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MULTIDIMENSIONAL DRIVING EFFECTS OF NEW ENERGY VEHICLE MARKET ON GDP GROWTH

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Abstract: In the context of global carbon neutrality and digital economy transformation, the new energy automobile industry has emerged as a pivotal catalyst for restructuring the global energy and industry landscape. However, this rapid growth is accompanied by inherent contradictions, including policy implementation deviations, which hinders its ability to meet the demands of conventional analytical frameworks. In this study, we constructed a multidimensional synergistic evaluation system and analyzed the market dynamics and economic transmission mechanism by using a combination of simulated annealing-moving average-long short-term memory (SA-MA-LSTM) models. The study identified a "threshold effect" in the driving force of industry on gross domestic product (GDP), indicating that infrastructure and supply chains can impede development. The analysis revealed a non-linear relationship between policy and market, emphasizing the necessity for diversified supply strategies. The study proposes the establishment of a dynamic subsidy mechanism, the construction of a technology sharing platform, and other policy insights. These measures will provide an assessment tool for the sustainable development of the industry and contribute to China's experience in economic transformation under global carbon neutrality.
Keywords: New energy vehicle market; SA-MA-LSTM prediction; Policy-Technology-Market synergy framework; GDP driving effect

1 INTRODUCTION

Against global carbon neutrality and digital economic transformation, the new energy vehicle industry drives reshaping the global energy and industrial landscape. China advances it via financial subsidies and double - integral policies, with 2024 market penetration expected at 47.8%, boosting regional growth. However, literature shows three research limitations: Policy impact studies are mostly one - dimensional. Liao Shuimei et al. built a policy intensity index [1], and Ye Zhouzhe analyzed policy synergies with a spatio - temporal tensor model, but both lack a dynamic game framework [2]. Enterprise tech innovation assessment leans toward patents and investment efficiency (Li Xiaoyi et al. decomposed total factor productivity via a DEA model [3], and Gong Xingyue analyzed R&D input impacts with PCA - GARCH - LSTM), yet both ignore tech innovation's effect on R&D investment [4]. Analyzing R&D investment impact needs aligning tech and market. Consumer demand research relies on static indicators, like Lin Chuchao's search index modeling and Zou Tingting's gray model for substitution effect, but misses real - time behavioral data [5]. The conventional framework struggles to quantify multi - dimensional synergies, so a systematic evaluation model is urgent. This paper proposes a novel approach that challenges the conventional paradigm. It employs a multi-dimensional, synergistic evaluation system encompassing government entities, business enterprises, and consumers. The paper utilizes PCA (principal component analysis) to extract the key driving factors. It then designs a simulated annealing algorithm-optimized moving average-long and short term memory network (SA-MA-LSTM) combination model [6]. The model systematically analyzes the dynamic evolution law of the new energy vehicle market and its macroeconomic transmission mechanism, thereby revealing the "threshold effect" of the industry's driving force on GDP. When the ecological health of the market breaks through a threshold, the marginal gains of economic growth are accelerated and released. At this point, the infrastructure carrying capacity and supply chain stability become key constraints. The findings of the research endeavor offer valuable insights that inform policy formulation, including the development of dynamic subsidy mechanisms and the establishment of technology sharing platforms. Furthermore, the study provides high-resolution assessment tools that facilitate the pursuit of sustainable industrial development.

2 MULTI-DIMENSIONAL FORECAST OF NEW ENERGY VEHICLE MARKET IMPACT ON GDP

The construction of a multi-dimensional evaluation system for the new energy vehicle market facilitates the development of a data-driven GDP prediction model. This model is constructed by measuring the impact of the annual average growth rate of the system and the annual growth rate of other variables contributing to the annual growth rate of GDP on the annual growth rate of the dependent variable GDP. A single variable is controlled to analyze the correlation between different development scenarios of the new energy vehicle market and the growth rate of GDP.

2.1 Feature Dataset Creation

2.1.1 Time-series dataset

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The data for this study were obtained from https://data.stats.gov.cn. In order to remove the effect of the quantitative scale, this paper first standardizes each indicator and calculates its corresponding annual growth rate. The meaning of each indicator for quantifying the GDP growth rate is shown in Table 1.

Table 1 GDP Growth Rate Indicators and Their Implications

Variable Symbol	Variable Meaning(%)
Y	Annual Growth Rate of GDP
X_1	Annual Growth Rate of Consumption Level of the Population
X_2	Annual Growth Rate of Total Import and Export Trade
X_3	Annual Growth Rate of Fixed Asset Investment
X_4	Annual Growth Rate of Total Retail Sales of Consumer Goods
X_5	Annual Growth Rate of Fiscal Expenditures
X_6	Annual Growth Rate of Value Added of Industry
X_7	New Energy Vehicle Market Indicators Annual Growth Rate

This study employs the annual GDP growth rate as the core dependent variable and systematically incorporates seven key independent variables for quantitative modeling, covering the complete observation cycle from 2017 to 2024. The process entails the systematic collection and organization of annual time-series data for each indicator, culminating in the establishment of a quarterly time-series dataset that boasts a complete structure and lucid dimensions.

2.1.2 Covariance diagnosis

The multicollinearity problem is manifested as the high linear correlation between independent variables, which may lead to the inflated variance of parameter estimation, widening of confidence interval and failure of hypothesis testing, and in extreme cases, even lead to unrecognizable model. In this paper, based on the Pearson correlation coefficient matrix analysis of the time series data, we identify the characteristic variables that are highly correlated with the target variable “GDP growth rate”, and set the absolute value of the correlation coefficient threshold at 0.7, and then we exclude the "growth rate of the level of consumption Accordingly, the three characteristics of “growth rate of consumption level of residents”, “growth rate of total retail sales of consumer goods” and “growth rate of value added of industry” are excluded to mitigate the risk of overfitting of the target variable.

The Variance Inflation Factor (VIF) method was further adopted to detect the covariance among features, and its calculation formula:

$$VIF(i) = \frac{1}{1-R_i^2} \tag{1}$$

R_i^2 is the coefficient of determination of the regression of a variable on other variables. The iterative algorithm was employed to remove the maximum covariance characteristics of the VIF value exceeding the threshold (set at 10). The calculation determined that the VIF value of "fixed asset investment growth rate" reached 74.98, indicating a severe covariance problem that was subsequently eliminated. Following this treatment, the VIF values of the three retained features—namely, the growth rate of total import and export trade, the growth rate of financial expenditure, and the growth rate of the comprehensive development index of new energy automobiles—are reduced to 1.65, 3.60, and 4.47, respectively. These values are significantly lower than the critical threshold.

As shown in Figure 1, the validation of the final feature set is completed by the heat map of the correlation coefficient matrix. The absolute value of the Pearson correlation coefficient between the retained features is lower than 0.5. For example, the correlation coefficient between "growth rate of total import and export trade" and "growth rate of fiscal expenditure" is -0.44, and the correlation coefficient between "growth rate of fiscal expenditure" and "growth rate of comprehensive development index of new energy vehicles" is 0.48.

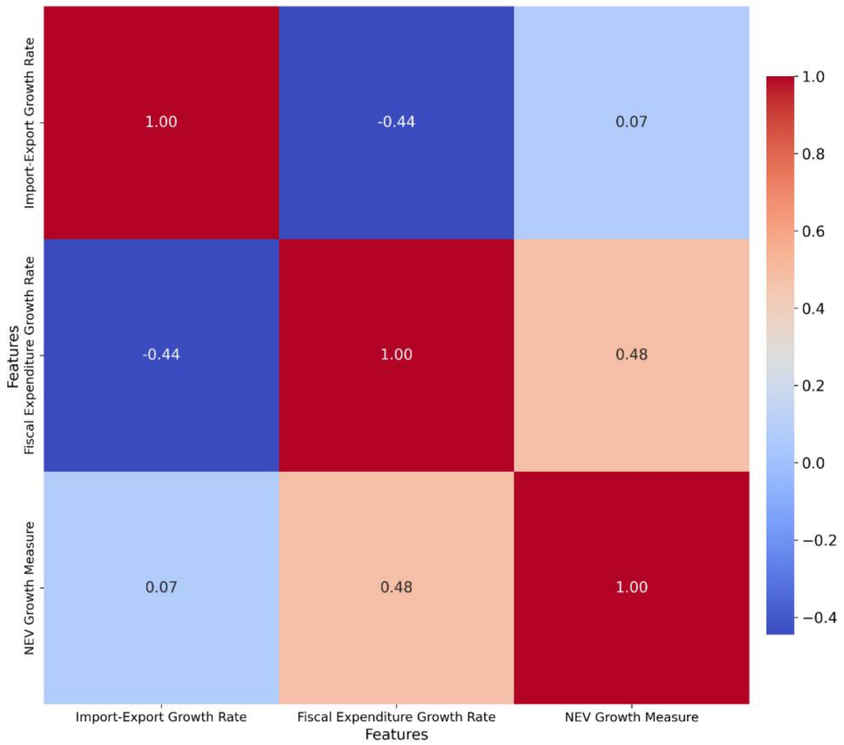

Figure 1 Heat Map of the Matrix of Eigen-correlation Coefficients

This indicates that the independence between features has significantly improved. The correlation coefficient between "growth rate of total import and export trade" and "growth rate of financial expenditure" is -0.44. The correlation coefficient between "growth rate of financial expenditure" and "growth rate of comprehensive development index of new energy vehicles" is 0.48. This indicates that the independence between features has significantly improved.

2.1.3 Feature training set

For time series data, this paper uses a sliding time window to convert the normalized multidimensional features into sequences for supervised learning. The training set covers data from 2018 to 2022, and the test set contains data from 2023 to 2024. The training and test sets are in the ratio of 71.4%：28.6%.

2.2 MA-LSTM Hybrid Model

For the processed time series set and feature dataset, the combined MA-LSTM model with the architecture of Figure 2 is used for prediction.

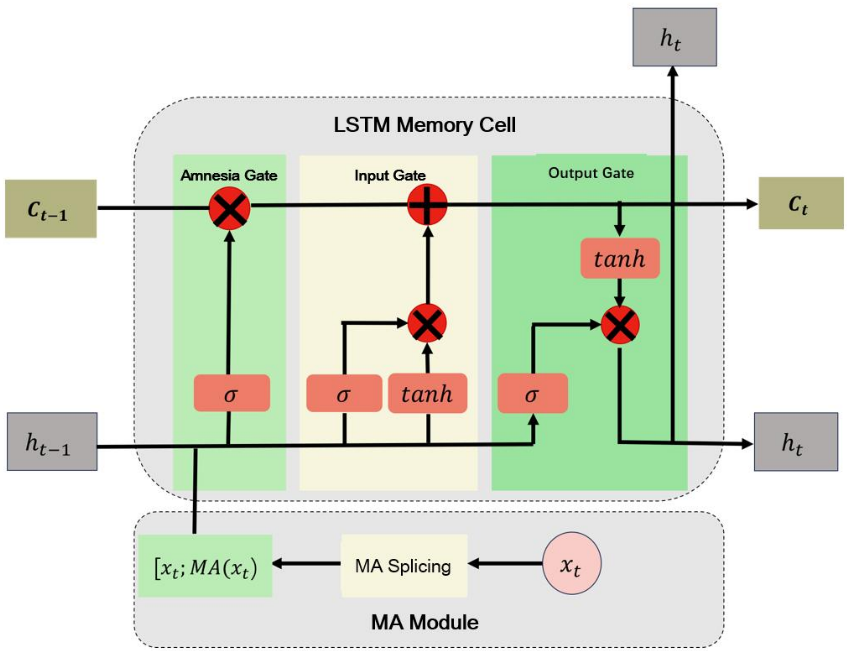

Figure 2 Schematic Diagram of Prediction Based on Combined MA-LSTM Modeling

2.2.1 MA

In macroeconomic time series forecasting, the moving average (MA) method effectively suppresses the interference of short-term stochastic fluctuations on trend identification through the calculation of the mean within a sliding window. The MA method is able to extract smoothed long-term evolutionary features from the original series. The proposed methodology involves the extension of unidimensional time series into continuous time segments through the implementation of a data resampling mechanism. This approach furnishes a structured input pattern for subsequent modeling endeavors. Its mathematical essence can be described as a linear weighting of historical observations within a specified time frame.

$$MA_t = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i} \tag{2}$$

In this context, "n" is defined as the length of the sliding window, and "x_{t-i}" is used to denote the observations made at a specific historical moment. This operation utilizes a low-pass filter to suppress high-frequency noise while preserving the trend component of the sequence. In the modeling flow of this study, the smoothed sequence of MA outputs is further reconstructed into multidimensional time segments to form continuous time-series samples. This structured input design has been demonstrated to effectively mitigate the impact of random fluctuations in the original data during model training. Additionally, it employs a window sliding mechanism to explicitly encode the time dependence, thereby generating a normalized feature space for subsequent LSTM time series modeling.

2.2.2 LSTM

The fundamental concept of LSTM is to incorporate memory cells (cells) into conventional RNNs and regulate the transmission of information through gating mechanisms. These gates serve to determine which information should be stored in the memory cell, which information should be forgotten, and which information should be output. The concept of "Gate" is not applicable in this context. The objective of this element is to establish the parameters by which information should be discarded in the present state of the memory cell. Firstly, the amnesia gate controls which information should be discarded in the current state of the memory cell. The input gate is responsible for regulating the amount of current input information that can be stored within the memory cell. The output gate is the function under consideration responsible for determining the output of the current memory cell. The fourth component is the memory cell, otherwise known as the cell state. The cell state is responsible for storing long-term memory, the maintenance of which is essential for the efficient progression of the sequence processing. The specific process can be described by the following equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t \tag{6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \circ \tanh(C_t) \tag{8}$$

In this system, f_t, i_t, and o_t serve the function of regulating the forgetting, input, and output gates, respectively. The candidate cell state is denoted by $\widetilde{C_t}$, and the updated cell state and hidden state are designated by C_t and h_t, respectively. In the application, the LSTM accepts the trended sequence of the front-end MA output as input, and captures the nonlinear interaction effects among multidimensional economic indicators through adaptive learning. In the model training stage, the mean square error loss function and gradient descent optimizer are used to dynamically adjust the network weights through backpropagation, and finally achieve the recursive prediction of GDP growth rate [7].

2.3 Parameter Optimization Based on Simulated Annealing Algorithm

2.3.1 Establishment of Evaluation Indicators

First is the mean square error (MSE). The average deviation of the predicted value from the true value is calculated by squared loss, amplifying sensitivity to outliers; it is used to quantify the overall level of error in the model's predictions, and the optimization is more concerned with penalizing extreme errors, as calculated by the formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \tag{9}$$

Then, the Root Mean Square Error (RMSE) is introduced. The RMSE is calculated by taking the square root of the MSE to ensure consistency with the original data magnitude. This provides an intuitive measure of the absolute value of the error, which is suitable for cross-sectional comparisons of predictive effects across models or scales. The formula used to compute the RMSE is as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2} \tag{10}$$

Finally, Mean Absolute Percentage Error (MAPE) is a crucial metric in this analysis. It quantifies the discrepancy between the anticipated value and the observed value as a percentage, thereby evaluating the precision of the forecast. The method accounts for variations in magnitude, making it suitable for assessing the responsiveness of economic indicators to policy interventions. The calculation of this index is as follows:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\bar{y}_i}{y_i}\right|\times 100\% \tag{11}$$

In this equation, "n" denotes the total number of sample data points, "y_i" represents the true value of sample "i" and "$\bar{y}$" denotes the predicted value of sample "i".

2.3.2 Simulated annealing algorithm

The simulated annealing algorithm, grounded in the physical mechanism of solid annealing, offers a robust optimization framework for addressing the hyperparameter sensitivity issue in LSTM models in small-sample economic forecasting. This framework utilizes dynamic temperature modulation to explore and exploit the capacity to balance the hyperparameter search. In macroeconomic time-series prediction scenarios, the discrepancy between model complexity and data scarcity frequently results in the traditional gradient-tuned parameterization converging towards local extrema. This phenomenon is exacerbated by hyperparameter mismatch, which can lead to overfitting or the under-expression of features. In this study, multi-objective evaluation indexes are introduced to traverse the parameter space barrier with the assistance of the high-temperature phase of simulated annealing, and the low-temperature phase refines the search to gradually approach the Pareto optimal solution. This strategy effectively coordinates the fitness relationship between network structure (hidden layer dimension) and learning dynamics (learning rate decay), thus releasing the full potential of LSTM for parsing multivariate nonlinear coupled features under limited data conditions [8].

The implementation of the simulated annealing algorithm in the optimization of macroeconomic forecasting models consists of the following core steps: first, the high-temperature parameter and hyperparameter search space is initialized; second, the initial solution is randomly generated; and third, the initial solution is evaluated based on the composite objective function. The objective function is defined as a linearly weighted sum of mean square error MSE, RMSE, and MAPE:

$$F=MSE+RMSE+MAPE \tag{12}$$

2.3.3 Parameter iteration process

During the iteration process, the algorithm employs a strict dominance criterion to ensure the global improvement of the solution. Specifically, a new solution is accepted only if its MSE, RMSE, and MAPE metrics are better than the current solution. Otherwise, it is filtered according to the Metropolis probability criterion. This strategy ensures a decrease in error metrics through dual mechanisms. First, the multi-objective aggregation property of the objective function directs the search toward comprehensive error minimization. Second, the parameter update rule explicitly constrains the new solution to be superior in all error dimensions to avoid biased convergence triggered by single-index optimization.

The temperature scheduling employs an exponential cooling mechanism, wherein a broad spectrum of parameter perturbations is permitted in the high-temperature phase to identify potentially high-quality regions. Conversely, the neighborhood radius undergoes a gradual contraction in the low-temperature phase to execute a locally refined search. To ensure the optimization of the solution space at the current temperature, multiple iterations are executed prior to each cooling cycle. The historical optimal solution is tracked independently of the current solution, and the parameter configuration that minimizes the integrated error in the whole search process is finally output.

This paper employed the simulated annealing algorithm to optimize the three parameters in the LSTM. The initial temperature T is set to 100°C, the temperature decay coefficient C is set to 0.95, and the iteration is continued until the MSE, RMSE, and MAPE converge to a sufficiently small value to halt. The temperature decay follows the exponential cooling formula:

$$T_{k+1}=C\times T_k \tag{13}$$

where T_k is the current temperature, C (the temperature decay coefficient, set to 0.95 in this paper) is the factor by which the temperature is reduced at each step, and T_{k+1} is the temperature for the next iteration.

Through this process, the study ascertained the optimal hyper-parameter configuration for the LSTM, which is outlined as follows. A new solution is accepted only if its MSE, RMSE, and MAPE metrics are better than the current solution. Otherwise, it is filtered according to the Metropolis probability criterion. The Metropolis probability P is given by:

$$P=\begin{cases}1,\text{if the new solution is strictly better}\\ \exp\left(-\frac{\triangle \mathrm{E}}{\mathrm{T}}\right),\text{if the new solution is not strictly better}\end{cases} \tag{14}$$

where $\triangle E$ is the difference in error between the new solution and the current solution, and T is the current temperature.

The values for the parameters of the model are as follows: 'hidden_size': 10.6925, 'learning_rate': 0.0028, 'epochs': 98.8112. These values correspond to the following metrics: mean squared error (MSE) = 0, root mean squared error (RMSE) = 0.0002, and mean absolute percentage error (MAPE) = 0.04%, and the specific parameter iteration process is shown in Figure 3.

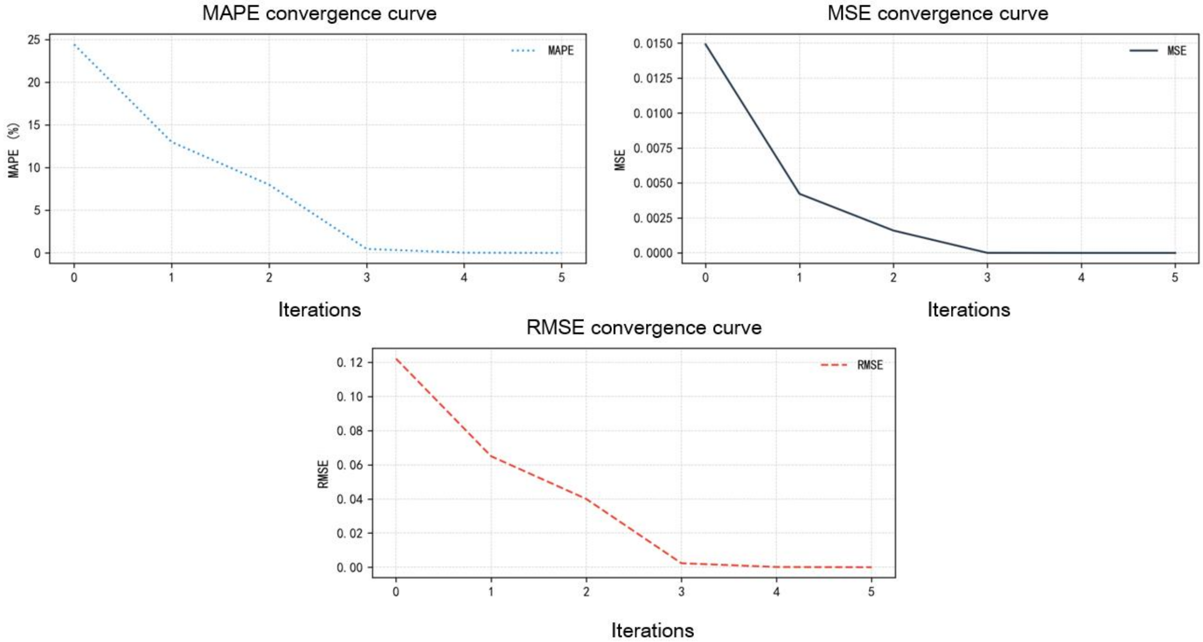

Figure 3 Iterative Process Diagram of Simulated Annealing Parameters

These formulas (MSE, RMSE, MAPE for error measurement; exponential cooling and Metropolis criteria for SA) work together: MSE/RMSE/MAPE quantify prediction accuracy, guiding SA to find better LSTM parameters. Temperature update and Metropolis balance exploration and convergence, ensuring the optimized parameters minimize errors, making the LSTM model highly accurate for component inspection and profit optimization tasks.

3 RESULTS AND ANALYSIS

3.1 Analysis of Results

According to the aforementioned model forecasting method, the study yielded the following results. Assuming that all indicators of the independent variables exhibit steady growth at the average annual growth rate, the image of China's annual GDP growth rate forecast for 2025-2030 can be obtained, as depicted in Figure 4.

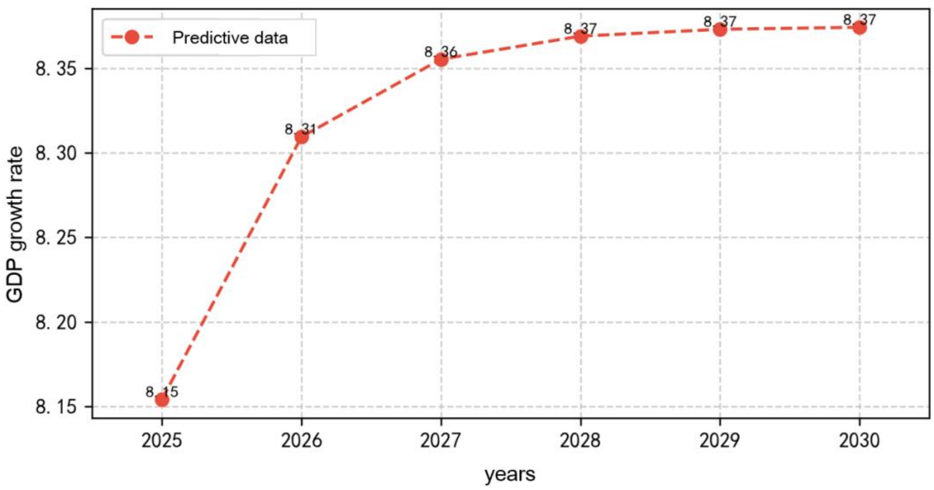

Figure 4 Forecast of China's GDP Growth Rate (2025-2030)

Assuming the stability of the growth rate of the independent variables, the annual GDP growth rate forecast exhibits characteristics of "short-term fine-tuning and long-term stabilization," with a narrow fluctuation in the range of 8.20%-8.37% from 2025 to 2027, and a slight pullback of 0.07 percentage points in the initial period due to the lag effect of the policy, subsequently stabilizing at the 8.37% plateau under the balanced effect of the core variables such as consumption, investment, and trade. 8.37% platform. This convergence suggests that once the external shocks are eliminated and the endogenous dynamics are stabilized, the national economic system possesses a self-balancing mechanism, and the steady-state value output from the model can be regarded as a reference benchmark for the potential growth rate under the current economic structure [9].

Scenario simulations of the growth rate of the comprehensive development index of the new energy vehicle market, controlling for the constancy of the remaining independent variables, reveal its differential driving effect on GDP growth, as shown in Figure 5.

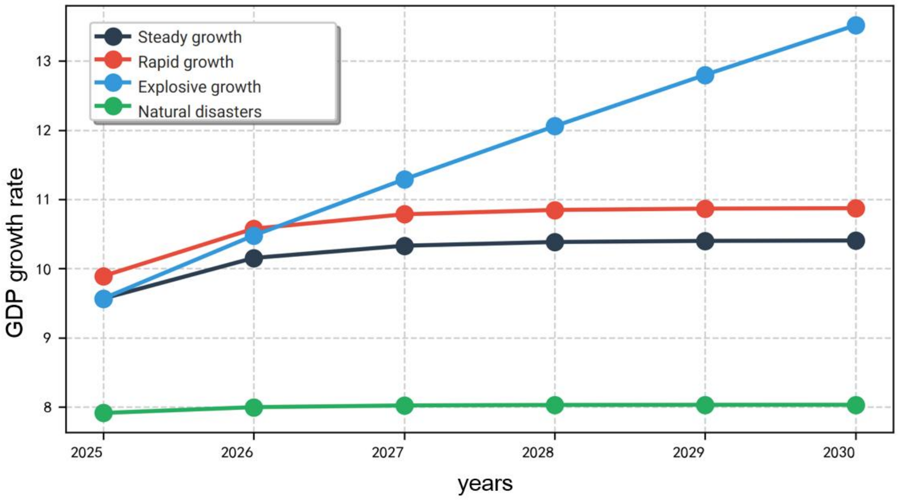

Figure 5 Impact of Different Scenarios of New Energy Vehicle Development on GDP Growth Rate

The market size of new energy vehicles exhibits stable growth (annual growth rate of 1.2 times), which corresponds to a gradual upward trend in the GDP growth rate, with a cumulative increase of 0.8 percentage points during 2025-2030. This reflects the gradual release of industry chain synergies. Conversely, under the rapid growth scenario (annual growth rate of 1.5 times), a growth inflection point occurs in 2027, and the GDP growth rate surpasses 10% and enters a plateau period. This indicates that under the rapid growth scenario, the GDP growth rate will exceed 10% and then plateau. The analysis indicates that the growth inflection point is expected to occur in 2027. Once this point is reached, the GDP growth rate will exceed 10% and enter a plateau period. This suggests the presence of a law of marginal diminishing returns to technological innovation [10]. The percentage points from the baseline scenario verify that the New Energy automobile industry has become a key economic stabilizer against systemic risks. This nonlinear response characteristic is fundamentally attributable to the dynamic interplay between the industry multiplier effect and resource carrying capacity.

3.2 Model Accuracy Comparison

In order to systematically evaluate the prediction performance of the SA-MA-LSTM hybrid model, this study compares and analyzes it with the classical machine learning model. As demonstrated in Table 9, the SA-MA-LSTM model exhibits a substantial accuracy superiority in the GDP growth rate prediction task, with minimal MSE, RMSE, and MAPE. This validates the model architecture and underscores its aptitude for capturing the intricate economic time-series dynamics**.**

Table 2 Comparison of Prediction Accuracy of Models

Model	MSE	RMSE	MAPE
SA-MA-LSTM	0	0.0002	0.04%
LSTM-XGBoost	7.0426	2.6538	52.04%
STL + Random Forest	0.1663	0.4078	6.76%
GRU+SVR	0.3363	0.5799	14.90%
ARIMA-XGBoost	1.7239	1.3130	25.76%
ETS+XGBoost	0.4452	0.6672	8.36%
MA-LSTM	0	0.0010	2.00%

4 CONCLUSIONS

Against the backdrop of digital economic transformation and carbon-neutral strategies, this study innovatively incorporates ecological health into a macroeconomic analysis framework. It systematically integrates three dimensions — government policy, enterprise innovation, and consumer demand — to analyze the new energy vehicle industry's driving effect on economic growth. The study finds that a one-unit increase in the market size of this industry can boost the marginal GDP growth rate by 0.23 to 0.41 percentage points, with significant acceleration during the growth period. These results verify the nonlinear driving mechanism and propose establishing a multidimensional industry value assessment system within the current SNA framework. This system provides an innovative way to quantify the contribution of emerging industries to total factor productivity. Additionally, it proposes targeted development strategies at the government, enterprise, and consumer levels to promote industry progress.

This study realizes the systematic quantification of the multi-dimensional driving effects of the new energy vehicle market, and innovatively reveals the relationship between the path of industrial policy and the growth threshold. It is expected that the industry will contribute 1.2-1.8 percentage points to GDP growth in 2025-2030, with technological innovation and infrastructure as the main drivers, but there is a bottleneck in scale expansion. In the future, we will seek breakthroughs in quantifying the regional impacts of policies, monitoring the risks of the industry chain, constructing a dual-account accounting system, and improving the economic analysis paradigm of new energy vehicles with both theoretical and practical values by establishing a dynamic CGE model, developing a blockchain monitoring system, and other innovative means.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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DIGITAL TRADE POLICY AND URBAN INNOVATION CAPACITY: EVIDENCE FROM 280 CHINESE CITIES

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Abstract: With the evolution of the digital economy, digital trade policies have increasingly demonstrated significant effects on enhancing urban innovation capacity. This study combines policy qualitative analysis with quantitative research methodologies, utilizing the establishment of Cross-border E-commerce (CBEC) Comprehensive Pilot Areas as a quasi-natural experiment, based on data from 280 prefecture-level cities in China from 2010 to 2021, to examine the impact of digital trade policies on urban innovation capacity and its underlying mechanisms. The findings indicate that the establishment of CBEC pilot areas significantly enhanced urban innovation capacity, with particularly pronounced effects in China's eastern developed regions, tertiary industry-dominated cities, and megacities. Mechanism analysis reveals that establishing CBEC pilot areas enhances urban innovation capacity by improving digital infrastructure, facilitating service industry agglomeration, and optimizing the business environment.
Keywords: Digital trade policy; Cross-border E-commerce comprehensive pilot areas; Urban innovation capacity

1 INTRODUCTION

Urban innovation capacity has emerged as the cornerstone of economic transformation in the digital era, with cities serving as critical nodes for technological advancement and competitive advantage [1]. China's elevation of innovation-driven development to national strategic priority, exemplified by the 2024 Implementation Opinions on Promoting Future Industries Innovation, underscores the urgent need to understand policy mechanisms that enhance urban innovation capabilities. China's cross-border e-commerce growing 15.3% annually to 2.37 trillion yuan in 2023 creates natural experiments for policy evaluation.

The intersection of digital trade policy and urban innovation represents a rapidly evolving research frontier. Digital trade, defined as cross-border flows leveraging digital technologies with data as core production factor, has demonstrated significant capacity to drive industrial agglomeration and technological diffusion [2]. Cross-border e-commerce, as digital trade's most visible manifestation, has shown measurable impacts on corporate innovation through reduced transaction costs and enhanced market access [3-4].

Research shows marketization and capital investment drive innovation through resource optimization [5], while infrastructure investment exhibits non-linear effects on innovation efficiency [6]. The digital economy literature further demonstrates that smart city initiatives and digital infrastructure create platforms concentrating innovation resources [7-8], with digital technologies facilitating industrial structure optimization and productivity enhancement [9].

Despite these advances, three critical gaps persist. First, existing studies predominantly employ theoretical analyses or case studies, lacking rigorous empirical investigation of digital trade policies' causal impact on urban innovation capacity [10]. Second, while research documents cross-border e-commerce's macroeconomic effects, the specific mechanisms through which digital trade policies influence urban innovation processes remain underexplored, particularly regarding policy instrument-innovation pathway relationship[11]. Third, limited attention addresses the correspondence between policy design content and actual innovation outcomes, constraining deeper understanding of policy logic-implementation effectiveness relationships.

This study addresses a fundamental question: Do digital trade policies enhance urban innovation capacity, and through what mechanisms do these effects operate? We hypothesize that Cross-border E-commerce (CBEC) Comprehensive Pilot Areas, as China's flagship digital trade policy innovation, promote urban innovation through three complementary mechanisms derived from endogenous growth theory [12]: digital infrastructure development (reducing information costs and enhancing knowledge application efficiency), service industry agglomeration (generating knowledge spillovers and scale economies), and business environment optimization (reducing institutional transaction costs and innovation uncertainties).

We examine this relationship using a quasi-natural experiment design leveraging China's staggered establishment of 105 CBEC pilot areas across 280 cities (2010-2021). Our empirical strategy employs multi-period difference-in-differences analysis, enhanced by propensity score matching and extensive robustness checks. We integrate qualitative policy text analysis of 64 policy documents with quantitative mechanism testing, providing novel evidence on policy transmission channels. The study reveals that CBEC pilot areas significantly enhance urban innovation capacity (average treatment effect: 0.69%-1.52%), with pronounced heterogeneity across regions, industrial structures, and city scales. Eastern

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regions, service-oriented cities, and megacities exhibit stronger policy responsiveness, reflecting differential absorption capacities for digital trade innovations.

Our findings advance theoretical understanding by demonstrating how institutional innovation promotes endogenous growth through optimized resource allocation and reduced transaction costs. We provide the first comprehensive empirical evidence linking digital trade policy to urban innovation outcomes, identifying specific transmission mechanisms validated through systematic policy text analysis and mediation testing. The results offer practical guidance for policy optimization, suggesting differentiated approaches based on regional characteristics and industrial structures, while highlighting the importance of synergistic development across digital infrastructure, service agglomeration, and institutional environments.

2 MECHANISM AND RESEARCH ASSUMPTIONS

2.1 Qualitative Textual Analysis of Digital Trade Policies

Institutional reforms influence economic development and innovation dynamics by shaping the behavior of market participants. As an emerging institutional arrangement, digital trade policies' specific content and implementation trajectory directly determine their efficacy in influencing urban innovation capacity. This section employs thematic analysis methodology to systematically review and extract word frequencies from national policy documents related to CBEC pilot areas issued between 2010 and 2024.

Table 1 Summary of Policies Related to CBEC Pilot Areas (2010-2024)

No.	Year	Issuing Authority	Document Title
1	2015	The State Council	Reply on the Approval to Establish China (Hangzhou) CBEC Pilot Area
2	2019	State Taxation Administration	Announcement on Issues Concerning Deemed Taxation of Enterprise Income Tax for Retail Export Enterprises in CBEC Pilot Areas
3	2021	Ministry of Commerce et al.	Notice on Expanding the Pilot Program for CBEC Retail Imports and Strictly Implementing Regulatory Requirements
...	...	...	...
64	2024	General Administration of Customs	Announcement on Further Promoting the Development of CBEC Exports

Table 1 presents the 64 CBEC pilot area-related policy documents we systematically collected, spanning from 2015 when the first pilot area was established to 2024's latest policy releases, covering multiple departments including the State Council, Ministry of Commerce, and General Administration of Customs. This provides a comprehensive policy text foundation for subsequent qualitative analysis. Policy text analysis results show that digital trade policy frameworks primarily focus on three core themes: digital infrastructure development (3.55%), service industry agglomeration (4.85%), and business environment optimization (2.57%).

