Information Resources Management Journal
Volume 37 • Issue 1

Application and Analysis of an Interspecific Competition Model in a Digital Economy Ecosystem

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ABSTRACT

Expanding industrial digitization is vital for a thriving digital economy. This article delves into the application of interspecies competition models within the digital economy ecosystem. Such models aid in analyzing competitive dynamics among enterprises and understanding innovation trends. Interspecies competition models offer insights into enterprise competition within the digital economy ecosystem. They illuminate competitive landscapes, enabling strategic planning for enterprises facing peer and cross-industry competition. Moreover, these models facilitate the study of innovation and evolution, predicting market trends and aiding decision-making for enterprises and policymakers. Empirical studies across e-commerce, fintech, and sharing economy sectors validate the effectiveness of interspecies competition models. Analysis using these models elucidates competitive dynamics and provides actionable insights for enterprises and policymakers. Furthermore, addressing data migration bandwidth issues in cloud processes fortifies digital ecosystem construction.

KEYWORDS

Digital Economy, Economic Ecosystem, Factor Analysis, Influencing Factors, Interspecific Competition

INTRODUCTION

With the continuous development of information, communication, and digital technology, the digital economy has become a powerful force on a global scale. The digital economy has played an important role in resource allocation, penetration, integration, and coordinated development by promoting industrial structure adjustment and sustainable economic development. In the process of digital economy development, the lack of a comprehensive and scientific evaluation system makes it difficult to accurately evaluate the level of digital economy development in different countries, and it is also difficult to effectively compare the development of digital economy between countries. In order to evaluate and characterize the level of digital economy development, this study selected indicators and representatives highly related to digital economy development, constructed a digital economy indicator evaluation system, and used factor analysis methods to quantitatively evaluate and characterize the level of digital economy development in 42 countries around the world. At the

DOI: 10.4018/IRMJ.339919 *Corresponding Author

same time, this study introduces variables based on the LRS model for the development level of the digital economy and analyzes the impact mechanism of the digital economy on the division of labor position in the global value chain (GVC). Through the analysis of cross-border panel data from 42 countries, this study further explores the impact of the digital economy on the GVC division of labor in different industries, countries, and industries in different countries. It also analyzes the forward and backward participation rates and draws richer conclusions. This study solves the pressure of data traffic processing and the bandwidth problem of data migration in cloud computing processes and strengthens the construction of digital ecosystems. The results of this study provide important references and guidance for the development of the digital economy, as well as new ideas and methods for building a digital ecosystem.

LITERATURE REVIEW

According to gray system theory, the main research includes correlation analysis, cluster evaluation, prediction, decision-making, and control (Chen et al., 2018). In recent years, the theory has derived a variety of different gray correlation analysis models and algorithms, such as area correlation model, slope correlation model, A-type correlation model, B-type correlation model, parametric gray correlation model, generalized gray correlation model, absolute gray correlation model and relative correlation model, and other algorithms to improve the calculation of correlation between data series, as well as gray cloud optimization-based whitening model and multi-attribute decision making of fuzzy complementary judgment matrix and other improvements on gray decision algorithms, optimization of gray cluster analysis algorithm of stomach, and refinement of multivariate gray control model (Ferasso et al., 2020). The grey correlation analysis method is an important part of grey system theory, and its basic idea is to calculate the correlation between curves by comparing the proximity between them concerning the data series and comparing the geometry of the data series. Scholars combine their research directions and analyze the characteristics of gray correlation models to propose many innovative and feasible solutions (Li et al., 2020).

The initiative, as well as the quantitative aspects of analysis, can be used as important technical tools for model evaluation, etc. The difference between these two is mainly the difference in the results obtained and the form of presentation. The rules are opposite between quantitative and qualitative modeling, where quantitative models start from statistically obtained relevant data and use mathematical methods to explain the intrinsic property relations of the object of study (Villa et al., 2018). Although the two approaches are different, they are not contradictory but complementary and indispensable for the study of complex problems. Qualitative analysis methods include scenario simulation and empirical discrimination; quantitative analysis methods include regression analysis, gray correlation analysis, principal component analysis, and data inclusion analysis (Sopa et al., 2020). Gray correlation analysis is often used in the analysis of operational management performance, such as the use of gray correlation analysis to study and analyze the status of the management performance of the relevant airline companies. Its main contents include firstly, selecting the more typical financial evaluation factors; secondly, obtaining the comprehensive score and ranking of each enterprise to analyze its operation effect and give a plan that meets the actual situation of the enterprise; and third, using the grey correlation method to analyze the important role played by the internal and external environment on the comprehensive performance score of each listed salt and chemical company through the grey correlation method to profitability, inventory management, asset quality, operation, and other indicators (Liu et al., 2018). The composite performance scores of the pharmaceutical companies under the composite scores of several logistics companies in terms of operational management effectiveness were explored using gray correlation and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) analysis (Nave et al., 2019).

In recent years, other emerging digital technologies within the digital economy have spread from the information industry to many aspects of society, and the digital economy has become the mainstream economic development direction worldwide (Chhay et al., 2018). The digital economy industry is deeply integrated with traditional industries such as agriculture, manufacturing, and services, promoting the transformation and upgrading of traditional industries, improving total factor productivity, and unleashing enormous development potential. The digital economy industry is driven by data as the key element, and the new generation of information technology as the main driving force. Through continuous technological innovation and cross-border integration, new industries, formats, and models are born. The platform economy is an important feature of the development of the digital economy, which achieves optimized resource allocation and efficient utilization through technological means such as the Internet, the Internet of Things (IoT), and big data, promoting innovation in industrial organization and service models. Digital technology with information and communication technology as the core is subtly changing the mode of multinational companies in international trade to develop business in overseas markets, and the digital economy is embedded in global business networks, creating new market entry methods and new economic models and promoting better integration of national industries into the GVC (Luthra et al., 2020). Along with the formulation of national digital economy development strategies, the gradual improvement of digital infrastructure and the upgrading, and optimization of digital technology, the competition for digital products and services has intensified. Traditional trade has shortened the time for information processing and exchange up to and down the supply chain with the development of the digital economy, realizing direct communication between enterprises to enterprises, enterprises to consumers, and enterprises to production factors, shortening the transaction links (Yüksel et al., 2017). It has reduced information search and exchange matching costs, enhanced resource allocation efficiency, increased the scale of international trade, and has had a significant impact on changes in the GVC division of labor status of national industries.

With the continuous improvement and deepening integration of digital technology, represented by information and communication technology, with all areas of the social economy, the real economy has been structurally upgraded. The development of the digital economy has broken the time and space restrictions on the participation of countries in the GVC, reduced the search and matching costs in international trade, compressed the transaction execution links in international trade, expanded the scale of international trade, promoted a high degree of refinement, improved the operational efficiency of each link, and realized the climbing of economies to the high value-added stage of the GVC (Rahman & Ahmad, 2019). The universal application and rapid update of information and communication technology have promoted the globalization of production services, breaking the time constraints and space limitations faced by traditional industrial chains. The investment, production, and trade of enterprises and the design, manufacture, and distribution of products have contributed to the decomposition of GVCs into subdivisions, enhancing the tradability of intermediate products and ultimately improving the rationality of global resource allocation (Thannimalai & Raman, 2018). The breadth and depth have become more and more perfect and mature. However, there is still a lack of research on the core driving factors and path analysis that affect the change in GVC division of labor, while the value creation method and the way digital products revolutionize the distribution of international trade benefits through substitution and embedding have disruptive effects on GVCs.

