30	50	20	40	30

Note: Table 1 displays data from 10 typical enterprises (full sample $n = 100$). Normality was verified via the Shapiro-Wilk test ($p > 0.05$), and variance inflation factor ($VIF < 2.5$) indicates no multicollinearity.

Conclusions and policy recommendations

In summary, through theoretical analysis, model construction, and empirical testing, this study comprehensively investigated the impact of China's economic policies on the development of AI in promoting industrial green and low-carbon development in the context of the *intelligent and green* transformation in 2025. The findings of the research indicate that China's economic policies have exerted a dynamic influence on the integration and advancement of AI and green and low-carbon technologies within the industrial sector. This, in turn, has led to the optimization of industrial structure, the enhancement of industrial performance, and the promotion of industrial sustainability. Consequently, these policies have culminated in a comprehensive enhancement of the level of industrial green and low-carbon development. Concurrently, factors such as the prevailing market environment and technological innovation capacity have also exerted a significant regulatory influence on this process, with notable variations observed among diverse industrial types and geographical regions.

In light of the aforementioned conclusions, the following policy recommendations are hereby proposed as follows.

- The ongoing refinement of economic policies is imperative. The government should further increase policy support for the *intelligent and green* transformation of the industry, improve financial subsidy and tax incentive policies, and ensure the accuracy and effectiveness of policies. Concurrently, efforts must be made to fortify industrial planning and guidance, elucidate the developmental trajectories and priorities of disparate industries, galvanize the harmonized advancement of diverse sectors, and establish a comprehensive intelligent green industrial ecosystem.
- The enhancement of the market environment is imperative. The implementation of measures such as cultivating market demand, strengthening market supervision, and standardizing market competition order is essential for the creation of a market environment conducive to the *intelligent and green* transformation of the industry. It is imperative to encourage consumers to purchase intelligent green and low-carbon products, and to promote enterprises to increase technological innovation and product upgrading efforts to improve market competitiveness.
- It is imperative to enhance technological innovation capabilities. It is imperative to augment the support for scientific research investment, while concurrently encouraging enterprises, universities, and research institutions to enhance their collaborative efforts. Furthermore, there is a necessity to cultivate interdisciplinary professionals, facilitate the resolution of technical impediments associated with the integration of AI and industrial green and low-carbon technologies, and enhance the technological innovation capacity and level. Moreover, it is essential to provide substantial technical support for industrial development.
- The promotion of industrial development must be conducted in accordance with the prevailing local conditions. It is imperative to comprehensively assess the resource endowments, industrial foundations, and developmental needs of disparate regions. This assessment should inform the formulation of nuanced industrial development policies. The eastern region should continue to leverage its competitive advantages to spearhead the development of intelligent green industries, while also fortifying international cooperation and competition. The central region can leverage its inherent industrial strengths to expedite the modernization and transformation of traditional industries. The western region should capitalize on its resource-based advantages to foster the growth of distinctive intelligent green industries. The northeastern region should promote the revitalization of traditional industrial bases and enhance technological innovation and industrial transformation.
- It is imperative to enhance the coordination of industrial policies. It is imperative that all departments enhance their co-ordination and cooperation to establish policy synergy, thereby mitigating potential conflicts and contradictions among different policies. Concurrently, the establishment and enhancement of a policy evaluation and feedback mechanism is imperative. The timely adjustment and improvement of policy measures is crucial to ensure the achievement of policy goals. Furthermore, the promotion of high-quality and sustainable development of China's industry in the process of *intelligent and green* transformation is essential. These measures will lay a solid foundation for the prosperity of China's economy in 2025 and beyond.
- Future research endeavors should aim to expand the sample range and research fields. A comprehensive analysis of the impact of other potential factors on the *intelligent and*

green transformation of the industry is also necessary. Furthermore, the exploration of international co-operation and competition strategies for the green and low-carbon development of China's industry in the context of global economic integration is essential. This will provide more comprehensive and in-depth theoretical support and practical guidance for the formulation and implementation of economic policies.
- The aforementioned content is intended for informational purposes only. The framework can be adapted and augmented in accordance with the specificities of the prevailing research context. It is my hope that this will prove beneficial to you. Should further inquiries arise, they are welcome.

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