Table 2 Qualitative Analysis Results of Policy Texts

Theme	Related Keywords	Theme Frequency
Digital Infrastructure	Electronic, payment, information, platform, data, network, technology, system, digitalization, cloud computing, logistics informatization, blockchain, API integration, smart terminals, cybersecurity	3.55%
Service Industry Agglomeration	Service, business, enterprise, institution, operation, commodity, collaboration, cluster, warehousing, logistics, supply chain, finance, marketing, consulting, training, innovation cooperation, brand, cross-border service ecosystem	4.85%
Business Environment	Customs, regulation, legislation, pilot programs, declaration policy, taxation, compliance, intellectual property, risk prevention and control, administrative licensing, standardization, trade facilitation, dispute resolution, local policy support	2.57%

Table 2 reveals policy priorities in promoting urban innovation: service industry agglomeration receives strongest emphasis (4.85%), followed by digital infrastructure (3.55%), while business environment optimization (2.57%) provides essential institutional support, reflecting policymakers' strategic focus on ecosystem development, technological enablement, and institutional foundations.

2.2 Research Hypotheses

Building on Romer's endogenous growth theory [12], we theorize how the three identified mechanisms enable CBEC pilot areas to enhance urban innovation capacity. Digital infrastructure development reduces information acquisition costs and enhances knowledge application efficiency. Service industry agglomeration increases R&D talent concentration and generates knowledge spillovers. Business environment optimization reduces institutional transaction costs and facilitates technology adoption. These complementary mechanisms promote sustainable innovation-driven growth by improving resource allocation efficiency and accelerating knowledge diffusion. To formalize this theoretical framework, we construct an endogenous growth model that captures how these mechanisms influence key parameters affecting urban innovation capacity.

2.2.1 Basic model

We model a representative city with final product and knowledge product sectors. The final product Y represents urban economic output produced through a technology that depends on various knowledge products as intermediate inputs:

$$Y=\left(\int_0^N \tilde{x}_i^{\alpha}\, di\right)^{\frac{1}{\alpha}} \tag{1}$$

Where $\tilde{x}_i$ represents the effective utilization of intermediate good i after accounting for transaction costs, α denotes the elasticity of substitution between intermediate products (determining their marginal contribution to final output), and N indicates the variety of available knowledge products.

2.2.2 Knowledge production and input

The dynamics of knowledge creation follow an R&D-driven process where both current research efforts and existing knowledge stock contribute to innovation:

$$\frac{dN}{dt}=\delta L_R^{\theta} N^{\phi} \tag{2}$$

Where L_R represents R&D labor input, δ captures baseline knowledge production efficiency, θ measures the elasticity of R&D input to knowledge creation ($0<\theta<1$, reflecting diminishing returns), and ϕ captures knowledge spillover effects from existing stock ($0<\phi<1$). The production of each intermediate good depends on the total knowledge stock:

$$\tilde{x}_i=\eta N^{\beta} \tag{3}$$

Where η represents production efficiency and $\beta>0$ indicates that accumulated knowledge enhances intermediate goods productivity.

2.2.3 Total output

Substituting the intermediate goods production function into the final output equation and integrating across all varieties：

$$Y=\left(\int_0^N \tilde{x}_i^{\alpha}\, di\right)^{\frac{1}{\alpha}} \tag{4}$$

$$Y=\left(\int_0^N \left(\eta N^{\beta}\right)^{\alpha} di\right)^{\frac{1}{\alpha}} \tag{5}$$

$$Y=\eta N^{\frac{\alpha\beta+1}{\alpha}} \tag{6}$$

The three identified mechanisms influence key model parameters through distinct economic channels. Digital infrastructure development reduces information acquisition and processing costs, enhancing knowledge application efficiency (affecting parameters β and α). Service industry agglomeration increases human capital input in R&D sectors (L_R) while facilitating knowledge spillovers (affecting ϕ). Business environment optimization reduces institutional transaction costs, enabling more effective transformation of knowledge into productive applications.

Based on the above analysis, we propose the following hypotheses:

H1: Digital trade policies, represented by the establishment of CBEC pilot areas, promote urban innovation capacity.

H2: The establishment of CBEC pilot areas promotes urban innovation capacity through three mechanisms: digital infrastructure development, service industry agglomeration, and business environment optimization.

3 MODEL, VARIABLES AND DATA

3.1 Variable Selection

3.1.1 Dependent variable

Urban Innovation Capacity Index (Inno) This study constructs an urban innovation capacity index based on the methodology from the 2017 China Urban and Industrial Innovation Power Report jointly released by Yicai Research Institute and Fudan University. We estimate patent values using authorized patent data and aggregate registered capital of newly established enterprises, applying normalization and outlier removal procedures.

3.1.2 Core explanatory variable

The CBEC pilot area cities (CBEC) variable is constructed as an interaction term between Treat and Ryear, where Treat equals 1 for pilot cities and 0 for non-pilot cities.

3.1.3 Control variables

Through systematic review of policy documents related to CBEC pilot areas, 105 pilot areas had been established nationwide by 2021. This study selected 98 prefecture-level cities, and, building on research, identified key factors potentially influencing the establishment of CBEC pilot areas, incorporating them as control variables in the analytical framework. Specifically, the selected variables include: population scale level (Popu), human capital level (Capi), economic development level (Econ), infrastructure development level (Infra), government intervention degree (Gov), urbanization level (Urban), resident consumption level (Consum), and internet user level (Inter). Using these as control variables, we constructed a panel binary logit model to identify key factors influencing a city's designation as a CBEC pilot area. Cities selected as CBEC pilot areas were assigned a value of 1, and 0 otherwise, thus forming the core variable. Results indicate that CBEC pilot area establishment is primarily driven by seven antecedent factors: population scale, human capital level, economic development level, infrastructure development level, government intervention degree, urbanization level, and internet user level.

3.2 Data Sources

To conduct a comprehensive analysis, this study examines a sample of 280 Chinese cities over the period 2010-2021. Data regarding the establishment of CBEC pilot areas were primarily collected through systematic review of policy documents published by the State Council. Patent data were obtained from the China National Intellectual Property Administration. City-level data were sourced from the China City Statistical Yearbook and individual city statistical yearbooks.

3.3 Model Specification

This study analyzes 280 prefecture-level cities (including 105 CBEC pilot zones) using a multi-period DID approach to assess the policy's dynamic impact on urban innovation. The model specification follows:

$$Inno_{it}=\alpha_0+\alpha_1 cbec_{it}+\alpha_2 Control+\mu_i+v_t+\varepsilon_t \tag{7}$$

Where i denotes city and t denotes year. The dependent variable Inno represents urban innovation capacity; the core explanatory variable *cbec* represents CBEC pilot area cities; *Control* represents a series of city-level control variables, included to mitigate endogeneity concerns such as omitted variable bias; μ_i and v_t represent city and year fixed effects, respectively; and ε_t is the random disturbance term. This study primarily focuses on coefficient α_1 , which captures the causal effect of CBEC pilot area policy on urban innovation capacity.

3.4 Descriptive Statistics

Descriptive statistical analysis results are presented in Table 3. The normalized mean value of urban innovation capacity is 0.0088, with maximum value of 1, indicating substantial variation across cities.

Table 3 Descriptive Statistics of Variables

Variables	Observations	Mean	Std. Dev	Minimum	Median	Maximum
Inno	3360	0.0088	0.3992	0.0000	0.0009	1
CBEC	3360	0.0929	0.2902	0	0	1
lnpop	3360	5.9148	0.6638	3.4002	5.9466	8.1362
lnaca	3351	7.6928	1.3123	2.4849	7.6104	11.2343
lngdp	3360	16.6105	0.9256	14.1773	16.5039	19.8843
Infra	3360	17.6985	7.463	1.37	16.27	60.07
lngov	3360	14.8929	0.7595	12.9718	14.8323	18.2500
lninter	3360	13.4386	0.9627	9.2103	13.4000	17.7617
Urban	3325	0.5522	0.1495	0.1806	0.5347	1
lncoms	3360	15.6009	1.0489	5.4723	15.5572	19.0129

4 EMPIRICAL RESULTS AND ANALYSIS

4.1 Baseline Regression

Table 4's baseline regression confirms H1, showing CBEC pilot areas significantly boost urban innovation (0.1% significance) across all specifications: (1) without controls, (2) with controls, and (3) excluding municipalities. The robust results validate the policy's positive impact.

Table 4 Baseline Regression Results

	Inno (1)	Inno (2)	Inno (3)
CBEC	0.0194***	0.0157***	0.0152***
	(29.77)	(7.81)	(7.25)
Control variable	No	Yes	Yes
Urban fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	3360	3316	3269
R-squared	0.5717	0.6432	0.6350

Note: ***, **,and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

4.2 Parallel Trends Test

The parallel trends assumption was verified through event study analysis (Figure 1), showing consistent pre-policy innovation trends between treatment and control groups (non-significant coefficients). Post-implementation, CBEC pilot cities exhibited significant innovation growth, confirming the policy's effectiveness.

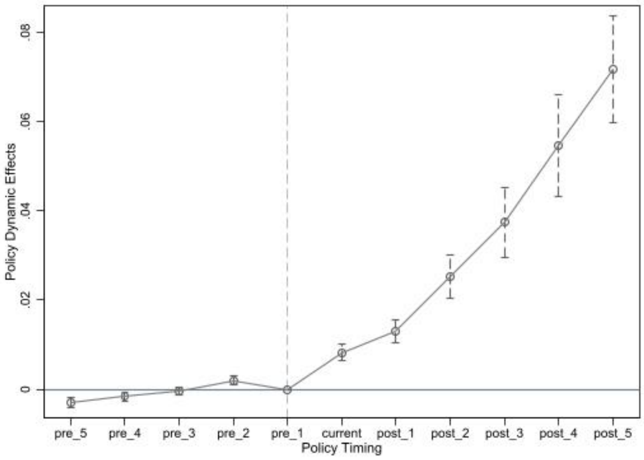


Figure 1 Parallel Trend Test

4.3 Robustness Tests

4.3.1 Placebo test

We conducted a placebo test by constructing random pseudo-treatment groups. As illustrated in Figure 2, which demonstrates that most pseudo-treatment coefficients cluster tightly around zero, with p-values exceeding 0.05, indicating statistical insignificance. This validates the authenticity of CBEC pilot area policy effects.

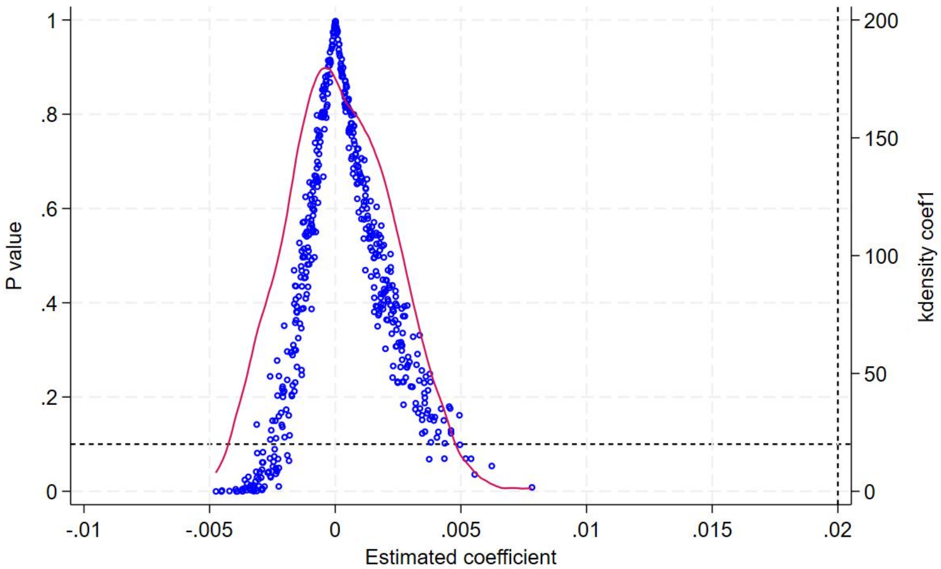


Figure 2 Placebo Test

4.3.2 PSM-DID test

We employ a Probit model to estimate the probability of CBEC pilot area city selection, deriving the propensity score:

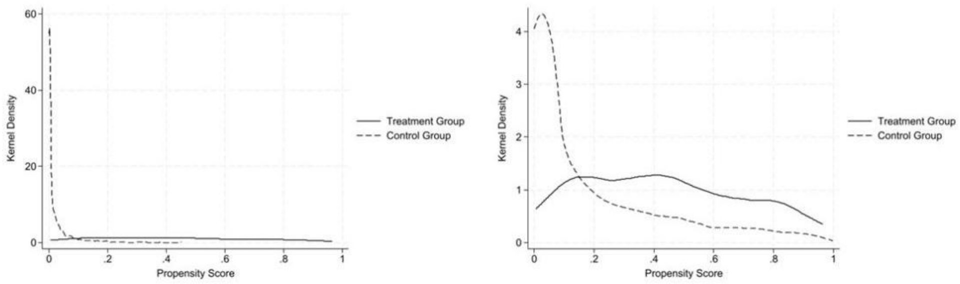
$$probit(treat_i=1)=\alpha+\beta X_i+\varepsilon_i \tag{8}$$

where *treat* is a dummy variable for CBEC pilot area establishment (1 for pilot cities, 0 otherwise), and X represents matching variables including urban innovation index, population, GDP, infrastructure, and other city characteristics. Based on propensity scores, we employ Epanechnikov kernel matching and 5:1 nearest neighbor matching for

robustness.
Balance tests demonstrate successful matching with substantially reduced standardized differences between treatment and control groups (Table 5). Common support tests reveal consistent propensity score distributions post-matching with expanded overlap regions (Figure 3), ensuring reliable estimation results.

Table 5 Balance Test Results

Variable	Sample	Mean Difference Test			Standardized Difference	
		Treatment Group	Control Group	t-test (p-value)	Standardized Bias	Reduction (%)
Population (logged)	Unmatched	6.3397	5.8842	11.94(0.000)	72.1	75.8
	Matched	6.3397	6.2293	2.00(0.046)	17.5	
Number of Full-time Teachers in Regular Higher Education Institutions(logged)	Unmatched	9.2327	7.5465	23.08(0.000)	140.0	83.2
	Matched	9.2327	8.9487	2.62(0.009)	23.6	
Regional GDP (logged)	Unmatched	17.909	16.486	28.58(0.000)	167.0	81.5
	Matched	17.909	17.645	3.36(0.001)	31.0	
Per Capita Road Area	Unmatched	18.918	17.498	3.19(0.001)	19.9	41.0
	Matched	18.918	18.08	1.33(0.185)	11.7	
Government General Fiscal Expenditure (logged)	Unmatched	16.005	14.786	30.25(0.000)	166.4	82.0
	Matched	16.005	15.786	3.02(0.003)	29.9	
Urbanization Rate (%)	Unmatched	0.7224	0.5351	22.30(0.000)	141.9	88.4
	Matched	0.7224	0.7006	1.83(0.068)	16.4	
Total Retail Sales of Consumer Goods(logged)	Unmatched	17.005	15.473	27.08(0.000)	166.7	81.5
	Matched	17.005	16.722	3.50(0.001)	30.9	
Internet User Data(logged)	Unmatched	14.785	13.307	28.53(0.000)	190.8	82.5
	Matched	14.785	14.527	3.84(0.000)	33.3	



(a) Before Matching (b) After Matching

Figure 3 Results of the Co-Support Test

We estimated the average treatment effect using kernel matching and 5:1 nearest neighbor matching methods. As shown in Table 6, kernel matching estimates an average treatment effect of 0.0102, while 5:1 nearest neighbor matching estimates 0.0069. These results indicate that CBEC pilot area establishment increased treatment group cities' innovation indices by 0.69%-1.02%, demonstrating the positive role of digital trade policy in strengthening urban innovation capacity.

Table 6 Average Treatment Effects of Digital Trade Policy

	Kernel Matching (1)	5:1 Nearest Neighbor Matching (2)
	Urban Innovation Capacity Index (Inno)	
Average Treatment Effect	0.0102^{***} (0.0025)	0.0069^{*} (0.0030)
Treatment Group Sample	3011	3011
Control Group Sample	305	305
Total Sample	3360	3360

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

4.4 Heterogeneity Analysis

4.4.1 Geographic location heterogeneity

Table 7 reveals strong regional variation in CBEC policy impacts, with eastern China showing the most significant innovation boost, followed by central and northeastern regions. Western regions show no significant effects, constrained by geographic and industrial limitations.

Table 7 Geographic Location Heterogeneity Test Results

	Eastern region (1)	Central region (2)	Western region (3)	Northeast region (4)
*East * CBEC*	0.0172^{***} (4.73)			
*Mid * CBEC*		0.0100^{*} (2.07)		
*West * CBEC*			0.0067 (1.58)	
*Northeast * CBEC*				0.0080^{*} (2.45)
Control variable	Yes	Yes	Yes	Yes
Urban fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	3316	3316	3316	3316
R-squared	0.6137	0.5487	0.5430	0.3925

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

4.4.2 Industrial structure heterogeneity

Table 8 shows CBEC policies significantly boost innovation in service-oriented cities, benefiting from streamlined trade processes and lower costs. However, manufacturing cities show no significant gains, suggesting they may need additional support or industrial upgrading to realize policy benefits.

Table 8 Industrial Structure Heterogeneity Test Results

	Second (1)	Third (2)
*Second * CBEC*	0.00162 (0.67)	
*Third * CBEC*		0.0172^{***} (6.73)
Control variable	Yes	Yes
Urban fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
N	3314	3314
R-squared	0.5382	0.6499

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

4.4.3 City scale heterogeneity

Table 9 reveals stark contrasts in CBEC policy effects by city size. Megacities show significant innovation gains, leveraging their strong research ecosystems to amplify policy benefits. Conversely, large/medium cities experience negative impacts, as their limited innovation resources make them vulnerable to megacities' resource-siphoning effects under the policy framework.

Table 9 Results of City Size Heterogeneity Test

	mega city (1)	large or medium-sized city (2)
*Large * CBEC*	0.0249^{***} (8.53)	
*Medium * CBEC*		-0.00438^{**} (-3.00)
Control variable	Yes	Yes
Urban fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
N	3316	3316
R-squared	0.7277	0.5417

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

4.4.4 Urban agglomeration heterogeneity

Table 10 shows significant regional variations in digital trade policy effects. The Yangtze River Delta demonstrates strong positive impacts, benefiting from robust innovation foundations and efficient resource flows. In contrast, Beijing-Tianjin-Hebei's effects are weakened by regional disparities, while the Pearl River Delta shows limited policy dependence despite its innovation strength.

Table 10 Results of City Size Heterogeneity Test

	JJJ (1)	YRD (2)	PRD (3)
*JJJ * CBEC*	0.0087 (1.04)		
*Yangtz * CBEC*		0.0338*** (5.62)	
*Pearl*CBEC*			0.0150 (1.64)
Control variable	Yes	Yes	Yes
Urban fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	3316	3316	3316
R-squared	0.5401	0.6645	0.5496

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.
Through this multidimensional heterogeneity analysis, our study comprehensively reveals the diverse impacts of digital trade policy, specifically the establishment of CBEC pilot areas, on innovation levels across different types of cities, providing more nuanced empirical evidence for policy formulation.

5 MECHANISM TESTING

This section empirically examines through mediation effect analysis whether the three major themes identified in policy texts constitute effective channels through which CBEC pilot areas enhance urban innovation capacity. Recent studies support these mechanisms: digital infrastructure promotes information flow and resource allocation efficiency [13]; service industry agglomeration enhances innovation factor concentration through specialized division of labor [14]; business environment optimization reduces institutional transaction costs and elevates innovation incentives [15-16]. We construct a mediation effect model using the Sobel test:

$$M_{it}=\beta_0+\beta_3 cbec_{it}+\gamma X_{it}+\lambda_i+\mu_i+\varepsilon_{it} \tag{9}$$

$$\gamma_{it}=\beta_0+\beta_1 cbec_{it}+\beta_4 M_{it}+\gamma X_{it}+\lambda_i+\mu_i+\varepsilon_{it} \tag{10}$$

In Equations (9) and (10), M_{it} represents mediating variables, which are substituted with the digital infrastructure index (Diginf), service industry agglomeration index (Spec), and China urban business credit environment index (Envir), while all other variables remain consistent with previous specifications.

5.1 Digital Infrastructure Development

Digital infrastructure serves as the technological foundation for CBEC pilot areas' innovation effects [17-18]. Table 11 reveals these zones significantly boost digital infrastructure, with Sobel tests (16.39) confirming strong mediation. By integrating cross-department digital services, CBEC areas establish comprehensive support systems spanning customs to foreign exchange, reducing information costs and enhancing resource allocation efficiency through digital transformation.

Table 11 Mechanism Test: Digital Infrastructure Construction

	(1)
Variable	Inno
Diginf	0.2024*** (24.29)
CBEC	0.0281*** (28.27)
Sobel Z	16.39***
Control variable	Yes
Urban fixed effect	Yes
Year fixed effect	Yes
N	3336
R-squared	0.5930

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

5.2 Service Industry Agglomeration

Service industry agglomeration represents the central mechanism through which CBEC pilot areas drive innovation. Research indicates that specialized agglomeration generates significant Marshallian externalities, enhancing regional competitiveness through resource sharing, knowledge spillovers, and specialized labor markets [19-20]. We construct producer service agglomeration indicators using employment proportions:

$$spec_{it}=\frac{\sum_{j=1}^{J} S_{ijt}/\sum_{i=1}^{N}\sum_{j=1}^{J} S_{ijt}}{S_{it}/\sum_{i=1}^{N} S_{it}} \tag{11}$$

Where S_{ijt} represents the total employment in industry j of city i in year t, S_{it} denotes the total employment across all industries in city i in year t, and N represents the number of cities.

Table 12 demonstrates that CBEC pilot areas significantly enhance producer service agglomeration, with the agglomeration index showing a 0.0241 coefficient on innovation capacity. The significant Sobel test confirms strong mediation effects. By fostering industrial ecosystems, these zones facilitate enterprise clustering and knowledge spillovers, accelerating technological diffusion.

Table 12 Mechanism Test: Service Industry Agglomeration

	(2)
Variable	Inno
Spec	0.0241***
	(29.44)
CBEC	0.0373***
	(30.27)
Sobel Z	12.59***
Control variable	Yes
Urban fixed effect	Yes
Year fixed effect	Yes
N	2799
R-squared	0.6610

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

5.3 Business Environment Optimization

The business environment serves as a crucial institutional foundation for innovation in CBEC pilot areas. Following Qian and Jia [21-22], we measure it using the China Urban Business Credit Environment Index (Envir). Results (Table 13) show CBEC pilot areas significantly improve business environments (1% significance), with Sobel tests confirming their mediating role in urban innovation. By reducing institutional transaction costs, these zones enhance market credibility, lower innovation uncertainties, and boost R&D investment. Though policy texts allocate only 2.57% to business environment themes, its substantial impact highlights institutional frameworks' fundamental importance in driving innovation.

Table 13 Mechanism Test: Business Environment Optimization

	(3)
Variable	Inno
Envir	0.1597***
	(30.38)
CBEC	0.0273***
	(28.96)
Sobel Z	16.89***
Control variable	Yes
Urban fixed effect	Yes
Year fixed effect	Yes
N	3350
R-squared	0.6401

Note: ***, **, and*indicate significant at the 0.1%, 1% and 5% levels, respectively, with standard errors in parentheses.

6 DISCUSSION

This study addresses the fundamental question of how digital trade policies influence urban innovation capacity development in the digital economy era. Based on the interactive relationship between institutional change and technological innovation [12], we investigate whether Cross-border E-commerce (CBEC) Comprehensive Pilot Areas serve as effective policy instruments for enhancing urban innovation, and through what specific mechanisms these effects operate.

CBEC pilot areas significantly enhance urban innovation, with treatment effects of 0.69% to 1.52%. Effects show strong heterogeneity, benefiting Eastern regions, tertiary industry cities, and megacities most. Three mechanisms drive this: digital infrastructure (reducing information costs), service industry agglomeration (knowledge spillovers), and business environment optimization (lowering institutional costs).

These findings align with Schumpeterian theory and industrial cluster theory but reveal greater regional heterogeneity than prior studies Chen and Luo and Li et al. [3, 23-25], highlighting varied absorption capacities across innovation systems [26].

This study advances understanding of digital trade policies by identifying three key transmission mechanisms: digital infrastructure development (3.55% of policy themes), which enhances knowledge application efficiency; service industry agglomeration (4.85%), generating knowledge spillovers; and business environment optimization (2.57%), providing institutional safeguards. However, the analysis is limited by its exclusive focus on China, potentially restricting generalizability, while the interactive relationships between mechanisms and long-term effects beyond 2010-2021 remain underexplored. The findings demonstrate that digital trade policies significantly boost urban innovation, with regional heterogeneity, by optimizing resource allocation and reducing transaction costs. Methodologically, the study integrates qualitative and quantitative approaches for robust policy evaluation. Practically, policymakers should tailor strategies to regional contexts, strengthen synergies among digital infrastructure, service agglomeration, and institutional reforms, and implement dynamic evaluation systems. China's CBEC experience highlights the potential of digital trade policies as innovation catalysts, though local absorption capacities must be considered. Future research should investigate mechanism interactions, heterogeneous effects, and long-term impacts to further refine policy frameworks.

Based on our findings, China's CBEC experience provides three policy implications for other countries:

(1) Tailor digital trade policies. Policy formulation should adapt support measures to urban industrial structures, scale, and development stages, emphasizing enhancement of absorption capabilities in central-western regions and manufacturing-dominated cities to prevent excessive resource concentration.

(2) Strengthen synergistic mechanisms. Digital infrastructure development, service industry agglomeration, and business environment optimization constitute an organic whole for promoting urban innovation. Policy design should comprehensively address these three dimensions to generate concerted effects for innovation factor agglomeration.

(3) Establish dynamic evaluation systems. Develop comprehensive assessment frameworks encompassing innovation outputs, industrial agglomeration, and institutional reforms to promptly identify implementation issues and continuously optimize policy instrument portfolios.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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THE IMPACT OF DIGITAL TRANSFORMATION ON FIRM EXPORT

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Abstract: This study employs a two-way fixed effects model to analyze the impact of businesses' digital transformation on their exports, using panel data from Chinese A-share listed companies from 2013 to 2023. The results demonstrate that enterprises' digital transformation significantly enhances their export value. Heterogeneity analysis reveals that digital transformation significantly increases export value for firms in technology-intensive sectors and those situated in the eastern region; moreover, advancements in artificial intelligence, cloud computing, and practical applications considerably enhance firms' export value, while the effects of blockchain and big data are minimal. This study enhances the theoretical understanding of digital transformation and export trade, offering practical guidance for business digital strategy, government policy development, and the facilitation of international trade.
Keywords: Digital transformation; Enterprise export; Two-way fixed model; Information factor theory; Transaction cost theory

1 INTRODUCTION

During a period of significant transformations in the global economic framework, the digital economy has emerged as a pivotal element in redefining the competitiveness of national economies. The utilization of digital technology diminishes the expenses associated with international trade, facilitating firms in overcoming geographical barriers and extending their presence in other marketplaces. China's progress in the field of technology is substantial. 2023 In February, the CPC Central Committee and the State Council published the Overall Layout Plan for the Development of Digital China, which expressly seeks to fully improve economic and social development, while also strengthening, optimizing, and expanding the digital economy.This document delineates the pathway for various industries in China to identify their roles within the digital economy and to attain high-quality development.

As the digital economy has emerged, enterprise export has encountered several obstacles in addition to previously unheard-of potential. Through the application of developments such as artificial intelligence and massive data sets, digital evolution empowers enterprises to modify their fundamental business processes, management frameworks, and production and operational systems[1]. However, the international economy is becoming more saturated, and businesses who are not keeping up with digital transformation are losing their advantages in terms of production efficiency, product quality, customer service, etc., and face the risk of a decline in export value (the literature is sourced from: https://www.geega.com/news/772). At the same time, new compliance issues for businesses' exports are brought about by variations in electronic commerce policies and privacy laws among nations and regions.To enhance their global competitiveness, businesses should formulate rational and scientific digital transformation strategies. However, by carrying out a thorough examination of the effects of digital transformation on export volume, the government can support the long-term expansion of China's international commerce as well as the superior development of the economy.

Most of the literature related to digital transformation focuses on the macro level, using cross-country, provincial and industrial samples. Dang Lin et al. [2] studied the impact of digital transformation on the technological complexity of exports based on cross-country data at different industry levels. Fan Xin[3] utilizes provincial data to test the impact of the development of the digital economy on export efficiency. Wang et al.[4] discovered that the advancement of the internet-based economy positively influences the enhancement of production efficiency in China. Research on the micro level of digital evolution is limited, primarily concentrating on corporate export performance[5]. Entrepreneurial innovation[6], organizational effectiveness[7,8], etc., and there is a lack of research on enterprise export turnover.

Additionally, the research of its determining elements is the primary focus of the associated literature on enterprise export volume. A category of literature examines the influence of macroeconomic conditions on the export volume of businesses.Wang Yaqi et al. [9] determine that exchange rate volatility adversely affects exports more significantly for firms with limited imports of intermediate goods and for small-scale exporters, based on a theoretical examination of firm heterogeneity.

2 MARGINAL CONTRIBUTIONS

This paper provides the following marginal contributions derived from present research. This paper extends previous research by examining the influence of digital transformation in firms on export commerce, specifically from the viewpoint of micro enterprises' digital transformation. Existing studies mainly focus on the macro impact of digital

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technology and economic effects, using transnational [2] and provincial [3] and Industry [4] samples to explore its impact on export technological sophistication, industrial restructuring, and national competitiveness, etc. Nonetheless, there is a dearth of research investigating the impact of digital change on exports at a smaller scale, which hinders the capacity to meet the specific requirements of firms in practice.The performance, effectiveness, and challenges encountered by enterprises during digital transformation exhibit significant heterogeneity and complexity. Consequently, understanding the impact mechanism of digital transformation on enterprises solely from a macro perspective proves to be difficult. This paper investigates the impact of exports through the lens of digital transformation in micro enterprises, aiming to facilitate sustainable development in the digital age.

Second, this paper further investigates the heterogeneous impact of different dimensions of enterprises' industries, regions, and digital transformation on export volume. Existing studies mainly analyze the heterogeneity based on enterprise size and export destination country [10], and lack the analysis of heterogeneity of industry and digital transformation dimensions. An extensive examination of the impact of digital evolution on the export value of businesses across diverse sectors, along with the effect of specific facets of digital transformation on this export value, can promote the cohesive development of both theoretical and practical elements of enterprise digital transformation. The heterogeneity analysis discussed in this study possesses practical importance.

3 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

This study examines the influence of corporate digital shifts on exports, utilizing information factor theory and transaction cost theory to analyze how digital transformation influences the internal dynamics of exports. The following is a comprehensive discussion:

Information factor theory is a modern factor of production theory that analyzes the composition and value transformation of information, and its core view is that information consists of factual elements and value elements in two dimensions [11]. The acquisition and validation of information facilitate trade, and as an inexhaustible resource, information influences costs, prices, and other production aspects in industrial manufacturing and commodities distribution. Investments in information technology (IT) can markedly improve productivity, and this improvement arises from IT capabilities, namely the capacity to utilize IT for resource integration. The essence involves utilizing information and data to facilitate the comprehensive integration of elements such as talent, technology, and capital, thereby maximizing organizational capabilities and enhancing productivity through the optimization of production processes, service levels, and operational efficiency.

Coase introduced the transaction cost hypothesis in his 1937 work, The Nature of the Firm, contending that transaction costs encompass the expenses associated with acquiring precise market information, as well as negotiating and contract costs. In microeconomics, transaction behavior is characterized by three primary attributes: first, the specificity of transaction assets, referring to the illiquidity of invested assets and the challenges associated with recovering costs and repurposing assets post-contract termination; second, the uncertainty risk inherent in transactions, which escalates due to the unpredictability of future outcomes and information asymmetry, consequently increasing execution and oversight costs; and third, the elevated frequency of transactions, which may augment management expenses. Transaction uncertainty significantly influences transaction costs. Prior to and during the export trade, firms will encounter the costs associated with information retrieval for aligning supply and demand, as well as the execution and oversight costs for each stage.

Digital transformation facilitates firms' exports by reducing information costs. Studies have shown that digital platforms can effectively break through geographical distance limitations and reduce information asymmetry [12], and improve export performance. Moreover, employing internet to engage with clients and vendors increases the likelihood of a business participating in exports by 11% [13]. Researchers investigating the impact of the World Wide Web on the global trade operations of companies in Asia and Sub-Saharan Africa found that the the web reduces information-related costs linked to entering international markets, and that the use of electronic mail and web pages enhances the significant margins of both exports and imports for these firms[14]. Accordingly, this paper presents the subsequent theoretical hypothesis.

H1: Digital transformation has a positive effect on firms' export volume.

4 RESEARCH DESIGN

4.1 Variable Selection

Explanatory variable: degree of digital transformation (DCG). The digital transformation degree indicator is derived using text analysis methods. Initially, utilizing Wu Fei's [15] concept, review the pertinent literature regarding digital transformation to summarize its specific keywords. Subsequently, improve these keywords by integrating relevant policy documents and research reports to develop a comprehensive feature thesaurus. Annual reports from all A-share listed companies are extracted using Python to establish a text data pool. Search matching and word frequency statistics utilize feature words to classify and summarize the frequencies of key technical aspects, leading to the final aggregated word frequencies that establish the overall indicators of enterprise digital transformation.

Variable explained: enterprise export amount (QUANTITY). The customs import and export data are aligned with the data of listed companies and compiled by Juchao Information Network. Juchao Information Network serves as the designated information disclosure platform for listed companies, as mandated by the China Securities Regulatory

Commission, ensuring the provision of authoritative and reliable data.
Control variables: (1) The enterprise's age (age), determined by subtracting the year of establishment from the current year, with 1 added prior to taking the natural logarithm (lnage). (2) Capital intensity (lnkl), measured by reference to Dumingway et al. utilizing the ratio ofenterprises' net fixed assets to their staff count, with the natural logarithm applied. (3) The logarithm of the number of employees at the end of the year (lnEmpft) is utilized in this study to represent the firm's labor force, thereby accounting for potential influences of the firm's size. (4) Asset turnover (turnover), assessed by the ratio of the operating revenue of a business to its entirety of assets. (5) Financial leverage (e-verage), which is the firm's gearing ratio, is measured using the ratio of the firm's total liabilities to its total assets. (6) Government grants (lnsubsidy), this paper takes the logarithm of year-end government grants to indicate government grants. (7) Profitability (PROFIT), using the return on net assets of the enterprise.

4.2 Data Processing

This research employs data from A-share publicly traded businesses in Shanghai and Shenzhen spanning the years 2013 to 2023.The primary data sources include the Cathay Pacific database (CSMAR), which provides financial information on publicly traded companies; the China Customs database, which encompasses extensive trade data for all import and export corporations in China, together with textual data from the yearly filings of publicly listed companies. The treatments applied to the consolidated panel data follow established methodologies in the literature. (1) Firms subjected to ST or * ST during the sample period are excluded; (2) Firms that were delisted during the sample period are excluded; (3) Firms with negative firm age are omitted; (4) Samples with significant missing values of the primary variables are discarded; (5) Individual missing value variables are addressed using the mean complementary value method; (6) To reduce the effects of outliers, all continuous variables undergo shrinkage at the 1% significance level; (7). All variables have undergone standardization. Subsequent to the processing described, 1,075 firms were chosen for analysis, resulting in 11,825 valid samples.