At present, there are many research methods on GVCs and value chain division of labor, which have made breakthroughs and influential research in both measurement and analysis and extended applications, but there is a relative lack of research on changes in the status of GVC division of labor, and at the same time, the digital economy, as a relatively new research field, involves fields that cross industry and geographical restrictions and the traditional statistical caliber. The traditional statistics cannot accurately measure the volume of the digital economy, which restricts the formulation of government policies and the control of the macroeconomic situation (Yang et al., 2019). The quantitative approach has great theoretical significance in exploring the influence mechanisms and heterogeneous characteristics of the development of the digital economy in different countries and industries on the changes in the division of labor in GVCs.

Digital technology has enabled global industries to upgrade, giving birth to new production methods, business models, and consumption concepts. Measuring the level of development of the digital economy, understanding the trend of the digital economy, and recognizing the level of digital development can provide the relevant departments with economic measures and market environments compatible with the digital economy, provide new strategic thinking for the digitalization of enterprises as soon as possible, provide a theoretical basis for reducing the digital divide between regions, and accelerate the development of the digital economy (Liu et al., 2017).

RELATED MATERIALS AND METHODS

Interspecies Competition Model

The interspecies competition model is one of the commonly used models in ecology, used to describe the interactions and competitive relationships between different species. These models are based on the limited competitive resources (such as food, habitat, etc.), assuming competition between different species and describing their interactions through mathematical equations. Common species competition models include the following:

- The Lotka Volterra model, also known as the predator-prey model, describes the interaction between predators and prey. This model takes into account the food demand of predators for prey and the rate of prey growth and describes the quantity changes of both through a set of differential equations.
- The Gause model, also known as the competitive exclusion principle model, describes the competitive relationship between two or more similar species. This model assumes that resources are finite, and competition between species leads to the exclusion of species with weaker competitiveness.
- The R Model describes the differences in resource utilization among species, taking into account their efficiency in resource utilization. When the resource supply is below a certain critical value, only the species with the highest resource utilization efficiency can survive.
- Continuous time model: This model describes the variation of species quantity over time through differential equations. It takes into account factors such as competition, reproduction, and death among specie and can more accurately describe the dynamic changes in species numbers.

These species competition models can be used to study ecological issues such as competition relationships between different species, species diversity, and ecosystem stability through mathematical modeling and computer simulation. They provide important tools and methods for us to understand and predict the dynamics of species interactions.

The interspecies competition model has a wide range of applications in ecological research. The competition model can calculate the quantity changes of different species in specific environments, thereby predicting the trend and stable state of species quantity changes. The interspecies competition model can help us understand the interactions between different species, the allocation of niches, and the structure of ecosystems. Competition models can be used to evaluate the stability and resilience of ecosystems, as well as their ability to respond to external disturbances. By establishing a competitive model, the response of ecosystems to different disturbances can be evaluated, and protection and management strategies can be proposed. The competition model can be used to study the generation and maintenance mechanisms of species diversity, as well as the influencing factors of species richness in ecosystems. In summary, species competition models are one of the most important tools in ecological research, as they can help us better understand the interactions between species, predict changes and responses in ecosystems, and develop conservation and management strategies. The general usage process of inter species competition models can be summarized as the following steps:

- Determine research questions: Based on specific research objectives and questions, determine the types and parameters of species competition models that need to be established.
- Data collection: Collect ecological data on relevant species, including species numbers, resource utilization efficiency, reproduction rates, as well as data on environmental factors such as temperature, humidity, light, etc.
- Establishing a model: Based on the collected data and the determined model types and parameters, establish a species competition model. Usually, it can be implemented using tools such as mathematical equations or computer programs.
- Model validation: To validate the established model, existing experimental data or actual observation data can usually be used for validation. By validating the model, the effectiveness and applicability of the model can be verified.
- Analysis results: Use the established model to analyze and predict the research problem and draw corresponding conclusions and suggestions.
- Result interpretation: Explain and discuss the analysis results, draw conclusions, and provide corresponding suggestions. If necessary, subsequent experiments or observations can be conducted to further validate the accuracy of the model and results.

In summary, the process of using the interspecies competition model requires steps such as problem determination, data collection, model establishment, model validation, result analysis, and result interpretation. It requires the comprehensive application of knowledge and methods from multiple disciplines such as ecology, mathematics, and computer science. The interspecies competition model has a certain effectiveness and relevance in understanding competitive dynamics and innovation trends. The following is a specific analysis:

- Competitive dynamics: Interspecific competition models can be used to study the competitive relationships and dynamic changes between species. By constructing mathematical models, it is possible to simulate the competition process between different species and analyze the factors that affect the competition results, such as competition intensity and population density. These analyses can provide decision support for ecosystem management and protection, thereby enhancing the sustainability of the ecosystem.
- Innovation trends: In interspecies competition models, competition between species can promote innovation and adaptive evolution, which to some extent reflects innovation trends. For example, when a species is threatened by other species, it may gradually evolve more adaptable characteristics to enhance its competitiveness. This innovative trend can be quantified and analyzed through mathematical models, providing a certain reference for the management and protection of ecosystems.
- Correlation: There is a certain correlation between the interspecies competition model and the actual ecological environment. In actual ecosystems, the interactions between different species are often complex, variable, and dynamically evolving. The interspecies competition model can model and analyze these interactions, providing theoretical support for understanding practical ecological problems.

In summary, the interspecies competition model has certain effectiveness and relevance in understanding competition dynamics and innovation trends. It can provide decision support for ecosystem management and protection, as well as promote understanding and resolution of practical ecological problems. Data migration usually refers to the changes and transfer of data between different environments or systems. Although interspecies competition models cannot be directly applied to data migration problems, by combining relevant concepts and methods with data migration, we can gain some insights and theoretical foundations, which can help us better understand the relevant information of data migration problems. In solving the problem of data migration, it is necessary to combine other applicable models and methods, such as data flow analysis, transfer learning, etc., to comprehensively understand and solve the problem of data migration.

