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Research Article

A Fuzzy Multi-Criteria Evaluation Model for the Coordination of Industrial Agglomeration and Regional Economic Growth

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The coordinated development between industrial agglomeration and regional economic growth is of great significance. Based on the theory, this article constructs a fuzzy multi-criteria evaluation model for the coordination of industrial agglomeration and regional economic growth. The model reveals the impact of industrial agglomeration on economic growth by establishing a regression model. The output value of the secondary industry and the tertiary industry are classified, and the initial value method is used for dimensionless processing. The experimental results show that using the panel unit root test, panel cointegration test, panel regression analysis, and gray correlation analysis to conduct empirical analysis and research, the capital agglomeration and labor agglomeration in regional industries both promote economic growth, and the correlation degree of sustainable agglomeration components reached 89.7%, which significantly and indirectly played a role in promoting the coordinated development of economic growth in regional economic growth.

1. Introduction

Netizens conduct various activities related to economy, life, communication, and digital information collection through the Internet, and the Internet plays an increasingly important role in the coordinated development of economic growth in production and life [1–4]. Various industrial agglomerations are carried out through the Internet to meet their own material and spiritual needs. Digital industrial agglomeration is an emerging mode of industrial agglomeration under the network economy. This model has many advantages and has different characteristics from traditional industrial agglomeration. The characteristics of digital industrial agglomeration and its inherent network rules have contributed to the vigorous development of digital industrial agglomeration [5–8]. Based on the definition and characteristic analysis of digital industrial agglomeration, this article further expounds on the current situation and existing problems of regional digital industrial agglomeration and briefly expounds on the future development trend in regional digital industrial agglomeration from the theoretical level.

From the perspective of the time-space connection of digital industrial agglomeration, digital industrial agglomeration is completed in the virtual network. This means that a large amount of personal digital information and materials, data, audio, video, etc. is stored in the virtual network. These online storages are convenient and efficient, which facilitates the online industry agglomeration behavior of netizens. However, the question is how to deal with the digital information, materials, audio, video, and other network products stored in the virtual space online when these netizens pass away [9–11]. This creates another problem that will be faced in the digital age and the problem of digital heritage. Digital heritage is that with the expansion and continuous advancement of digital industrial agglomeration, economic and legal issues have arisen between network platform providers and demanders. This problem is not significant in contemporary times, but with the mass death of the first generation of netizens, the dispute over the issue of digital heritage will come into people's field of vision [12–15].

This article focuses on the coordinated development of industrial agglomeration and regional economic growth. The main contributions are as follows:

(i)From a macro perspective, this article studies the impact of regional residents' income, education level, and Internet on the industrial agglomeration behavior of digital industrial agglomerators through regression analysis.

(ii)At the micro level, based on the planned behavior theory and technology acceptance model, this article constructs the influence model of the willingness of digital industry agglomerators. Through theoretical analysis, we know that the behavior of digital industrial agglomeration depends on the perception and usefulness of the digital industrial agglomeration.

The rest of article is structured as follows: Section 2 describes the related works. In Section 3, the growth of digital information and the industrial agglomeration of collaborative technology are analyzed in detail. In Section 4, based on the collaborative technology of digital information growth, this article constructs the collaborative development model of industrial agglomeration and regional economic growth. In Section 5, the application of the proposed model is analyzed, and concluding remarks are presented in Section 6.

2. Related Works

There are many ways to classify the externalities of coordinated development of regional economic growth. According to the difference in the way of production, direct network means that the mutual economic growth and synergistic development between industrial agglomerations using the same product or service. The use of one user will affect the efficiency of other users. When the number of users increases, the social value of the tool itself also increases, which is the direct network externality, the complementary products of the product or service will also increase, and the price will decrease, which is an indirect network externality according to the different final results produced by the synergistic development of mutual economic growth among users [16–19].