4.3 Descriptive Statistics

Table 1 displays the statistical data for the principal variables in this investigation, encompassing 11,825 observations.The mean enterprise export value is 2,923 million yuan, with a minimum of -200 million yuan and a maximum of 210,000 million yuan, indicating significant variability in export values across different years. Additionally, the observations regarding the level of digital transformation reveal considerable differences, with minimum and maximum values of 0 and 6,117, respectively.

Table 1 Descriptive Statistics

Meaning	Variable	Sample size	Mean	Standard deviation	Minimum	Median	Maximum
Digital Transformation	DCG	11825	98.522	183.586	0	34	6117
Exports of products	quantity	11825	2923	10320	-2,000,000	410	210000
Age of the company	age	11825	20.606	6.108	5	21	57
Number of workers employed by enterprises	empft	11825	9129.021	26974.893	58	3317	570060
Asset turnover	turnover	11825	0.66	0.499	0.573	0.573	12.105
Financial leverage	everage	11825	0.446	0.216	0.008	0.008 0.436	8.612
Government subsidies	subsidy	11825	69027478	208493851.826	-92000000	19000000	5.500e+09
profitability	profit	11825	-0.011	2.496	-235.096	0.059	34.716
Capital Intensity	kl	11825	3.352	37.731	0.083	1.745	2302.072

5 EMPIRICAL RESULTS

5.1 Benchmark Regression

This research utilizes the two-way fixed effects model to examine the impact of digital transformation on firm export volume, with regression outcomes displayed in Table 2.
Lines (1) and (2) display model outcomes devoid of control variables, whereas lines (3) and (4) incorporate c ontrol variables. Columns (1) and (3) do not include person and year fixed effects, whereas columns (2) and (4) include two-way fixed effects. The findings from rows (1) and (2) indicate that digital transformation mar

kedly enhances the export performance of firms. The findings in columns (3) and (4) are significantly positive, suggesting that digital transformation enhances the export performance of enterprises when additional control variables are included. This aligns with the findings of the present research.

Table 2 Benchmark Regression Results

Explained variable: lnquantity	(1)	(2)	(3)	(4)
lndcg	0.163*** (17.93)	0.051*** (5.07)	0.019 ** (2.40)	0.026*** (2.81)
lnage			0.046*** (6.09)	0.103*** (4.34)
lnempft			0.375*** (37.33)	0.15*** (17.15)
turnover			0.054*** (3.52)	-0.066*** (-4.50)
everage			0.130*** (15.32)	0.045*** (5.80)
lnsubsidy			0.170*** (17.35)	0.128*** (18.08)
profit			0.050*** (6.48)	0.022*** (5.07)
lnkl			-0.930*** (-6.05)	-0.237*** (-15.31)
Constant term	0.000*** (0.009)	0.000 (0.004)	0.000 (0.007)	-0.116*** (0.026)
Firm	No	No	N0	Yes
Year	No	No	N0	N0
N	11825	11825	11825	11825
R^2	0.026	0.150	0.403	0.265

Note: t-values are presented in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, as illustrated in the table below.

5.2 Robustness Test

In order to solve the problems of sample selection bias and measurement error in the regression and to ensure the robustness of the regression results, this paper carries out the robustness test from three aspects: adding control variables, changing the sample period, and changing the explanatory variables

5.2.1 Increase control variables

This study incorporates two control variables, specifically the cash flow ratio, defined as the ratio of net cash flow from operational activities to the sum of property.Tobin's Q value (tobinq) denotes the ratio of a firm's market asset value to the replacement cost of such assets, acting as a measure of market resource allocation efficiency. Table 3 presents the analysis of variance, indicating a correlation coefficient of 0.026 for digital transformation, significant at the 1% level, aligning with the benchmark regression findings.The conclusions of this research are shown to be solid.

5.2.2 Excluding the effect of the new crown epidemic

The selected time interval for the benchmark regression in this article is 2013-2023. The detrimental impacts of the COVID-19 epidemic have led to a significant decrease in exports from Chinese companies, potentially skewing the outcomes of the benchmark regression. This study omits all samples from 2020 to 2022 and recalculates them. The estimation findings reveal that the coefficient for digital transformation is 0.028, significant at the 1% level. This discovery corroborates the benchmark regression and reinforces the validity of the arguments articulated in this research.

5.2.3 Replacement of Explained Variables

The quantity_growth denotes the yearly growth rate of export volume. This study replaces quantity_growth with lnquantity as the explanatory variable to evaluate the robustness of the relationship between the primary explanatory variable (the extent of companies' digital transformation) and the explanatory variable (enterprises' export volume). The estimation results indicate that the corresponding coefficient of the explanatory variables is 0.070 and is significant at the 5% level, aligning with the benchmark regression and confirming the robustness of the conclusions presented in this study.

Table 3 Robustness Test Regression Results

Explained Variables	(1) lnquantity	(2) lnquantity	(3) quantity_growth
lndcg	0.026*** (2.80)	0.028*** (2.63)	0.070*** (2.54)
lnage	0.111*** (4.74)	0.136*** (4.66)	-0.214*** (-2.93)
lnempft	0.143***	0.083***	0.022

	(16.43)	(8.40)	(0.87)
turnover	0.076***	-0.069***	0.034
	(-5.21)	(-3.83)	(0.80)
everage	0.044***	0.057***	0.072***
	(5.76)	(6.26)	(3.16)
lnsubsidy	0.122***	0.131***	-0.023
	(17.27)	(16.16)	(-1.11)
profit	0.023***	0.021***	0.086***
	(5.39)	(3.96)	(7.24)
lnkl	-0.257***	-0.233***	-0.066
	(-16.58)	(-12.10)	(-1.48)
cashflow	0.011**		
	(2.44)		
tobinq	0.011**		
	(2.44)		
Constant term	-0.122***		
	(0.026)		
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	11825	11825	11825
R^2	0.275	0.247	0.019

Note: t-values are presented in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, as illustrated in the table below.

5.3 Heterogeneity Analysis

5.3.1 Heterogeneity analysis based on the industry to which the firm belongs to

Significant variances exist in technology intensity, capital intensity, and labor intensity across industries as China's digital technology revolution progressively influences each sector. Is the effectiveness of digital transformation, and its subsequent impact on firms' export trade, contingent upon the technological levels of the industries in which these firms operate? Enterprises are assigned a value of 1 if they operate within a technology-intensive industry, and a value of 0 if they belong to a capital-intensive or labor-intensive sector. The estimated coefficient for the digital evolution of technology-intensive enterprises is 0.052, demonstrating statistical significance at the 1% level, as indicated in Table 4, column (1), presenting the regression results for these sectors. Figure illustrates the results of digital transformation in technology-intensive sectors. The regression analysis of digital transformation in capital-intensive and labor-intensive sectors yields an estimated coefficient of 0.019, which is not statistically significant. This indicates that digital transformation is more effective in improving the growth of export value for enterprises within technology-intensive industries.

Table 4 Heterogeneity Regression Results Based on the Industry to Which the Firm Belongs to

Explained variable: lnquantity	(1) Technology-intensive industries	(2) Capital-intensive and labor-intensive
lndcg	0.052***	0.019
	(4.11)	(1.37)
Control Variables	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	11825	11825
R^2	0.302	0.217

Note: t-values are presented in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, as illustrated in the table below.

5.3.2 Heterogeneity analysis based on the region where the firms are located

Significant disparities exist across different locations in terms of policy support, infrastructure, market conditions, and human resources. The eastern regions generally experience more favorable policies and enhanced infrastructure, which attract significant foreign investment and advanced technology, alongside a greater degree of business digital transformation and strong export competitiveness. A firm located in the eastern region of China is assigned a value of 1, while a firm situated in the middle or western regions is assigned a value of 0. Table 5, Column (1), lists the enterprises situated in the eastern region. The estimated coefficient of digital transformation for firms in the eastern region is 0.028, significant and positive at the 5% level. The estimated coefficient for firms in the central and western regions of China, presented in column (2) of table 5, is 0.007, indicating an insignificant result. Significant. The estimated coefficient for digital transformation in firms located in the central and western regions, as shown in Table 5 (2), is 0.007, which suggests it is not statistically significant.

Table 5 Heterogeneity Regression Results Based on Enterprises' Regions

Explained variable: lnquantity	(1) East	(2) Midwest
lndcg	0.028**	0.007
	(2.55)	(0.40)
Control Variables	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	11825	11825
R^2	0.261	0.291

Note: t-values are presented in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, as illustrated in the table below.

5.3.3 Heterogeneity analysis based on different dimensions of enterprise digital transformation

Enterprise digital transformation represents a spectrum that includes various technological distinctions, each defined by unique structural characteristics. This paper aims to refine the analysis of "digital transformation on enterprise exports" by utilizing the method developed by Wu Fei et al. This method categorizes five indicators: artificial intelligence (AI), blockchain (BD), cloud computing (CC), big data (DT), and application of practice (ADT). It subsequently correlates enterprise data associated with these indicators with word frequency statistics to derive digital transformation indexes. The analysis encompasses data across five indicators and includes word frequency statistics related to enterprise matching within these indicators, aiming to capture the multidimensional aspects of digital transformation. Table 6 illustrates that the estimated coefficients for enterprise digital transformation in the areas of artificial intelligence (AI), cloud computing, and practical application are significantly positive. The estimated coefficients for enterprise digital transformation in the areas of blockchain and big data are not statistically significant. The evidence suggests that digital transformation in artificial intelligence (AI), cloud computing, and practical applications promotes the expansion of corporate exports.

Table 6 Regression Results of Heterogeneity Analysis based on Different Levels of Enterprise Digital Transformation

	(1) lnquantity	(2) lnquantity	(3) lnquantity	(4) lnquantity	(5) lnquantity
lnai	0.033***				
	(6.04)				
lnbd		-0.002			
		(-0.33)			
lncc			0.025***		
			(3.58)		
lndt				-0.004	
				(-0.84)	
lnadt					0.018**
					(1.97)
Indicators	Artificial Intelligence	Blockchain	Cloud Computing	Big Data	Practical Applications
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	11825	11825	11825	11825	11825
R^2	0.267	0.264	0.265	0.264	0.264

Note: t-values are presented in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, as illustrated in the table below.

6 CONCLUSION AND POLICY RECOMMENDATIONS

This research assesses the influence of corporate digital transformation on export value, employing a two-way fixed effects model with panel data from China's A-share listed companies in Shanghai and Shenzhen spanning 2013 to 2023. The digital transformation of firms significantly enhances their export value. This finding is robust when control variables are incorporated, the sample period is modified, and explanatory variables are replaced. The industry heterogeneity test indicates that digital transformation significantly impacts the export value of enterprises in technology-intensive sectors. Geographical Variation The analysis reveals that companies in the eastern region get a more significant increase in export value due to digital transformation than those in the central and western regions. Variability Across Different Phases of Digital Transformation The assessment reveals that digital transformation in artificial intelligence, cloud computing, and practical application substantially increases firms' export value, but the influence of blockchain and big data is negligible.

This document outlines the following policy proposals based on the previously stated conclusions: The government ought to strengthen policy support for the digital evolution of enterprises, especially within technology-intensive sectors and the eastern region. This can be achieved through the provision of incentives, including tax benefits, capital subsidies, and technical assistance, to support digital transformation efforts. Enhance infrastructure development for digital transformation in the central and western regions through improved network coverage, optimized data center configurations, and strengthened cloud computing and big data platforms. This aims to reduce the digital divide in the eastern regions and foster equitable development in national digital transformation. Organizations need to enhance talent development and acquisition in digital transformation, particularly in advanced technological areas such as artificial intelligence and cloud computing, to effectively support their digital transformation efforts. Enhance foundational research and application development for technologies like blockchain and big data, while investigating their potential roles in enterprise digital transformation. Establish a thorough assessment and oversight framework for corporate digital transformation. Regularly assess the progress of digital transformation initiatives, promptly identify and address challenges, and ensure the effective implementation and promotion of digital transformation efforts. Enhance oversight to deter unlawful and irregular activities by businesses during digital transformation, thereby ensuring fair market competition and protecting consumer rights and interests.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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SHOULD DIGITAL PLATFORMS BE BANNED FROM THE DUAL MODE OPERATION?

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Abstract: Increasingly, e-commerce platforms like Amazon and JingDong serve not just as intermediary markets that facilitate transactions between third-party sellers and consumers but also function as sellers themselves, offering their self-operated products on their platforms. When platforms commence selling their self-operated products, they may replicate the offerings of third-party sellers or engage in self-preferential practices favoring their own products. Consequently, it is essential to investigate the market equilibrium and welfare implications of platforms' dual mode, and evaluate whether such the dual mode should be banned. This paper examines the equilibrium of platforms according to the Hotelling model across three operation modes: the pure marketplace mode, the pure seller mode, and the dual mode. Furthermore, we examine the selection of modes for platforms. Additionally, we investigate the welfare, profits of platforms, and social welfare in the context of banning the dual mode of platforms. Finally, we briefly examine the contemporary policy implications of platforms' dual mode. The findings indicate that: (i) the dual mode of platforms is advantageous for consumers, platforms, and social welfare; (ii) platforms may intrinsically implement the dual mode for profit maximization; (iii) When platforms are banned from the dual mode and their choices of operation modes are endogenous, they will choose the pure marketplace mode; (iv) Consumer surplus, profits of platforms and social welfare decrease in the ban the dual mode of platforms.
Keywords: Digital platforms; Dual mode operation; Self-preferencing; Competitive strategies

1 INTRODUCTION

In recent years, more and more e-commerce platforms, such as Amazon, Jingdong, Target, and Walmart, play the role of both intermediary marketplaces (i.e., facilitating transactions between third-party sellers and consumers), and sellers (i.e., selling products on the platforms on their own behalf); in other words, these platforms are not only referees but also players[1]. In practice, this dual mode strategy is known as the self-operation strategy. Particularly, the platforms which adopt the dual mode strategy are mostly dominant firms with a large market share. For instance, Amazon is the dominant e-commerce platform in the United States with a market share of 38.7% in 2020. Moreover, these platforms are referred to as “gatekeepers” due to their dominant position in the market. Besides its presence in e-commerce platforms, the self-operation strategy exists in many default applications, such as Apple's Appstore, Google's Playstore, Apps for Windows, Intuit's Quickbooks Apps, Salesforce's AppExchange, and the Nintendo Switch video game console. They provide third-party applications and their own applications.

The dominance and the dual model operation of platforms raise concerns for antitrust enforcers. At least two concerns may arise when platforms begin selling their self-operated products: One is product imitation, as the platform may imitate the products of third-party sellers. This is because platforms have easy access to third-party sellers' product information and can imitate the product successfully. The second concern is that self-preferencing platform companies may limit consumer access to third-party sellers' products and display their own products more prominently, then consumers will buy their own products. The European Commission and the U.S. House Judiciary Committee's Antitrust Subcommittee have found that Google directly manipulates search results by promoting its own contents in search results while ignoring competitors' content (even if Google's own content is inferior). Therefore, the dual model of platforms raises regulatory concerns about the lack of a fair competitive environment. Later on, the European Union and the United States conduct antitrust investigations against some famous firms such as Google, Apple, and Amazon. Moreover, they also put forward some legislative proposals to regulate large tech firms, such as the “Digital Markets Act” and “the Digital Services Act” proposed by the European Commission, and five bills in the United States[2-6]. The End Platform Monopolization Act, proposed by the United States in 2021, prohibits large technology companies from competing with third-party sellers by selling their products or applications on their own marketplaces.

In practice, countries such as European countries and the United States begin to adopt appropriate regulatory measures for platforms’ self-operation strategies. Nonetheless, academic research on this aspect lags behind practice, and is still an emerging topic[7]. Although some scholars have begun to evaluate the welfare of dual mode of platforms, no consistent conclusions have been reached, and further research on the strategy is needed to clarify whether dual mode of platforms should be banned.

Against the backdrop of the above phenomenon, this paper aims to address (1) How does the self-operation strategy of platforms affect pricing and the welfare of participants? (2) What are the implications of banning the dual mode of platforms, and what is the optimal mode for platforms? (3) What are the effects of current policies on platforms’ self-operation strategies?

This paper constructs a Hotelling model to analyze the market equilibrium and mode choice of the platform, followed by an analysis of the welfare implications of the ban on the platform's dual mode. Moreover, we briefly discuss the effects of the current policy on platform self-operated strategy, then we investigate whether antitrust regulation should be imposed on the dual mode. The results show that platforms' self-operation strategy is advantageous for consumers, platforms, and social welfare. When platforms adopt a dual mode, they benefit consumers through two mechanisms: the provision of cost-advantaged products or the enhancement of consumers' intergroup network externalities. Additionally, platforms' dual mode is an inherent decision in their pursuit of profit maximization. Furthermore, when platforms are banned from dual mode and their decision of operation mode is endogenous, they will opt for the pure seller mode if and only if platforms have a product cost advantage and the difference of the marginal costs between third-party sellers and the platform is larger than the profits of the intergroup network externalities that consumers obtained from the pure market mode; otherwise, the platform will shift to the pure marketplace model. Finally, consumer surplus, platforms' profits and social welfare will decrease with the ban on dual mode for platforms. Consequently, the structural separation policy that prohibits dual mode of platforms may not genuinely enhance consumer and social welfare.

The contribution of this paper is the focus on platforms' self-operation strategies. The previous researches on platforms' self-operation seldom consider intergroup network externalities, therefore, this paper introduces a Hotelling model that examines the distinctions between products offered by platforms and those provided by third-party sellers in both online platform channels and offline direct channels. We characterize the different patterns of operation modes of platforms by the intergroup network externalities between online consumers and third-party sellers. That is, the inter-group network externalities cannot benefit online consumers if platforms choose the pure seller model. On the contrary, the inter-group network externalities can benefit online consumers if platforms choose the dual mode. Moreover, owing to the increase in the number of sellers on the platform, the inter-group network externalities of the dual mode will benefit online consumers more than that of the pure seller operation mode. The presence of intergroup network externalities yields numerous new conclusions.

The remainder of the paper is as follows: In Section 2, we review the relevant literature. In Section 3, we set up a model between the platforms and third-party sellers. In Section 4, we present the equilibrium analysis of platforms' self-operation strategy. In Section 5, we investigate the welfare changes of banning platforms' dual mode. In Section 6, we evaluate the policy effect of platforms' dual mode. Section 7 concludes the paper.

2 LITERATURE REVIEW

Research on the self-operation strategy of platforms is an emerging topic[7], which involves the own operation mode of the platform, self-preferencing treatment of platforms, and the welfare analysis of dual modes of platforms.

2.1 The Self-Operation Strategy of Platforms

Platforms can either provide a marketplace for third-party sellers to sell products, or they can sell their self-operated products. Platforms can change their organization or ownership structure over time. Hagiu and Wright show examples of Amazon and Zappos[8]. Amazon starts as a one-sided retailer platform and gradually shifts to a two-sided platform, while Zappos is in the opposite. Thus, the organization structure of a platform is not fixed and it may change with the condition of the market.

In terms of the decision of the operation mode of the firm, Hagiu states that the pure seller model is strictly better than the two-sided platform model when the probability of adopting the platform model being unfavorable is positive[9]. Since coordination problems are alleviated in the pure seller mode, it is easier to persuade third-party sellers to sell their products directly than to sell their products on a platform. Therefore, there exists a trade-off between the pure seller model and the two-sided platform model. This suggests that intermediaries, especially for new products, typically start with the pure seller model, then they move to the platform model which is cheaper for each seller and allows intermediaries to offer a wider variety of products when there are enough sellers and they become affiliated.

The platform frequently needs to evaluate whether they should offer their own products or not. Hagiu and Spulber consider a platform that faces a coordination problem of whether the chicken or the egg should come first in user engagement[10], and they derive that the problem can be mitigated by bringing in third-party sellers' products and the platform's self-operated products. Farrell and Katz and Jiang et al. conclude that platform owners face a trade-off between capturing rents and incentivizing innovation of sellers on the platform by self-operation strategies[11-12]. Moreover, empirical research on this issue suggests that Amazon is more likely to compete with sellers on the platform in product categories where sales are more successful[13].

2.2 Self-Preferencing of Platforms

Platforms can be seen as "gatekeepers" since they can not only decide which sellers can enter the platform, but also decide the ranking of products recommended to consumers. When platforms select the dual mode, they have an incentive to recommend their own products to consumers first rather than those of third-party sellers. Scholars refer to this behavior as self-preferencing (own-content bias). De Cornie re and Taylor investigate the determinants of self-preferencing in search engines and its impact on website strategies[14]. Since intermediaries often do not recommend the most suitable goods to consumers when consumers need intermediaries to recommend goods, especially when intermediaries also sell their own products to consumers, De Cornie re and Taylor conclude that firms that benefit from the self-preferencing have incentives to offer better products than their competitors when the interests of sellers and consumers are aligned[15], and consumers are better off than that without the self-preferencing. However, when sellers and consumer interests are in conflict, firms that benefit from the self-preferencing offer worse products, which leads to a decrease in the consumer utility. That is, the self-preferencing may do harm to consumers. Furthermore, they find that the consumer welfare will increase as the separation of the self-operation and intermediary-acting business model under price competition (as opposed to quantity competition). Kittaka and Sato consider a scenario where the commissions from sellers and the distortion of the order of consumer searches which leads to the priority of the self-operated product offered by the platform themselves[7], they find that the distortion and self-operation strategy will weaken price competition, and social welfare improves with the ban of the dual mode. Zennyo examines how self-operation and self-preferencing interact in e-commerce platforms and concludes that self-preferencing is not necessarily anticompetitive[16], but rather pro-competitive. Etro investigates the choices of a platform between earning commissions from competing third-party sellers and offering private label products or third-party sellers' products[17]. When the platform enters, the platform completely eliminates competition between the platform and the third-party sellers through an extreme form of self-preferencing. They find that the entry incentives of the platform are aligned with the interests of consumers when all sellers are in perfect competition. On the contrary, when sellers have significant market power, the platform's entry is usually insufficient. Additionally, Hagiu et al. investigate whether the dual model of platforms should be banned and construct a model with platforms[18], innovative sellers, and third-party marginal sellers, then they find that self-preferencing and product imitation create inefficiency.

2.3 Effects of the Self-Operation Strategy of Platforms on Welfare

Researches concerning the effects of the self-operation strategy of platforms on welfare are emerging, and scholars have not yet reached a consistent conclusion. Some scholars believe that the dual mode of platforms is beneficial to consumers and social welfare[17-21]. Hagiu et al. find that consumer surplus or social welfare will decrease if the ban the dual mode of platform[18]. Therefore, policies that prevent platform imitation and biased recommendations are always better than those completely ban the dual mode of platform.

However, some scholars argue that dual mode of platform will do harm to social welfare[21-22]. Anderson and Bedre Defolie consider a scenario where platforms are price leaders and compete with third-party sellers who show horizontal differentiation from the platforms, and they derive that commissions in the dual mode are larger than those in the pure seller mode, which leads to a decrease in the number of sellers and the range of products. Therefore, the ban on the dual mode of the platform should be taken.

To sum up, researches on the self-operation strategy of platforms are still emerging, and scholars have not reached a consensus about the effects of the dual model of platform on welfare. Moreover, it is not clear whether the self-operation strategy should be banned, so further research is needed.

3 MODEL

Suppose there is a platform A, two types of users, consumers, and third-party sellers in the marketplace. The platform facilitates transactions since it acts as an intermediary that connects consumers and third-party sellers. The operation model of the platform in this scenario is called the pure marketplace model. Additionally, there also exists a dual mode of the platform. That is, the platform can also sell its own products on the platform, which may be from the platform's own brand, such as "Made in Beijing" on Jingdong, "Amazon Basics" on Amazon, or it may be from the upstream manufacturer's product, which is not distinguished in this paper. Thus, profits of the platform are comprised of the commission from third-party sellers and profits earned from the sale of self-operated products. Moreover, the transaction between third-party sellers and consumers on the platform can generate intergroup network externalities, i.e., the positive network externalities increase in the number of sellers. For simplicity, we do not consider intra-group network externalities between consumers and third-party fringe sellers. Next, we characterize the behavior of platforms, consumers and third-party sellers, respectively.

3.1 Platforms

There exists a platform A with a certain dominant position, which can decide the operation type of the platform: the pure marketplace model, the pure seller model, or the dual model. When a platform adopts a pure marketplace model, it imposes a transaction fee of τ ($\tau \geq 0$) on third-party sellers for each transaction, while not charging any fees to consumers. These third-party sellers distribute their products through two channels: the online channel (the platform) and direct channels (the offline store). Consumers experience intergroup network externalities when purchasing from the platform, which are absent in direct channels. Moreover, product prices are often different between the two channels. Consequently, online and offline products offered by third-party sellers exhibit heterogeneity in consumer preferences, which is characterized by the Hotelling model. In this paper, we assume that the platform is positioned at point 0, while the offline store of third-party sellers is situated at point 1. Consumers are uniformly distributed along this unit, and each consumer can purchase only one product. For simplicity, the total number of consumers is normalized to 1.

When a platform adopts the pure marketplace model, its profit arises from the transaction fees charged to third-party sellers, expressed as $\Pi_A = \tau D(\cdot)$, where Π_A represents the platform's profit and $D(\cdot)$ denotes consumer demand on the platform. Given that each consumer purchases only one product, $D(\cdot)$ corresponds to the number of consumers engaging with platform A.

When a platform adopts the pure seller model, it will set a high enough transaction fee to prevent any third-party sellers from joining the platform. In this scenario, the platform exclusively sells its own products, which may be either produced internally or sourced from an upstream producer, with no distinction made in this analysis. Assume that the platform decides the product price p_A, and their marginal costs are c_A. Third-party sellers can only sell their products through offline stores, competing with the platform's offerings. The distinction between the platform's products and those of third-party sellers is still illustrated within the Hotelling model. In this pure seller model, the platform's profits generate from selling its products, expressed as $\Pi_A = (p_A - c_A)D(\cdot)$.

In the dual model, we assume that the platform can imitate and replicate third-party sellers' products with no cost, then the products of the platform are the same as those of third-party sellers. We denote the utility of each product as v, and we further assume that v is sufficiently large that each consumer will purchase one unit of product in equilibrium. Assume that when consumers perceive no differences between the platform's product and that of third-party sellers, they will opt for the platform's offering. The "gatekeeper" platform can prioritize its own products by displaying them more prominently in search results ceteris paribus. Consequently, when there is no discernible difference between the products, consumers are more likely to choose the platform's offerings, which is consistent with reality.

3.2 Third-Party Sellers

There are $N(N \geq 2)$ symmetric competitive third-party sellers in the marketplace, each of which has two channels to reach consumers, i.e., the online channel (the platform) and direct channels (the offline store). Assume that third-party sellers decide the product price p, and their marginal cost is c. According to Bertrand competition games, third-party sellers will set the price equal to the marginal cost of products in the offline store, i.e., $p=c$. The price set by the third-party seller on the platform is the sum of the marginal cost of the product and the transaction fee, i.e., $p=c+\tau$. We assume that when a third-party seller's perception of the difference between joining the platform and not joining the platform makes no difference, it will choose to join the platform. This assumption is aligned with the reality that third-party sellers can get more channels to reach consumers by joining the platform, and even if the consumers do not transact with it on the platform, it has more channels to know the consumers.

3.3 Consumers

Consumers can choose to purchase products either on the platform or through the offline store of third-party sellers. When the platform A hosts a third-party seller, consumers experience intergroup network externalities regardless of whether they buy products from the third-party seller's online channel or platform A's self-operated products. If only third-party sellers' products are available on the platform, the benefit from intergroup network externalities is αN, where $\alpha > 0$. However, if the platform offers both third-party sellers' products and its own self-operated products, the intergroup network externalities benefit is $\alpha(N+1)$. Since the platform also provides its self-operated products, the total number of sellers increases by one, resulting in greater intergroup network externalities under the dual model compared to the pure marketplace model, which aligns with existing literature on intergroup network externalities, such as Armstrong. Furthermore, the consumer's unit transportation cost is denoted as t ($t>0$). If the distance between the consumer and the platform is x, the transportation cost for purchasing a product from the platform is represented as tx.

In summary, if platform A chooses the pure marketplace model, the utility earned by a consumer x units away from platform A by purchasing a product from the third-party seller's online channel is $u=v+\alpha N-(c+\tau)-tx$. If platform A chooses the pure seller model, the utility of purchasing a product sold by platform A is $u=v-p_A-tx$. If platform A chooses the dual model, the utility of purchasing products from the third-party seller's online channel is $u=v+\alpha(N+1)-(c+\tau)-tx$, and the utility obtained from purchasing platform A's self-operated products is $u=v+\alpha(N+1)-p_A-tx$. The utility obtained from purchasing products from the third-party seller's direct offline channel under all three models is $u=v-c-t(1-x)$.

3.4 Game Timing and Equilibrium

Stage 1: Platform A chooses the operation model. If it chooses the pure marketplace model or the dual model, platform A also needs to decide the transaction fee τ.

Stage 2: The third-party seller and platform A set the prices of products p and p_A respectively.

Stage 3: Consumers make the purchasing decisions after observing the prices of the products on the different channels and their own preferences.

Since the game is a complete information dynamic game, the equilibrium of the game is a subgame-perfect Nash equilibrium. The equilibrium of this game can be obtained by backward induction.

4 EQUILIBRIUM ANALYSIS

This section evaluates three operation modes of platform , and subsequently endogenizes the model choice of the platform. Motivated by Hagiu et al.[18], in the first stage, platform A chooses one of the three models, and the choice is common knowledge.

4.1 The Equilibrium of the Pure Marketplace Model

If platform A chooses the pure marketplace model in the first stage, there exists only products of the third-party seller on platform . Moreover, products on the platform are different from those of the third-party seller's offline direct channels, which is reflected in the Hotelling model.

We assume that the marginal consumer z is the consumer for whom there is no difference between purchasing products from the third-party seller on the platform and buying it from the third-party seller's offline direct channel. This implies that the marginal consumer z receives the same utility from purchasing the product from both channels, i.e., $v+\alpha N-(c+\tau)-tz=v-c-t(1-z)$. Then we have

$$z=\frac{1}{2}+\frac{\alpha N-\tau}{2t} \tag{1}$$

This indicates that consumers in the interval $\left[0,\frac{1}{2}+\frac{\alpha N-\tau}{2t}\right]$ will purchase products from the online channel of the third-party seller, and consumers in the interval $\left[\frac{1}{2}+\frac{\alpha N-\tau}{2t},1\right]$ will purchase products from the offline direct channel of the third-party seller. When the sub-game equilibrium of the third stage of the game is obtained, the equilibrium of the second stage of the game is solved.

Since the prices of products on both the online channel and the offline direct channel of the third-party seller are known, it is only necessary to decide the transaction fee τ set by platform A in the first stage of the game under the pure marketplace model. The profit maximization problem of platform A is $\max_{\tau}\Pi_A=\tau z$, and substituting Equation (1) to solve for the first-order derivatives of Π_A with respect to τ and make it equal to 0, i.e. $\frac{\partial\Pi_A}{\partial\tau}=\frac{1}{2}+\frac{\alpha N}{2t}-\frac{\tau}{t}=0$. Then we have

$$\tau^{mkt}=\frac{t+\alpha N}{2} \tag{2}$$

where the superscript “*mkt*” represents the case where platform A chooses a pure market-based model.

From Equation (2), it can be seen that the equilibrium transaction fee of platform A under the pure marketplace model is determined by the consumer's unit transportation cost t and the total intergroup network externalities benefit αN obtained by the consumer. The equilibrium transaction fee τ^{mkt} charged by platform A increases in the consumer's unit transportation cost. When t becomes larger, the degree of differentiation between the third-party seller's online channel product and the offline direct channel product will become larger, then platform will charge a higher transaction fee. In addition, as the unit benefit of the intergroup network externality α increases, the platform can set a higher transaction fee. Similarly, as the number of third-party sellers on platform A increases, the platform can set a higher transaction fee.

Substituting Equation (2) into Equation (1) yields

$$z^{mkt}=\frac{1}{4}+\frac{\alpha N}{4t} \tag{3}$$

Since $0\leq z^{mkt}\leq 1$, $0\leq z^{mkt}=\frac{1}{4}+\frac{\alpha N}{4t}\leq 1$, $\alpha N>0$, we have

$$0<\alpha N\leq 3t \tag{4}$$

Therefore, the equilibrium profit of platform A is

$$\Pi_A^{mkt}=\frac{(t+\alpha N)^2}{8t} \tag{5}$$

Proposition 1 (Pure marketplace model equilibrium): *When platform A chooses the pure marketplace model in the first stage, the equilibrium transaction fee is* $\tau^{mkt}=\frac{t+\alpha N}{2}$, *the marginal consumer is located at* $z^{mkt}=\frac{1}{4}+\frac{\alpha N}{4t}$, *and the equilibrium profit of platform A is* $\Pi_A^{mkt}=\frac{(t+\alpha N)^2}{8t}$.

4.2 The Pure Seller Model Equilibrium

Assume that platform A chooses the pure seller model in the first stage, meaning that the platform only sells its own products and there is no third-party seller on the platform. The products of the platform compete with those of third-party seller's offline direct channel, which is reflected in the Hotelling model.

We assume that the marginal consumer z is the consumer for whom there is no difference between purchasing products from platform A and purchasing products from the direct channel of the third-party seller, so the utility acquired from purchasing the product from both channels is the same, i.e., $v-p_A-tz=v-c-t(1-z)$. Then we have

$$z=\frac{1}{2}+\frac{c-p_A}{2t} \tag{6}$$

This suggests that consumers in the interval $\left[0,\frac{1}{2}+\frac{c-p_A}{2t}\right]$ will buy products from platform A, and consumers in the interval $\left[\frac{1}{2}+\frac{c-p_A}{2t},1\right]$ will buy products from the direct channel of the third-party seller.

The profit maximization problem of platform A is $\max_{p_A} \Pi_A=(p_A-c_A)z$. Substituting Equation (6) into the profit function of platform and solving the first-order derivative of the profit Π_A with respect to p_A, it follows that

$$p_A^{sell}=\frac{c_A+c+t}{2} \tag{7}$$

Where the superscript "*sell*" represents the case where platform A chooses the pure seller model.

From Equation (7), it can be seen that platform A will take into account the marginal cost of its own product c_A, the marginal cost of its competitors' third-party sellers c, and the per unit transportation cost t when it decides the product price under the pure seller model. Clearly, p_A^{sell} increases in c_A and c. Similar to the pure marketplace model, p_A^{sell} increases in t, i.e., the price of the platform's products increases in the degree of differentiation of platform A's products compared to third-party sellers' products.

Substituting Equation (7) into Equation (6) yields the location of the marginal consumer in equilibrium

$$z^{sell}=\frac{1}{4}+\frac{c-c_A}{4t} \tag{8}$$

Since $0\leq z^{sell}\leq 1$, we have $0\leq z^{sell}=\frac{1}{4}+\frac{c-c_A}{4t}\leq 1$, then

$$-t\leq c-c_A\leq 3t \tag{9}$$

Therefore, the equilibrium profit of platform A is

$$\Pi_A^{sell}=\frac{(t+c-c_A)^2}{8t} \tag{10}$$

Proposition 2 (Pure seller model equilibrium): *When platform A chooses the pure seller model in the first stage, the equilibrium price of platform A is $p_A^{sell}=\frac{c_A+c+t}{2}$, the marginal consumer is located at $z^{sell}=\frac{1}{4}+\frac{c-c_A}{4t}$, and the equilibrium profit of platform A is $\Pi_A^{sell}=\frac{(c+t-c_A)^2}{8t}$.*

4.3 Dual Mode Equilibrium

Assume that platform A chooses a dual model in the first stage, acting both as a market intermediary carrying third-party sellers and as a seller selling its own product. The marginal cost of platform A's self-operated products is c_A. Platform decides the transaction fee τ in the first stage and the product price p_A in the second stage. Then consumers make the purchase decision in the third stage.