The Influencing Factors of the Digital Economy Ecosystem

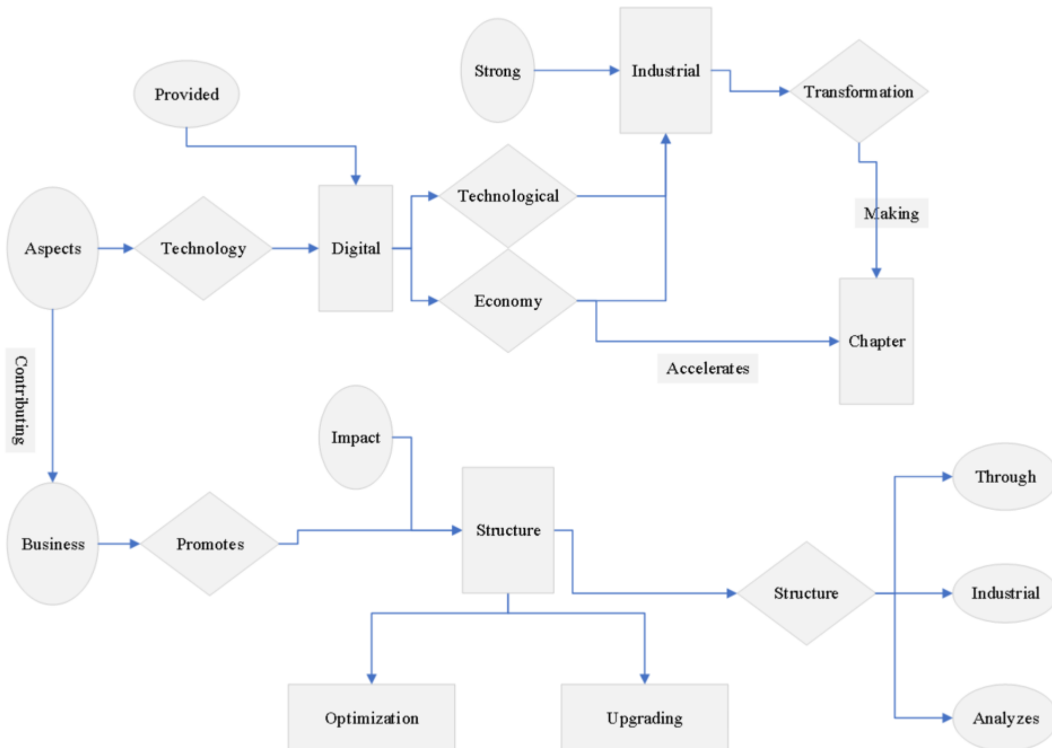
The widespread application of digital technology has promoted the digital transformation of traditional industries. By combining digital technology with traditional industries, automation and intelligence in the production process can be achieved, improving production efficiency and product quality. At the same time, digital technology can also promote product innovation and service upgrading in traditional industries, meet the constantly changing needs of consumers, and enhance market competitiveness. The path of the impact of digital economy industry on industrial structure is shown in Figure 1. First, the digital economy industry provides technical support to produce traditional industries, prompting changes in the production methods, business processes, and organization of traditional industries, improving the efficiency of traditional industries and the technical content of products. From the perspective of market demand, the development of the digital economy industry has also profoundly changed the demand structure of the market. With the increasing demand for digital products and services from consumers, the market's demand for digital technology is also growing accordingly. This change has led to the adjustment of industrial structures, causing more and more enterprises to focus on digital transformation to meet changing market demand.

In addition, the development of the digital economy industry has also promoted cooperation and collaborative innovation among enterprises. Through data sharing, resource integration, and other means, enterprises can better achieve complementary advantages and improve overall competitiveness. This cooperation model also helps to promote the innovative development of industries and accelerate the promotion and application of new technologies.

The application of digital economy technology has made the production processes of traditional industries more intelligent and automated, improving production efficiency. For example, by introducing the industrial internet, interconnection between devices can be achieved, improving the collaborative efficiency of production lines. Big data analysis can help enterprises accurately understand market demand and consumer behavior and achieve optimized resource allocation. Enterprises can make more scientific and reasonable decisions based on data analysis results and improve the efficiency of resource utilization. The digital economy industry has given birth to new business models and service forms, providing enterprises with a broader development space. For example, emerging formats such as e-commerce, online education, and remote healthcare have broken the limitations of traditional industries and met the diverse needs of consumers. Internet platforms simplify transaction processes, reduce transaction costs, and enable enterprises to respond more quickly to market changes. At the same time, it also enables consumers to obtain goods and services more conveniently. With the continuous progress of digital technology and the expansion of its application scope, more and more traditional industries are undergoing digital transformation. By introducing digital technology, traditional industries can improve production efficiency, reduce costs, optimize the service experience, and better meet market demand. At the same time, digital transformation also helps enterprises achieve innovative management models and optimized organizational structures, enhancing overall competitiveness.

The development of the digital economy industry has given birth to a large number of emerging formats and business models, injecting new vitality into economic growth. These emerging formats and business models not only create new employment opportunities but also provide consumers with more convenient and efficient service experiences. For example, the rapid development in fields such

Figure 1. Pathways of the Impact of Digital Economy Industries on Industrial Structure



as e-commerce, mobile payments, and the sharing economy has changed people's consumption habits and lifestyles. The application of technologies such as big data analysis and cloud computing helps enterprises more accurately understand market demand and consumer behavior and achieve optimized resource allocation. At the same time, digital technology can also reduce transaction and logistics costs and improve the economic benefits and market competitiveness of enterprises. Through digital transformation, enterprises can better achieve personalized customization and precision marketing and improve customer satisfaction and loyalty.

The decision making trial and evaluation laboratory (DEMATEL) method is a method commonly used to determine the degree of influence and mechanism of action among factors, but the application of the method still has certain limitations, mainly in that the method generally requires the establishment of a direct relationship influence matrix based on the scoring of the expert group, and the data is affected by the subjective tendency of experts. In recent years, some scholars have tried to eliminate the subjective influence caused by expert scoring, and there are two types of innovative and representative methods: the back propagation (BP) neural network-DEMATEL method and the fuzzy set theory-DEMATEL method.

The BP neural network-DEMATEL method uses the BP neural network to train the initial data to replace the subjective scoring data of experts and then analyzes the degree of interaction between influencing factors by the DEMATEL method; the fuzzy set theory-DEMATEL method uses triangular fuzzy numbers to quantify the subjective scoring of the expert group and then analyzes the degree of interaction between influencing factors by the DEMATEL method. The fuzzy set theory-DEMATEL method uses triangular fuzzy numbers to quantify the subjective scores of the expert group and then analyzes the degree of interaction between the influencing factors using the DEMATEL method. In summary, the fuzzy set theory-DEMATEL method is used in conjunction with the actual selection.

The reasons are as follows: first, fuzzy set theory can effectively reduce the influence of subjective tendency brought by the expert scoring method; second, the organization of experts in the field can better reflect the relevance of this study; third, the BP neural network-DEMATEL method cannot completely bypass the expert scoring and obtain all quantitative data, and there is still some difficulty in obtaining qualitative data.

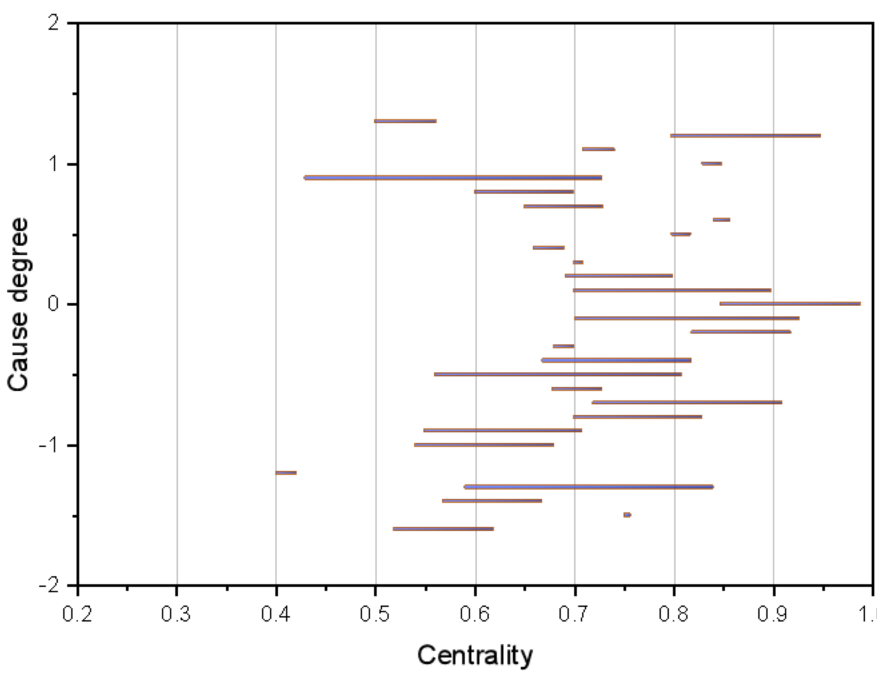
Data Standardization

Using the triangular fuzzy number principle, the scoring data of the above eight experts is standardized, including steps such as reducing the fuzzy number, calculating the left and right standard values, the total standard value, and the overall standardized influence degree value, to obtain the direct influence matrix A. Where