Aiming at some shortcomings of the growth pole theory, Nathan et al. [20] proposed the dual economic structure (Geographical and Economic) theory by using the dynamic disequilibrium analysis method. In addition to the research on developed regions and backward regions, Voronkova et al. [21] proposed how to take the coordinated development role of developed regions in leading economic growth and stimulate the development of backward regions, so as to eliminate the development of developed regions and backward regions. Gureev et al. [22] systematically introduced foreign theoretical results on industrial agglomeration and applied the theoretical results outside the region to conduct a classification and empirical study on regional industrial clusters. Eisebith et al. [23] believe that an industrial cluster is an organized concentration of capital, labor, growth synergistic technology, and entrepreneurs in certain industries, with very strong growth ability and rapid market development, so it must be very attractive to enterprises and organizations outside the cluster. Relevant enterprises and organizations will definitely migrate to cluster areas if they have the conditions, and this is most prominent in reality, which is the attraction of foreign investment by industrial agglomeration. Yuan et al. [24] studied the nonlinear impact of manufacturing agglomeration on Gee and its action path theoretically and empirically by using the dynamic spatial panel Dobbin model and intermediary effect model. Shi et al. [25] measured and analyzed the coupling coordination and spatiotemporal heterogeneity of economic development and ecological environment in 17 tropical and subtropical regions by geographical and time-weighted regression. The internal growth model emphasizes that knowledge spillovers not only generate increasing returns themselves, but also make other factors such as physical capital and labor have increasing returns, resulting in unconstrained growth. For the diffusion of growth synergy technology, industrial agglomeration has more obvious advantages. Due to the close geographical location and close connection between enterprises within the cluster, the diffusion speed of digital information and growth synergy technology is very fast. The rapid spread of digital information and growth of collaborative technologies enables every enterprise to quickly update equipment, adopt new production processes, and adjust the optimal input mix of factors, which can generally improve the productivity and output of enterprises, thereby increasing regional economic aggregates and market competitiveness and promote clusters. For example, social credit, social norms, and social networks will be greatly improved [26, 27].

In view of this, on this basis, this article constructs a fuzzy multi-index evaluation model for the coordination between industrial agglomeration and regional economic growth. The model reveals the impact of industrial agglomeration on economic growth by establishing a regression model.

3. Analysis of the Agglomeration of Digital Information Growth Collaborative Technology Industry

3.1. Transformation of Digital Information Domain. When a digital product information field is downloaded from the Internet, it is easy to copy, and the same is true for digital product manufacturers. When the first digital product is produced, it can be copied at a low cost later, so that the digital product is raising new economic problems, the reproducibility of digital products forces companies to change their traditional competitive strategies, and the supply and demand of digital products in the market also complicates.

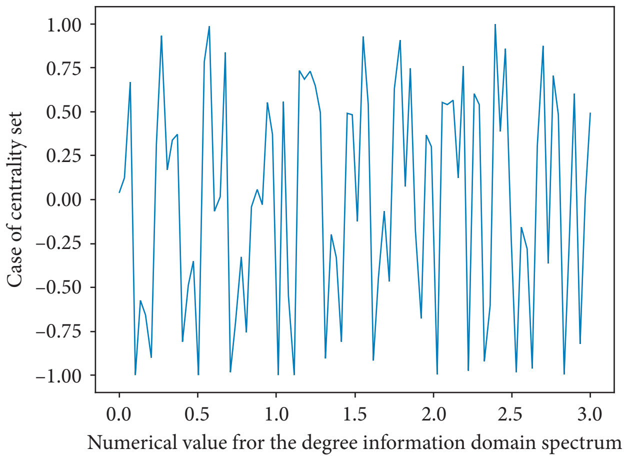

Figure 1: The transformation of the degree of network centrality in the digital information domain.

$$\mathrm{zermst}(x'') - \mathrm{zermst}(x'' - x') - \mathrm{zermst}(x'' - x' - x) - 1 = 0. \quad (1)$$

When the industrial scale location quotient is greater than 1, there was a significant difference in performance between simple and complex conditions, and this difference was not due to insufficient processing time. From the average observation, it is found that the correct rate of complex conditions is lower than that of simple conditions under various presentation time conditions. The industry in the Figure 1 is at a comparative disadvantage and its competitiveness is weak.

The centrality of the information domain is an index to measure the degree to which an industry is located in the center of the entire industrial network. Specifically, it is measured by four indicators: degree centrality, intermediate centrality, closeness centrality, and eigenvector centrality. Among them, degree centrality is the most direct measure of network centrality.

$$\begin{bmatrix} s(x'', x) \\ s(x'' - x, x' - x) \end{bmatrix} \times \begin{bmatrix} s(x', x' - x) \\ s(x'' - x, x') \end{bmatrix} = \begin{bmatrix} s(x', x) \\ s(x' - x, x') \end{bmatrix}. \quad (2)$$

The larger the value of an industry's degree centrality, the more important the status of the industry is. Betweenness centrality measures the ability of an industry to act as a mediator for other industries by occupying the position of "middleman" on the shortest path connecting other industries. The greater the intermediate centrality, the stronger the effect of the industry on the indirect restriction of economic growth and coordinated development of other industries.