According to the previous assumptions, platform A can imitate the third-party seller's products with no cost. That is, the utility that each product brings to the consumer, whether it is a self-owned product of platform A or a product of a third-party seller, is v. A consumer x who chooses to purchase a product through the platform obtains a utility of $u=v+\alpha(N+1)-p_A-tx$ if he purchases a self-operated product of platform A. If he purchases a product from a third-party seller's online channel, he obtains a utility of is $u=v+\alpha(N+1)-(c+\tau)-tx$. This implies that when $v+\alpha(N+1)-p_A-tx\geq v+\alpha(N+1)-(c+\tau)-tx$, i.e., $p_A\leq c+\tau$, the online consumer will purchase only the self-operated products of platform A. When $v+\alpha(N+1)-p_A-tx<v+\alpha(N+1)-(c+\tau)-tx$, i.e., $p_A>c+\tau$, online consumers will purchase only products from the online channel of the third-party seller. The selection of the equal sign in the inequality is determined by the rule in the hypothesis that consumers will choose the product of platform A when there is no difference between platform A's self-operated product and the product of the third-party seller's online channel.

Platform A expects online consumers to buy its self-operated products, so the minimum price it can set for its self-operated products will be equal to the marginal cost of the products, i.e., $p_A=c_A$. In addition, in the dual model, platform A sells its self-operated products to all online consumers while it also carries third-party sellers due to the existence of the intergroup network externalities that attract more consumers. Therefore, platform A will set the lowest transaction fee, i.e., $\tau=0$. From the previous assumption, it follows that third-party sellers will still join the platform even if their demand in the online channel is zero.

As a result, the condition $p_A\leq c+\tau$ for online consumers to buy only platform A's self-operated products will become $c_A\leq c$, and the condition $p_A>c+\tau$ for online consumers to buy only the third-party seller's online channel products will become $c_A>c$. These two conditions imply that, when platform A's self-operated products have a cost advantage over the third-party seller's products, the dual mode will make the demand for the online channel products of the third-party sellers on the platform zero, and online consumers will only buy the self-operated products of platform A. When platform A's products do not have cost advantages, even though platform A chooses to operate in the dual mode and sells its self-operated products, its demand is 0 and online consumers only buy products from the online channel of the third-party seller. The above conditions of product cost advantage can also be replaced with other conditions such as product quality advantage. Therefore, the equilibrium conditions of platform A choosing the dual mode in the first stage of the game will be related to the size of c_A and c.

First, consider the first scenario where platform A has a product cost advantage, i.e., $c_A\leq c$. Online consumers only purchase platform A's self-operated products. There is a difference between platform A's self-operated products and the products of the third-party seller's offline direct channel, which is still reflected in the Hotelling model.

Let the marginal consumer z be the consumer who purchases platform 's self-operated product and purchases the product from the third-party seller's direct offline channel without any difference, i.e., $v+\alpha(N+1)-p_A-tz=v-c-t(1-z)$. Then we have

$$z=\frac{1}{2}+\frac{c+\alpha(N+1)-p_A}{2t} \tag{11}$$

The profit maximization problem of platform A is $\max_{p_A}\Pi_A=(p_A-c_A)z+\tau z$. From the previous analysis, we have $\tau=0$. Substituting Equation (11) into the profit function, solving the first-order derivative of profit Π_A with respect to p_A, then we can obtain the equilibrium price of platform A

$$p_A^{dual}=\frac{c_A+c+t+\alpha(N+1)}{2} \tag{12}$$

where the superscript "*dual*" represents the case where platform A chooses the dual model.

From Equation (12), it can be seen that when platform A chooses the dual mode and has cost advantages, the price p_A^{dual} is positively affected by c_A, the marginal cost of third-party sellers' products c, the transportation cost t, and the intergroup network externalities gain $\alpha(N+1)$.

Substituting Equation (12) into Equation (11) yields

$$z^{dual}=\frac{1}{4}+\frac{c+\alpha(N+1)-c_A}{4t} \tag{13}$$

The equilibrium profit of platform A is

$$\Pi_A^{dual}=\frac{[c+t+\alpha(N+1)-c_A]^2}{8t} \tag{14}$$

Comparing the equilibrium prices of the dual mode and the pure seller mode, i.e., Equations (12) and (7), it can be seen that $p_A^{dual}>p_A^{sell}$ since $\frac{\alpha(N+1)}{2}>0$. This suggests that when platform A switches from the pure seller mode to the dual mode, online consumers need to pay higher prices for the same self-operated products of platform A. However, since consumers can obtain the intergroup network externalities benefits $\alpha(N+1)$ (which does not exist in the pure seller mode) when platform A operates in the dual mode, which is greater than the loss of utility $\frac{\alpha(N+1)}{2}$ due to the increase in the price of platform A's self-operated products. Thus, the total utility of the online consumers will still increase, and the number of consumers who choose platform A in equilibrium will also increase. Compared to the pure seller model, the marginal consumer will be located further away from the platform. Therefore, the increase in the price and the quantity demand will result in higher equilibrium profits of platform A in the dual model than those in the pure seller model.

Next, consider another scenario where platform A does not have product cost advantages, i.e., $c_A>c$. Online consumers only buy products from the online channel of the third-party seller, and the demand for platform A's self-operated products is 0. There is a discrepancy of products between the online channel and the direct channel of the third-party seller, which is still reflected in the Hotelling model.

Denote z as the location where there is no difference between purchasing products from third-party sellers' online channels and purchasing products from direct offline channels. That is, $v+\alpha(N+1)-(c+\tau)-tz=v-c-t(1-z)$, by rearranging the equation, we have $z=\frac{1}{2}+\frac{\alpha(N+1)-\tau}{2t}$. Similar to the analytical steps of the first scenario, the equilibrium transaction fee is given as

$$\tau^{dual}=\frac{t+\alpha(N+1)}{2} \tag{15}$$

Substituting Equation (15) into the expression for the location of the marginal consumer yields

$$z^{dual}=\frac{1}{4}+\frac{\alpha(N+1)}{4t} \tag{16}$$

The equilibrium profit of platform A is

$$\Pi_A^{dual}=\frac{[t+\alpha(N+1)]^2}{8t} \tag{17}$$

Comparing the equilibrium transaction fees in the dual mode and the pure marketplace mode, i.e., Equation (15) and Equation (2), it can be seen that platform A will set higher transaction fees when it selects the dual mode. It is that the number of firms on the platform will increase by one when platform A switches from the pure marketplace mode to the dual mode, which in turn increases the intergroup network externalities gains for consumers. Moreover, due to the fact that the price of the third-party seller's online channel product remains unchanged at $c+\tau$, there is no utility loss for consumers, then consumers' utility of choosing the online channel product increases, which in turn makes the increase in the number of consumers on the platform. This makes platform charge a higher transaction fee to third-party sellers. Therefore, in equilibrium the marginal consumer will be located further away from platform A, and the equilibrium profit of platform A in the dual mode is higher than that of the pure marketplace model on account of the increase in the number of consumers on the platform and the volume of transactions. As a result, even though platform A's demand for its own product is zero, it is still more willing to choose in the dual model.

By comparing the equilibrium profits $\Pi_A^{dual}=\frac{[c+t+\alpha(N+1)-c_A]^2}{8t}$ and $\Pi_A^{dual}=\frac{[t+\alpha(N+1)]^2}{8t}$, we find that $\frac{[c+t+\alpha(N+1)-c_A]^2}{8t}>\frac{[t+\alpha(N+1)]^2}{8t}$ when $c_A\le c$, meaning that platform A obtains higher profits from selling self-operated products. On the contrary, when $c_A>c$, we have $\frac{[c+t+\alpha(N+1)-c_A]^2}{8t}<\frac{[t+\alpha(N+1)]^2}{8t}$, meaning that platform A earns more profits from selling products of the third-party sellers in the online channel. Therefore, the previous condition can still be verified in equilibrium.

The above equilibria in the dual mode can be summarized by Proposition 3.

Proposition 3 (Dual mode equilibrium): When platform A chooses the dual mode in the first stage, there exist two equilibria:

(1) If $c_A \leq c$, i.e., platform A has cost advantages, we drive the transaction fee $\tau^{dual}=0$, the equilibrium product price $p_A^{dual}=\frac{c_A+c+t+\alpha(N+1)}{2}$, and the equilibrium profit $\Pi_A^{dual}=\frac{[c+t+\alpha(N+1)-c_A]^2}{8t}$. The marginal consumer is located at $z^{dual}=\frac{1}{4}+\frac{c+\alpha(N+1)-c_A}{4t}$. In equilibrium all consumers on platform A will purchase platform 's self-operated products, and the demand for products of the third-party seller's online channel is zero.

(2) If $c_A>c$, i.e., platform A does not have cost advantages, we have that the equilibrium transaction fee $\tau^{dual}=\frac{t+\alpha(N+1)}{2}$ and the equilibrium profit $\Pi_A^{dual}=\frac{[t+\alpha(N+1)]^2}{8t}$. The marginal consumers are located at $z^{dual}=\frac{1}{4}+\frac{\alpha(N+1)}{4t}$. In equilibrium all consumers buy the third-party seller's products and the demand for platform A's self-operated product is zero.

From Proposition 3 and the previous analysis, it is clear that when platform A chooses a dual mode, they will always choose to sell products that have cost advantages with intergroup network externalities, which ultimately benefits consumers. Despite considering the assumption of costless imitation of third-party sellers and the self-preferencing behavior by platforms, we still find that the platforms' self-operation strategy benefits consumers through two channels: offering cost-advantaged products or increasing the benefits of consumers' intergroup network externalities.

4.4 Mode Selection

In this section, we explore the endogenous decision of the operation mode. Platform A will compare the equilibrium profits of the three models and choose the optimal operation model.

From the previous analysis, we find that the equilibrium profits of platform A in the pure marketplace model are $\Pi_A^{mkt}=\frac{(t+\alpha N)^2}{8t}$, the equilibrium profits of platform A in the pure seller model are $\Pi_A^{sell}=\frac{(t+c-c_A)^2}{8t}$, and the equilibrium profit of the dual model is related to c_A and c. If platform A has cost advantages over the third-party seller, i.e., $c_A \leq c$, the equilibrium profit of platform A in the dual model is $\Pi_A^{dual}=\frac{[c+t+\alpha(N+1)-c_A]^2}{8t}$. If platform A has no cost advantages over the third-party seller, i.e., $c_A>c$, then the equilibrium profit of platform A in the dual model is $\Pi_A^{dual}=\frac{[t+\alpha(N+1)]^2}{8t}$. The above equilibrium profits of platform A need to satisfy both Equation (4) and Equation (9). The decision of the operation model for platform A can be summarized in Proposition 4.

Proposition 4 (Model choice of platform A): Comparing the equilibrium profits under different models, we have:

(1) $\Pi_A^{mkt}>\Pi_A^{sell}$ when $c_A>c$, or $c_A \leq c$ and $c-c_A \leq \alpha N$;

(2) $\Pi_A^{mkt}<\Pi_A^{sell}$ only when $c_A \leq c$ and $c-c_A>\alpha N$;

(3) $\Pi_A^{dual}>\Pi_A^{mkt}$;

(4) $\Pi_A^{dual}>\Pi_A^{sell}$.

Therefore, platform A will choose the dual model.

From Proposition 4, when the platform's self-operated products do not have cost advantages over third-party sellers' products, i.e., $c_A>c$, the platform will choose the pure marketplace model. Even if platform A's products have cost advantages, platform A will choose the pure marketplace mode if its cost advantage is smaller than the intergroup network externalities, i.e., $c-c_A \leq \alpha N$. Only when platform A not only has cost advantages, but also its cost advantages are greater than the intergroup network externalities, i.e., $c-c_A>\alpha N$, then platform A will choose the pure seller model.

Comparing the dual model to the pure marketplace model, the profits of platform in the dual model are more profitable than those in the pure marketplace model, regardless of whether it has cost advantages or not. The economic intuition behind this is that platform A can choose whether to sell its self-operated products or products of third-party sellers on the platform due to the market dominance of platform A. Platform maximizes profits by choosing products with cost advantages. When $c_A>c$, platform does not have cost advantages and will choose to sell the third-party seller's products on the platform, this indicates that profits of platform A in the dual model are higher than those in the pure marketplace model due to the existence of intergroup network externalities according to the previous analysis. When $c_A \leq c$, platform has cost advantages and will sell its self-operated products on the platform in the dual model. The marginal revenue of each product is $p_A^{dual}-c_A=\frac{c+t+\alpha(N+1)-c_A}{2}$, while the transaction fee under the pure marketplace model is $\tau^{mkt}=\frac{t+\alpha N}{2}$, then we derive that the marginal revenue of the product is greater than the transaction fee. On the other hand, compared to the pure marketplace model, although online consumers in the dual model have to pay higher prices which results in a loss of utility, the consumer utility increases as the intergroup network externalities improve. Since the increase in utility is greater than the decrease in utility, consumers on the platform are more than those in the pure marketplace model, meaning that there is a larger transaction volume. These two items lead to higher profits for platform A in the dual model than in the pure marketplace model. Therefore, platform 's profits in the dual model are higher than those in the pure marketplace model, regardless of whether it has product cost advantages or not.

Consider the dual model and the pure seller model: when $c_A>c$, platform A in the dual model only sells the products of the third-party sellers on the platform, and acquires profits by charging a transaction fee $\tau^{dual}=\frac{t+\alpha(N+1)}{2}$. In contrast, in the pure seller model, the marginal profit of each product is $p_A^{sell}-c_A=\frac{c+t-c_A}{2}$. Since $c_A>c$, the platform obtains a higher transaction fee in the dual model than that in the pure seller model. In addition, due to the existence of intergroup network externalities, the volumes of transactions in the dual model are larger than those in the pure seller model. These two items result in higher profits for platform A in the dual model than those in the pure seller model. On the contrary, when $c_A \leq c$, profits of platform A in the dual model are higher than those in the pure seller model according to the previous analysis. Therefore, profits of platform A in the dual model are higher than those in the pure seller model, regardless of whether there are product cost advantages or not.

In conclusion, platforms achieve the highest equilibrium profits in the dual mode under the three modes, which suggests that it is an inherent choice for platforms to maximize their profits by adopting a self-operation strategy to some extent.

5 WELFARE OF BANNING DUAL MODE OF PLATFORMS

This section analyzes the welfare of platforms and consumers when the antitrust authority or the corresponding policymaking department introduces a policy that bans platforms from operating in a dual mode. When a platform is banned from operating in a dual mode, it can only choose from a pure marketplace mode or a pure seller mode which depends on the profits. Since profits of third-party sellers are always zero, the ban on dual mode of platforms has no effect on them.

Based on Proposition 4 and the previous equilibrium analysis of the three models, the impact of the dual mode ban of the platform on the platform's profit (Π_A), consumer surplus (CS), and social welfare (W) are obtained in Proposition 5.

Proposition 5 (Welfare effects of a ban on dual modes): The effect of the ban on the dual mode of platforms on platforms' profits, consumer surplus and social welfare is shown in the Table 1:

Table 1 Welfare of Banning Dual Mode of Platforms

	Platform A's model selection	CS	Π_A	W
If $c_A > c$	pure marketplace model	↓	↓	↓
If $c_A \leq c$ and $c\text{-}c_A \leq \alpha N$	pure marketplace model	↓	↓	↓
If $c_A \leq c$ and $c\text{-}c_A > \alpha N$	pure seller model	↓	↓	↓

Note: where "↓" stands for decline.

From Proposition 5, it can be seen that banning dual mode of platforms, whether by switching to a pure marketplace model or a pure seller model of operation, the profits, consumer surplus and social welfare of platform A will decrease. The reasons for the decrease in platform A's profits are explained later in Proposition 4, and the reasons for the decrease in consumer surplus and social welfare can be explained as follows.

When the dual mode is banned, if $c_A > c$, platform A will choose the pure marketplace mode, and consumer surplus will decrease. When platform A shifts from the dual mode to the pure marketplace model, the number of third-party sellers on the platform decreases, then the intergroup network externalities which can benefit online consumers also decrease. Although the product price decreases, the decrease in the utility due to the decrease in the intergroup network externalities is greater than the increase in utility due to the decrease in price. Thus, online consumer surplus will decrease. In contrast, offline consumer surplus remains unchanged, so the total consumer surplus decreases. Since both platforms' profits and the total consumer surplus decrease, social welfare decreases.

If $c_A \leq c$ and $c\text{-}c_A \leq \alpha N$, platform A also chooses the pure marketplace model in the ban of the dual model. Since platform A has cost advantages $c_A \leq c$, the online consumers will buy only the platform's self-operated products for $p_A^{dual} = \frac{c_A + c + t + \alpha(N+1)}{2}$ and get the benefits of $\alpha(N+1)$ from the intergroup network externalities without the ban of the dual mode. On the contrary, when the dual model is banned, due to the fact that platform 's cost advantage is smaller than the benefits obtained from the intergroup network externalities, i.e., $c\text{-}c_A \leq \alpha N$, platform A will choose the pure marketplace mode. Online consumers buy the third-party seller's products for $c + \tau^{mkt} = c + \frac{t + \alpha N}{2}$, and they obtain benefits αN from the intergroup network externalities. Compared to the dual mode, the net surplus of online consumers will decrease in the pure marketplace mode. As a result, both the total consumer surplus and social welfare will decrease. Even though the platform has product cost advantages, the platform will not choose the pure seller model under the ban of the dual model, and consumers can no longer access products with cost advantages.

If $c_A \leq c$ and $c\text{-}c_A > \alpha N$, the platform will shift from the dual model to the pure seller model in which the dual model is banned. Before the ban on the dual mode, the platform will only sell its self-operated products without any third-party sellers on the platform since the platform has cost advantages. When the platform transforms the dual mode to the pure seller mode, the price of the platform's products decreases from $p_A^{dual} = \frac{c_A + c + t + \alpha(N+1)}{2}$ to $p_A^{sell} = \frac{c_A + c + t}{2}$. The decrease of consumers' utility that the intergroup network externalities bring is more than the increase of utility that the decrease of the product price brings, then the net surplus of online consumers will decrease. Therefore, both the total consumer surplus and social welfare will decrease.

To sum up, under the ban of the dual model, benefits obtained from the intergroup network externalities will diminish, and the platform can no longer have cost advantages, leading to a decrease in the consumer surplus, profits of platforms and social welfare.

6 THE POLICY EFFECT OF DUAL MODE OPERATION OF PLATFORMS

This section analyzes the effectiveness of the main policies about the dual mode of platforms. There are two types of policies against the dual mode of platforms: One is structural remedies (vertical separation), which prohibits platforms from operating in a dual mode; the other is behavioral remedies, which permits platforms to operate in a dual mode but takes remedial measures against unfair competition or behaviors detrimental to consumers' interests.

6.1 Structural Separation

The structural separation policy involves the ban on dual mode operation of platforms. The European Commission raised the policy during its antitrust investigation against Google in 2019. India also banned Amazon from the dual mode in 2019.

From Proposition 5, even in situations where platforms are allowed to imitate the products of third-party sellers and to perform self-preferencing, both the consumer surplus and social welfare will decrease in the ban on the dual mode operation. Since consumers cannot obtain products with cost advantages and benefits that intergroup network externalities bring, structural separation policies do not improve consumers' situation. In addition, profits of platforms will decrease in the structural separation policy, which may not be conducive to the sustainability of platforms.

6.2 Behavioral Remedies Policy

The behavioral remedial policy involves the ban of copying and imitating from the products of third-party sellers, the ban of self-preferencing to platforms' self-operated products, or both. When the platform is banned from imitating the third-party seller's products, the self-operated and the third-party seller's products bring different utilities to consumers, i.e., v in this paper will be different. Moreover, the platform will sell both its self-operated products and third-party sellers' products in the equilibrium of the dual mode. This may intensify the price competition between the platform and third-party sellers, which may benefit consumers.

When self-preferencing of the platform to its self-operated products is banned, consumers will randomly choose the products of platforms or third-party sellers if there is no difference between the products of platforms and those of third-party sellers. Given the existence of the self-preferencing, consumers will purchase the platform's self-operated products rather than products from third-party sellers. The ban on self-preferencing of the platform can improve the market environment, which is beneficial to consumers and can increase social welfare.

Therefore, policies that implement behavioral remedies against unfair competition arising from dual modes of platforms may behave better than structural separation policies that directly prohibit the dual mode of platforms [18].

7 CONCLUSION

As platforms achieve market dominance, more and more giant platforms adopt the dual mode. They serve as both the intermediary marketplaces and sellers of self-operated products. As "gatekeepers", platforms may engage in unfair competition, which leads to investigations by antitrust authorities. However, researches on platforms' self-operated strategies are emerging, and there is no consistent conclusion concerning the welfare effects and whether platforms' dual mode should be banned. In this paper, we utilize the Hotelling model to explore the equilibrium of platforms under three modes, i.e., the pure marketplace mode, the pure seller mode, and the dual mode. Furthermore, we endogenize the model selection of platforms and analyze the impacts of the ban on the dual mode of platforms on consumer welfare, profits of platforms, and social welfare. Finally, we briefly discuss the current policy effects of the self-operation strategy of platforms. We conclude the following :

(1) The platform's self-operation strategy benefits consumers, the platform and social welfare. When platforms adopt the self-operation strategy and operate in a dual mode, they benefit consumers through two mechanisms: offerings of products with cost advantages and benefits of intergroup network externalities.

(2) Compared to the pure marketplace model and the pure seller model, platforms achieve the largest profits in the dual model, which indicates that platforms will endogenously choose the self-operation strategy and the dual mode for profit maximization.

(3) When platforms are banned from the dual mode and enable them to endogenously choose their operation mode, they will choose the pure seller mode only when platforms have cost advantages and the difference between the marginal cost of third-party sellers and that of the platform is larger than benefits that intergroup network externalities bring; otherwise, the result is reserved, they will choose the pure marketplace model.

(4) Consumer surplus, profits of platforms and social welfare will decrease in the ban of the dual mode of platforms. Therefore, the structural separation policy that directly prohibits the dual mode of platforms cannot improve consumer surplus and social welfare.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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CAN DIGITAL TRANSFORMATION ENHANCE INFORMATION DISCLOSURE QUALITY?

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Abstract: Amid the rapid development of the artificial intelligence era, digital technology has become deeply embedded in corporate development, and the implementation of digital transformation has emerged as a primary driver for the transformation and upgrading of the real economy. This paper examines a sample of Shanghai and Shenzhen A-share listed companies from 2010 to 2021. By quantifying the degree of corporate digital transformation through text mining and constructing a moderated mediation model, this study analyzes the underlying mechanism linking digital transformation, internal control, and information disclosure quality. It further explores the moderating role of the marketization process. The findings indicate that corporate digital transformation significantly enhances information disclosure quality, with this effect being more pronounced in state-owned enterprises (SOEs), high-tech firms, and industries with high market concentration. The mechanism analysis reveals that internal control plays a partial mediating role in the relationship between digital transformation and information disclosure quality. Furthermore, the marketization process moderates both the direct effect and the mediation effect. A higher degree of marketization strengthens the positive impact of digital transformation on disclosure quality. This moderation of the mediation effect is primarily concentrated on the first stage of the path, amplifying the positive influence of digital transformation on internal control. These conclusions enrich the literature on the economic consequences of digital transformation and the determinants of information disclosure quality, and they hold significant practical implications for firms implementing digital transformation and innovating their business models.
Keywords: Digital transformation; Internal control; Information disclosure quality; Marketization process; Moderated mediation effect

1 INTRODUCTION

Driven by the rapid development of the digital economy and the advancement of Industry 4.0, corporate digital transformation has emerged as a crucial strategic shift for adapting to contemporary trends. In its *China Digital Economy Development Report (2022)*, the China Academy of Information and Communications Technology (CAICT) called for the deepening of corporate digital transformation and upgrading, the implementation of digital management, and the creation of data-driven operational management systems to ensure effective information feedback. The digital economy has become both a "stabilizer" and an "accelerator" for the national economy. In 2021, its scale reached 45.5 trillion CNY, accounting for nearly 40% of GDP, with industrial digitalization comprising over 80% of this total. It is evident that the digital economy is now of paramount importance for promoting high-quality economic development, and corporate digital transformation has become an indispensable step for industrial upgrading. Fundamentally, corporate digital transformation involves leveraging next-generation information technologies to enhance capabilities in data collection, processing, and analysis. This, in turn, optimizes the allocation of internal and external resources, drives technological, organizational, and managerial change, and ultimately enhances a firm's core competitiveness [1]. Information disclosed by a firm enables external users to make objective assessments of its operating status, making high-quality disclosure a critical safeguard for sound investment decisions. When information asymmetry or managerial opportunism leads to earnings manipulation and compromises the disclosure process, the resulting information becomes distorted, thereby lowering disclosure quality. In this context, digital transformation has been shown to effectively curb real earnings management activities [2]. Furthermore, digital transformation can reshape a firm's internal operational mechanisms, strengthening internal controls and thereby influencing accounting information comparability [3]—a key attribute of information disclosure quality. Therefore, proceeding from this critical trend, this study investigates a key economic consequence of digital transformation. It explores the pathway through which digitalization impacts information disclosure quality, with internal control as the mediating mechanism. Building on this, the study further examines how disparities in the external environment—specifically, the uneven development of the marketization process—moderate this causal chain and its overall effect. This research aims to provide actionable strategies and pathways for firms to achieve high-quality information disclosure. Simultaneously, it enriches the literature on the economic consequences of digital transformation and provides a decision-making basis for firms seeking to accelerate their digitalization efforts.

2 HYPOTHESIS DEVELOPMENT

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2.1 Digital Transformation and Information Disclosure Quality

Digital transformation represents a multi-faceted overhaul of a firm's business processes, business models, and strategic thinking. It not only triggers disruptive changes in production management and daily operations but also influences a firm's motivation and ability to adhere to accounting standards, thereby affecting its financial reporting process and the quality of its information disclosure. This influence manifests in two primary ways.

First, digital transformation can curb managerial opportunism and strengthen the monitoring of potential earnings management activities. By deeply embedding digital technologies, firms can make information generated by all parties more transparent, thus enhancing disclosure quality. The rapid growth of the digital economy has intensified market competition, which can increase a firm's liquidity risk and place considerable pressure on its earnings [4]. Such pressure often incentivizes managerial earnings management, leading to suboptimal accounting policy choices that artificially inflate profits and degrade the quality of disclosed information. The implementation of digital transformation can mitigate this issue by suppressing managerial opportunism [5]. Specifically, the adoption of intelligent technologies during transformation facilitates the creation of real-time monitoring mechanisms based on both operational and financial data [6-7]. Digital enablement allows for the seamless sharing of data across departments, which not only enhances internal collaboration and oversight but also makes managerial decisions regarding accounting policies and estimates more transparent. This increased transparency provides external stakeholders with timely access to crucial information via digital platforms, thereby strengthening external monitoring and compelling firms to disclose higher-quality information.

Second, digital transformation improves a firm's internal information environment, alleviating information asymmetry between the firm and outside stakeholders, which in turn leads to higher disclosure quality. The information a firm discloses is a cornerstone for stakeholders' investment decisions; high-quality disclosure enhances the decision-usefulness of information and reduces the cost of decision errors [8]. In practice, however, managers may engage in opportunistic behaviors, leveraging their authority and informational advantages to interfere with the information reporting process. Digital transformation counters this by employing technologies like big data, artificial intelligence, and blockchain to optimize information transmission methods and efficiency. This ensures that information remains shared and transparent throughout its entire lifecycle—from production and transmission to final reporting—thus improving the information environment and, consequently, the quality of disclosure [9]. Specifically, digitalization enhances a firm's data analytics capabilities. AI can convert data from various departments into standardized, structured information, which helps optimize business processes and improves the accuracy and timeliness of information flows, laying a solid foundation for enhanced disclosure quality [10]. Based on this analysis, we propose the following hypothesis:

Hypothesis 1 (H1): Digital transformation is positively associated with information disclosure quality.

2.2 Digital Transformation and Internal Control

The quality of a firm's internal control is reflected across five key components: the control environment, risk assessment, control activities, information and communication, and monitoring. Digital transformation impacts all five of these areas. First, it fosters a deep integration of digital technology into the firm, fundamentally improving the control environment. Digital technologies permeate the entire process of production, operation, and management, blurring traditional organizational boundaries and enabling more efficient and diverse connections between internal and external entities. This interconnectedness of equipment, products, and resource systems facilitates data sharing, gives rise to digital management practices, and promotes a flatter organizational structure [11-12]. Second, technologies like cloud computing, AI, and blockchain enable the generation and aggregation of vast amounts of data, providing real-time insights into customer demand and market changes. This supports the development of risk-warning models, allowing firms to proactively identify, assess, and respond to potential risks. Third, digital transformation influences control activities by shifting business processes from traditional to digital and intelligent modes. It also reshapes the workforce, as firms increasingly seek to cultivate and recruit hybrid talent with expertise in both management and big data analytics, thereby fundamentally improving internal management efficiency. Fourth, it revolutionizes information and communication by transforming hierarchical information structures into networked ones. Digital platforms not only enhance the efficiency of data processing but also reduce information distortion during transmission [13-14]. Finally, digital transformation strengthens internal monitoring. The shared data resources on digital platforms create an inherent internal oversight system, while the move toward flatter organizational structures further enhances routine supervision. Therefore, as digital transformation improves all five components of internal control, we hypothesize:

Hypothesis 2 (H2): Digital transformation is positively associated with the quality of internal control.

2.3 The Mediating Role of Internal Control

Digital transformation strengthens a firm's internal control monitoring mechanisms. High-quality information disclosure depends on the reliability of financial reports, which in turn is closely linked to the effectiveness of these mechanisms. Consequently, strong internal control enhances information disclosure quality [15]. Specifically, effective internal control significantly improves earnings quality. A higher quality of internal control indicates a more robust corporate governance structure [16], which is better equipped to restrain managerial earnings manipulation [17-18]. Since earnings management directly affects the truthfulness and accuracy of disclosed information, stringent internal controls are crucial for improving disclosure quality. Given our argument in H2 that digital transformation enhances internal control quality, we posit that this enhancement is a key pathway through which digitalization ultimately improves information disclosure.

Hypothesis 3 (H3): Internal control partially mediates the relationship between digital transformation and information disclosure quality.

2.4 The Moderating Role of the Marketization Process on the Digital Transformation-Disclosure Quality Relationship

The marketization process represents a systemic transition involving dynamic changes across economic, social, legal, and political spheres. Regional differences in geographical location led to variations in resource endowments, market environments, and the direction and intensity of state policies [19]. Regions with a higher degree of marketization typically exhibit more advanced economic development and a faster adoption of next-generation information technologies, providing the necessary infrastructure for digital transformation. According to signaling theory, a higher degree of marketization facilitates a smoother flow of information within the market. This helps transforming firms to acquire more external environmental information in a timely manner [20], which aids in the construction and application of digital platforms and enhances the efficiency of internal information transmission. This fundamentally alleviates information asymmetry and provides both the technological and environmental foundation for improving information disclosure quality.

Hypothesis 4 (H4): The marketization process positively moderates the relationship between digital transformation and information disclosure quality.

2.5 The Moderating Role of the Marketization Process on the Digital Transformation-Internal Control Relationship

The external supervisory environment also varies with the degree of marketization. Regions with a higher marketization process tend to have more developed and sounder legal and institutional frameworks. In these regions, the separation of government and enterprise is more complete, legal oversight and penalties are stricter, and the economic order is more stable. This fosters a stronger external monitoring mechanism, which deters opportunistic behaviors like earnings management. As digital transformation improves internal control through data sharing and efficient information flows, this effect is amplified by the strong external oversight present in highly marketized environments. The combination of internal digital monitoring and external market discipline creates a powerful synergy, further strengthening the positive impact of digital transformation on internal control quality. Based on this analysis, we propose:

Hypothesis 5 (H5): The marketization process positively moderates the relationship between digital transformation and internal control.

Based on the theoretical analysis above, we construct a model illustrating the mechanisms through which digital transformation affects corporate information disclosure quality, as shown in Figure 1.

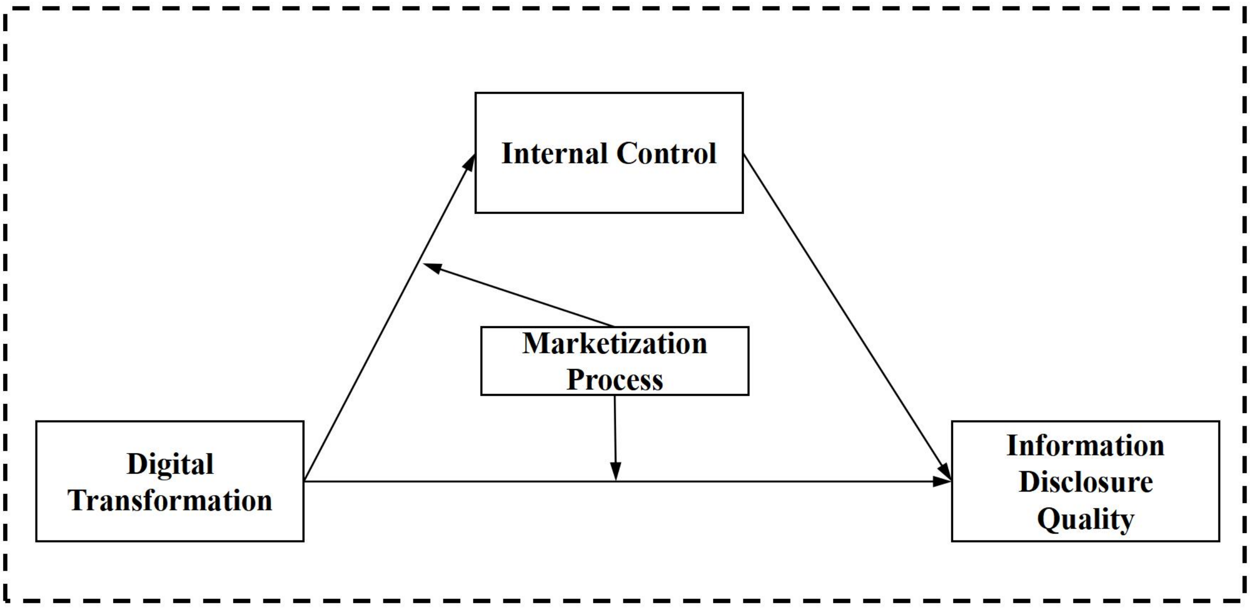

Figure 1 Theoretical Model

3 RESEARCH DESIGN

3.1 Sample Selection and Data Sources

This study selects a sample of companies listed on the Shanghai and Shenzhen A-share markets, using panel data from the period 2010-2021. The sample was refined according to the following criteria: (1) financial firms, such as banks, securities firms, and insurance companies, were excluded due to their unique asset structures; (2) firms with an operational history of less than one year were excluded; (3) firms designated as ST, *ST, or PT during the study period, as well as those with significant missing data, were excluded.

The data for this study were sourced as follows: data on digital transformation were extracted from corporate annual reports; internal control data were obtained from the DIB database; marketization process data were sourced from the China Marketization Index database; information disclosure quality data were based on the rating results from the Shenzhen Stock Exchange website; and other financial data were primarily collected from the CSMAR database. After applying the exclusion criteria, all continuous variables were winsorized at the 1% level to mitigate the influence of outliers. The final sample consists of 20,168 firm-year observations. All empirical analyses were conducted using Stata 17.0.