$$\Delta_{\min}^{\max} = \min r_{ij}^{k} + \max l_{ij}^{k} \tag{1}$$

C7, C8, C9, C10, C11, C12, C13, C14, and C15 are causal factors, (i.e., the above factors actively influence other factors). Among them, information sharing (C11) shows extremely strong proactivity, with the highest degree of cause as well as influence; however, the degree of being influenced is low (i.e., information sharing can strongly influence other factors). However, the degree of being influenced by itself is low; similarly, the comprehensive strength of funds payment and settlement platform (C15), information access (C8), information integration (C10), and government regulation (C12). The factors of information extraction (C9), the comprehensive strength of fund payment and settlement platform (C15), and information system integration level (C7) are low in influence and are loosely related to other factors. Trustworthiness (C13) is the fourth most influential and influenced factor, which means that it is more closely related to other factors. The relationship between the factors' influencing mobility is shown in Figure 2.

Figure 2. Relationship Between Factors Influencing Mobility



As the development of the digital economy affects different products. The labor endowment is assumed to be L = Ls + Ln, where Ls is skilled labor and Ln unskilled labor. The country is assumed to produce only two final consumption goods, primary good A, and skilled good I. The unskilled labor used to produce A and I is Luna and Lane, respectively, and the wages of the two labor forces are Ws and Wn, respectively, and Ws = Wn + t (t > 0).

Assume that the production of primary A requires only the input of unskilled labor, Luna, with $A = Lu_{na}/TA$. where Lu_{na} is the amount of unskilled labor used to produce primary A, TA (TA > 0) is the amount of unskilled labor per unit of primary A, and the wage of unskilled labor is Wn= 1/TA.

Suppose that the production process of technological good is continuous subprocess between [0,1] corresponding to intermediate good 0 (0 ∈ [0,1]) and does not require factors other than labor and technology. Let P(C) denote the price of intermediate good 0. Then the price of technological goods I is:

$$p_I = \int_O^I p(d)\theta \tag{2}$$

If all consumers in dominant and digitally disadvantaged countries have the same preferences in the free trade process, those countries are required to bear the price differences due to the digital economy development gap when trading digitally in the digitally disadvantaged countries due to the existence of the digital economy development costs (Luthra et al., 2018). Therefore, digital technology services provided by product producers are included in the model to study their impact on the status of the global value chain division of labor, considering the development costs of the digital economy.

Gray Correlation Model

Gray systems can use the degree of similarity between the geometric features of the change curves of each reference factor as a technique for discerning the level of association between the reference factors. An important property of orthogonal transformation is that the angle between two vectors remains unchanged after orthogonal transformation. Orthogonal basis refers to mutually perpendicular basis vectors. We can think that an orthogonal transformation does not change the shape of the curve. As long as all orthogonal similar matrices can be obtained, the relationship between quadratic term coefficients of quadratic curves with the same eccentricity can be obtained. In general, the best reference series is given first, and then all the comparison series are allowed to calculate their gray correlation values with the reference series (Lin et al., 2019). When this value is larger, the comparison sequence to be analyzed is considered to have more correlation with the reference sequence, which simply understood, means that this comparison sequence is closer to the reference sequence of this criterion. So, it is said that by carefully analyzing the comparison and reference sequences, the final sample ranking can be achieved. The gray correlation model can give a definite analysis solution for a certain developing nonlinear system, which can achieve good dynamic use. The main computational steps of the model can be decomposed as follows: 1) the samples to be analyzed and their indicator data are normalized and other dimensionless processing is done; 2) the best indicator factor is extracted from many samples to form the reference sample (or reference sequence), so that the remaining samples to be compared (which can be called the comparison sequence), can be analyzed with the reference sample for gray correlation; 3) The correlation coefficient of each comparison sample is calculated using the gray correlation formula; 4) The correlation coefficient of each comparison sample is calculated; 5) Find the correlation value of all the comparison samples and rank the correlation value. 6) Evaluate the results of the gray correlation analysis (Cavallo et al., 2019).

In the modeling and analysis of data, the problem of different magnitudes and units arises due to different sources of data. To make them comparable, dimensionless, and, if necessary, normalized, methods are used to eliminate bias. After the raw data is dimensionless and normalized in SPSS, the indicators are situated in the same order of magnitude range and are suitable for modeling calculations or comprehensive assessments. This is the method of data normalization (Cui et al., 2018). The actual experimental process is as follows:

1. We need to download a Chinese version of SPSS software, open the software on a screen, and enter the need to mark quantified data.
2. Execute the command: Analyze, Describe Statistics, Describe (D), go to the list of descriptions.
3. Above the box describing the list, in the lower left-hand corner, check the box “Save” standardized score as a variable (Z), then click OK.
4. After the result, you will see that a column of ZA is automatically generated, which is the data after Z standardization. Repeat and normalize all the data to prepare for min-max later.

After the above z-score data normalization, it is found that there is a problem of positive and negative values, which will cause some difficulty and error in the construction of the model later. The Min-Max standardization (also known as deviation standardization) was applied to the original data using SPSS to perform a linear transformation so that the resulting values were mapped to the range [0, 1]. The formula and results are as follows:

$$X^{'} = \frac{X + \max}{\max + \min} \tag{3}$$

The Goal of Normalization. 1. Drop the number into the interval [0,1]; 2. Change a quantified expression into a dimensionless expression.

Benefits of Normalization. 1. Improve the speed of convergence of the model; 2. Improve the accuracy of the model.

Max and min are the maximum and minimum values of the sample data, respectively. The above data processing results were imported into SPSS software for normalization. The data within the interval [0,1] were obtained, as shown in Table 1.

Table 1. Normalized Results of the Indicator System

Indicator A	**A**											
Indicator A	**a1**				**a2**				**a3**			
Particular Year	**b1**	**b2**	**b3**	**b4**	**b5**	**b6**	**b7**	**b8**	**b9**	**b10**	**b11**	**b12**
2020	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2019	1.00	1.00	1.00	0.78	0.07	0.88	1.00	1.00	1.00	1.00	0.50	0.90
2018	1.00	1.00	0.75	0.56	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.12
2017	1.00	0.00	0.00	0.00	0.90	0.07	0.88	1.00	1.00	0.50	1.00	1.20
2016	1.00	0.00	0.00	0.00	0.76	0.05	0.45	0.00	0.80	0.54	1.00	0.00
2015	1.00	0.00	0.00	0.00	0.17	0.56	0.00	0.00	0.90	0.07	0.88	1.00
2014	1.00	0.00	0.00	0.00	0.56	0.56	0.00	0.00	0.76	0.05	0.45	0.00
2013	0.00	0.00	0.39	0.02	0.37	0.00	0.75	0.25	0.24	0.23	0.45	0.20
2012	0.00	0.00	0.35	0.03	0.39	0.00	0.71	0.17	0.20	0.10	0.48	0.20
2011	0.00	0.00	0.16	0.01	0.21	0.00	0.00	0.76	0.11	0.31	0.34	0.20
2010	0.00	0.00	0.09	0.02	0.06	0.00	0.79	0.10	0.21	0.19	0.16	0.10