3.2. Network Mode Training. The network model can find that this is mainly to measure the comparison of a certain industry in a certain region with the regional average, so as to measure the agglomeration ability and relative competitiveness of a certain industry. The larger the location quotient of the industry, the stronger the agglomeration and competitiveness of the industry in the region.

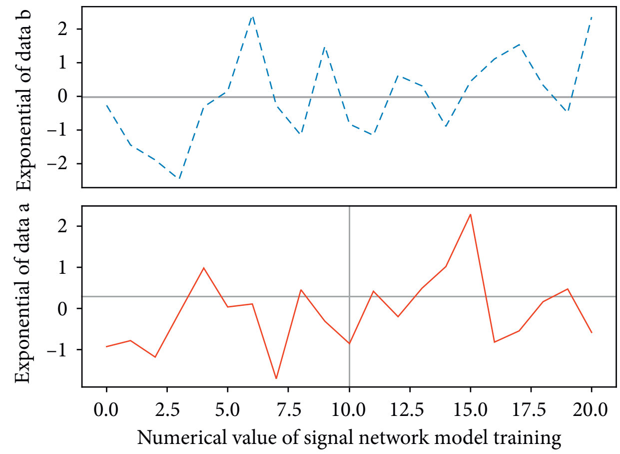

Figure 2: Digital signal network model training.

$$f(x,t) = \frac{1-x}{x} \times \mathrm{exwers}\left[x(t) + x(t'-t) - x(t') + x(t'+t)\right]. \quad (3)$$

Since we choose time-series data, this article uses the Granger causality test to illustrate the relationship between financial industry agglomeration, economic growth, and financial industry development. The basic principle of Granger causality is: when doing the co-regression of A to other variables (including the past value of A itself), if the lag value of B is included, the expectation of A can be significantly improved, that is, B is A's (Granger) cause; similarly define A as B's (Granger) cause.

$$\begin{gathered} \mathrm{when}\{x(t) + x(t'-t) = 1 - t\}, \\ \mathrm{fget}\{x(t) - x(t'-t) = c(t,1)\}. \end{gathered} \quad (4)$$

The specific process includes examining whether each variable is single-integrated, performing unit root test of time-series data on each variable, conducting cointegration test, and using Granger causality test to examine the relationship between variables.

It is calculated that the in-degree of the Internet of things industry in Figure 2 is 10 and the out-degree is 20, which to a certain extent directly reflects the significant input-output relationship between the regional Internet of things industry and many industries. Secondly, the out-degree of industrial association ranks in the top ten among the 40 industries, while the in-degree of industrial association ranks relatively low, at 22, indicating that the consumption level of the IoT industry to other industries is relatively low, while the production process of other industries is relatively low.

3.3. Industry Agglomeration Signal Compression. The closeness centrality of industrial agglomeration signals measures the average distance between an industry and other industries. A certain industry is denoted as node i, and the average distance from this node to all nodes in the network is di, then the reciprocal of d is the proximity centrality of node i. The shorter the average distance between an industry and other industries, the greater the closeness