3.2 Variable Definitions

3.2.1 Dependent variable: information disclosure Quality ($QID_{i,t}$)

Based on the information disclosure quality ratings provided by the Shenzhen Stock Exchange, we measure this variable by quantifying the four rating levels: A, B, C, and D are assigned values of 4, 3, 2, and 1, respectively. A higher score indicates higher information disclosure quality.

3.2.2 Independent variable: digital transformation ($DT_{i,t-1}$)

Corporate digital transformation is a key strategy in the era of big data and artificial intelligence, and information related to it is most likely to be reflected in comprehensive and guiding documents like annual reports. Therefore, following the methodology of Wu et al., we measure the degree of digital transformation by the frequency of related keywords in corporate annual reports. First, referencing the structured keyword list developed by [21]—which covers five dimensions: artificial intelligence, big data technology, cloud computing technology, blockchain technology, and digital technology application—we use Python's Jieba library to extract and sum the frequencies of these keywords from the annual reports. To account for the typical right-skewed distribution of this data, we take the natural logarithm of the total frequency plus one.

3.2.3 Mediating variable: internal control ($IC_{i,t-1}$)

The quality of internal control is measured using the DIB Internal Control Index. Given the large scale of this index, we take the natural logarithm of the index value plus one to facilitate comparison with the other core variables in this study.

3.2.4 Moderating variable: marketization process ($Mkt_{i,t}$)

This variable is measured using the marketization index developed by Fan Gang and Wang Xiaolu [22].

3.2.5 Control variables

We include a standard set of control variables: Return on Assets (ROA), calculated as net profit divided by the average of total assets; Leverage (LEV), measured as total liabilities to total assets; Cash Flow Ratio (Cash), calculated as cash flow from operating activities divided by main business revenue; Firm Size (Size), the natural logarithm of year-end total assets; Firm Age (Age), the natural logarithm of the number of years since establishment; Growth (Growth), the firm's main business revenue divided by the average main business revenue of the previous period; Proportion of Independent Directors (Bind), the ratio of independent directors to the total number of board members; First Largest Shareholder's Holding (First dummy), a dummy variable equal to 1 if the first largest shareholder's stake is above the sample mean, and 0 otherwise; Audit Opinion (Opinion), a dummy variable equal to 1 for a standard unqualified audit opinion, and 0 otherwise; and Auditor Size (Big4), a dummy variable equal to 1 if the firm is audited by one of the Big Four accounting firms, and 0 otherwise. We also control for industry and year fixed effects.

3.3 Model Construction

3.3.1 Mediation effect model

Drawing on the mediation effect testing procedures proposed by Baron and Kenny [23]and Wen et al. [24].

$$QID_{i,t} = \alpha_1 + \beta_1 DT_{i,t-1} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{1}$$

$$IC_{i,t-1} = \alpha_2 + \beta_2 DT_{i,t-1} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{2}$$

$$QID_{i,t} = \alpha_3 + \beta_3 DT_{i,t-1} + \delta_1 IC_{i,t-1} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{3}$$

3.3.2 Moderated Mediation Effect Model (First Stage)

Following the testing procedures for moderated mediation proposed by Wen and Ye [25], we construct the following models to test our hypotheses.

$$QID_{i,t} = \alpha_4 + \beta_4 DT_{i,t-1} + \lambda_1 Mkt_{i,t} + \mu_1 DT_{i,t-1} * Mkt_{i,t} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{4}$$

$$IC_{i,t-1} = \alpha_4 + \beta_4 DT_{i,t-1} + \lambda_2 Mkt_{i,t} + \mu_2 DT_{i,t-1} * Mkt_{i,t} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{5}$$

$$QID_{i,t} = \alpha_5 + \beta_5 DT_{i,t-1} + \lambda_3 Mkt_{i,t} + \mu_3 DT_{i,t-1} * Mkt_{i,t} + \varphi IC_{i,t-1} + \sum \gamma control + \sum Year + \sum Ind + \varepsilon \tag{6}$$

First, to test the moderating effect of the marketization process （$Mkt_{i,t}$） on the relationship between digital transformation（$DT_{i,t-1}$）and information disclosure quality（$QID_{i,t}$）, we examine the coefficient μ_1 of the interaction term $DT_{i,t-1} * Mkt_{i,t}$ in model (4). If this coefficient is statistically significant, it indicates that the moderation of the main effect is supported. Second, to test the moderating effect of the marketization process（$Mkt_{i,t}$）on the first stage of the mediation path, we examine two coefficients: the coefficient of the interaction term μ_2 in model (5) , and the coefficient φ of the internal control（$IC_{i,t-1}$）in model (6). If both coefficients are statistically significant, it confirms the existence of a moderated mediation effect.

4 EMPIRICAL ANALYSES

4.1 Descriptive Statistics

The descriptive statistics for the main variables are presented in Table 1. The mean of Information Disclosure Quality (*QID*) is 2.893 with a standard deviation of 0.762, indicating some variation in disclosure ratings among firms. While the overall quality is good, there is significant room for improvement in certain companies. For Digital Transformation *(DT)*, the mean is 1.225 with a standard deviation of 1.472, and the values range from 0 to 4.976, suggesting a considerable disparity in the degree of digitalization across firms. The Internal Control *(IC)* variable has a mean of 6.29, indicating a generally high level of internal control quality. However, with a standard deviation of 0.734 and a range from 0 to 6.805, significant differences exist between firms. The Marketization Process *(Mkt)* has a mean of 7.315 and a standard deviation of 1.579, with values ranging from -0.243 to 9.571, clearly showing the phenomenon of uneven regional development in marketization. Among the control variables, the mean for ROA is 0.04 (ranging from -0.236 to 0.196), and the mean for leverage is 0.375 with a standard deviation of 0.214. The means for cash flow ratio, firm size, firm age, growth, and independent director proportion are 0.179, 23.058, 2.833, 0.184, and 0.395, respectively. The mean for the first largest shareholder's holding dummy is 0.426. Additionally, approximately 93.1% of firms in the sample received a standard unqualified audit opinion, while only 5.9% engaged one of the Big Four accounting firms for their external audits. In summary, the descriptive statistics reveal significant heterogeneity among listed companies in terms of their operational and financial status, as well as their management and organizational structures.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
QID	20,168	2.893	0.762	1.000	4.000
DT	20,168	1.225	1.472	0.000	4.976
IC	20,168	6.290	0.734	0.000	6.805
Mkt	20,168	7.315	1.579	-0.243	9.571
ROA	20,168	0.040	0.058	-0.236	0.196
LEV	20,168	0.375	0.214	0.059	0.899
Cash	20,168	0.179	0.150	0.016	0.747
Size	20,168	23.058	1.303	18.339	27.942
Age	20,168	2.833	0.416	1.587	3.579
Growth	20,168	0.184	0.563	-0.558	3.903
Bind	20,168	0.395	0.061	0.316	0.582
First dummy	20,168	0.426	0.151	0.070	0.750
Opinion	20,168	0.931	0.168	0.000	1.000
Big4	20,168	0.059	0.243	0.000	1.000

4.2 Correlation Analysis

A correlation analysis of the main study variables is presented in Table 2. The correlation coefficient between Digital Transformation *(DT)* and Information Disclosure Quality *(QID)* is 0.056 and is significant at the 1% level, providing preliminary evidence that digital transformation enhances disclosure quality. The correlation coefficients for the mediator (Internal Control) and the moderator (Marketization Process) with *QID* are 0.102 and 0.137, respectively, both significant at the 1% level. This suggests that both factors are also positively associated with information disclosure quality, although further regression analysis is required to establish causality.

Table 2 Correlation Matrix of Key Variables

Variable	*QID*	*DT*	*IC*	*Mkt*
QID	1			
DT	0.056***	1		
IC	0.102***	0.055***	1	
Mkt	0.137***	0.216***	0.149***	1

*Note: ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively (the same applies hereafter).*

4.3 Regression Analysis

The results of the mediation effect tests are shown in columns (1), (2), and (3) of Table 3. In Model (1), the regression coefficient of $DT_{i,t-1}$ on $QID_{i,t}$ is 0.0009 and is significant at the 1% level. This indicates that a higher degree of digital transformation is associated with higher information disclosure quality, thus supporting H1. In Model (2), the regression coefficient of $DT_{i,t-1}$ on $IC_{i,t-1}$ is 0.0021 and is also significant at the 1% level, demonstrating that digital transformation enhances the quality of internal control. This validates H2. In Model (3), after including the mediator, the coefficient of $DT_{i,t-1}$ on $QID_{i,t}$ remains significant at 0.0008 (p < 0.01), but its magnitude is smaller than in Model (1). This finding, combined with the significance of the $IC_{i,t-1}$ variable in the model, confirms that internal control acts as a partial mediator in the relationship between digital transformation and information disclosure quality. This supports H3.

The results of the moderated mediation tests are presented in columns (4), (5), and (6) of Table 3. First, in Model (4), the interaction term $(DT_{i,t-1} * Mkt_{i,t})$ has a coefficient of 0.0483 and is significant at the 1% level. This confirms that the marketization process positively moderates the relationship between digital transformation and information disclosure quality. The positive effect of digitalization on disclosure is stronger in regions with a higher degree of marketization, thus supporting H4. Second, in Model (5), the interaction term $(DT_{i,t-1} * Mkt_{i,t})$ has a coefficient μ_2 of 0.0629 and is significant at the 1% level. In Model (6), the coefficient of the mediator $IC_{i,t-1}$ remains significant at 0.0023 (p < 0.01). Together, these results confirm the existence of a moderated mediation effect in the first stage of the path. The marketization process moderates the mediating effect of internal control by strengthening the positive influence of digital transformation on internal control quality, thereby validating H5.

Table 3 Regression Analysis Results

Variable	Model（1）	Model（2）	Model（3）	Model（4）	Model（5）	Model（6）
	$QID_{i,t}$	$IC_{i,t-1}$	$QID_{i,t}$	$QID_{i,t}$	$IC_{i,t-1}$	$QID_{i,t}$
$DT_{i,t-1}$	0.0009*** （3.76）	0.0021*** （6.85）	0.0008*** （3.68）	0.0007** （1.83）	0.0021*** （6.84）	0.0009*** （3.75）
$IC_{i,t-1}$	—	—	0.0011*** （2.93）	—	—	0.0023*** （3.62）
$Mkt_{i,t}$	—	—	—	0.0362*** （9.72）	0.1784*** （4.285）	0.0298*** （8.87）
$DT_{i,t-1} * Mkt_{i,t}$	—	—	—	0.0483*** （7.488）	0.0629*** （5.338）	0.0393*** （7.224）
$ROA_{i,t}$	-0.0036*** （-2.94）	0.0017 （0.89）	-0.0037*** （-2.89）	-0.0160*** （-5.201）	0.0016 （0.87）	-0.0166 （-1.344）
$LEV_{i,t}$	-0.0048*** （-8.91）	-0.0055** （-1.74）	-0.0051*** （-9.01）	-0.0053** （-3.29）	-0.0049** （-1.91）	-0.0048** （-1.82）
$Cash_{i,t}$	0.0006（0.47）	0.1211*** （5.02）	0.0006（0.48）	0.0008*** （6.53）	0.1187*** （4.97）	0.0006***（6.59）
$Size_{i,t}$	-0.0024** （-1.75）	0.0570** （1.92）	-0.0030** （-1.69）	-0.0235** （-1.76）	0.0317** （1.76）	-0.0214** （-1.83）
$Age_{i,t}$	-0.0029*** （-8.24）	0.0003** （1.87）	-0.0026*** （-9.12）	-0.0062*** （-6.56）	0.0005** （1.89）	-0.0078*** （-7.47）
$Growth_{i,t}$	-0.0006 （-1.21）	0.0008** （1.89）	-0.0007 （-1.27）	-0.0005** （-1.68）	0.0021** （1.78）	-0.0016** （-1.73）
$Bind_{i,t}$	0.0009 （0.32）	0.0021** （1.69）	0.0008 （0.30）	0.0012 （0.47）	0.0030** （1.86）	0.0036* （1.59）
$First\_dummy_{i,t}$	-0.0031** （-1.89）	-0.0294** （-1.85）	-0.0036** （-1.93）	-0.0046** （-1.77）	-0.0285** （-1.70）	-0.0039** （-1.73）
$Opinion_{i,t-1}$	0.0045*** （6.03）	0.0204*** （4.47）	0.0052*** （6.95）	0.0061** （1.84）	0.0236*** （4.65）	0.0084** （1.84）
$Big4_{i,t-1}$	-0.0052** （-1.93）	0.2311*** （3.76）	-0.0059** （-1.79）	-0.0078** （-1.77）	0.2326*** （4.05）	-0.0066** （-1.86）
Cons	0.0299*** （9.63）	0.3655*** （10.02）	0.0317*** （8.48）	0.0225*** （6.35）	0.3104*** （11.73）	0.0238*** （7.15）
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	20,168	20,168	20,168	20,168	20,168	20,168
$Adj\text{-}R^2$	0.1766	0.2387	0.2291	0.1904	0.1297	0.1756
F	58.9030***	49.7321***	53.0384***	63.0643***	46.2037***	49.3992***

4.4 Robustness Checks

4.4.1 Endogeneity test

Although key control variables were included, the determinants of information disclosure quality are complex, and the potential for omitted variable bias exists. To address this endogeneity concern, we employ an instrumental variable (IV) approach. We use the one-year lagged industry average of digital transformation（$In\_DT_{i,t-1}$）as the instrument. This variable is theoretically correlated with a firm's individual level of digital transformation but is unlikely to directly affect its information disclosure quality, thus satisfying the requirements for a valid instrument. We further conducted diagnostic tests to validate the instrument, with the results shown in Table 4. The first-stage F-statistic is 57.7834 (p <

0.001), passing the exogeneity test. The Sargan statistic is 0, and the Cragg-Donald Wald F-statistic is 56.3362, indicating no issues with over-identification or weak instruments. We then performed a two-stage least squares (2SLS) regression, with the results presented in columns (1) and (2) of Table 4. The findings are consistent with the baseline regression results, and the coefficients in the 2SLS model are even larger, confirming the robustness of our initial conclusions.

4.4.2 Alternative measure of digital transformation

The degree of digital transformation may vary across industries. To eliminate this industry-level effect, we adopt the measurement method of Yuan [13] and use an industry-adjusted digital transformation indicator ($Adj\_DT_{i,t-1}$). This metric reflects a firm's level of digitalization relative to its industry peers. The regression results using this alternative measure are shown in column (3) of Table 4. The coefficient of $Adj\_DT_{i,t-1}$ is 0.0009 and is significant at the 1% level, demonstrating that our findings remain robust after changing the measurement of the independent variable.

Table 4 Robustness Checks

	2SLS		Alternative Measure of DT
	$DT_{i,t-1}$	$QID_{i,t}$	$QID_{i,t}$
$DT_{i,t-1}$		0.0011^{***} (3.89)	
$In\_DT_{i,t-1}$	0.0438^{***} (10.56)		
$Adj\ DT_{i,t-1}$			0.0009^{***} (3.92)
$ROA_{i,t}$	0.0178^{***} (7.93)	-0.0054^{***} (-4.03)	-0.0046^{***} (-2.38)
$LEV_{i,t}$	0.0046^{**} (1.74)	-0.0056^{***} (-8.02)	-0.0042^{***} (-8.77)
$Cash_{i,t}$	0.0323^{**} (1.85)	0.0005 (0.46)	0.0007 (0.49)
$Size_{i,t}$	0.2689^{***} (7.34)	-0.0026^{**} (-1.95)	-0.0045^{**} (-1.79)
$Age_{i,t}$	0.0054^{**} (1.91)	-0.0056^{***} (-6.73)	-0.0045^{***} (-9.49)
$Growth_{i,t}$	0.0163^{**} (1.95)	-0.0008 (-0.94)	-0.0008 (-0.95)
$Bind_{i,t}$	0.1746^{*} (1.43)	0.0013 (0.53)	0.0011 (0.63)
$First\_dummy_{i,t}$	-0.3765^{**} (-1.74)	-0.0034^{**} (-3.45)	-0.0037^{**} (-1.92)
$Opinion_{i,t-1}$	0.1179^{**} (1.88)	0.0046^{***} (6.04)	0.0068^{***} (6.49)
$Big4_{i,t-1}$	0.2168^{**} (1.73)	-0.0045^{**} (-1.93)	-0.0077^{**} (-1.86)
Cons	0.0047 (0.85)	0.0311^{***} (9.88)	0.0357^{***} (8.90)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
N	20,168	20,168	20,168
$Adj\text{-}R^2$	0.2676	0.1967	0.2375
F	57.7834^{***}		53.0384^{***}
C-D Wald F test	56.3362		
P-value	0		
Sargon Test	0		

4.4.3 Bootstrap test for the difference in mediation effects

To further ensure the reliability of the empirical results, this study employs a bootstrap analysis to test the significance of the difference in the mediation effect across different levels of marketization. Specifically, we conduct a simple slope analysis at one standard deviation above and below the mean of the marketization process variable to verify whether the difference in the mediation effect between these groups is statistically significant. The results are presented in Table 5. As shown in the table, the 95% confidence intervals for the effects do not contain zero. This indicates that the mediating effect of internal control is significantly stronger in environments with a higher degree of marketization, once again validating H4 and H5.

Table 5 Bootstrap Test for the Difference in Mediation Effects

Marketization Process	Effect	Boot SE	95% Confidence Interval

			Lower Bound	Upper Bound
-1 Standard Deviation	0.128	0.054	0.059	0.317
Mean	0.127	0.054	0.060	0.320
+1 Standard Deviation	0.437	0.089	0.285	0.617

5 FURTHER ANALYSES: HETEROGENEITY TESTS

Having confirmed through baseline regressions and multiple robustness checks that digital transformation enhances information disclosure quality, we now explore whether this effect varies across different contexts. Differences in industry competition and firm characteristics could lead to variations in the impact of digitalization. Therefore, this study conducts a heterogeneity analysis from the perspectives of industry concentration, ownership structure, and technological attributes. The results are presented in Table 6.

From the perspective of industry concentration, the positive effect of digital transformation on information disclosure quality is more pronounced in firms within highly concentrated industries ($\beta = 0.0012$, $p < 0.01$). This suggests that in more competitive environments, firms are more motivated to leverage digital transformation to improve information sharing and transparency. Doing so helps attract external investors and solidify their competitive advantage within the industry.

From the perspective of ownership structure, the effect is stronger for state-owned enterprises (SOEs) than for non-SOEs ($\beta = 0.0136$, $p < 0.01$). This finding underscores the leading role SOEs should continue to play in responding to the trends of the digital economy, continuously improving their information disclosure systems and enhancing disclosure quality.

From the perspective of technological attributes, the impact of digital transformation on disclosure quality is significantly stronger for high-tech firms ($\beta = 0.0026$, $p < 0.01$). Compared to their non-high-tech counterparts, high-tech firms inherently possess a more advanced digital foundation and stronger innovation capabilities, making them more willing and able to adopt and apply digital technologies. This advantage should be fully utilized to strengthen the governance effects of their digital transformation, thereby driving the transformation of non-high-tech firms and elevating the overall information disclosure quality across all industries.

Table 6 Heterogeneity Analysis Results

Variable	Industry Concentration		Ownership Structure		Technological Attribute	
	High	Low	SOEs	Non-SOEs	High-Tech	Non-High-Tech
$DT_{i,t-1}$	0.0012^{***} (3.83)	0.0004 (1.02)	0.0136^{***} (4.09)	0.0005 (0.97)	0.0026^{***} (4.15)	0.0010 (1.27)
Cons	0.0299^{***} (9.63)	0.1603^{***} (11.69)	0.2046^{***} (6.82)	0.1375^{***} (8.38)	0.2003^{***} (8.92)	0.0729^{***} (6.65)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	8,734	11,434	9,045	11,123	8,092	12,076
Adj-R²	0.2045	0.1987	0.2011	0.1895	0.2134	0.1994
F	47.4554^{***}	50.2846^{***}	49.6775^{***}	46.9022^{***}	47.0981^{***}	50.6566^{***}

6 CONCLUSIONS

In the era of the digital economy, digital transformation has become an essential path for firms to achieve high-quality development. Implementing digital transformation has a profound and comprehensive impact on all aspects of a firm, including its production and operations, resource allocation, financial decision-making, and business models. Using a sample of Shanghai and Shenzhen A-share listed companies, this paper established a series of regression models, including a moderated mediation model, to empirically test the mechanisms linking digital transformation, internal control, and corporate information disclosure quality. It also explored the moderating role of the marketization process. The main conclusions are as follows:

First, the implementation of digital transformation significantly enhances corporate information disclosure quality. A higher degree of digitalization leads to higher disclosure quality, an effect that is more pronounced in state-owned enterprises (SOEs), high-tech firms, and highly concentrated industries. Further analysis reveals that internal control plays a partial mediating role in this relationship; that is, digital transformation improves disclosure quality in part by enhancing the quality of internal control.

Second, the marketization process positively moderates the relationship between digital transformation and information disclosure quality. The positive impact of digitalization on disclosure is stronger in regions with a higher degree of marketization.

Third, the moderated mediation analysis confirms that the marketization process moderates the first stage of the mediation path. Specifically, it strengthens the positive effect of digital transformation on internal control, which in turn enhances the overall mediating role.

Under the current wave of digitalization, increasing the emphasis on and support for corporate digital transformation is crucial. Accelerating this process not only promotes the rapid development of China's digital economy at the macro level but also effectively enhances corporate information disclosure quality and improves the information environment of the capital market at the micro level. Therefore, this study offers the following recommendations:

First, government departments should continue to strengthen digital infrastructure construction, implement relevant support policies, and optimize industry market structures. They should leverage the leading role of SOEs and the developmental advantages of high-tech firms, encouraging all companies to integrate digital technologies into every facet of production, operation, and management. By fostering a competitive mindset and enhancing the efficiency of data integration, transmission, and disclosure, firms can standardize their disclosures. Digital transformation can thus fortify the bridge of communication between external information users and internal management, alleviating information asymmetry at the procedural level and curbing managerial opportunism at the source, thereby ensuring high-quality information disclosure.

Second, firms must increase the depth and scope of their digital technology application. While creating a favorable information environment, they must also prioritize the establishment of intelligent risk-warning and assessment systems. This will minimize the probability of risk occurrence, improve internal control quality, and consequently enhance information disclosure quality.

Finally, regarding the marketization process, government bodies should further advance market-oriented reforms. This includes strengthening external oversight during the digital transformation process, ensuring that firms are held accountable for continuously providing high-quality information to the capital market.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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THE IMPACT OF THE NEW ASSET MANAGEMENT REGULATION ON BANK STABILITY RISK

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Abstract: The Guiding Opinions on Regulating the Asset Management Business of Financial Institutions (the New Asset Management Regulation) jointly issued by the People's Bank of China and four other departments in April 2018 effectively cuts off the risk transmission paths of the shadow banking business, but it also poses a challenge to the conduct of business of commercial banks. This paper selects the annual panel data of 42 listed banks from 2013 to 2022, and analyzes the impact of the policy shock of the new regulation on bank stability risk by double difference model (DID). The results show that the introduction of the new regulation on capital management significantly reduces the stability risk of banks; when banks have lower capital adequacy and face more risks, the greater the positive impact of the new regulation on them.
Keywords: New asset management regulation; Commercial banks; Stability risk; Capital adequacy ratio

1 INTRODUCTION

Since 2012, the asset management sector has seen rapid growth, with products like bank wealth management reaching a scale of one trillion dollars, and their role in the financial system becoming increasingly prominent. Meanwhile, the prevalence of channel business has made mixed operations a more notable feature of the financial market. The emergence of cross-market and cross-institutional financial products has led to frequent issues such as rigid redemption and multi-layer nesting. Additionally, asset management business has caused a significant increase in risk-free interest rates, which deviates from the principle of matching risk and return, elevates systemic risks in the financial sector, and goes against the fundamental role of financial institutions in promoting industrial development. In this context, in April 2018, the Central Bank and other relevant departments jointly issued the Guiding Opinions on Regulating the Asset Management Business of Financial Institutions.The implementation of these new regulations helps mitigate the excessive risks in the asset management business.

Currently, China's financial system remains largely dependent on indirect financing, with commercial banks playing a pivotal role. These banks are not only central to the credit transmission mechanism but also serve as the largest participants in the asset management market. On the asset side, banks primarily operate through financial products, which can be classified—based on accounting treatment—into on-balance-sheet and off-balance-sheet categories.

On-balance-sheet financial products are typically subject to stricter regulatory oversight, as their risks are retained within the bank's formal financial structure. In contrast, off-balance-sheet products are generally structured so that investment risk and returns are borne entirely by investors. As a result, regulatory scrutiny over off-balance-sheet activities tends to be less rigorous. However, in practice, competitive pressures in the banking industry have led institutions to implicitly guarantee returns. To attract more capital, banks often compensate investors for losses using their own resources, thereby creating what is known as "rigid redemption" or "rigid payment."

This behavior effectively reintroduces risk exposure from off-balance-sheet operations back onto the banks' financial positions, undermining the intended risk segregation. The internalization of these risks poses significant threats to the stability of the financial system.

Furthermore, in order to expand their asset management business, banks frequently collaborate with non-bank financial institutions to raise capital, which is predominantly allocated to non-standard credit assets. These assets—such as those tied to infrastructure development or real estate—are characterized by long maturity periods, low transparency, and poor liquidity. Due to the lack of standardized trading mechanisms and limited disclosure, such investments cannot be easily liquidated in times of stress.

Consequently, this structural illiquidity increases the vulnerability of financial institutions to cash flow mismatches and redemption pressures. When compounded across the system, these weaknesses can evolve into systemic liquidity crises, posing broader risks to financial stability.

In response to these problems, the new asset management regulations have set forth requirements such as restricting rigid payment on the liability side, curbing non-standard business on the asset side, and limiting financial institutions' channel operations and multi-layer nesting. This study adopts the DID model to assess how the newly introduced regulations influence bank risk, treating the policy as an external shock and examining the variation in its effects across different banks.The innovation out of this paper is reflected in the following points. First, the existing literature has inconsistent views on the impact of the new regulation on bank stability risk, in view of this, this paper collects data from 2013-2022 and uses the double-difference-in-differences (DID) method to analyze and explore the impact of the

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new regulation on bank stability risk. Second, this paper finds that the impact of the new capital management regulations on banks is heterogeneous and has a greater impact on banks with lower capital adequacy ratios.

2 LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Literature Review

The introduction of the new asset management regulations aims to incorporate the asset management operations of financial institutions into a unified regulatory framework, thereby addressing loopholes in financial supervision and curbing regulatory arbitrage. These new rules adopt a "penetrating supervision" approach, tracing multi-layered nested products both upward to identify ultimate investors and downward to uncover underlying assets. Nonetheless, the regulatory constraints placed on shadow banking activities have also introduced new risks to the stability of commercial banks.

On the liability side, the updated regulations impose tighter controls on banks' funding sources. Specifically, investors are now classified into two groups: the general public and qualified investors. By subjecting shadow banking participants to formal regulation, the scope for banks to attract funds is narrowed, potentially affecting their liquidity positions [1]. Prior to the enforcement of these rules, wealth management products often offered high yields and principal guarantees, making them a more attractive option than low-return deposit products. With the new regulation tightening the eligibility criteria for qualified investors based on risk tolerance and financial capacity, banks may find it harder to attract funds. To address potential liquidity shortfalls, banks could be forced to liquidate assets, increasing the likelihood of cross-market fund flows and amplifying systemic risk within the banking sector [2].

On the asset side, Under the new asset management regulations, banks are no longer permitted to engage in capital pooling practices or implement maturity mismatches, compelling a fundamental shift away from their traditional business models and making transformation inevitable [3]. Historically, much of the shadow banking activity conducted by commercial banks has relied on pooling funds and investing in credit bonds through mismatched maturities. The ban on such mismatches severely disrupts the viability of the capital pooling structure, which had previously been a core feature of their operations, thereby necessitating a redesign of legacy shadow banking practices. Currently, bank-issued financial products are predominantly structured as expected return types, while net asset value (NAV)-based products remain limited in scale. The explicit prohibition of expected return financial instruments under the new framework presents significant challenges for banks in meeting long-term non-standard asset allocation demands.

The transition between legacy and newly introduced financial products presents significant challenges, heightening the liquidity risk faced by commercial banks. While the revised asset management regulations may initially disrupt traditional banking models and increase operational instability, they offer long-term benefits by clearly prohibiting practices such as capital pooling, rigid payment guarantees, expected yield commitments, and channel-based operations. These regulatory changes help redirect funds from speculative or non-productive uses to the real economy, mitigate cross-sectoral risk transmission, and strengthen the financial system's overall resilience. According to Fang Xianming and Chen Chu [4], the inherent complexity of shadow banking—characterized by overlapping markets and institutions—substantially raises the likelihood of systemic risk contagion. The new asset management rules aim to break these interconnections, thereby minimizing systemic correlations and enhancing the stability of commercial banks. Additionally, Duan Xisheng [5] argues that these regulatory updates mark the beginning of a new era in comprehensive asset management, where the evolving supervisory framework encourages industry-wide standardization and realigns asset management practices with their foundational purposes. This transformation is expected to foster sustainable growth in banks' asset management operations.

2.2 Theoretical Hypotheses

In conclusion, the new asset management regulations exhibit a dual impact on the stability risk faced by banks. On one hand, they heighten risk by limiting banks' ability to attract and utilize funds; on the other, they help mitigate systemic risk by curbing shadow banking activities and banning nested financial operations. Despite this dual nature, existing literature has yet to clearly assess how these regulations influence the overall stability of commercial banks. This paper contends that, while the implementation of the new regulatory framework initially exposed banks to liquidity constraints and transformation pressures, its long-term effect has been a reduction in stability risk. Now, five years after the regulations were introduced, most banks have moved beyond the initial adjustment phase. Based on this context, the paper proposes the following hypotheses:

H1: The implementation of the new regulations on asset management will have an impact on the stability risk of the bank .

Compared with state-owned banks, joint-stock banks face relatively looser regulatory supervision and have experienced faster growth in their shadow banking activities. Since the new regulations explicitly ban practices such as capital pooling, multi-layer nesting, and shadow banking, it is expected that these rules will exert a stronger influence on joint-stock banks. Consequently, the reduction in risk is anticipated to be more pronounced for joint-stock banks than for state-owned banks. Based on this reasoning, the following hypothesis is proposed:

H2: The arrival of the new regulations on capital management makes the stability risk of joint-stock banks will fall more than state-owned commercial banks.

3 BENCHMARK MODEL, DATA AND VARIABLE DESCRIPTION

3.1 Benchmark Model

To examine how the new asset management regulations affect listed banks, this study employs DID approach, treating the introduction of these regulations as a quasi-natural experiment. The DID model is a common and effective tool for evaluating policy impacts, particularly because it helps mitigate endogeneity issues. Following the DID methodology, the model in this paper is specified as follows:

$$Y_{i,\ t} = \beta_0 + \beta_1 \cdot Treat_i \times Post_t + \sum_{i=0}^{n} X_i \cdot \theta + \lambda_i + \sigma_t + \varepsilon_{i,\ t} \tag{1}$$

Y_{it} is the stability risk indicator of bank i in period t, denoted by Z-score. Treat is a treatment group dummy variable with Treat=1 if it is a joint-stock bank, and Treat=0 if it is a state-owned commercial bank. Post is a policy dummy variable with the implementation time of the new regulation policy on capital management set to 2018. The coefficient β_1 of the cross-multiplier term is the policy impact effect. $\sum_{i=0}^{n} X_i$ is a set of control variables. In order to exclude the influence of other omitted variables, this paper adds individual fixed effects $\varepsilon_{i,\ t}$ and time fixed effects σ_t

3.2 Sample Selection

This study selects 42 A-share listed banks (including those dual-listed in Hong Kong) as the research sample and constructs a panel dataset spanning from 2013 to 2022. Financial indicators and wealth management product data are sourced from Wind, the CSMAR database, and the banks' annual reports, while macroeconomic variables are obtained from the National Bureau of Statistics (NBS). Two main criteria guided the sample selection. First, listed banks are chosen due to their standardized disclosure practices and the completeness of their annual data, which ensures the availability of key variables necessary for empirical analysis. As a result, 42 A-share listed banks were selected. By the end of 2022, these banks collectively accounted for 76.72% of total banking assets in China, offering strong industry representativeness. The sample includes six major state-owned commercial banks—namely, Bank of China, Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, Bank of Communications, and Postal Savings Bank—and 36 joint-stock commercial banks such as Industrial Bank, China Merchants Bank, Huaxia Bank, Minsheng Bank, CITIC Bank, and Zheshang Bank. Secondly, in view of the transitional phase of the new asset management rules, this study incorporates the most recent data available up to 2022 to enhance empirical robustness. To ensure sample adequacy and continuity, a decade-long panel dataset from 2013 to 2022 is utilized.

3.3 Variable Description

Explanatory Variable:To capture the stability risk of individual banks, this study employs the Z-score as the primary indicator. A higher Z-score (Z-value) reflects lower risk levels and indicates greater operational stability for the bank.
Core Explanatory Variable:Within the framework of the Difference-in-Differences (DID) model, the key explanatory variable is defined as the interaction term between a treatment group indicator and a policy implementation dummy, representing the policy's differential impact on affected banks.
Control Variables:Drawing on existing literature, this paper incorporates a range of control variables. These include bank-specific indicators such as return on assets (ROA), non-performing loan ratio, loan-to-deposit ratio (LDR), net interest margin (NIM), and cost-to-income ratio. Additionally, macroeconomic conditions are controlled for using the M2 money supply growth rate.

4 EMPIRICAL RESULTS

4.1 Results of Empirical Analysis

According to Table 1, the coefficient of the interaction term $Treat_i \times Post_t$ is always significantly negative regardless of whether the control variables are added or not, which verifies hypothesis H2: the introduction of the new regulations on capital management makes the stability risk of the joint-stock commercial banks decrease significantly compared with that of the large state-owned banks.The results also validated the hypothesis H1.

Table 1 Benchmark Regression Results

	(1)	(2)
VARIABLES	Z-score	Z-score
$Treat_i \times Post_t$	23.89	24.47
	(10.20)	(10.63)
ROA		13.00

		(21.54)
NIM		-3.564
		(8.868)
CIR		-0.507
		(0.789)
NPL		-0.492
		(9.037)
LDR		-0.0799
		(0.337)
M2		0.550
		(1.413)
Constant	15.49	32.95
	(6.135)	(42.94)
Observations	459	440
R-squared	0.094	0.099
Company FE	YES	YES
Year FE	YES	YES

Standard errors in parentheses
* p<0.01,   p<0.05, * p<0.1

4.2 Robustness Test-Parallel Trend Test

The DID model needs to satisfy the parallel trend assumption, i.e., the development trend of the treatment group and the control group is the same when there is no policy intervention. In this paper, four years before and after the implementation of the policy are selected as samples, with 2018 as the benchmark, pre_* as the pre-implementation year, current as 2018, post_* as the post-implementation year, 2015-2013 as pre_*3, and 2021-2022 as post_4, and pre_1 is removed to avoid multicollinearity. Figure 1 indicates that prior to the implementation of the new capital management regulations, the Z-score was not statistically significant, suggesting that the treatment and control groups exhibited similar development trends, thereby meeting the parallel trend assumption. After the policy was introduced, the Z-score coefficient turned positive and statistically significant.