In gray correlation analysis, the discrimination coefficient p has an important influence on the analysis results, and its value is usually related to the stability of the data series and should obey two basic principles: 1. When the data series is smooth; that is, the overall distribution of the difference between the series is uniform, p should take a larger value; 2. When the data series is fluctuating; that is, the overall distribution of the difference between the series is unbalanced, p should take a smaller value. If the discrimination coefficient p is fixed, in some cases the results of gray correlation analysis may deviate from the actual situation. For example, if the first half of a comparative data series belongs to a stable series while the second half has anomalous data, the correlation degree obtained by using a fixed discrimination coefficient may be significantly reduced due to the presence of outliers, resulting in inconsistency with the actual correlation order of the reference series (i.e., the correlation order qualitatively determined from the line graph of the series data) association sequence is not consistent.

In this paper, we will use the criterion for determining whether the data is singular (i.e., the maximum extreme difference between data sequences is greater than or equal to the average of three times the difference) to perform the calculation and adjust the discrimination coefficient in a targeted manner. In the information domain, information entropy is often used to describe the uncertainty of a system, the magnitude of which is inversely proportional to the uncertainty of the system. The formula for calculating the information entropy H is given, drawing on the concept of thermodynamics, as follows:

$$H(x) = \sum_{k=1}^{m} p(x_k)\min(\mathrm{x}_k) \tag{4}$$

$p(x_k)$ represents the probability that a state x_k will occur in the system.

Information entropy measures the degree of disorder of information, and the information entropy of information is proportional to its degree of disorder and inversely proportional to its amount of information. To improve the accuracy of correlation order in grey system, it is necessary to reduce the information entropy of the system. In this paper, the grey correlation degree to measure the curve approximation similarity is regarded as the probability of similarity, so the probability is used to measure the uncertainty of grey system. It reduces the uncertainty in the system and provides a guarantee for obtaining the relationship between the correlation degree and information entropy in the grey system. The relationship between information entropy and gray correlation is shown in Figure 3, and the gray correlation has a great value of information entropy in the interval (0, 1].

The “x” Group rose from 14th place in 2012 to 11th place in 2014, and from 10th place in 2015 to 8th place in 2016. In the five years from 2012 to 2020, it showed an overall upward trend (see Figure 4). This upward trend in the ranking of the overall operating performance reflects the excellent operating ability and market competitiveness of the “x” Group. By investigating the business characteristics of “x” Group and its status in recent years, it is found that “x” Group has increased its main products such as “ñan gum and blood granules, Niu Huang and antidote pills and wu qi bai Feng pills” in these years and has continued to develop strong products. It is found that “x” Group has increased its main products such as “ñan gum and blood granules, Niu Huang antitoxin pills and wuji bai Feng pills,” continued product innovation and increased publicity, thus, the sales volume of these main products had a large increase in 2012 to 2020. On the other hand, “x” Group has explored the market scope well and proposed new products such as stem cell therapy in myocardial infarction, and other innovations have been well received. The key to the success of “x” Group in these years has been the improvement of the quality of the already strong products, good marketing communication, and continuous market development measures. These measures are a good reference for the above-mentioned companies, which continue to decline in ranking.

Figure 3. The Relationship Between the System Information Entropy in Grey Correlation

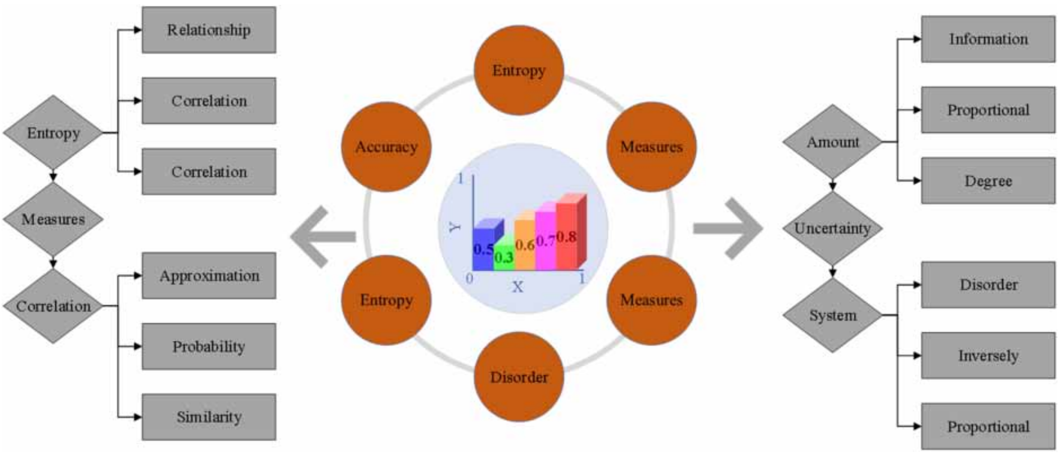
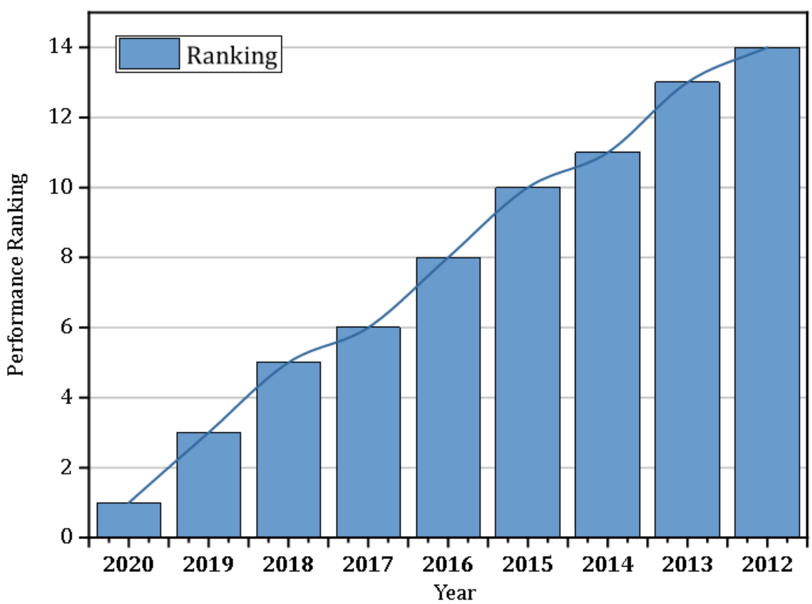


Figure 4. Change in Business Performance Ranking of Company X, 2012-2020



In the process of industrial development, whether it is to promote the transformation of economic development mode from rough to intensive or the transformation of industrial structure from low to the high level, it can essentially be attributed to the optimization of inter-industry linkage and relationship structure. The most used method for industrial linkage research is Leontief's input-output method. However, it cannot reflect the characteristics of the relationship structure such as closeness, hierarchy, and degree of centralization of the relationship between industrial sectors in the industrial system. The social network analysis method can make up for the deficiencies of input-output analysis and enhance the ability to analyze and judge the industrial structure. Combining input-output tables with the social network analysis method can fuse the advantages of both methods and study industrial structure issues with a new perspective.