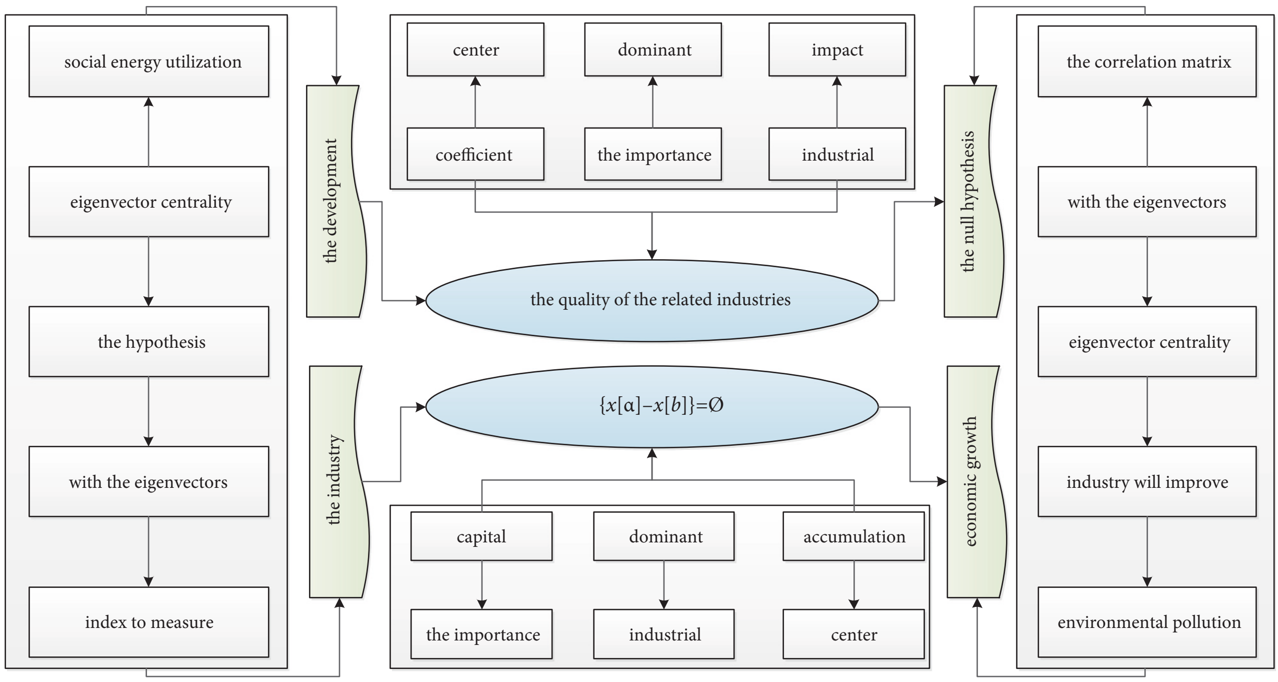

Figure 3: Industry aggregation signal compression topology.

centrality of the industry, and the greater the impact on other industries.

$$\text{barcase}\,(a|b-a)=\frac{x(t)+x(t'-t)}{1-x(t)+x(t'-t)}-y(t)+y(t'-t). \tag{5}$$

The eigenvector centrality is an index to measure the quality of the related industries of a certain industry with the eigenvectors of the correlation matrix. The larger the calculated value of the relevant indicators of the industrial center, the more often the industry is a dominant industry or a bottleneck industry.

$$\frac{1-n(x,y)}{n(x,y)}\times\sum\left[n(x,y)-n(x'-x,y'-y)\right]-\sqrt{\frac{n(x,y)-1}{n(x',y')}}=1. \tag{6}$$

The path coefficient of the impact of human capital accumulation on economic growth is 0.153 ($t-2.259$), the accumulation of human capital has a negative impact on economic growth, which contradicts the null hypothesis and rejects the hypothesis H4b. The path coefficient of the development affecting energy utilization efficiency is 0.804 ($t=36.187$) and the path coefficient of the impact of energy utilization efficiency on economic growth is 0.290 ($t-4.278$), indicating that the development will improve social energy utilization efficiency and reduce environmental pollution in promoting economic growth, accepting assumptions H5a, H5b.

The influence path coefficients of digital information perception level, digital information transmission level, and digital information processing level on the industry are 0.348 ($t-20.214$), 0.305 ($t=14.876$), 0.348 ($t-20.214$), 0.305 ($t=14.876$), and 441 ($t-28.629$), indicating that the higher the level of digital information perception, transmission, and processing in Figure 3 will significantly improve the development level industry, and the assumptions Hla, Hlb, and HlC are accepted. The path coefficient of the direct economic growth and coordinated development of IoT type industry development on economic growth is 0.333 ($t-2.408$), indicating that the development of IoT type industry has a case impact on economic growth, and the hypothesis H2 is accepted.

The path coefficient of the development of IoT type industry affecting growth and collaborative technological innovation is 0.895 ($t=55.975$) and the path coefficient of the growth of collaborative technological innovation affecting economic growth is 0.406 ($t-3.193$), indicating that the development of IoT type industry will promote the improvement in social growth synergistic technological innovation ability, and the improvement in growth synergistic technological innovation ability will further drive economic growth, accepting assumptions H3a, H3b. The path coefficient of the impact of IoT industry development on human capital accumulation is 0.739 ($t-13.888$), indicating that IoT industry development will accelerate human capital accumulation, and the hypothesis H4a is accepted.