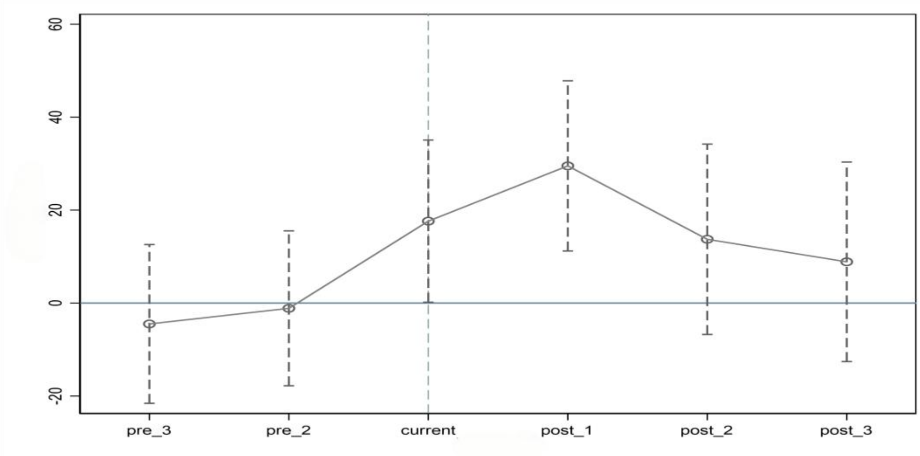

Figure 1 Parallel Trend Test

4.3 PSM-DID Test

To strengthen the analysis, this research utilizes the Propensity Score Matching (PSM) technique, adopting the approach from Shi Dachan et al. (2018) ¥[6]. A logit regression estimates the policy indicator and control variables, facilitating the matching of samples with similar propensity scores. This process enables a comparison between treatment and control groups to determine if significant differences are present. As shown in Table 3, the matching results reveal no statistically significant differences between the groups, validating the combined PSM-DID methodology. Furthermore, the regression results in Table 2 align with previous outcomes, confirming the robustness of the empirical findings.

Table 2 Robustness Test

Variable Matched	Treated （mean）	Control （mean）	%reduct (%bias)	%reduct (|bias|)	t	p>t	V(T)/V(C)
ROA U	0.940	0.983	-18.100		-1.410	0.159	0.79*
M	0.966	0.982	-6.700	62.900	-0.830	0.405	1.050
NIM U	2.405	2.255	32.800		2.220	0.027	1.94*
M	2.298	2.280	3.8	88.400	0.470	0.637	1.91*
CIR U	30.306	33.915	-39.800		-4.370	0.000	0.14*
M	31.160	30.596	6.2	84.400	0.880	0.380	0.22*
NPL U	1.323	1.298	6.4		0.460	0.645	1.27*
M	1.324	1.304	5.3	17.400	0.570	0.566	1.63*
LDR U	73.257	69.404	26.800		2.080	0.038	0.830
M	70.532	70.362	1.2	95.600	0.140	0.892	0.67*
M2 U	9.946	9.655	8.6		0.680	0.498	0.75*
M	9.974	9.239	21.700	-152.100	2.330	0.020	0.76*

* if variance ratio outside [0.82; 1.23] for U and [0.78; 1.29] for M

In order to avoid the problem of sample selection bias, this paper uses the PSM office to process the samples. Using the processed samples to regress again, the regression results of the PSM-screened samples are shown in Table 3, and the regression results of the screened samples remain significant[7-8].

Table 3 PSM-DID Regression Results

	(2)
VARIABLES	z1
$Treat_i \times Post_t$	21.31*
	(12.58)
control variable	YES
Observations	302
R-squared	0.105
Number of id2	42
Company FE	YES
Year FE	YES

5 HETEROGENEITY ANALYSIS

The benchmark model above estimates the average effect of the new regulation on bank stability risk, but does not capture differences in bank characteristics. This paper further examines the heterogeneous effects of these characteristics on stability. Using the capital adequacy ratio as a dividing criterion to reflect the loss-bearing capacity of banks' own capital, the sample is divided into two groups, above and below the median, and regressed separately, and the results are shown in Table 4. The regressions show that banks with lower capital adequacy ratios are more affected by the policy and the stability risk decreases after the implementation; banks with higher capital adequacy ratios also experience a decrease in risk, but it is not significant[9].

Table 4 Heterogeneity Analysis Regression Results

	(1)	(3)
VARIABLES	Crar>median	Crar<median
$Treat_i \times Post_t$	10.29	26.62*
	(14.60)	(15.52)
ROA	-3.011	30.02
	(33.45)	(37.23)
NIM	0.902	-5.876
	(13.46)	(14.34)
CIR	-0.196	-0.385
	(0.944)	(1.393)
NPL	9.176	-4.125
	(18.17)	(14.80)

LDR	0.535	-0.381
	(0.503)	(0.510)
M2	0.146	2.217
Constant	-19.87	44.45
	(56.40)	(79.18)
Observations	168	272
R-squared	0.090	0.126
Number of id2	38	39
Company FE	YES	YES
Year FE	YES	YES

6 CONCLUSIONS AND RECOMMENDATIONS

In this paper, we select the panel data of 42 listed banks from 2010 to 2022, and analyze the impact of the new regulation on banks' stability risk by constructing a double difference model (DID)[10]. The conclusions are as follows.
Firstly, the new asset management regulations substantially lower banks' stability risk by limiting fundamental characteristics of their asset management operations, including capital pooling, guaranteed returns, rigid payments, public fundraising, and channeling activities—all of which tend to increase banks' inherent stability risks.
Secondly, the impact of the new regulations on different banks is heterogeneous, with a greater impact on banks with lower capital adequacy ratios, which can reduce their stability risk to a greater extent.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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THE IMPACT AND INFLUENCE OF DIGITAL CURRENCIES ON THE TRADITIONAL FINANCIAL SYSTEM: OPPORTUNITIES, CHALLENGES AND TRANSFORMATION

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Abstract: Digital currency, as an emerging financial instrument, is having a profound impact on the traditional financial system. This paper explores the transformative role of digital currencies on the global financial system by analysing the types of digital currencies, their technological foundations and their impact on the areas of money supply, banking, payment systems and capital markets. First, digital currencies have improved payment efficiency and financial inclusion, especially central bank digital currencies (CBDC) and decentralized finance (DeFi) have driven innovation in payment systems and cross-border payments. Second, the popularity of digital currencies also poses regulatory and compliance challenges, particularly in terms of monetary policy, financial stability, and cross-border regulation. Finally, the paper highlights the potential of digital currencies to drive financial services inclusion and market innovation, particularly in the area of decentralised finance. Nonetheless, issues of technical security, market risk and legal compliance still need to bead dressed. In the future, the development of digital currencies will depend on technological advances and regulatory harmonization on a global scale.
Keywords: Digital currency; Central bank digital currency (CBDC); Decentralised finance (DeFi); Cross-border payment

1 INTRODUCTION

Over the past decades, digital currencies have evolved from an emerging technological innovation to a force to be reckoned with in the global financial arena. Especially in recent years, with the rise of cryptocurrencies such as Bitcoin and the promotion of the experimentation and landing of central bank digital currencies (CBDC) by central banks, the concept and application of digital currencies have transcended the technological realm and have become an important variable affecting the traditional financial system[1-2]. Digital currencies not only represent a new payment method, but also challenge, to some extent, the definition of traditional money, the implementation mechanism of monetary policy, and the role of financial intermediaries. Its potential impact and changes to the financial system have become the focus of attention of financial academics, policy makers and financial market participants around the world.
The purpose of this paper is to explore the impact and influence of digital currencies on the traditional financial system, in particular, to analyse the three aspects of opportunities, challenges and transformation. Firstly, the paper will review the basic concepts, types and technical basis of digital currencies to help readers understand the characteristics of this emerging financial instrument. Then, this paper will focus on analysing the impact of digital currencies on the traditional financial system, exploring its role in money supply, banking, capital market and financial stability. Subsequently, the paper will discuss the policy and regulatory challenges posed by digital currencies, particularly in terms of monetary policy, financial regulation, and compliance. Finally, the article will explore the potential of digital currencies to drive transformation of the financial system, particularly in the areas of decentralized finance (DeFi), payment system innovation and cross-border payments.
With the rapid development of digital currencies, their impact and influence on the traditional financial system is not only an object of academic research, but also a core issue in policy making and financial practice. Therefore, the research in this paper is not only of academic significance, but also of extensive practical value, providing theoretical support and policy recommendations for understanding and responding to the transformative challenges posed by digital currencies.

2 OVERVIEW AND CLASSIFICATION OF DIGITAL CURRENCY

2.1 Definition of Digital Currency

Digital currency is a form of currency that exists in digital form, and its value relies on cryptography, distributed ledger or centralised credit system to ensure that it can realise the digital transfer of value and settlement. From the technical point of view, digital currency breaks through the physical form of traditional physical currency (such as banknotes and coins), and completes the circulation in the network through binary data, which is the product of the deep integration of information technology and financial industry.
In academic research, the definition of digital currency needs to be defined in terms of technical basis and core features. From the technical basis, most digital currencies rely on cryptography to ensure the security and anonymity of

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transactions[3]. At the same time, they use distributed ledger technology to achieve decentralized transaction recording and verification, which makes them tamper-proof and traceable. The core features are reflected in three aspects: first, the digital carrier, completely detached from the physical form, relying on electronic equipment for storage and transactions; second, the value of the anchor mechanism, part of the digital currency and the legal tender pegged, part of the market through the supply and demand to form the price; third, the circulation of the inter-temporal space and time, can be realised in a global network environment for instantaneous transfer of funds, not subject to traditional financial institutions business hours or geographical restrictions[4-5].

2.2 Types of Digital Currency

2.2.1 Central Bank Digital Currency (CBDC)

Central Bank Digital Currency (CBDC) is a digitised legal tender issued by the central bank, with the same legal status and unlimited legal tender as banknotes and coins, with the core features of centralised issuance and legal credit endorsement, and the issuance mechanism articulating the traditional monetary policy framework, aiming to supplement or replace the circulation of cash and enhance payment efficiency.

The technology path is divided into "account-based" and "token-based" categories: the former is similar to the traditional bank account system, where transactions are completed through identity authentication; the latter draws on the design of cryptocurrencies, with digital signatures to verify ownership and support offline transactions (e.g., China's digital RMB). At present, China's digital RMB and Sweden's electronic krona (e-krona) have entered the pilot stage, with application scenarios covering retail payments, government subsidy disbursement, and cross- border settlement.

2.2.2 Cryptocurrency

Cryptocurrencies are decentralized digital currencies based on blockchain technology, relying on cryptographic algorithms to guarantee transaction security and anonymity, with transaction records permanently stored in the blockchain, and not relying on centralised financial institutions or government regulation. 2008 saw the introduction of Bitcoin by the pseudonym Satoshi Nakamoto, which was launched in 2009, and has become the first and best known cryptocurrency. Since then, Ethereum, XRP and Litecoin have emerged, each using different technologies and algorithms. For example, Ether is not only a cryptocurrency, but also supports smart contracts and decentralized applications (DApps). These currencies operate through a decentralized network, eliminating the need for intermediaries, making transactions faster and cheaper.

The cryptocurrency market has a high degree of volatility, which is regarded as both an "emerging asset" and poses a financial stability risk, and has become a global regulatory focal point due to the lack of regulation and vulnerability to use in money laundering, terrorist financing and other illegal activities.

2.2.3 Stablecoin

Stablecoins aim to reduce the volatility of the cryptocurrency market, with values usually linked to a single fiat currency (e.g., the U.S. dollar, the euro) or a basket of commodities (e.g., gold) at a relatively stable price, which solves the problem of high volatility of cryptocurrencies, and makes them more suitable for payments and daily transactions.

Tether (USDT) and USD Coin (USDC) are representative projects that maintain exchange ratios with fiat currencies through different mechanisms, e.g.,

Tether is always equal to US$1. With the rise of decentralized finance (DeFi), stablecoins are widely used in cross-border payment, lending and derivatives markets.

2.3 The Technical Basis of Digital Currencies

The core technical foundation of digital currency includes blockchain technology, cryptography, consensus mechanism and smart contracts. Blockchain, as a decentralized distributed ledger, guarantees security and trustworthiness by virtue of tamper-proof data storage and transparent transaction records; cryptography ensures the privacy and integrity of transactions through public key encryption, hash algorithms and digital signatures to support security verification in a decentralized network; consensus mechanisms such as Proof of Work (PoW) and Proof of Stake (PoS), which are the protocols reached by nodes of the blockchain to guarantee the validity of transactions and network security; smart contracts support the automatic execution of contractual agreements without intermediaries to promote decentralised finance (DeFi) and other financial innovations. Together, these technologies ensure the validity of transactions and the security of the network, forming an efficient and reliable transaction system that accelerates the digitalization and decentralization of financial services [4].

3 THE IMPACT OF DIGITAL CURRENCY ON THE TRADITIONAL FINANCIAL SYSTEM

The emergence of digital currencies has not only changed the traditional means of payment and transaction methods, but also had a far-reaching impact on the multifaceted structure and function of the traditional financial system. Specifically, digital currencies have had a significant impact on a number of areas, including money supply, banking, payment systems, capital markets, and financial stability. The following will explore in detail the impact of digital money on the traditional financial system from these perspectives.

3.1 Money Supply and Circulation

The money supply is a crucial part of the traditional financial system and is usually controlled by national central banks through fiat currencies. However, the emergence of digital currencies, in particular Central Bank Digital Currency (CBDC) , has the potential to redefine the mechanism of money supply and circulation. Unlike traditional currencies that rely on physical notes and coins, CBDC, as an electronic form of legal tender, not only offers advantages in terms of speed of circulation and ease of payment, but also enables more precise regulation of money supply through more efficient management tools.

In addition, the emergence of digital currencies may also affect the transmission mechanism of monetary policy. Monetary policy implemented by the central bank through the CBDC will no longer rely on the transmission of commercial bank intermediaries, but can directly affect the payment behaviour of individuals and enterprises, thus potentially improving the effectiveness of monetary policy. For example, the programmability of digital currencies may enable the CBDC to implement more refined monetary policy, such as directly regulating the amount of money in circulation in a particular industry or region[7].

3.2 Banking and Financial Institutions

In the traditional financial system, banks play a crucial role, providing basic services such as savings, loans and payments. However, the popularity of digital currencies, especially central bank digital currencies (CBDC) and cryptocurrencies, may pose a significant impact on the core business of commercial banks. On the one hand, the ease of payment and transparency of digital currencies may prompt some customers to transfer their deposits to digital currencies as the preferred payment instrument for individuals and businesses. On the other hand, the decentralized nature of digital currencies may undermine the role of banks as financial intermediaries, particularly in their core functions of payment settlement and funds movement.

Nonetheless, the rise of digital currencies also presents an opportunity for banks to innovate. Commercial banks can develop financial products and services related to digital currencies and drive the digital transformation of their business through technological cooperation and innovation. The integration of financial technology (Fintech) with the banking industry will be a key direction for future development. Banks can make use of emerging technologies such as blockchain to optimise payment, clearing and transaction systems, thereby reducing costs and improving operational efficiency[8].

3.3 Payment systems and cross-border payments

Innovation in payment systems is one of the most intuitive impacts of digital currencies. Traditional payment systems typically rely on third-party intermediaries (e.g., banks or payment companies) and often face higher costs and slower settlements in cross-border payments. Digital currencies, particularly CBDCs and cryptocurrencies, can provide faster and lower-cost payment solutions through decentralized technology. The implementation of CBDCs can make cross-border payments more efficient as it avoids the need for multiple layers of intermediaries and complex foreign exchange conversion processes, and dramatically improves the timeliness of settlements.

3.4 Capital Market Impact

The impact of digital currencies on the capital market is multifaceted. Firstly, as an emerging asset class, cryptocurrencies have attracted the participation of a large number of investors, leading to changes in the structure of risky assets in the capital market. The high volatility and decentralized nature of cryptocurrencies such as Bitcoin and Ether have made them popular targets for speculative investment, and while this feature has increased the risk in the market in the short term, it has also brought unprecedented return opportunities for investors.

Second, the combination of digital currencies and blockchain technology promotes innovation in the capital market. Blockchain technology not only improves the transparency and traceability of assets, but also automates trading through smart contracts, reducing the risk of market manipulation. New financial products and market forms such as digital asset securitisation and decentralized finance (DeFi) are also emerging under the impetus of digital currencies, changing the landscape of traditional capital markets[6].

4 CHALLENGES OF DIGITAL CURRENCY TO FINANCIAL POLICY AND REGULATION

With the rise of digital currencies, especially the popularity of central bank digital currencies (CBDC) and cryptocurrencies, the regulatory framework of the global financial system is facing unprecedented challenges. The decentralized nature of digital currencies, global cross-border liquidity and deep integration with the traditional financial system make it difficult for the existing financial regulatory regime to adapt to this emerging field. In response to these challenges, policymakers and regulators need to revisit and adapt existing policy tools and regulatory mechanisms to ensure the stability and transparency of the financial system.

4.1 Adaptation of Monetary Policy

The introduction of CBDCs may reconfigure the monetary policy transmission mechanism. Under the traditional model, the central bank regulates the money supply through the intermediation of commercial banks, while the popularity of

CBDC allows the central bank to provide e-money directly to the public, bypassing the commercial banking system, which may trigger the loss of bank deposits and weaken its credit creation function.
The programmability of digital currencies expands the space for monetary policy operations. The central bank can regulate the flow of funds to specific industries or regions through technical means, such as relying on smart contracts to regulate the supply of funds to specific economic sectors, which breaks through the operational boundaries of traditional monetary policy. How to effectively integrate such new tools with the existing policy framework and ensure their effectiveness has become a core issue for central banks.
At the same time, CBDCs may also enhance the precision of policy transmission. By issuing money directly to the public, central banks can more directly influence the behaviour of microeconomic agents, for example, by implementing precise interest rate regulation or targeted monetary stimulus.

4.2 Challenges to Financial Stability

The rise of cryptocurrencies poses a systemic challenge to financial stability. Their markets are highly volatile and subject to manipulation risks: sharp price fluctuations in bitcoin, ethereum, etc. not only affect investors' balance sheets, but may also impact financial institutions holding related assets, triggering a chain reaction of sell-offs and systemic risks.
The decentralized nature of digital currencies (especially in the field of decentralized finance (DeFi)) increases the difficulty of regulation, leading to an increase in the risk of illicit financial flows, money laundering and other financial crimes. Asset management and transparency of stable coins are also critical, if the reserve assets are not properly operated, its price collapse may trigger a chain reaction in the financial market, so the regulation of stable coins has become the core link to maintain market stability.

4.3 Complexity of Cross-Border Regulation and Coordination

The cross-border and decentralized nature of digital currencies puts global regulation in a difficult position. While traditional regulation relies on country- specific frameworks, the global nature of digital currencies makes it difficult for them to be controlled by a single jurisdiction, leading to a divergence of regulatory attitudes among countries (from a total ban to leniency and inclusiveness).
The lack of regulatory harmonisation has led to multiple problems: regulatory arbitrage has been highlighted, with market players tending to operate in regulatory pockets; and inconsistencies in international standards have led to legal and tax differences in cross-border transactions, increasing trade and investment uncertainty.
The Bank for International Settlements (BIS), the Financial Stability Board (FSB) and others are promoting global regulatory harmonisation, with the aim of establishing a unified framework to safeguard transaction transparency and prevent capital flow risks. This requires countries to strengthen cooperation and information sharing, and gradually achieve harmonisation of regulatory standards.

4.4 Future Development of Regulatory Framework

Global regulators need to accelerate the construction of a regulatory framework for digital currencies, which not only covers traditional financial regulatory elements, but also incorporates technological regulatory dimensions (e.g. blockchain compliance, smart contract standards, cross-chain technology transparency, etc.), and seeks to strike a balance between security, privacy protection and technological innovation, so as to avoid impacting market stability.
International coordination is a key direction for framework construction. As applications deepen, regulatory reforms in areas such as cross-border payments, stable coins, and CBDCs need to rely on global institutions to advance. Global regulatory integration can reduce market uncertainty and enhance the resilience of the financial system.
At the same time, the framework needs to be dynamically adaptable to cope with technological changes, and safeguard the vitality of market innovation while preventing and controlling systemic risks.

5 THE ROLE OF DIGITAL CURRENCIES IN THE TRANSFORMATION OF THE FINANCIAL SYSTEM

5.1 Enhancement of Financial Inclusion

The popularisation of digital currencies has injected a strong impetus to financial inclusion, especially in developing countries and areas with weak traditional financial coverage, breaking down service barriers and expanding the scope of participation in the global financial system.
CBDC and cryptocurrencies provide new access to the unbanked. In many underdeveloped areas of developing countries, a large number of people have difficulty in accessing traditional banking services, and with the help of smartphones and the Internet, users can directly access digital currency platforms to carry out payment, savings, lending and other activities, which will significantly increase the penetration rate of financial services. India, Kenya and other countries have gradually improved financial access in poor areas through digital currency and payment technology.
In addition, the decentralized nature of digital currencies breaks through the limitations of traditional banking networks, further reducing intermediation costs and enabling financial services to reach more remote users. This enhanced inclusiveness is important for promoting global economic growth and narrowing the gap between the rich and the poor.

5.2 Cross-border Payments and Global Financial Integration

CBDC can be designed as a cross-border payment tool to realise direct fund transfers between countries and regions, reducing intermediation costs and foreign exchange risks. For example, the People's Bank of China is promoting digital RMB cross-border payment pilots, and plans to improve efficiency through co-operation with central banks in other countries. Through the interconnection of CBDC systems in various countries, it is expected to break the dollar-dominated global payment system and promote the balanced development of multi-currency payment and settlement methods.

At the same time, the cross-border payment capability of digital currencies simplifies the international trade and investment process and reduces market uncertainty in terms of capital flows and exchange rate fluctuations. With the improvement of the relevant systems in the future, the process of global financial integration will be further accelerated.

5.3 The Rise of Decentralized Finance (DeFi)

Decentralized finance (DeFi) is the core area of digital currency-driven financial innovation. It relies on blockchain technology to build a financial ecosystem without traditional intermediaries, supporting users to carry out lending, trading and other activities on a decentralized platform, with the core advantages of disintermediation, high transparency and operational flexibility, which has great potential to enhance service accessibility and reduce financial costs.

The DeFi platform allows individuals and organisations to lend, pay and trade directly without the need for intermediaries such as banks. For example, users can automate loan agreements through smart contracts, freeing them from reliance on traditional financial institutions. This disintermediation not only improves market efficiency, but also provides low-cost financial services to investors and borrowers around the world.

However, the development of DeFi is also accompanied by new risks, especially in terms of liquidity, compliance and smart contract security. Its decentralized nature makes it difficult to regulate, and smart contract loopholes may be exploited by attackers to cause capital loss. Therefore, balancing innovation with risk prevention and control is key to its development.

6 CHALLENGES AND RISKS FACING DIGITAL CURRENCY

While the rapid development of digital currencies brings opportunities for innovation, it also triggers challenges and risks in multiple areas such as technology, regulation and market, involving key areas such as financial stability, privacy protection and cross-border regulation. Effectively identifying and addressing these risks is a prerequisite for their healthy integration into the global financial system.

6.1 Technical Risks and Security Issues

Blockchain and cryptographic algorithms, as the core technology of digital currencies, have security risks despite their decentralized and tamper-proof characteristics. The blockchain network may encounter distributed denial-of-service attacks; encryption algorithms, if breached or technological loopholes exist, may trigger large-scale capital theft or data leakage, impacting the financial market. In addition, digital currency storage and trading platforms often become the target of hackers, and in recent years, a number of exchange data leakage and capital theft incidents have led to huge losses for investors, so improving technical security has become an urgent issue.

6.2 Legal and Compliance Risks

It is a challenge to establish a unified and effective legal and regulatory framework for digital currencies globally, and there are large differences in attitudes and policies among countries, leading to legal uncertainty in cross-border transactions. The anonymity and decentralized nature of digital currencies are vulnerable to being used for money laundering, terrorist financing and other illegal activities, which are difficult to be covered by the existing anti-money laundering and anti-terrorist financing frameworks, and relevant regulations are lacking. The lack of uniformity in regulatory standards and legal frameworks increases the legal risks and compliance costs for market participants, and achieving regulatory compliance is key to stabilising the market and protecting investors.

6.3 Market Risk and Volatility

The cryptocurrency market is notably characterised by high volatility, with dramatic price fluctuations in Bitcoin, Ether and other currencies, posing greater market risks to investors, especially retail investors, whose fluctuations are subject to multiple influences such as speculative behaviours, technological factors, regulatory policies, and market sentiments, which may give rise to asset bubbles and increase financial systemic risks. At the same time, the limited depth and liquidity of the market is prone to market manipulation, price manipulation and false trading, and speculation also attracts short-term capital to move in and out of the market quickly, exacerbating market instability.

6.4 Cross-border Regulation and Privacy Protection

Although the cross-border liquidity of digital currencies is an advantage, it makes cross-border regulation more complicated, and it is difficult for the existing framework to adapt to its transaction model that does not rely on a single country's central bank or financial institution, and the use of stable coins may have a greater impact on the international payment and foreign exchange markets, which the existing system fails to effectively address. In addition, privacy protection has raised widespread concerns, and the anonymity of cryptocurrencies facilitates illegal activities while protecting users' privacy. Balancing privacy protection and regulatory compliance, and ensuring security and traceability, is key to developing a reasonable regulatory framework.

7 CONCLUSION

This paper comprehensively examined the impact of digital currencies on the traditional financial system, focusing on opportunities, challenges, and transformational pathways. By analyzing the structural characteristics and application scenarios of central bank digital currencies (CBDCs), cryptocurrencies, and decentralized finance (DeFi), the study identified how digital currencies have significantly enhanced payment efficiency, broadened financial inclusion, and driven technological innovation within the financial sector. Furthermore, the paper discussed how digital currencies are reshaping core functions such as money supply management, banking intermediation, capital market dynamics, and cross-border transactions.

However, digital currencies still face many challenges in the process of large-scale promotion and application, including technical security risks, insufficient international regulatory coordination, and high market volatility. Moreover, there is a significant tension between the decentralized nature of digital assets and the practical requirements for regulatory compliance, which hinders the transparency, stability, and standardized development of the digital currency ecosystem.

In the future, digital currencies will occupy a more important position in the global payment system. The promotion of central bank digital currencies (CBDC) will promote the digitization of fiat currencies and enhance payment efficiency and transparency. Central banks in several countries, such as China, Europe and the United States, are actively researching and piloting CBDC, which is expected to become part of the financial system in the next few years and promote the integration of global financial markets.

It is necessary for all countries to enhance international cooperation in the regulation of digital currencies, improve the legal adaptability of existing monetary and financial systems to emerging technologies, and accelerate the construction of new digital infrastructure that is secure, programmable and interoperable. Subsequent research should also focus on the long-term impact of digital currencies on financial governance, the transmission of monetary policy, and global financial integration. Only by promoting innovation while strengthening risk prevention and control can digital currency truly become an important cornerstone of the future financial system.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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FACTORS INFLUENCING DATA ELEMENTS EMPOWERING NEW QUALITY PRODUCTIVE FORCES AND THEIR SPATIOTEMPORAL EVOLUTION: A STUDY BASED ON PANEL DATA FROM 31 PROVINCES IN CHINA

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Abstract: In the context of the deep integration between the digital and real economies, data elements have become a core force driving economic growth and social transformation. China has positioned market-oriented allocation and value realization of data elements as a national development strategy; however, challenges such as regional development imbalances and widening digital divides persist in the empowerment of new-quality productive forces. This study employs panel data from 31 Chinese provinces and municipalities between 2012 and 2022, integrating entropy-based TOPSIS models, ARIMA models, and spatial econometric models to systematically explore the impact mechanisms and spatiotemporal evolution characteristics of data elements on new-quality productive forces. The ARIMA model predicts that China's national coupling coordination degree will show a yearly growth trend over the next three years, with eastern regions outperforming central and western regions, though regional disparities are gradually narrowing. The spatial econometric model further reveals heterogeneous response characteristics of data element policies: "rapid effectiveness in eastern regions with delayed effects in central and western areas." This study aims to bridge the digital divide, optimize data governance, and provide robust support for achieving high-quality development goals in China's digital economy during the 14th Five-Year Plan period.
Keywords: Data element; New quality productivity; Regional development imbalance; Coupling coordination degree; ARIMA models

1 INTRODUCTION

Amid the rapid advancement of digital technologies and the ongoing Fourth Industrial Revolution, data elements are emerging as a new type of production factor, gradually becoming the core engine driving economic growth and social transformation. The World Economic Forum's 2023 Global Competitiveness Report indicates that data contributes over 15% to global economic growth, with its permeability, non-exclusivity, and technology-integration characteristics playing pivotal roles in restructuring production functions [1]. Theoretically, Liu Huachu and Tang Tang [2], building on Marx's theory of productive forces, propose that data drives qualitative transformations in new productivity through reshaping labor tools, objects, and workforce structures—a perspective echoing the assertion in The Second Machine Age [3] about exponential efficiency gains from data-driven intelligent technologies. Currently, China is vigorously promoting deep integration between the digital economy and real economy [4], elevating market-oriented allocation and value realization of data elements to a national strategic level. However, multiple challenges hinder empowering new productivity in practice: On one hand, the China Digital Economy Report (2023) [5] shows that China's digital economy reached 50.2 trillion yuan (41.5% of GDP) in 2022, yet significant regional development imbalances have widened spatial disparities in new productivity [6]; On the other hand, obstacles such as redundant platform construction, low utilization rates of public data, and insufficient professional service capabilities constrain value realization, further exacerbating resource allocation conflicts between emerging industries and traditional sectors [7].

Prior to this, some scholars have proposed perspectives on data elements and new quality productive forces. Wang Haijie and Wang Kaiyang [8] pointed out that data, as a new type of production factor, possesses characteristics such as non-excludability, high reusability, and technological integration. It can permeate the entire production chain, giving rise to intelligent production tools, high-end labor objects, and a digital workforce. However, there is a lack of concrete empirical data to support this. Although some countermeasures are mentioned, most remain at the macro level without specific implementation details or operational steps, making them difficult to implement. Xu Zhongyuan and Zheng Huangjie [9] proposed the theoretical foundation for empowering new-quality productive forces through marketization of data elements, namely data property rights theory, information sharing theory, and transaction cost theory, establishing a systematic, holistic, and collaborative data element market system. The shortcomings are as follows: While mentioning the practical challenges and constraints faced by current data element marketization, the analysis and case studies of these issues are relatively superficial, failing to thoroughly examine the actual challenges encountered during the empowerment process of new-quality productive forces. Hui Ning and Shi Xiaorong [10] used panel data from A-share manufacturing listed companies between 2015 and 2022 as research samples. By constructing fixed-effect models and conducting descriptive statistics, benchmark regression analysis, and various tests, they explored the impact

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of data elements on enterprises' new-quality productive forces. However, they did not further analyze the time-space effects triggered by data elements or provide predictions for future trends in the development of new-quality productive forces.

Therefore, this study conducts a comprehensive analysis of existing research gaps, employing a dynamic-spatial dual-dimensional framework to quantify the direct impact of data elements on new-quality productivity and their spatiotemporal evolution patterns. Through a three-dimensional evaluation system encompassing "new-quality laborers, production materials, and work objects," we empirically demonstrate how data elements drive regional disparities via technology spillovers and resource optimization. By reconstructing regional differentiation patterns through an economic-geographic composite weighting matrix, this work challenges the conventional view that regional gaps stem solely from infrastructure limitations. Furthermore, integrating ARIMA forecasting with spatial effect decomposition, we propose a "regional coordination-stage adaptation" policy framework that translates spatiotemporal characteristics into actionable measures. This innovation provides both theoretical depth and practical value for optimizing data element market allocation and bridging the digital divide.

2 MODEL

2.1 Entropy TOPSIS Model

Data elements and new-quality productivity are the core research subjects of this study. The Entropy Value TOPSIS method not only avoids subjective factors affecting weight determination by automatically adjusting weights based on data variability, but also enables clear prioritization of outcomes through "positive ideal solutions" and "negative ideal solutions" to enhance visual clarity. Therefore, this study employed this method to evaluate new-quality productivity levels. The model calculation steps are as follows.

1) Min-max standardization of indicators

Forward pointer:

$$X_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{1}$$

Negative indicators:

$$X_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{2}$$

2) Calculate the information entropy of indicators

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{n} P_{ij} \ln(P_{ij}) \tag{3}$$

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \tag{4}$$

3) Calculate the proportion of each indicator

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m} e_j} \tag{5}$$

4) Calculate the weighted matrix

$$X = (x_{ij})_{m\times n} \tag{6}$$

$$R = (r_{ij})_{m\times n}, r_{ij} = w_j \times x_{ij} \tag{7}$$

$$(i = 1,2\cdots m; j = 1,2\cdots n)$$

5) Determine the positive and negative ideal solutions

$$R_j^+ = \max(r_{1j}, r_{2j}\cdots r_{nj}), R_j^- = \min(r_{1j}, r_{2j}\cdots r_{nj}) \tag{8}$$

6) Calculate the Euclidean space distance between each object and the positive and negative ideal solutions

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (R_{ij} - R_j^+)^2} \tag{9}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} (R_{ij} - R_j^-)^2} \tag{10}$$

7) Calculate the comprehensive evaluation index of each object

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{11}$$

2.2 ARIMA Model

Based on the calculated coupling coordination degree between data elements and new-quality productive forces, this study employs an ARIMA model to conduct a short-term trend prediction analysis. The ARIMA model primarily consists of four types: Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Moving Average with differencing (ARIMA). Given the non-stationary nature of the time series in this study, the ARIMA model was adopted for processing.
The basic formula for the ARIMA model is as follows:

$$\varphi(L)(1-L)^d Y_t = c + \theta(L)\varepsilon_t \tag{12}$$

where Y_t represents the value of the time series at time t , L is the lag operator defined as $LY_t = Y_{t-1}$, $\varphi(L)$ is the autoregressive polynomial with the form $\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - ... - \varphi_m L^m$, where denotes the coefficients of the autoregressive component, $(1 - L)^d$ is the difference operator representing the order difference operation applied to the original sequence for stationarity, $\theta(L)$ is the moving average polynomial with the form $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_n L^n$, where denotes the coefficients of the moving average component, ε_t represents the white noise error term, and c is the constant term.
1) Data stabilization
The ADF test is used to determine whether the series is stationary or not. If there is a unit root (p value>0.05), the series should be differenced by order, which is shown in the formula $(1 - L)^d Y_t$.
2) Determine model parameters
The difference order is typically determined by the results of the Autoregressive Integrated Function (ADF) test, where a value of 1 or 2 generally indicates non-stationarity can be eliminated. The autoregressive order can be identified by observing the partial autocorrelation function (PACF) plot of the differenced series. If the plot shows significant truncation beyond the confidence interval, an AR(p) model should be selected. For the moving average order, the Autocorrelation Function (ACF) plot serves as the diagnostic tool. When truncation occurs after the specified order, a MA(q) model becomes the appropriate choice.
3) Model fitting and parameter estimation
The parameters are solved by maximum likelihood estimation or least squares method according to the formula. The parameter combination is optimized using AIC/BIC criterion and the model with the minimum AIC/BIC value is selected.
4) Model test and diagnosis
White noise test (residual test): The residual sequence should satisfy the independence (ACF has no significant correlation), which is verified by Ljung-Box test.
5) Model prediction
The fitting model is used to predict the future value, and the prediction effect is verified by actual data.

2.3 Spatial Measurement Model

To further explore the spatial correlation between provincial data elements and new quality productivity and their radiation effect on neighboring provinces, this study adopts a spatial econometric model for more in-depth and detailed research. The core purpose of this model is to separate the direct effect (the effect of local variables) and the indirect effect (spatial spillover effect) generated by the variables.