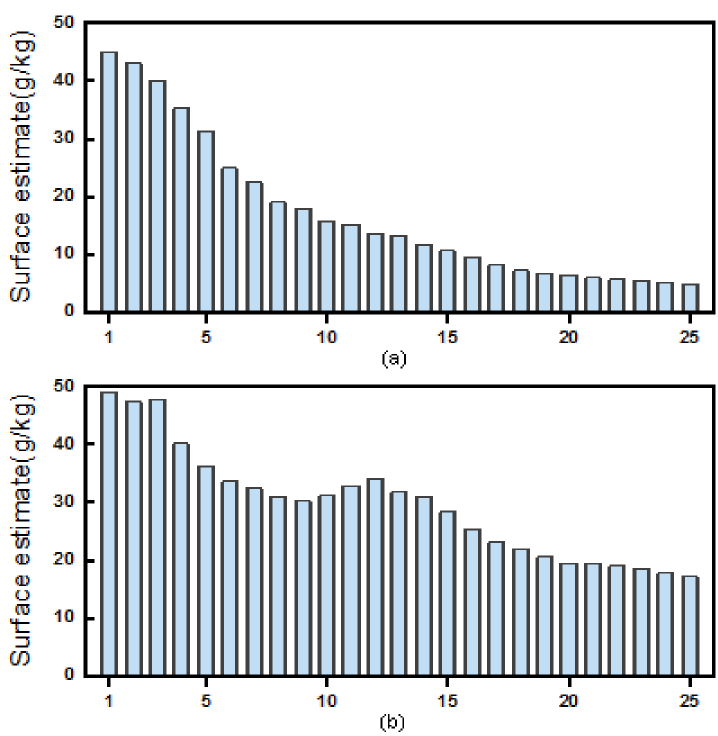
RESULTS AND ANALYSIS

Analysis of the Results of Grey Relational Model

The 74 pre-processed samples were sorted, from which 16 samples were evenly selected as the samples to be estimated, and the remaining 58 samples were used as modeling samples. The two new forward and backward gray correlation models introduced in this paper were compared and analyzed to demonstrate the effectiveness of the estimation of organic matter content by using the above models. The interspecific competition model can give a clear analytical solution of the developing nonlinear system. In order to reduce the error in the calculation process, the average relative error and determination coefficient of area difference forward and reverse grey correlation model and index difference forward and reverse grey correlation model are proposed in this paper. First, the area difference S between each sample to be estimated and the known model is found. to derive the maximum positive and negative gray correlation of the 16 models to be estimated, and then the estimation results are obtained, and the relative error, average relative error, and R2 of the estimation results are calculated to evaluate the estimation accuracy. For comparison and illustration, the results of positive and negative correlations are identified for estimation (see Figure 5).

The absolute correlation had the same and lowest precision as the similar correlation estimation with a coefficient of determination R2 less than 0.1, indicating that these two grey correlations are not suitable for hyperspectral estimation of soil organic matter content. The mean relative error and R2 of the coefficient of determination of the close correlation were 10.796% and 0.821, respectively, which were slightly more accurate than the Dunn's correlation. In contrast, the average relative errors,

Figure 5. Scatter Plot of Positive and Negative Correlation Identification Estimation: (a) Analysis Results of Forward Grey Correlation Model, (b) Analysis Results of Backward Grey Correlation Model



and determination coefficients R2 of the area-difference forward and reverse gray correlation and indicator-difference forward and reverse gray correlation models proposed in this paper were 5.312%, 0.930 and 5.911%, 0.898, respectively, and obviously, the two forward and reverse gray correlation models proposed in this paper had higher estimation accuracy.

The dematerialized form of data is distinctly different from the regime of property rights applicable to physical carriers containing data (Nordhoff et al., 2019). Moreover, while property rights are characterized by independent possession as a key feature, personal data are often held and used by different subjects, and it is not natural for one party to achieve full domination and control over such data, nor can data be equated with trade secrets, and in the context of big data, the rapidly changing nature of data, coupled with network effects and multiple attributions, makes complete secrecy of data inherently unrealistic. Moreover, the initiative to generate the underlying data is often in the hands of ordinary people, making it difficult to apply confidentiality. The personality rights attributes of data cannot be derogated from as a result.

In this paper, we analyze the impact of digital economy industry development on industrial structure optimization and upgrading by constructing a panel data model. Panel data is two-dimensional data with both time series data characteristics and cross-sectional data characteristics.

$$TL=\sum_{i=2}^{n}\left(\frac{Y_i}{Y}\right)\ln\left(\frac{L_i}{L}\right) \tag{5}$$

Where i denotes individual, t denotes time, Y is the explained variable and is the explanatory variable, a is a scalar, and 0 is the regression coefficient. The cross-sectional N denotes the number of individuals, and T denotes the length of time, called the random perturbation term.

By guiding and supporting traditional enterprises to apply digital technology, improve production efficiency and product-added value, and achieve the transformation and upgrading of traditional industries, at the same time, strengthening industry-university research cooperation, cultivating high-quality digital economy talents, and providing intellectual support for the digital transformation of traditional industries (Li, 2020). The government should streamline administration and delegate power, reduce institutional transaction costs for enterprises, and improve market efficiency. In the context of global economic integration, countries should strengthen cooperation and exchanges in the field of the digital economy and jointly explore the development path and model of the digital economy and promote the prosperity and development of the global digital economy through sharing experiences, exchanging technologies, and collaborative innovation. In summary, the development level of the digital economy industry has a significant positive impact on the advanced industrial structure. To further unleash the potential of the digital economy and promote the optimization and upgrading of industrial structures, the government and enterprises should work together to increase support for the digital economy, promote the digital transformation of traditional industries, optimize the business environment, and strengthen international cooperation and exchanges. Through the implementation of these measures, we can expect to achieve sustainable development of the digital economy and the optimization and upgrading of advanced industrial structures, injecting new impetus into economic growth and social progress. The elasticity coefficient of consumption demand is also positive and positively correlates with the advanced industrial structure. Direct investment, on the other hand, hurts the advanced industrial structure (-0.034), which is explained in that investment is mainly invested in the secondary industry and less in the tertiary industry. The industrial skewness of investment is an important reason for the advanced industrial structure.

The digital economy industry studied in this paper provides technical support for the emergence of traditional industries, promotes the transformation of production modes, business processes, organizational structures of traditional industries, improves the efficiency of traditional industries and the technical content of products, and promotes the optimization and upgrading of traditional industries. Compared with traditional industries, integration accelerates the birth of new models and new business models.

Analysis of Factors Influencing the Digital Economy Ecosystem

The data is sourced from authoritative statistical agencies and international organizations that have released statistical data related to the digital economy. The explanatory variables include technological progress, policy environment, market demand, and industrial synergy. The dependent variable is the overall level of development of the digital economy ecosystem. Control variables include factors such as economic development level and industrial structure that may affect the digital economy ecosystem (Koopialipoor et al., 2018). The government can support the research and innovation activities of digital technology through policies such as finance and taxation, promoting technological progress. At the same time, strengthening intellectual property protection and stimulating innovation vitality. The government should formulate policy measures that are conducive to the development of the digital economy, such as encouraging open data sharing and optimizing the business environment while at the same time, strengthen supervision to ensure the healthy development of the digital economy, explore the potential market demand, and expand the application scenarios of the digital economy (Parsajoo et al., 2021). The government and enterprises should actively promote digital transformation, expand the application of digital technology in various fields, meet the growing market demand, strengthen consumer education, and improve public awareness and acceptance of the digital economy. The government should also strengthen industrial collaborative innovation and promote the healthy development of the digital economy ecosystem, guide and support cooperation and collaborative innovation among enterprises, and promote the connection and integration of the upstream and downstream of the industrial chain, as well as strengthen cooperation and communication with the international community and jointly explore the development path and model of the digital economy.