3.4. Clustering Weight Distribution. The weight of agglomeration is mainly reflected in the influence of capital on agglomeration, so these three growth synergy factors are defined as the capital factors of industrial agglomeration; the second public growth synergy factor has a large load in the ratio of the number of enterprises and the number of employees, which is manifested as labor force. The impact on industrial agglomeration is therefore defined as the labor force growth synergistic factor of industrial agglomeration.

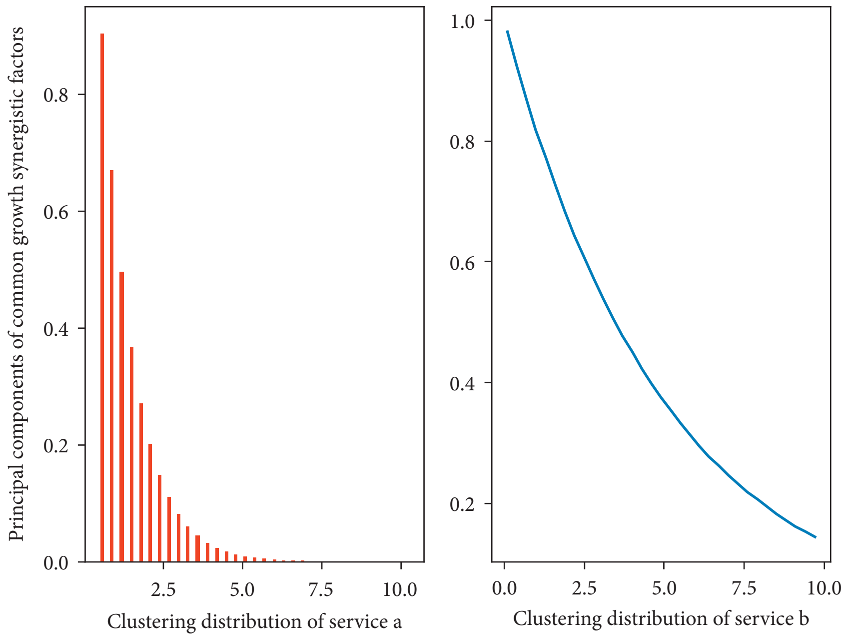

Figure 4: Clustering distribution of public growth synergistic factors.

$$g(r,t)=\begin{cases}1-\dfrac{1-r(x,y)}{1-t(x,y)}, & r>t,\\[2ex] \dfrac{1-r(x,y)}{1-t(x,y)}, & r\le t.\end{cases} \tag{7}$$

The two public growth synergy factors both have a certain load on the fixed asset-to-equity ratio, and according to the nature of the asset-to-net value ratio, they are classified as the first public growth synergy factor. And the value of each growth synergy factor is greater than 0 in each common growth synergy factor, indicating that this classification is meaningful. In this way, two synergistic factors of public growth are obtained, one representing the capital factor and the other representing the labor factor, which also reflects the most essential requirements of industrial agglomeration.

This shows that the digital information in Figure 4 contained in 1 lnx (Internet penetration rate) can basically be reflected by the information in 2 lnx (logarithm of per capita income of urban residents) and 3 lnx (logarithm of higher education level). In fact, the increase in income level and education level has indeed led to the development of the Internet. As a result, more and more people use the Internet, and the Internet penetration rate is also higher.

$$\begin{aligned}&\sum\frac{1-x}{2x}\left[z(x,y)-z(x'-x,y'-y)\right]\\&-\sum\frac{x}{2-x}\left[z(x',y')-z(x,y)\right]=z(x,y).\end{aligned} \tag{8}$$

The coefficient of the Internet penetration rate is negative because in the model, we performed the natural logarithm transformation of the data, the Internet penetration rate is less than 1, so the natural logarithm of the Internet penetration rate is negative, and the negative coefficient indicates the Internet penetration rate here is a correlation between the network industry agglomeration and the digital industry agglomeration.

4. Construction of a Collaborative Development Model of Industrial Agglomeration and Regional Economic Growth Based on Digital Information Growth Collaborative Technology

4.1. Digital Information Coding Optimization. The research assumptions of digital information coding are as follows: the level of digital information perception has a case effect on the development of IoT type industry and promotes the coordinated development of economic growth; the level of digital information transmission has a case on the development of IoT type industry. The level of digital information processing has a case effect on the development of IoT type industry and promotes the coordinated development of economic growth; the development of IoT type industry directly promotes economic growth; the development of IoT type industry has a case impact on the improvement in growth and collaborative technological innovation capabilities; the growth and technological innovation promote economic growth, and the development of IoT type industry has a case impact on the accumulation of human capital; the accumulation of human capital promotes economic growth; the development of IoT type industry has a case impact on the improvement in energy utilization efficiency.