2.3.1 Build the spatial weight matrix

The spatial weight matrix is mainly divided into the adjacency weight matrix, geographical distance weight matrix, and economic distance weight matrix. A single type of matrix cannot completely reflect the economic and geographical correlation of provinces; therefore, this study adopts a combination of both to construct the economic-geographical distance weight matrix.

$$W_{ij} = \begin{cases} \dfrac{\left|\overline{Q_i} - \overline{Q_j}\right|}{(Y_i - Y_j)^2}, i \neq j \\ 0, i = j \end{cases} \tag{13}$$

where $\overline{Q_i}$ and $\overline{Q_j}$ are the average GDP of the two provinces, and $(Y_i - Y_j)^2$ is the square of the distance between the two provinces.

2.3.2 Spatial autocorrelation test

Global Moran's I test:

$$I = \frac{n}{\sum_i \sum_j W_{ij}} \cdot \frac{\sum_i \sum_j W_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{\sum_i (Y_i - \overline{Y})^2} \tag{14}$$

If the value is significant and greater than zero, there is a positive spatial correlation.
Local Moran's I test:

$$I' = \frac{Y_i - \overline{Y}}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} \cdot \sum_{j=1}^{n} W_{ij}(Y_j - \overline{Y}) \tag{15}$$

Similarly, if the value is significant and greater than zero, there is a spatial positive correlation. Based on this, Moran's I scatter plot was drawn to identify local hot spots (High-High) and cold spots (Low-Low) regions.

2.3.3 Classification of spatial measurement models

Spatial econometric models are mainly divided into three types: spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM).

Space lag model (SLM):

$$y = \lambda Wy + X\beta + \varepsilon \tag{16}$$

where y is the dependent variable vector, λ is the lag coefficient of the dependent variable, which represents the intensity of spatial spillover, W is the spatial weight matrix, Wy is the spatial lag term, X is the explanatory variable matrix, β is the corresponding coefficient vector, and β is the error term vector.

Spatial error model (SEM):

$$y = X\beta + \varepsilon, \varepsilon = \rho W\varepsilon + \mu \tag{17}$$

where β contains spatial correlation, ρ is the spatial autoregressive coefficient, and μ is an independent, identically distributed random error vector.

Spatial Dubin model (SDM):

$$y = \lambda Wy + X\beta + WX\theta + \varepsilon \tag{18}$$

where λ and θ are the lag coefficients of the dependent and independent variables, respectively.

2.3.4 Model test and selection

When selecting a spatial econometric model, the process begins with the least maximum (LM) test to determine the appropriate model type. The Hausman test then determines whether to use a fixed-effects or random effects model. If a fixed-effects model is chosen, further verification is required to decide between individual fixed effects and time-fixed effects. If both tests are passed, the two-way fixed-effects model becomes viable. Additionally, if the LM test selects a spatial Durbin model, Wald and likelihood ratio (LR) tests must be conducted separately to assess potential degradation into spatial lag or spatial error models.

2.3.5 Space effect decomposition

After selecting the research model, the sample data of 31 provinces were decomposed by spatial effects to analyze the significance degree of explanatory variables and control variables in direct, indirect, and total effects, so as to explore the influence degree on the explained variable in the province and surrounding areas.

3 RESULTS AND ANALYSIS

3.1 Evaluation Index System and Benchmark Model Construction

The numerical indicators related to new productive forces discussed in this study primarily draw from the research of Han Wenlong et al., while those concerning data elements mainly reference studies by Ye Lu and colleagues. The specific data acquisition channels included the CSMAR database, EPSDATA official website, and annual statistical yearbooks. The control variable data involved in this study were mainly obtained through authoritative sources, such as the National Bureau of Statistics official website, provincial statistical yearbooks, and the China Statistical Yearbook, ensuring data accuracy and consistency.

3.1.1 Evaluation index system and benchmark model construction

In this study, the new quality productivity data collected were divided into three index layers, and the comprehensive evaluation index system of new quality productivity was established, as shown in Table1. The entropy TOPSIS method is used to assign certain weights to each third-level index to calculate the annual level of new quality productivity in each province.

Table 1 Comprehensive Evaluation Index System of New Quality Productivity

The first indicator	The second indicator	Third indicator	Direction
New quality workers	Workers in emerging industries	Total number of employees in emerging industries	+
	Technologically innovative workers	The number of R&D personnel in high-tech enterprises	+
New qualitative means of production	Digitization of labor data	Robot installation density	+
		Number of mobile users	+
		Integrated circuit production	+
		Total telecom business volume	+
		Software revenue	+
		E-commerce sales	+
		Number of Internet broadband access ports	+
		Optical cable line length/area of the region	+

		Mobile Internet access traffic	+
	Flexible and customized labor data	Research and development investment of high-tech enterprises	+
		The number of R&D institutions in high-tech enterprises	+
		Regulate industrial innovation funds for industrial enterprises above designated size	+
		Full-time equivalent of R&D personnel in industrial enterprises above designated size	+
		Number of patents granted by region	+
		Revenue from high-tech industries	+
	Environmental protection and energy conservation of labor materials	Energy consumption/GDP	-
		Industrial water use/gross domestic product	-
		Industrial wastewater discharge/gross domestic product	-
		Industrial SO2 emissions/gross domestic product	-
		Comprehensive utilization/production of industrial solid waste	+
New quality objects of labor	The object of digitalization and informatization	Number of data exchanges	+
	Green environmental protection and sustainable development of labor objects	Investment in industrial pollution control	+
	The object of labor for high-end equipment and intelligent manufacturing	Number of enterprises with e-commerce transactions	+
		Number of AI enterprises	+
	The object of labor in the future industry	Proportion of new energy generation	+
		Number of ultra-high voltage transmission lines	+
		New energy utilization efficiency	+
		Output value of new materials	+
		Number of new material enterprises	+

3.1.2 Data element evaluation index system

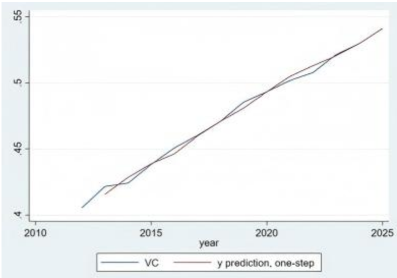
In this study, starting from the entire process of data value conversion, data elements are categorized into three levels: data generation, data transformation, and data application. Each level is further explained using the corresponding indicators, as shown in Table 2. The entropy value TOPSIS method was applied to assign weights to each indicator, thereby determining the annual data element levels for each province.

Table 2 Comprehensive Evaluation Index System of Data Elements

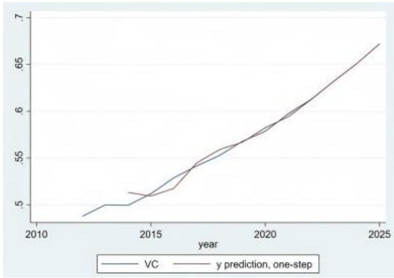
The first indicator	The second indicator	Third indicator	Direction
Data elements	Data generation	Number of pages	+
		Number of domain names	+
		There are 100 websites owned by every 100 enterprises	+
	Data transformation	Revenue from information technology services	+
		Information security revenue	+
	Data applications	Digital financial insurance	+
		Digital financial payments	+
		Degree of digitization of digital financial data	+

3.2 Short-term Trend Analysis of Coupling Coordination Degree

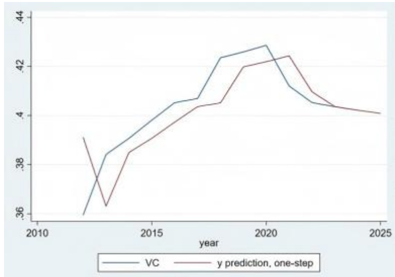
To explore the short-term trend of the coupling coordination degree nationwide and regionally, the ARIMA model was used for prediction and analysis. Based on the model selection and white noise test results, considering the limited sample size, we fitted the national and regional coupling coordination levels to predict their development trends from 2023 to 2025, with specific results shown in Figure 1.



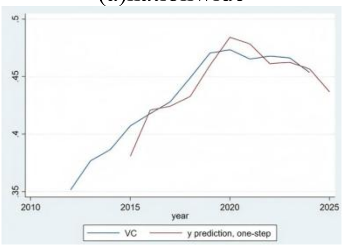
(a)nationwide



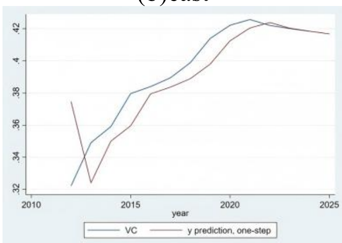
(b)east



(c)northeast



(d)central



(e)west

Figure 1 Trend Forecast of Coupling Coordination Degree Nationwide and Regionally

The fitting results indicate that the national coupling coordination level exhibits a steady upward trend. The predicted values lagged by one period compared to the actual values closely matched, demonstrating strong predictive validity and suggesting continued growth over the next three years. The eastern regions exhibited similar upward trends with consistent predictions, maintaining rising levels through the forecast period. The coupling coordination in Northeast China peaked around 2020 before declining, likely due to pandemic's impact, although the overall upward trend persisted with close alignment between the actual and predicted values. This region is expected to maintain this level over the next three years. Similarly, the central regions experienced a decline around 2020 due to the pandemic effects, with discrepancies between the predictions and actual values caused by the second-order lag data. However, their overall downward trend aligns with the predicted outcomes, which is likely attributed to the uneven development of data elements. The western regions experienced a notable slowdown in growth around 2015, followed by rapid recovery and stabilization post-2020. The predictions closely matched the actual values, indicating a probable maintenance of stable trends over the next three years.

3.3 Spatial Evolution Analysis

3.3.1 Correlation analysis between data elements and collaborative development space of new quality productivity

To further study the spatial correlation between the coordinated development of data elements and new quality productivity levels in different provinces, this study first uses the Moran index to analyze the spatial autocorrelation of the coupling coordination degree.

Table 3 Global Moran Index of Spatial Autocorrelation of Coupling Coordination Degree in 31 Provinces from 2012 to 2022

year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Moran'I	0.082	0.074	0.064	0.052	0.069	0.073	0.072	0.072	0.065	0.069	0.080
Price Z		2.069	1.866	1.642	1.971	2.056	2.043	2.048	1.939	2.009	2.203
	2.191										
Price P	2.029	0.039	0.062	0.101	0.049	0.040	0.041	0.041	0.053	0.045	0.028

As shown in Table 3, the global Moran indices for both subsystems remained above zero from 2012 to 2022, indicating a significant spatial positive correlation in their coordinated development. Only three years showed P-values exceeding the 0.05 significance threshold, with the overall test passing statistical validity for the remaining years. Notably, around 2015, when eastern coastal provinces such as Guangdong and Zhejiang initiated big data industry policy pilots, this initiative may have temporarily disrupted spatial correlation stability. Meanwhile, delayed policy responses in the central and western regions resulted in a slight decline in the global spatial correlation during that period.

3.3.2 Spatial econometric regression results and spatial effect analysis

After choosing the Dubin effect two-way fixed model, regression analysis was performed on the model to explore the significance of the spatial influence of data elements and a series of control variables on new quality productivity. The regression results are presented in Table 4.

Table 4 Regression Results of Spatial Dubin Model

	(1) Back β to results β	(2) WX Back to results WX
Del	0.179***	0.320***
	(0.040)	(0.231)
Led	0.003***	0.056**
	(0.002)	(0.009)
Rdi	3.794	-2.268
	(0.067)	(3.249)
Dow	-0.046*	0.305*
	(0.019)	(0.107)
Hcl	-2.262	-0.212
	(0.195)	(0.924)
Gil	0.090**	0.064
	(0.037)	(0.216)
***p<0.01, **p<0.05, *p<0.10		

Regression analysis reveals that both data factor levels and economic development levels reach the 1% significance level in terms of β values, with coefficients of 0.179 and 0.003, respectively. This indicates a positive spatial interaction between these factors and new-quality productivity. The degree of openness to the outside world and government intervention shows significant effects at the 10% and 5% levels, with coefficients of-0.046 and 0.09, respectively. These findings suggest that increased openness may lead to a slight loss of data factors, thereby affecting new quality productivity levels, while government policies play a positive regulatory role.

The WX value further explains the spatial spillover effect based on β. The data element level, economic development level, and degree of opening to the outside world show significant effects at the 1%,5%, and 10% levels, respectively, with coefficients of 0.320,0.056, and 0.305. This indicates that all three factors exhibit positive spatial spillover effects, demonstrating that neighboring provinces exert a positive transmission effect on their own province's new quality productivity level.

4 CONCLUSIONS AND OUTLOOKS

Through an in-depth analysis of panel data from 31 provinces and municipalities spanning 2012-2022, this study systematically explores the impact mechanisms and spatiotemporal evolution characteristics of data elements on new-quality productive forces. The results reveal that data elements play a significant positive role in driving the development of new-quality productive forces, while the influence of economic development level and R&D intensity remains noteworthy. In terms of temporal evolution, ARIMA model predictions indicate that the national coordination level will continue to rise over the next three years, signaling a new phase in the coordinated development of data elements and new quality productive forces. Regarding spatial evolution, spatial autocorrelation tests revealed spatial correlations between the data elements and the new-quality productive forces.

Although this study developed a comprehensive model to analyze the impact of data elements on new-quality productivity and their spatiotemporal evolution characteristics, several limitations remain. First, the model primarily relies on panel data for processing, which may fail to fully capture dynamic changes and nonlinear relationships in the time series. Second, although the model incorporates multiple dimensions of indicators when constructing the coupling coordination degree, it still exhibits subjectivity and limitations in indicator selection, failing to comprehensively reflect all relevant factors. Additionally, the prediction component mainly depends on ARIMA models, which could affect accuracy when dealing with complex economic environments and policy changes. Future research can enhance the model's explanatory power and predictive precision by introducing additional data sources and refining the modeling methodologies.

COMPETING INTERESTS

The authors declare no relevant financial or non-financial interests.

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SUPPLY CHAIN TRANSFORMATION IN THE DIGITAL WAVE: A THEORETICAL PERSPECTIVE ON AGRICULTURE AND MANUFACTURING

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Abstract: This paper systematically explores the internal mechanism and practical path of China's supply chain digital transformation in enhancing the efficiency of agriculture and manufacturing. The study first dissects the core mechanism of digital technology empowering supply chains. Through comparative analysis of typical application cases, it reveals the differentiated characteristics and commonalities of digital transformation in different industries. The research further identifies practical challenges and proposes industry-specific policy recommendations. Finally, it points out future research directions, including the construction of a digital transformation maturity assessment framework and differentiated policy research, providing theoretical support and practical guidance for deepening supply chain digital transformation.
Keywords: Agriculture; Manufacturing; Supply chain digitalization; Blockchain; Digital twin

1 INTRODUCTION

With the rapid development of the digital economy, the supply chain management model and innovation have undergone a historic transformation. The necessity of building a digital supply chain stems from the driving forces at three levels: technological innovation, environmental pressure, and demand change. From the perspective of technological change, the application of the Internet of Things has made data visible, turning the information black box of traditional supply chain management transparent and visual, and solving the problem of information discontinuity between enterprises; blockchain is dedicated to the immutability of data, and by recording and analyzing real operational data, it has solved the problems of information asymmetry and data silos in the supply chain [1]; the wide application of artificial intelligence technology has optimized supply chain management decisions, achieving the optimal allocation of resources and risk prevention and control. Based on environmental demands, the traditional supply chain, from raw material acquisition to product disposal, inevitably leads to excessive exploitation and waste of resources, causing significant environmental pressure. Digitalization, through digital twin simulation of risk scenarios and blockchain tracking of carbon footprints, has become a driving force for the construction of sustainable supply chains. Based on consumer demand, due to the rise of consumerism and the growth of personalized consumption trends, traditional batch production can no longer meet the diverse consumer demands, and it is urgent to build models through digital technology to interpret consumer demands and achieve a flexible combination of personalized and large-scale supply chain production.

The core value of a digital supply chain lies in reconfiguring the analysis process based on data integration and analysis, thereby optimizing decision-making and enhancing supply chain resilience. The digital supply chain not only alleviates the predicament of low efficiency, information asymmetry and risk contagion in the traditional supply chain, but also emempowerment enterprises on the chain to strengthen win-win cooperation, thereby achieving the goal of sustainable development [2]. Due to the differences in business attributes, product features and market demands, various industries present diverse innovation paths and challenges in digital transformation. For instance, the manufacturing industry focuses on the coordinated optimization of production and logistics, while agriculture emphasizes product traceability, supply and demand matching, and risk prevention. Therefore, studying the digital innovation of supply chains in different industries helps to distill common patterns, identify industry characteristics, and provide theoretical support and practical references for cross-domain collaboration.

This study selects the digital innovation of supply chains in agriculture and manufacturing as the research object. The main reason for this choice is that agriculture and manufacturing form the foundation of the real economy, covering the entire process from raw materials to finished products, with numerous supply chain links and a wide range of coverage. First, agriculture and manufacturing hold strategic positions. Agriculture and manufacturing belong to the bottom pillars of the supply of human survival materials and production materials, and the efficiency of their supply chains is directly related to the stability of national economy and people's livelihood. Second, there is an urgent need for the transformation and upgrading of agricultural modernization supply chains. Due to the perishable nature and natural dependence of agricultural products, data integration is urgently needed to optimize logistics and inventory management, and real-time data visualization can reduce information asymmetry [3]. The effectiveness comparison formed during the application process of supply chain digital innovation in different industries can better explain the key role of

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digitalization in improving supply chain efficiency and risk resistance capabilities. Third, the digitalization process of supply chains in agriculture and manufacturing is actually a typical representative of the upgrade of two different supply chain paradigms. The goal of digitalizing the agricultural supply chain is to achieve traceability throughout the entire process and risk prevention and control, as well as other supply chain optimizations oriented towards trust [4], while manufacturing uses digital supply chains to solve efficiency-oriented problems such as low efficiency, high costs, and resource optimization allocation [5]. The complementarity of the two forms constitutes the reference paradigm for the upgrade path of supply chain digitalization, respectively verifying the repair mechanism of technology for the two core weaknesses of supply chain traceability and trust crisis; Fourth, the challenges faced during the digital transformation of agricultural and manufacturing supply chains represent the issues encountered in building sustainable supply chains. The manufacturing sector grapples with incomplete technical standards and the struggle for data control rights, while agriculture faces a digital divide among small farmers, inadequate infrastructure, and insufficient learning capabilities. These challenges highlight the fundamental contradictions of technological deficiencies and a lack of human resources in digital transformation [6]. Fifth, there is a differentiation in policy formulation and promotion mechanisms. Digitalization in manufacturing is driven by industrial policies, whereas digitalization in agriculture relies on inclusive institutional designs. Together, they form typical cases of how governments and markets jointly promote digital construction in the era of the digital economy.

Therefore, by focusing on agriculture and manufacturing as the main subjects and conducting research on the digitalization of supply chains, it is possible not only to summarize the intrinsic differences in the internal laws of industrial development empowered by digital technology through comparative analysis, but also to extract a universal transformation framework based on its driving effect, providing a theoretical fulcrum for exploring mechanisms that integrate digital productivity and promote the development of the real economy.

This paper takes the digital transformation of agricultural and manufacturing supply chains as the research object. By deconstructing the internal mechanisms of data-driven decision optimization and full-chain visualized collaboration, and through the comparison of typical cases in manufacturing and agriculture, it reveals the logic of differentiated industrial transformation. The research aims to systematically identify common challenges and industry bottlenecks, propose a sector-specific policy framework and future breakthrough directions, and provide theoretical support and practical routes for building an efficient and secure digital supply chain system.

2 RESEARCH REVIEW

2.1 Review of Supply Chain Digitalization Research

Regarding academic research on the digitalization of supply chains, scholars have focused more on examining issues such as supply chain data visualization, supply chain resilience, supply chain toughness, risk control, and the construction of digital supply chains from a network perspective during the digital transformation process. Based on the conceptual level of supply chain digitalization, Buyukozkan et al. pointed out that the digital transformation of supply chains is centered around customer needs [7], utilizing a series of digital technologies to achieve supply chain data visualization and intelligent supply chain management. Supply chain digitalization transformation is based on data and uses information technology to promote the overall structure and mode transformation of the supply chain [8]. From the perspectives of research fields and contents, scholars have conducted studies based on theories and empirical models, focusing on aspects such as the development process, influencing factors, and economic effect assessment of supply chain digitalization transformation. Supply chain digitalization transformation is not merely the application of digital technologies; it also emphasizes using digital technologies and other means for internal coordination within the supply chain, external resource management, and data element generation to promote the shaping of a digital supply chain [9]. Supply chain digitalization is the process of data collection and processing, thereby orderly integrating suppliers and customers, with digital technologies and digital human resources being key elements [10]. Zhao et al. empirically analyzed the impact of supply chain digitalization on supply chain resilience and supply chain performance [2], and found that supply chain digitalization can enhance the response and recovery capabilities of the supply chain, thereby improving supply chain performance.

2.2 Review of Research on Digitalization of Agricultural Supply Chain

Regarding the research on the digitalization of agricultural supply chains, some scholars believe that the application of Internet of Things (IoT) technology plays a role in the process of promoting the digitalization of agricultural supply chains by optimizing processes and achieving collaborative integration, precisely matching supply and demand, reducing operational risks in the supply chain, and thereby enhancing supply chain performance [6]. Digitalization of agricultural supply chains, such as blockchain and smart contracts, can solve problems of information asymmetry, quality fraud, and trust loss in the agricultural product circulation process [11]. Subsequently, the researchers selected three Thai food manufacturers as case samples to explore the challenges and opportunities faced during the digital transformation of the food supply chain, proposed a framework for the digital transformation of the food supply chain, and identified key factors that need to be focused on in the digital transformation of the food supply chain, including supply chain operational efficiency, information transparency, product traceability, environmental and social impact, and legal responsibilities [12].

2.3 Review of Research on Digitalization of Manufacturing Supply Chain

Regarding the research on the digitalization of manufacturing supply chains, scholars mainly focus on the application of digital twin technology in manufacturing supply chains. The application value of digital twin in industrial processes is manifested as predictive analysis, agility, and stronger adaptability [13]. Subsequently, scholars have endeavored to explore the broader application value of manufacturing digital twins. Digital twin integrates physical product data, virtual product data, and associated data to provide more efficient support for product design, manufacturing, and services, and enhance sustainability. Digital twin technology simulates the manufacturing environment, processes data handling and analysis, and assists in optimizing and upgrading the supply chain and achieving the purpose of risk warning and control [5].

Although existing studies have conducted multi-level and multi-angle investigations and analyses on the ways and economic consequences of digital transformation in agricultural and manufacturing supply chains, there are still limitations such as insufficient theoretical depth and insufficient cross-domain integration. Further exploration and improvement are needed in research on the feasibility of supply chain digitalization. Firstly, existing studies mostly focus on the application effects of a single technology, while there is relatively less systematic research on the synergy effects among technologies. Additionally, existing studies have discussed the digitalization paths of large enterprises more, but the research on small and medium-sized enterprises is somewhat lacking. Small and medium-sized enterprises face core challenges such as technical application compatibility bottlenecks, shortage of digital talents, and data security risks. However, the existing results mostly remain at the general strategy level and lack precise solutions tailored to specific industries and regions.

3 INNOVATIVE PRACTICES IN THE DIGITAL TRANSFORMATION OF SUPPLY CHAINS

With the increasing individualization and diversification of consumer demands, the core contradiction faced by traditional agriculture has shifted from "insufficient total output" to "misalignment between supply and demand". The decision-making based on experience in the production process has led to the frequent occurrence of the phenomenon where agricultural product prices plummet. Moreover, due to the lack of bargaining power among scattered farmers and the existence of information asymmetry, farmers suffer severely from the exploitation of profits by middlemen. Under this background, it is urgent to deepen the digital reform of the agricultural supply chain. To achieve the full-chain digital reform of agriculture, on one hand, digital technology can reshape the production decision-making model by collecting real-time data on farmland conditions, crop growth, and meteorological environment, combined with historical patterns and intelligent algorithm models, to optimize resource allocation, reduce production costs and risks, and thereby achieve precise prediction of agricultural product output; downstream, through blockchain and big data analysis technologies, integrate the diversified and personalized demand information of end consumers, and feed it back to the production end through the data platform, truly allowing demand to guide supply. This digital supply chain process, by integrating data information from production, processing, circulation, and sales links, forms a "data-driven decision-making" smart governance paradigm, enabling enterprises at each node of the supply chain to dynamically adjust resource allocation based on real-time market signals. Therefore, the digital reform of the agricultural supply chain has restructured the sustainable development paradigm of the agricultural value chain [14].

Similarly, with the intensification of global competition, the gradual personalization of market demands, and the uncertainty of the global economic environment, the digitalization of manufacturing supply chains is also an inevitable requirement for modern industrial development. The inevitability of the digital transformation of manufacturing supply chain stems from the structural flaws of the traditional manufacturing supply chain model. Firstly, the traditional manufacturing supply chain has information black boxes such as distorted demand information transmission and inventory mismatch, as well as the whip effect of risk contagion. The production progress and raw material inventory status data of upstream suppliers cannot be shared in real time with manufacturers. Once raw materials are cut off, it will trigger a chain-like transmission of risks [15]. Moreover, the downstream distribution data and customer demands can only be transmitted to the production end through hierarchical aggregation, resulting in production plans lagging behind the actual market demand. Traditional supply chain management decisions rely on manual decisions and hierarchical approvals, leading to a delayed response to market changes. However, through big data analysis to achieve real-time demand prediction and automatically generating production plans through intelligent algorithms, the agility and efficiency of the supply chain in response to the market are significantly improved. Digitalization builds real-time data monitoring and intelligent emergency mechanisms, which can predict risks in advance and enhance supply chain resilience [15]. Thirdly, the product quality screening in traditional supply chains relies on sampling inspections, resulting in low efficiency in quality product traceability, lagging problem identification, and through the construction of digital supply chains, it is possible to achieve full traceability of data information and preventive intervention through the immutable recording of data information. In conclusion, digitalization is a systematic solution to break through information islands, resource rigidity, and risk vulnerability [5].

3.1 The Internal Mechanism of How Digitalization of Supply Chain Can Enhance the Efficiency of Agriculture and Manufacturing

The digitalization of supply chains has a significant enabling effect on the manufacturing industry, mainly by significantly improving the efficiency of resource allocation and the collaborative capabilities of the value chain. For the agricultural supply chain digitalization, the core objective is mainly to cope with natural uncertainties and improve timeliness. Emerging digital technologies, by reconfiguring the temporal and spatial logic of agricultural product circulation and the decision-making model of agricultural production, promote the traditional supply chain to achieve the prediction of future risks and the exploration of hidden demands, transforming "post-event remediation" into "pre-event insight". First, relying on satellite remote sensing to monitor the areas of drought, flood, and pests and diseases in farmland, it solves the information blind spots at the production end; using the field sensor network can detect soil temperature, humidity, and light intensity in real time, and issue early warnings of risks. Second, blockchain builds a direct connection channel between "consumers" and "farmers", eliminating quality concerns. The essence of agricultural supply chain digitalization is to break through the constraints of natural economy and institutional deficiencies, reorganize the agricultural value chain through data flow, penetrate the constraints of natural economy with technology, and achieve optimal resource allocation, minimal risk, and fair value distribution revolution [3].

The digitalization of the manufacturing supply chain enables real-time sharing of product status information through the Internet of Things. These data are stored and shared through blockchain to ensure the authenticity and non-modifiability of the data, thereby enhancing the authenticity of supply chain information transmission and alleviating the phenomenon of data silos, achieving resource optimization allocation. Moreover, through the integration of multiple data on the cloud computing platform, enterprises can dynamically adjust production plans based on actual demands, avoiding overcapacity [10]. Secondly, the manufacturing industry utilizes the construction of digital supply chains such as digital twins to achieve simulation and simulation of the entire supply chain from suppliers, factories, distributors, to customers. Through digital algorithms, it can achieve real-time insight into supply chain status and risk prediction, thereby enhancing supply chain resilience [5]. Thirdly, in the field of market demand analysis, with the assistance of artificial intelligence in engineering analysis of consumers' preferences, purchasing behaviors, and demand trends, enterprises can precisely target the market and develop products that better meet market demands; in the aspect of after-sales service, data analysis helps enterprises establish a complete customer feedback mechanism, responding promptly to customer needs and enhancing customer satisfaction [15]. Table 1 compares and analyzes the similarities and differences in the application of supply chain digitalization in agriculture and manufacturing.

Table 1 Comparative Analysis of Digital Transformation Characteristics between Agricultural and Manufacturing Supply Chains

Comparison Dimensions	Digitalization of Agricultural Supply Chains	Digitalization of Manufacturing Supply Chains	Common Characteristics
Motive Factors	Coping with natural risks, improving the ability to trace the quality of agricultural products, and enabling small farmers to adjust planting decisions according to market demand signals	Enhancing production efficiency and improving supply chain resilience	Affected by technological innovation, changes in market demand and policy promotion
Application of Key Technologies	Internet of Things (soil/climate sensors)Blockchain (traceability)Artificial intelligence technology	Industrial Internet platformDigital twinArtificial intelligence technology	Dependent on the improvement of digital infrastructure
Difficulties in Transformation	Weak digital capabilities of small farmersBackward digital infrastructure in rural areas	Non - uniform cross - enterprise standardsLong payback period for technical investment	All face problems such as high technical costs, talent shortage and inherent path dependence
Core Transformation Goals	Improving resource utilization efficiency and ensuring food safety and sustainability	Achieving cost reduction and efficiency improvement, and quickly responding to market demand	Pursuing the visualization and collaborative optimization of the entire supply chain

3.2 Digital Application of Supply Chains in Agriculture and Manufacturing

The theoretical framework and core driving forces of the digital transformation of the supply chain have been systematically elaborated in the previous text. To deeply explore the innovative practice paths and differentiated effects of this transformation in different industrial fields, this study specifically selects the apple industry in Yanchuan County of China and Haier Group as typical cases for analysis. The former represents how the agricultural sector can leverage digitalization to reshape the agricultural product value chain under the small-scale farming economy, achieving precision, branding, and value enhancement; the latter, as a manufacturing benchmark, its in-depth digital transformation of the supply chain provides an outstanding model for large-scale customization in industrial scenarios and the ecological transformation from user demands to product delivery. Together, these two cases have constructed a new paradigm of precise demand response and industrial ecosystem collaboration in the digital transformation of the supply chain.

The digitalization practice of the apple industry chain of a certain brand in Shaanxi Province of China has achieved ideal results. Its success has verified the feasibility of digital technology in economically underdeveloped regions. This model adopts an innovative approach of supply chain services + ICT (Information and Communication Technology) +

financial services to realize the digitalization of the entire supply chain from the planting end, processing end, to agricultural product production, logistics, sales and services. The application practice of digitalization in the apple industry chain demonstrates the enabling effect of supply chain digitalization on agriculture [16]. The application of ICT (Information and Communication Technology) in Yanchuan Four Apples mainly focuses on three aspects: First, the farmer's information, planting management data, planting area, planting years, historical yield, estimated yield, etc. are all agricultural information and are presented intuitively in the intelligent management system, so data mining and calculation can be carried out based on the constantly updated big data. Second, for real-time monitoring of micro-weather data, it is to integrate various sensing nodes on the agricultural production site, including planting environment, soil, images, etc., and wireless communication networks, integrate meteorological, market, and planting data, realize real-time monitoring and early warning of the agricultural production environment, and through data analysis, push irrigation and fertilization suggestions to farmers, providing precise data support for the efficient operation of each link of the apple and other agricultural product industry chain [16]. Thirdly, blockchain traceability ensures that all the information from the planting to the sales process of apples can be recorded as unalterable data, providing consumers with the entire process data. Fourthly, the innovation in supply chain financial services is that farmers can convert their planting process data, such as organic fertilization records, IoT irrigation compliance rates, and other agricultural data, into financial credit. They then establish the "agriculture + finance" and "agriculture + insurance" models, solving the problem of farmers' loan difficulties in traditional industrial and agricultural supply chains. This shows that the agricultural intelligent supply chain, through the application of digital technology, not only can maximize the protection of farmers' interests, but also, through agricultural production technology services, production material services, and financial services, ultimately achieve the goals of revitalizing the county economy, connecting the interests of small farmers, and building the resilience of the supply chain.

In the practical exploration of the digital transformation of the manufacturing industry supply chain, the practical innovations of Haier Group have provided practical and theoretical references for the same industry. The remarkable achievements of its digital transformation not only reflect the improvement of internal operational efficiency, but also lie in its exploration of an innovative path that integrates advanced information technology, reconfigures the corresponding market mechanisms, and promotes value chain collaboration. First, through the digital platform, the scope of procurement is expanded and procurement costs are reduced. In terms of procurement digitalization, Haier Home Appliances utilizes CRM (Customer Relationship Management) and BBP (Electronic Procurement) platforms to build a seamless communication bridge between users and suppliers. Moreover, this platform conducts strict qualification reviews of suppliers, effectively reducing the default risk and costs of suppliers [17]. Second, from "chain control" to "network ecology". Haier launched COSMOPlat, which introduces an industrial internet platform where users participate in the entire process of experience. The traditional supply chain follows the logical structure of enterprises independently developing, enterprises purchasing, and product production, but Haier's "chain group contract" model and COSMOPlat essentially transform enterprises into an open value co-creation network, and the two together support the operation of the networked ecology [18]. This model achieves the synergy between organizational efficiency and user value through user demand-driven approach and chain group's autonomous order-taking. In essence, user demand-driven means shifting from the traditional model where enterprises solely define product performance and usage to users directly participating in the innovation of product design concepts. The essence of chain group's autonomous order-taking is to dismantle the traditional supply chain into numerous autonomous decision-making groups. Through user demand-driven, each node of the chain group independently assesses its capabilities and then takes the order. The core value of Haier COSMOPlat lies in leveraging industrial internet technology to simultaneously achieve a significant increase in production efficiency and the precise satisfaction of users' personalized needs.

Through the brief analysis of the above cases, the digitalization of agricultural supply chains has connected the information flow from the field to the table, enhanced the transparency of agricultural product quality and the matching degree of market demand, and effectively solved the problem of small farmers' connection with the large market. The digitalization of manufacturing supply chains has achieved the transformation from large-scale manufacturing to large-scale customization. Through data-driven methods, it has realized precise demand forecasting, flexible production and efficient collaboration, greatly improving the response speed and resource efficiency.

3.3 Challenges of Supply Chain Digitalization

Although the digitalization of supply chains has demonstrated significant innovative value and transformation potential in the agricultural and manufacturing sectors, its implementation process still faces numerous deep-seated structural challenges. Identifying and clarifying the actual challenges and predicaments is an indispensable step in assessing the sustainability of the transformation and planning the future development path.