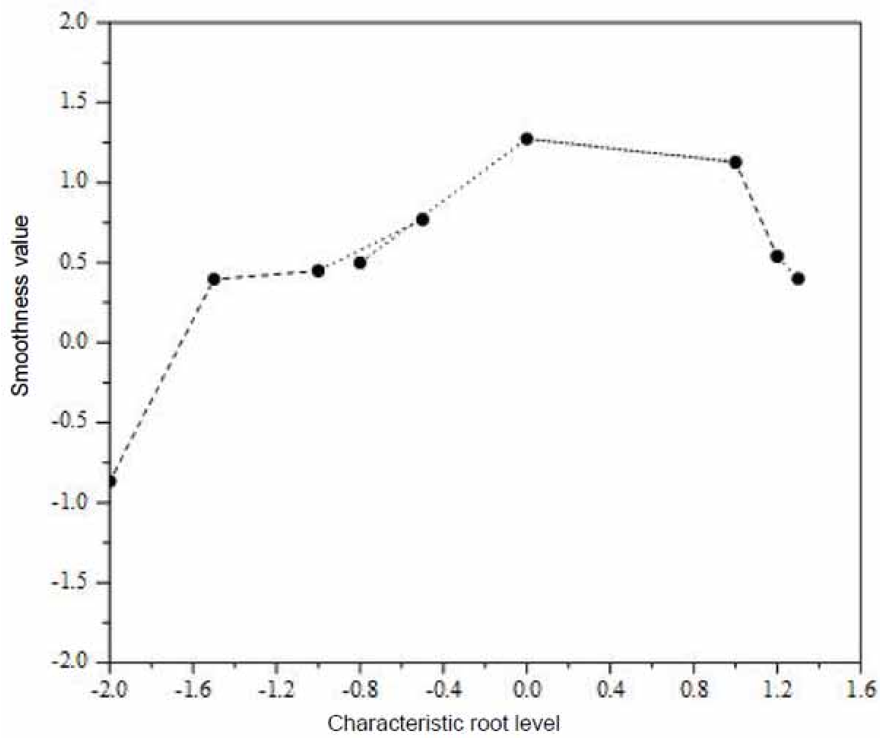
$$TL=\sum_{i=2}^{n}(\frac{Y_i}{Y})\ln(\frac{L_i}{L}) \tag{6}$$

Consumers keep increasing the degree of participation, and business websites maintain an excellent brand image. The main position of consumers and value creation ability is mainly expressed in the degree of consumer participation in the value creation process (Zeng et al., 2022), while the main position of business websites/distributors and value creation ability are reflected mainly in good reputation and excellent brand image. With the development of time, the degree of user participation increases, and the evolution rate of choosing an “active cooperation” strategy is accelerated, which indicates that the degree of consumer participation has a positive impact on the willingness of business sites/distributors to cooperate actively (Liu et al., 2022). Conversely, as the ownership of the commerce site/distributor increases, it is also effective in promoting the willingness of consumers to cooperate actively. In other words, in the process of synergistic value creation between the two parties, their ability level has great influence on the cooperation strategy, and the game subjects are more inclined to cooperate actively with other subjects with higher status to maximize their interests.

Conducting an impulse response analysis is useful to further explore the relationship between the total value of the digital economy and the factors involved. The first step in conducting impulse response is to ensure that the model must be stable. This can be tested using the AR root icon, which yields the results shown below (see Figure 6).

In the VAR model established in this paper, the lag is 2, the number of variables is 4, and the number of its characteristic roots is equal to 8. The results show that the results of the inverse model

Figure 6. Plot of Feature Root Smoothness Test

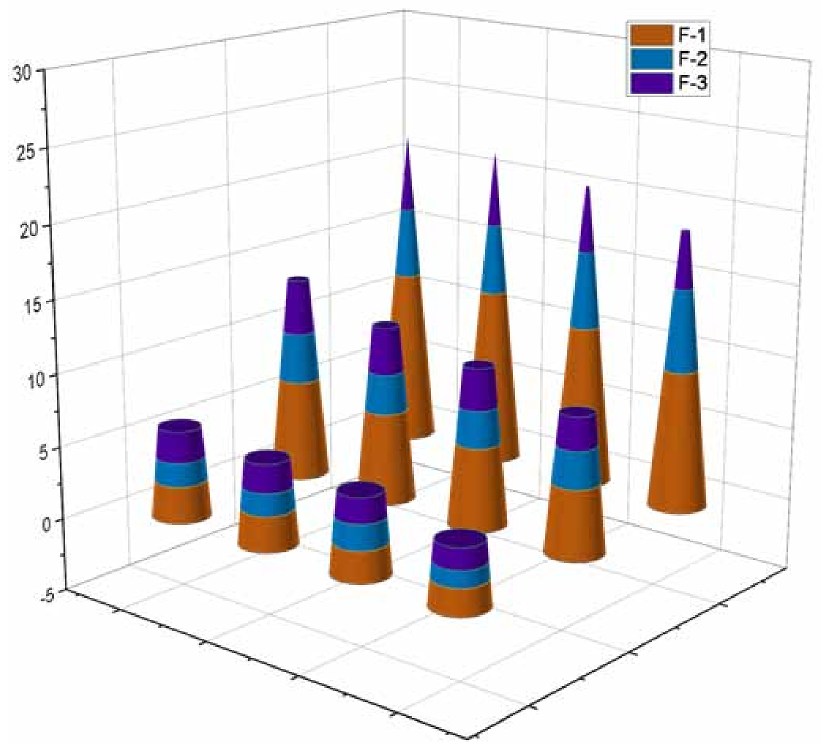


of the above 8 characteristic roots are all less than 1, and of the AR roots presented, if all 8 points fall within the unit circle, it proves the VAR model is smooth, if there is at least one characteristic root with an inverse mode equal to 1 or greater than 1, that is. If some points are on or outside the unit circle, which indicates that this VAR model is not smooth. Therefore, the VAR model established above can pass the stability test and can be considered stable (i.e., the next step of impulse response analysis can be performed) (Zhang et al., 2021).

The ability of data to drive economic development has been proven time and again, but schemes that promote data flow by simply granting users property rights in data to break the one-way strong protection of data, such as the GDPR, do not reflect the core characteristics of the data-driven economy itself of two-way interaction and rapid change, and placing the individual data producer at the center of the construction of property rights does not meet the goal of smooth data transactions. The goal of a property interest mechanism that maximizes social welfare is also blind to the reality of data practitioners as an important party structure in the marketplace. The timeliness of data and its similarity to industrial property rights determine that it is difficult to establish the absolute nature of data asset rights like property rights, and the form and value of data products will continue to upgrade or decline over time. When specific conditions are met, a patent-like compulsory license could be established to facilitate data sharing (Bo et al., 2022).