To promote the comprehensive digitalization of the agricultural supply chain, a series of practical challenges rooted in the characteristics of the industry need to be overcome. Firstly, the current coverage of digital technology application in the agricultural supply chain is relatively small. Farmers lack a clear understanding of the digitalization of the supply chain and have poor learning abilities, which results in insufficient application of technologies such as big data, the Internet of Things, and artificial intelligence. Secondly, due to the fact that agricultural production is mainly concentrated in remote areas, the construction of digital infrastructure such as broadband, 5G, and data centers is relatively weak, and there is a shortage of digital technology talents in remote areas, which leads to a lack of application foundation for digital technologies. Thirdly, due to the numerous and long supply chain links in the agricultural products, the organizational structure of the supply chain cannot well adapt to the needs of digital transformation, and the response speed is relatively slow. The loose relationships among supply chain entities make information sharing difficult, especially core enterprises have a low willingness to share advantageous information resources, and supply chains often experience information islands, resulting in the slow development of transparent supply chain organization structures [14]. Fourthly, due to the relatively low level of specialization among the entities in the agricultural supply chain and insufficient digital integration of business processes, as well as the incomplete establishment of a digital operation system for business processes, a complete digital operation system has not yet been established [14]. Moreover, due to the problems such as poor internal information exchange within the agricultural industry chain, unstable cooperation among entities, and unbalanced distribution of benefits, the integration of blockchain and the agricultural industry chain is difficult. It requires the use of information sharing, risk control, and benefit distribution mechanisms. Finally, the governance of the agricultural product supply chain is limited to the joint governance among the supply chain members, ignoring the governance effect of third-party organizations, especially government-led supply chains. This requires the government departments to establish sound guarantee policies for digital governance and break the mechanism obstacles of digital governance in the supply chain [9].

During the digital transformation of the manufacturing supply chain, many challenges are also encountered. Firstly, the issue of uneven data quality is particularly prominent. Some data have problems such as low accuracy, lack of completeness, and inconsistent data formats, which makes the effective utilization of data difficult. Secondly, as data is widely used in the manufacturing industry, data security faces severe threats. Risks such as data leakage and malicious attacks are constantly increasing, which not only may damage the business interests of enterprises but also may affect the stable operation of the entire supply chain [19].

4 SUGGESTIONS AND FUTURE RESEARCH DIRECTIONS

Supply chain digitization has become a key driving force for the transformation and upgrading of agriculture and manufacturing industries. In agriculture, the focus is on enhancing the data decision-making capabilities and economic feasibility of the participating entities, especially farmers. In manufacturing, the core objective is to achieve deep integration of technical systems and secure governance of data assets. Based on the summary of this research, this paper proposes the following suggestions: First, the government should strengthen the construction of digital platforms and focus on cultivating a number of supply chain platforms that are fully traceable throughout the chain and fully visible across the entire domain. Second, the government should promptly improve the standardization application system of digital technologies related to agriculture, with a particular emphasis on developing key artificial intelligence technological innovations and application standards for information intelligent decision-making and management, blockchain traceability, smart warehousing and logistics, etc. in the supply chain, and promote the digitalization process of the supply chain [14]. Finally, the government should promptly improve the laws and regulations related to supply chain digitization, establish a support mechanism for digital transformation, coordinate the interests of all parties in the supply chain, promote the construction of digital infrastructure, guide farmers to actively improve their own digital literacy, and ensure the sustainable progress of digital transformation [4].

Based on the findings and limitations of this study, it is suggested that future research can conduct in-depth exploration in the following directions. First, based on the role evolution and interaction mechanism of stakeholders in the digitalization process of the supply chain, explore how consumer demands can be reverse-driven to standardize agricultural production through digital platforms; study the deep integration of technology between technology suppliers and traditional enterprises, especially the applicable innovation in the small-scale agricultural economy scenarios in developing countries. Second, based on the research level of institutional adaptability innovation, the adaptability of digital technology application in different regions needs to be focused on, such as quantifying the return on investment of digital infrastructure, establishing a cost-benefit assessment model applicable to developing countries, and conducting more in-depth regional institutional analysis on the impact of regional heterogeneity on the digitalization of agricultural supply chains [10]. Third, research on how to deeply integrate artificial intelligence, digital twins, and blockchain technologies to achieve real-time optimization of the entire supply chain. Explore cross-enterprise data sharing mechanisms to solve the problem of "data islands", and how to balance data openness and protection of business secrets. Fourth, with the development of green supply chains, deeply study how digital technologies can help achieve precise tracking and visualization of the entire life cycle carbon footprint, and empower the circular economy model is also a topic that needs to be focused on.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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FORECAST OF ECONOMIC DEVELOPMENT IN GUANGXI ZHUANG AUTONOMOUS REGION AND ITS VARIANCE ANALYSIS

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Abstract: Today in the process of economic development across China, the economic differences between regions are not well handled. As it is often said in economics, differences in economic development are inevitable because different regions have different development patterns. Appropriate regional economic differences can reasonably optimize and allocate resources and promote regional economic development, but if the regional economic differences are too large, the regional Gini coefficient will increase, which will easily generate social conflicts and is not conducive to the development and construction of society. The balanced development of Guangxi is related to the people's livelihood and well-being of Guangxi people and the important interests of Chinese nation, as well as the long-term stability of China's frontier regions. Therefore, it is of great practical significance to discuss the differences in economic development across Guangxi and their influencing factors in order to solve the economic development problems in the less developed regions in the west. This article focuses on the differences of regional economic development in Guangxi, studies its balanced development, statistically analyzes the historical data of Guangxi's economy, predicts the future trend, analyzes the existing problems and puts forward optimization suggestions through methods such as principal component analysis, cluster analysis and establishment of ARIMA model.
Keywords: Guangxi; Regional economic differences; Principal component analysis; ARIMA model; Cluster analysis

1 INTRODUCTION

1.1 Research Background

The core issue facing China in today's world is development. High-quality development is the primary task of building a modernized socialist country in all respects. At the same time, “unbalanced and inadequate development” remains a problem in China’s current development process, reflecting the imbalanced nature of the country’s economic growth. To address these issues under such development conditions and patterns, efforts must be made to enhance the quality and efficiency of development, continuously narrow the urban-rural income gap, increase consumption levels, reduce regional economic disparities, and ultimately achieve high-quality and sustainable development.
The Guangxi Zhuang Autonomous Region is situated at the intersection of three economic circles: South China, Southwest China, and ASEAN. It features coastal and border areas, giving it distinct regional characteristics. Superficially, Guangxi enjoys a favorable geographical location and has experienced rapid economic growth in recent years, with gradual improvements in development quality and structure. However, internally, its economic development remains unbalanced. As an economically underdeveloped region in western China, an area with a revolutionary history, and a region adjacent to ASEAN, Guangxi is a key focus for achieving coordinated regional economic development in China. Studying the internal economic development disparities within Guangxi and analyzing its overall development situation will help accelerate the region’s development pace and achieve high-quality growth. Moreover, it holds significant importance for promoting economic development in western China and realizing coordinated regional economic development across the country.

1.2 Research Purpose and Significance

China is a multi-ethnic country where every ethnic group is an inseparable part of the larger Chinese nation. The destinies of all ethnic groups are closely intertwined, and their prosperity and development are directly related to the rise and fall of the Chinese nation as a whole. The Guangxi Zhuang Autonomous Region is not only an ethnic autonomous region but also a border area, sharing a direct boundary with Vietnam. Additionally, it is located north of the Beihai Sea and possesses the Beibu Gulf port. In summary, Guangxi holds a significant position among China’s ethnic regions.
Since the implementation of policies such as the “Western Development Strategy” and the “China-ASEAN Free Trade Area,” Guangxi’s economic and social development has undergone significant changes. However, due to variations in geographical location, environmental conditions, and regional advantages, development across its cities and prefectures presents diverse situations.
Regional economic development in Guangxi is a major issue. This paper aims to analyze the economic development

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conditions of various cities in Guangxi through data collection and statistical research, explore their economic development levels and disparities, identify existing problems, and propose targeted optimization paths and high-quality development recommendations. This is of great significance for narrowing regional development gaps and improving people's wellbeing.

1.3 Research Status

Disparities in regional economic development have increasingly attracted attention from various sectors of society and have gradually become a critical issue in economic and social development.

From the perspective of national economic development disparities, Yang Kaizhong [1][2] used the coefficient of variation and per capita national income data from 1952 to 1985 to calculate relative differences. He found that regional economic disparities among provinces generally followed an inverted "U" shape, while disparities among the six regions—North China, Northeast China, East China, Central South China, Southwest China, and Northwest China—generally followed an inverted "S" shape.

Using indicators such as the per capita national income index to reflect the level of regional economic disparities, the standard deviation to measure the absolute value of regional economic disparities, and the coefficient of variation, weighted coefficient of variation, weighted divergence coefficient, and Gini coefficient to measure the relative value of regional economic disparities, Liu Shucheng [3] pointed out that the absolute value of regional economic disparities in China has continuously expanded over the past 40 years.

Zhang Qinghua et al. [4] noted that since the implementation of the "Western Development Strategy" in 2000, the economic growth rate of western China has surpassed that of eastern China and continues to maintain this trend. Although the economic gap between the eastern and western regions is gradually narrowing, the absolute disparity between them will continue to widen in the long run due to the weak economic foundation and low economic indicators of the western region.

Qin Chenglin[5], Chen Guang[6], and Nie Hualin[7] studied the coordinated economic development issues in China's regions. Chen Tian[8], Lei Yuan[9], and Lu Xiao[10] researched regional economic issues in Guangxi as well as rural economic development in the area. These studies have provided significant inspiration for this paper.

2 RELATED CONCEPTS AND THEORETICAL FOUNDATIONS

2.1 Related Concepts

2.1.1 Regional economic disparities

Regional economic disparities refer to the phenomenon within a unified country where some regions experience faster growth rates, higher levels of economic development, and stronger economic capabilities than others, resulting in a spatial pattern where developed and underdeveloped regions coexist. At the same time, economic disparities between regions are a common economic phenomenon. Addressing regional economic disparities is one of the core issues in regional economic research.

2.2 Theoretical Foundations

2.2.1 Regional economic growth theory

Regional economic growth theory explores the differences in economic growth and development among different regions. This theory posits that disparities in economic growth and development between regions primarily depend on the following factors:

Geographical Location and Resource Endowment: Geographical location and resource endowment are significant factors influencing regional economic growth. For instance, regions near seaports or major transportation hubs often have better trade and logistics conditions, making it easier to achieve economic growth.

Technological Innovation and Human Capital: Technological innovation and human capital are key drivers of regional economic growth. High-tech industries and knowledge-intensive sectors often require highly skilled talent, which tends to concentrate in cities and regions with an innovative environment.

Policy and Institutional Environment: The policy and institutional environment plays a crucial role in regional economic growth. Government policies, such as industrial and tax policies, can positively or negatively impact regional economic development.

Capital and Financial Markets: The development level of capital and financial markets also influences economic growth disparities between regions. If a region lacks financing channels or financial institutions, it may constrain local businesses' ability to secure funding and expand.

Based on these factors, regional economic growth theory suggests that disparities in economic growth and development among regions result from the interaction of multiple factors. Therefore, achieving balanced regional economic development requires measures such as policy and institutional reforms to improve the local economic environment and resource endowment conditions, enhance human capital quality, promote technological innovation, develop capital markets, and strengthen economic cooperation between regions.

2.2.2 Regional balanced development theory

Regional balanced development theory is an economic theory that emphasizes promoting economic development across

different regions through policy interventions to achieve economic and social balance.
This theory argues that within a country or region, differences in economic development levels between regions may lead to unequal distribution of resources and wealth, which in turn can trigger social and political issues. To prevent such problems, governments can employ a range of policy measures to promote balanced economic and social development.

3 RESEARCH DESIGN

3.1 Research Methods

3.1.1 Principal Component Analysis

Principal Component Analysis (PCA) is an analytical technique used to examine multiple variables and is a common method for reducing data dimensionality. It transforms several correlated variables into a set of less correlated variables. PCA is widely applied in mathematical modeling, data analysis, and social and economic research.
In this study, PCA is used to reduce the dimensionality of 12 indicators reflecting regional economic development in Guangxi. These 12 indicators are transformed into three principal components, which collectively capture the majority of the original information.

3.1.2 Cluster analysis

Cluster analysis, also known as grouping analysis, is a multivariate statistical analysis method that classifies samples or indicators based on the principle of "birds of a feather flock together." It deals with large numbers of samples that need to be reasonably categorized according to their respective characteristics, without any pre-existing model or prior knowledge to reference. Cluster analysis is conducted in the absence of prior knowledge.
In this study, cluster analysis is employed to classify the regional economies of Guangxi's 14 cities using multiple variables. The classification is based on extracted principal component scores and comprehensive scores, and the differences among the categories are analyzed.

3.1.3 ARIMA model forecasting

The ARIMA forecasting model is a statistical analysis method for time series forecasting, which fits time series data with stationarity. In the ARIMA (p, d, q) model, "d" represents the number of times the time series is differenced, "p" denotes the order of the autoregressive component, and "q" indicates the order of the moving average component. Building an ARIMA forecasting model requires ensuring the time series is stationary, selecting an appropriate model for fitting, and evaluating the model based on metrics such as the AIC value and DW value.
In this study, the ARIMA model is used to predict Guangxi's economic growth in the coming years.

3.2 Indicator System

To study the regional economic disparities in the Guangxi Zhuang Autonomous Region, this paper selects three first-level indicators—economic development level, social development level, and social stability—based on the definition of regional economic development quality in Guangxi and the principles of indicator selection, combined with Guangxi's current stage of economic development. The economic development level is further decomposed into four second-level indicators, social development level into five second-level indicators [11], and social stability into three second-level indicators. The results are shown in Table 1.

Table 1 Evaluation Indicator System for Regional Economic Disparities in Guangxi

First-level Indicators	Second-level Indicators	Unit	Indicator Code
Economic Development Level	Per Capita GDP	10,000 Yuan	x_1
	Per Capita Fiscal Revenue	Yuan	x_2
	Total Import and Export Volume	100 Million Yuan	x_3
	Growth Rate of Fixed Asset Investment	%	x_4
Social Development Level	Urbanization Rate	%	x_5
	Number of Students Enrolled in Regular Institutions of Higher Education	10,000 Persons	x_6
	Number of Health Institution Personnel	Person	x_7
	Number of Beds in Health Institutions	Unit	x_8
	General Public Budget Expenditure	100 Million Yuan	x_9
	Percentage of GDP from Secondary and Tertiary	%	x_{10}

Social Stability	Industries Value-added of GDP from Secondary and Tertiary Industries	100 Million Yuan	x_{11}
	Year-end Permanent Resident Population	10,000 Persons	x_{12}

3.3 Data Sources

The indicators and data selected in this paper are primarily sourced from the Statistical Yearbooks published by the Guangxi Zhuang Autonomous Region Bureau of Statistics and the bureaus of statistics of its subordinate prefecture-level cities. The specific data are presented in Table 2.

Table 2 Values of Indicators for Each City

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
Nanning	5.83	9383.66	1231.92	3.1	69.8	65.20	103071	60576	775.40	88.1	3814.97	883.28
Liuzhou	7.33	9639.55	354.07	-8.5	70.3	11.18	46912	29579	423.98	91.6	2259.59	417.53
Guilin	4.68	4400.82	91.61	-4.3	53.4	28.07	52353	28508	461.79	76.2	911.31	494.59
Wuzhou	4.85	4770.23	80.81	21.6	55.6	3.63	29192	18046	259.05	85.7	666.38	282.67
Beihai	8.07	12343.52	300.10	11.1	58.9	NA	17181	10282	179.27	85.0	1045.09	187.24
Fangchenggang	7.75	9496.59	885.56	-13.2	62.5	0.02	8884	4899	143.03	85.3	583.71	105.68
Qinzhou	4.98	6186.12	256.03	27.1	42.8	3.47	30397	21487	246.11	80.8	566.51	331.08
Guigang	3.46	3517.69	45.76	4.5	50.4	0	34744	24546	292.81	82.7	692.50	435.03
Yulin	3.56	2420.82	38.86	25.4	50.4	2.27	47172	39432	375.91	80.7	627.53	581.58
Baise	4.39	4673.29	426.33	26.4	44.6	2.46	37312	25855	430.55	81.2	461.82	357.20
Hezhou	4.50	4222.34	21.26	13.4	49.7	2.15	16872	10423	219.09	81.9	483.81	202.66
Hechi	3.05	2849.29	58.49	31.0	45.9	2.85	32972	21260	372.92	77.9	305.28	341.91
Laibin	4.01	3776.11	13.23	20.4	49.1	2.91	17918	13908	234.15	76.5	335.51	207.78
Chongzuo	4.73	3526.37	2127.11	11.5	44.9	12.06	18203	10244	260.14	79.8	202.24	208.77

3.4 Data Processing

The data were standardized. Due to missing data for the number of higher education students in Beihai in 2021, this study used data from 2003 to 2020 to predict the value, resulting in an estimated 46,800 students.

4 PRINCIPAL COMPONENT ANALYSIS

4.1 KMO and Bartlett's Test

Principal Component Analysis (PCA) is based on the existence of correlations among indicator data. Before conducting PCA, the KMO and Bartlett's tests were performed on the indicator data. The results are shown in Table 3.

Table 3 Results of KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.531
Bartlett's Test of Sphericity	225.316
	66
	0.000

The KMO test results indicate that the data exhibit a moderate level of correlation, making them acceptable for Principal Component Analysis.

4.2 Extraction of Principal Components

Principal components with eigenvalues greater than 1 were extracted. The analysis was conducted using SPSS 26.0, and the results are presented in Table 5. In this study, the 12 indicators were transformed into three principal components. The first principal component accounts for 51.956% of the variance, the second principal component accounts for 28.915%, and the third principal component accounts for 8.768%. The cumulative variance contribution rate of the three principal components is 89.640%, indicating that they collectively capture 89.640% of the original information. Detailed data are provided in Table 4.

Table 4 Eigenvalues and Variance Contribution Rate of Principal Components

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	Variance%	Cumulative%	Total	Variance%	Cumulative%
1	6.235	51.956	51.956	6.235	51.956	51.956
2	3.470	28.915	80.872	3.470	28.915	80.872

3	1.052	8.768	89.640	1.052	8.768	89.640
4	0.572	4.764	94.404			
5	0.382	3.185	97.589			
6	0.127	1.062	98.650			
7	0.065	0.545	99.195			
8	0.060	0.497	99.692			
9	0.024	0.200	99.892			
10	0.010	0.085	99.977			
11	0.002	0.014	99.992			
12	0.001	0.008	100.000			

4.3 Principal Component Analysis

Table 5 Rotated Component Matrix

	Component		
	1	2	3
Per Capita GDP	-.182	.933	.167
Per Capita Fiscal Revenue	.014	.924	.070
Total Import and Export Volume	.085	.155	.948
Growth Rate of Fixed Asset Investment	-.049	-.721	-.287
Urbanization Rate	.379	.881	-.009
Number of Students Enrolled in Regular Institutions of Higher Education	.836	.239	.383
Number of Health Institution Personnel	.991	.109	.029
Number of Beds in Health Institutions	.981	.016	-.083
General Public Budget Expenditure	.969	.028	.105
Percentage of GDP from Secondary and Tertiary Industries	.215	.840	-.075
Value-added of GDP from Secondary and Tertiary Industries	.785	.588	.080
Year-end Permanent Resident Population	.982	-.013	-.049

As can be seen from Table 5, Principal Component 1 has high loadings on x6, x7, x8, x9, x11, x12, indicating that it is correlated with the level of social development and stability. In contrast, Principal Component 2 and Principal Component 3 are associated with the level of socioeconomic development.

4.4 Score Calculation

Using SPSS 26.0, the scores of Principal Component 1, Principal Component 2, and Principal Component 3 for each city in the Guangxi Zhuang Autonomous Region were calculated. The comprehensive scores were then computed using Formula $F = \frac{(F_1 \times 51.956 + F_2 \times 28.915 + F_3 \times 8.768)}{89.640}$. The 14 cities in Guangxi were ranked based on their comprehensive scores, and the results are shown in Table 6.

Table 6 Scores and Rankings

Rank	City	Score
1	Nanning	2.01613
2	Liuzhou	0.74716
3	Guilin	0.27039
4	Yulin	0.01673
5	Beihai	-0.11755
6	Guigang	-0.14766
7	Baise	-0.17359
5	Wuzhou	-0.20853
9	Fangchenggang	-0.22356
10	Qinzhou	-0.33610
11	Chongzuo	-0.37516
12	Hechi	-0.39813
13	Hezhou	-.049123
14	Laibin	-.057892

As the capital of the Guangxi Zhuang Autonomous Region, Nanning achieved the highest comprehensive score, leading other cities in terms of socioeconomic development, social development level, and social stability. However, in terms of per capita GDP and per capita fiscal revenue, Liuzhou, Fangchenggang, and Beihai outperformed Nanning. Additionally, the proportion of GDP contributed by the secondary and tertiary industries in Liuzhou was higher than that in Nanning.

5 CLUSTER ANALYSIS

5.1 Hierarchical Clustering

The initial 12 standardized indicators were used as variables for hierarchical clustering. The 14 cities of the Guangxi Zhuang Autonomous Region were divided into four categories:Category 1 includes Nanning (1 city).Category 2 includes Fangchenggang and Beihai (2 cities).Category 3 includes Liuzhou (1 city).Category 4 includes Chongzuo, Guilin, Hezhou, Laibin, Wuzhou, Guigang, Hechi, Qinzhou, Baise, and Yulin (10 cities).

5.2 Analysis

Table 7 Average Scores of Each Category

	Category1	Category 2	Category 3	Category 4
Mean of F_1	2.81288	-1.14006	0.35519	-0.0888
Mean of F_2	0.89898	1.454285	1.86888	-0.56764
Mean of F_3	0.97924	0.21596	-0.62926	-0.7819
Mean of F	2.01613	-0.17056	0.74716	-0.24222

As shown in Table 7, Category 1 has the highest scores in Principal Component 1, Principal Component 3, and the comprehensive score, indicating that Nanning excels in social development, economic development, and stability among the 14 cities in Guangxi, demonstrating comprehensive development. Category 2 cities have relatively high scores in Principal Component 2 and Principal Component 3, outperforming Categories 3 and 4, suggesting better economic development and stability in these regions. Category 3, represented by Liuzhou, a renowned industrial city in Guangxi, exhibits a high level of economic development, with the second-highest comprehensive score. Category 4 regions have low scores across all three principal components, all negative, indicating significant gaps in social and economic development compared to the other categories.

In Category 1, Nanning's F1 and F4 scores far exceed those of the other categories, highlighting disparities in economic and social development between Nanning and other cities. Nanning leads in higher education development, with the highest general public budget expenditure and the largest number of higher education students. It also significantly outperforms other regions in healthcare, with the highest number of health institution personnel and beds. Additionally, Nanning's foreign trade volume far surpasses that of other regions. The other three categories show progressively lower F1 and F4 scores, accompanied by decreasing public budget expenditures, resulting in poorer public infrastructure and healthcare facilities. Categories 2 and 3 have relatively high F2 mean scores, attributed to their strong industrial and tourism foundations, which serve as pillar industries. Coupled with smaller populations compared to Nanning, these

cities achieve higher per capita fiscal revenues. However, their overall development levels still lag behind Nanning, with economic disparities evident in per capita GDP and total import-export volume, while social development gaps are reflected in general public budget expenditure, higher education development, and healthcare standards.
The above analysis reveals significant disparities in economic and social development among cities in the Guangxi Zhuang Autonomous Region, particularly between Category 1 (Nanning) and Category 4 cities. This underscores the issues of inadequate and unbalanced development within Guangxi.

6 ARIMA MODEL

6.1 Data Sources

All data were sourced from the *Statistical Yearbooks* published by the Guangxi Zhuang Autonomous Region Bureau of Statistics over the years. The specific data are shown in Table 8.

Table 8 GDP of Guangxi from 2001 to 2021

Year	GDP	Year	GDP	Year	GDP	Year	GDP
2001	2279.34	2007	5823.41	2013	12448.36	2019	21237.14
2002	2523.73	2008	7021	2014	13587.8	2020	22120.87
2003	2821.11	2009	7759.16	2015	14797.8	2021	24740.86
2004	3433.5	2010	8552.44	2016	16116.55		
2005	3984.1	2011	10299.94	2017	17790.68		
2006	4746.16	2012	11303.55	2018	19627.81		

The unit of GDP is 100 million yuan

6.2 Unit Root Test and Randomness Test

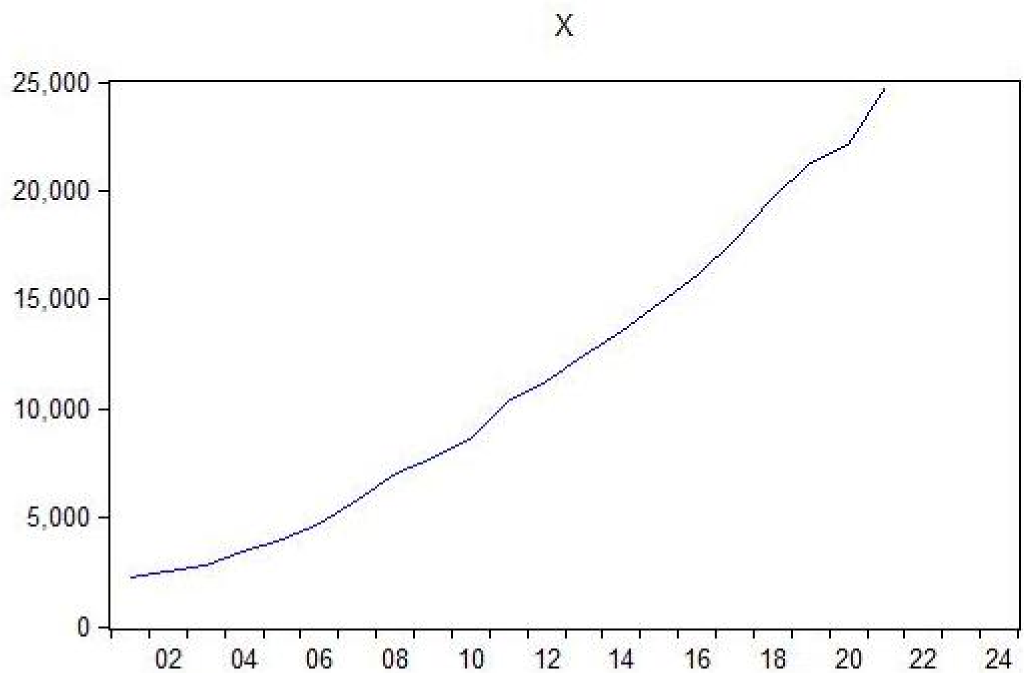

Figure 1 GDP Time Series Plot

The time series plot of Guangxi's GDP from 2001 to 2021 is shown in Figure 1 and 2. To eliminate heteroscedasticity, logarithmic transformation and first-order differencing were applied to the data. Unit root and randomness tests were subsequently conducted.

Table 9 Unit Root Test Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.480733	0.0119
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

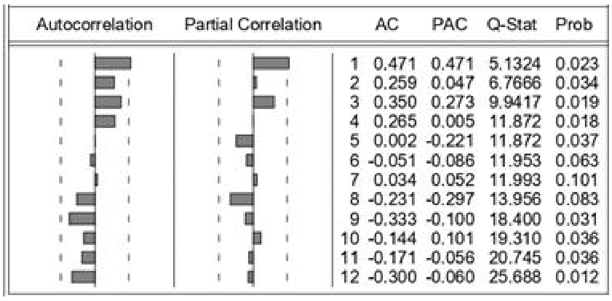

Figure 2 Autocorrelation Results

As shown in Table 9 and Figure 2, the data passed the unit root test and randomness test, indicating that an ARIMA model can be constructed.

6.3 Model Construction

Figure 2 shows the tailing and truncation characteristics, leading to the preliminary selection of an AR(1) model, with an MA(1) model as an alternative.

Table 10 AR(1) Model Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.120616	0.018636	6.472279	0.0000
AR(1)	0.471258	0.213027	2.212194	0.0409
R-squared	0.223525	Mean dependent var		0.120143
Adjusted R-squared	0.177850	S.D. dependent var		0.047358
S.E. of regression	0.042940	Akaike info criterion		-3.358706
Sum squared resid	0.031346	Schwarz criterion		-3.259292
Log likelihood	33.90771	Hannan-Quinn criter.		-3.341882
F-statistic	4.893802	Durbin-Watson stat		2.024824
Prob(F-statistic)	0.040930			
Inverted AR Roots	.47			

As shown in Table 10, the AR(1) model is reasonable, and the p-values of its residual tests are all greater than 0.05.

Table 11 MA(1) Model Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.119768	0.013837	8.655464	0.0000
MA(1)	0.474044	0.213946	2.215717	0.0398
R-squared	0.204205	Mean dependent var		0.119229
Adjusted R-squared	0.159995	S.D. dependent var		0.046276
S.E. of regression	0.042412	Akaike info criterion		-3.388108
Sum squared resid	0.032379	Schwarz criterion		-3.288535
Log likelihood	35.88108	Hannan-Quinn criter.		-3.368670
F-statistic	4.618903	Durbin-Watson stat		1.898568
Prob(F-statistic)	0.045472			
Inverted MA Roots	-.47			

As shown in Table 11, the MA(1) model is reasonable, and the p-values of its residual tests are all greater than 0.05. Based on the above conclusions, both AR(1) and MA(1) are reasonable models. Therefore, we will compare specific details to select one as the final model, see Table 12.

Table 12 Comparison of AR(1) and MA(1) Models

	AIC	SBC	DW
AR(1)	-3.358706	-3.259292	2.024824
MA(1)	-3.388108	-3.288535	1.898568

We selected the MA(1) model with smaller AIC and SBC values. The final mathematical expression of the model is

$$\begin{cases} y_t = \log\left(x_t / x_{t-1}\right) \\ y_t = 0.119768 + \varepsilon_t - 0.474044\varepsilon_{t-1} \end{cases}$$

First, the model was used for in-sample prediction, and the data from the last three years were taken to analyze the model's fitting performance.

Table 13 Comparison of Actual and Predicted Values

Year	Actual Value (100 Million Yuan)	Predicted Value (100 Million Yuan)	Relative Error
2019	21237.14	21943.77	3.33%
2020	22120.87	23570.67	6.55%
2021	24740.86	24196.22	2.20%

As shown in Table 13, the relative error is within an acceptable range, indicating a good model fit. Dynamic forecasting was conducted based on the above model, yielding the following results: the GDP for 2022 is predicted to be 28,184.62 billion yuan, followed by 31,770.70 billion yuan in 2023, and 35,813.06 billion yuan in 2024.

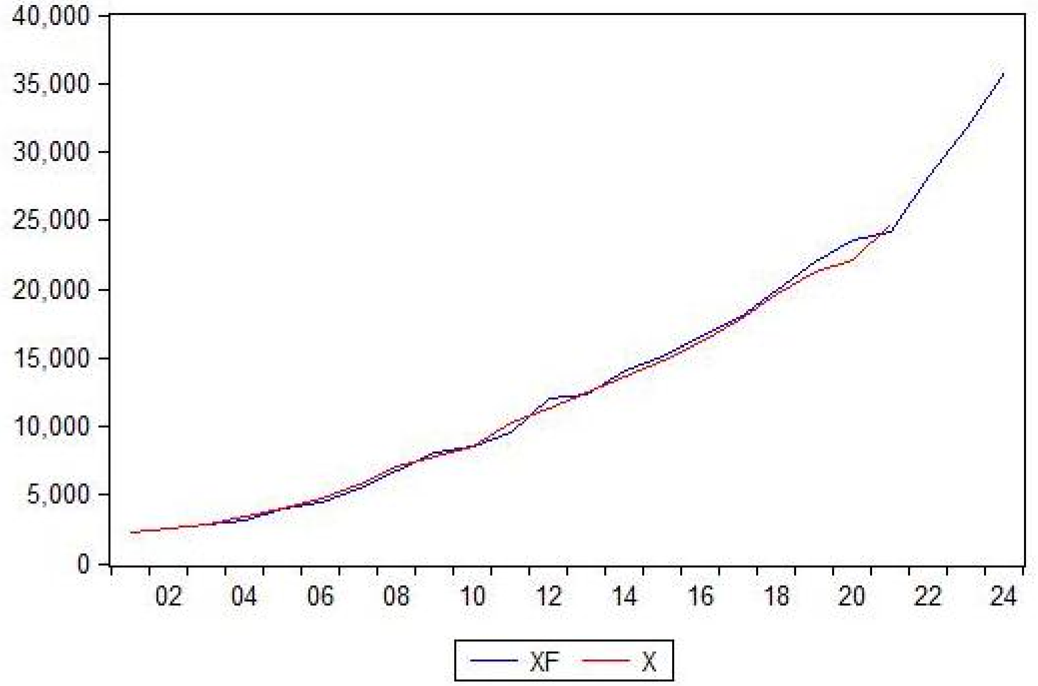

Figure 3 Comparison of Predicted and Actual Values

As can be seen from Figure 3, the model demonstrates a good fit, and Guangxi's future GDP shows a rapid growth trend.

7 Research Conclusions and Outlook

7.1 Basic Conclusions

The coastal economic zone of southern Guangxi has experienced relatively rapid economic development, while the eastern and western economic zones lag behind. This regional economic imbalance is influenced by factors such as natural conditions, policy support, infrastructure development, and population quality.

Based on the above research, Nanning, as the capital of the Guangxi Zhuang Autonomous Region, far surpasses other cities in terms of economic development level, social development level, and social stability. Cities such as Liuzhou and Beihai also exhibit considerable economic and social development levels due to their industrial and tourism development. However, other cities in Guangxi still lag significantly behind the aforementioned ones. Although economic disparities among Guangxi's cities have narrowed in recent years, the gap remains substantial.

Overall, the economic and social development levels of Guangxi's cities are continuously improving. Among them, cities such as Nanning, Guilin, and Liuzhou demonstrate strong economic development and comprehensive strength, while cities like Guigang and Beihai possess certain advantages in developing port trade and modern service industries. Additionally, all cities in Guangxi prioritize the development of tourism and cultural industries to enhance their soft power and attractiveness.

7.2 Strategies to Narrow Disparities

Promote the construction of urban clusters by strengthening cooperation and exchange among cities, particularly in the urban clusters formed by Nanning, Liuzhou, and Guilin, to facilitate the flow and allocation of resources and enhance the overall strength of these clusters. Develop advanced manufacturing by actively introducing advanced manufacturing enterprises, upgrading industrial technology and added value, and promoting the transformation of manufacturing towards high-end, intelligent, and green development to support Guangxi's industrial upgrading. Foster the digital

economy by strengthening digital infrastructure construction, promoting digital transformation, cultivating new digital industries, and improving the technological content and added value of industries to drive economic transformation and upgrading. Enhance infrastructure construction by accelerating the development of transportation, energy, and information infrastructure to reduce regional distances and disparities, thereby increasing regional development vitality and attractiveness. Advance rural revitalization by strengthening rural infrastructure construction, developing rural tourism and industries, improving farmers' income levels, and promoting integrated urban-rural economic development.
Through the implementation of these measures, coordinated development among various regions in Guangxi can be further strengthened, promoting balanced and sustainable economic growth.

7.3 Research Outlook

In recent years, disparities in regional economic development in Guangxi have narrowed. Guangxi has made positive progress in implementing regional development strategies and promoting urban cluster construction, gradually reducing development gaps between different regions.
Cities such as Nanning, Liuzhou, and Guilin have consistently served as pillars of Guangxi's economy, leading in economic output and development speed. Simultaneously, Guangxi has vigorously developed the Beibu Gulf Economic Zone and the ASEAN Economic Circle, strengthening cooperation and exchange with surrounding regions and enhancing its economic influence. On the other hand, Guangxi has also adopted a series of measures to promote economic development in impoverished areas, including strengthening infrastructure construction, supporting rural industrial development, and facilitating talent introduction, achieving remarkable results. These initiatives help promote balanced economic development across regions and narrow development gaps.
The future development prospects for Guangxi are positive. As the only open coastal economic zone in southwestern China, Guangxi has always been an important gateway for China's opening-up and will continue to play a significant role in the future. In summary, Guangxi will continue to leverage its unique geographical, resource, and cultural advantages, strengthen cooperation and exchange with surrounding regions, strive for high-quality economic development and comprehensive social progress, and become a modern open economic zone with international competitiveness.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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