Impulse response analysis is done on the VAR model established for the total value of the digital economy and shown as a solid line in the figure 7, in the model The lag of the information shock effect is set to 10 years, and the dashed lines above and below indicate the standard deviation offset bands of plus or minus two times, meaning the interval in which the impulse response may occur.

Figure 7. Impulse Response Results



By constructing a Vector Autoregression (VAR) structural model and using empirical analysis to analyze the influencing factors of the digital economy, through Augmented Dickey-Fuller unit root test (ADF) unit root test, Johansen cointegration test, Granger causality test, impulse response analysis, and variance decomposition, we get that the long-distance fiber optic cable line density, the number of employees in the digital economy industry, and the ratio of R&D expenditure to Gross Domestic Product (GDP) in the digital economy industry are sustainable from a long-term perspective. The ADF unit root is used to test the data for smoothness to avoid the problem of "pseudo-regression," and then Johansen cointegration is used to test the cointegration between the variables and prove that there is indeed a long-term cointegration relationship between the total value of the digital economy and the influencing factors and provides ideas for the development of the digital economy.

Analysis of Practical Applications

In today's digital age, the digital economy has become a powerful force on a global scale. It not only promotes the adjustment of industrial structure and sustainable economic development but also profoundly changes people's way of life and social operation. However, due to the lack of a comprehensive and scientific evaluation system, it is difficult to accurately evaluate the level of digital economy development in different countries, and it is also difficult to effectively compare the development of digital economy between countries. This article aims to explore the current situation and trends of the development of the digital economy, analyze the impact of the digital economy on the position of the global value chain, and propose a digital economy evaluation system and development solutions to provide support for the sustainable development of the digital economy. However, there are several limitations to this study, as follows:

- Data collection limitations: This study may be subject to limitations in data collection, such as limitations in the reliability and completeness of data sources, which may affect the accurate assessment of the level of digital economy development. Researchers should obtain data from multiple reliable sources as much as possible and combine them with different datasets for analysis to reduce bias caused by a single data source. At the same time, they should ensure strict validation and screening of data are carried out to preserve its quality and reliability.
- Sample selection bias: There may be selection bias in the samples used in the study, and the representativeness of the samples may not be sufficient, which may affect the universality and reliability of the research conclusions. By increasing the sample size and covering a wider range of regions and industries, we aim to improve the representativeness and universality of the sample, in order to reduce the impact of sample selection bias on research conclusions.
- Methodological limitations: Research methods may have certain limitations, such as the rationality of model setting and the scientificity of variable selection, which may require more discussion and validation to ensure the credibility of research conclusions. There is a need for more innovative research methods and the adoption of a comprehensive analysis of multiple methods, such as mixed research methods, model fusion, etc., to increase the accuracy and credibility of research conclusions.
- Conclusion generalizability: Due to limitations in research scope and depth, the conclusion of this article may have certain limitations and cannot fully cover all aspects of digital economy development. Further expansion and deepening are needed in future research. When promoting the conclusion, it is important for researchers to carefully explain the scope and limitations of the research results, clearly point out the limitations of the research, and propose future research directions and improvement points.
- Limitations of research framework: The research framework of this article may have limitations, as certain influencing factors or related variables may not have been taken into account, which may affect a comprehensive understanding of the factors influencing the development of the digital economy. Future research will need to add more dimensions and influencing factors to the research framework and comprehensively consider various aspects of the development of the digital economy in order to fully understand its impact mechanism and development trends.

By taking these measures, we can effectively address the limitations described in this article and improve the reliability, accuracy, and applicability of our research while at the same time, encourage the academic community and research institutions to conduct more in-depth research in order to continuously improve the digital economy evaluation system.

The practical applications of this article can include the following aspects:

- Policy formulation: The digital economy evaluation system and development solutions proposed in this article can provide a basis for government departments to formulate relevant policies. The government can take corresponding policy measures to promote the sustainable development of the digital economy based on the level of digital economy development in different countries or regions.
- Corporate strategy: For enterprises, understanding the current situation and trends of digital economy development is crucial for making strategic decisions. The research results of this article can provide reference for enterprises to identify and grasp the business opportunities and challenges brought by the digital economy, optimize resource allocation, and improve competitiveness.
- Investment decisions: Investors can evaluate the potential and risks of digital economy development in different countries or regions based on the research results of this article and make corresponding investment decisions. Meanwhile, investors can also evaluate the competitiveness

and sustainability of specific enterprises in the digital economy field based on the digital economy evaluation system proposed in this article.
- International cooperation: The digital economy is global, and cross-border cooperation is crucial for the development of the digital economy. The research results of this article can provide reference for international organizations, multinational enterprises, and other partners to promote cooperation and development of the global digital economy.

In summary, the research findings of this article have broad practical application significance, providing decision-making support and strategic guidance for various stakeholders, such as governments, enterprises, and investors, and promoting the healthy and sustainable development of the digital economy. In the future, the following development directions can be considered:

- Digging deeper into the underlying mechanisms of digital economy development: The digital economy is a complex system that involves the interaction and influence of multiple factors. Future research needs to delve deeper into the internal mechanisms of digital economy development, explore the interactive relationships and influencing mechanisms between different factors, in order to better understand the development trends and future directions of the digital economy.
- Strengthening the construction of the digital economy evaluation system: The digital economy evaluation system is one of the core contents of digital economy research. In the future, it is necessary to strengthen the construction of the digital economy evaluation system, optimize the indicator system and data collection methods, improve the accuracy and reliability of the evaluation, and develop more comprehensive digital economy evaluation tools and platforms.
- Strengthening interdisciplinary cooperation: The digital economy is an interdisciplinary field that involves multiple disciplines. In the future, it is necessary to strengthen interdisciplinary cooperation, fully leverage the advantages and strengths of each discipline, and jointly explore the problems and challenges of the development of the digital economy.
- Strengthening international cooperation: The digital economy is global, and in the future, it is necessary to strengthen international cooperation, promote exchanges and cooperation among countries, and jointly promote the development and popularization of the digital economy.
- Promoting the integration of digital economy and sustainable development: The development of digital economy has brought both enormous opportunities and some challenges. In the future, it is necessary to combine the digital economy with sustainable development, promote the sustainable development of the digital economy, and promote the balanced development of the digital economy with various aspects such as society and the environment.

CONCLUSION

With the continuous progress of information, communication, and digital technology, the digital economy has played an important role in promoting industrial structure adjustment and sustainable economic development. However, in the rapid development of the digital economy, due to the lack of a comprehensive and scientific evaluation system, it is difficult to accurately evaluate the level of digital economy development in different countries, and it is also difficult to effectively compare the development of digital economy between countries. This article aims to explore the impact of digital economy development on the position of the global value chain and construct a digital economy indicator evaluation system and development level variables based on the LRS model. This study quantitatively evaluates the development level of digital economy in 42 countries through factor analysis method and deeply analyzes the impact mechanism of digital economy on the GVC division of labor status. Meanwhile, this study also proposes solutions to the challenges in data processing and cloud computing, providing technical support for the sustainable development of the digital economy. This article provides a new perspective for understanding the evolution of the global economic landscape. In addition, the proposed solutions help to strengthen the construction of digital ecosystems, improve network security, promote sustainable development of the digital economy, and provide useful ideas for future research. However, this study has some limitations, such as limitations in data collection and sample selection, which require further expansion of sample size and improvement of data quality. Future research can improve the evaluation system and analytical framework through more empirical analysis and in-depth research in order to better understand the development trends and impact mechanisms of the digital economy.

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