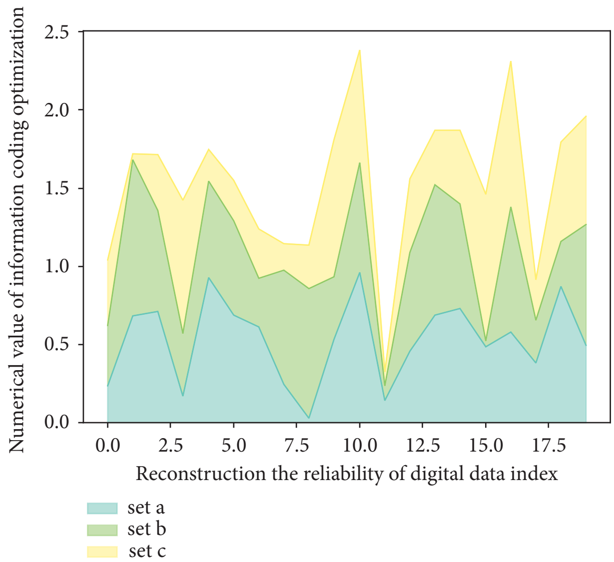

Figure 5: Optimal reliability of digital information coding.

$$Y[a,b,c] = a[x(t) - t' - 1] + b[y(t) - t' - 1] + c[z(t) - t' - 1] + 1. \quad (9)$$

Secondly, in the causal relationship between financial agglomeration and the development of the financial industry, there is also a mutual causal relationship. It is worth noting that there is an active influence of the financial industry on financial agglomeration in the case of a 1-stage lag, while in the case of a 2-stage lag, financial agglomeration actively images the development of the financial industry. This shows that the regional financial agglomeration first developed with the support of the development of the financial industry, but at the same time it also had an impact on the development of the financial industry.

Reliability is used to test the reliability of the measurement item to the subject to be measured, and to test whether the set of measurement items in Figure 5 is the measurement index of this subject. Cronbach's coefficient α is the most commonly used reliability analysis index, and the size of its coefficient represents the size of reliability.

$$\forall r(i,j) = r(i' - i, j' - j),$$
$$\exists \sum \frac{1-x}{2x}\left(\overline{z(x,y)} - z\left(\overline{x' - x}, \overline{y' - y}\right)\right) = 1. \quad (10)$$

When it is above 0.8, the reliability is the best. When it is between 0.7 and 0.8, it indicates that it has considerable reliability. When the Cronbach coefficient is above 0.6, the reliability is acceptable. When it is below 0.6, the reliability is insufficient. Validity means it, and the validity analysis of a questionnaire refers to the degree to which the analysis methods and means reflect the things that need to be measured.

4.2. Shielding Effect of Industrial Agglomeration. However, the cost of collecting digital information increases with the expansion of the shielding scale of industrial agglomeration. Therefore, with the increase of the number of people accessing the network, the cost of digital information network shows a decreasing form, but its marginal cost decreases relatively slowly, and the overall benefit increases, and the total benefit and marginal benefit will increase with the increase of the network scale.

$$y(x, x(a), x(b)) = \begin{cases} b + a, & a > b, \\ \dfrac{x(b) - x(a)}{x(b) - x(a) - a - b}, & a = b, \\ b - a, & a < b. \end{cases} \quad (11)$$

Secondly, digital information investment can not only bring general investment remuneration to investors, but also bring value-added remuneration to investors from the accumulation of digital information. It can be seen that the digital industrial agglomeration in Figure 6 shows a trend in increasing marginal returns.

The correlation between IoT-perceived manufacturing and economic growth ranks in the middle, but the correlation also reaches 0.770, which shows two problems. Firstly, the correlation between IoT-perceived manufacturing and economic growth is very high. Sensing equipment, intelligent instrumentation, measurement and control equipment, and radio frequency identification (RFID) growth synergy technology have been widely used in electric power, transportation, security, logistics, medical, and other industries.

$$y(c, c(a), c(b)) = \begin{cases} c + b + a, \\ \dfrac{\exp(b) - \exp(a)}{c - a - b}, \\ 0. \end{cases} \quad (12)$$

They are essential to realize the intelligence and networking of traditional industries. Basic equipment products and technologies develop together. It is precisely by virtue of extensive industrial connections that the IoT perception industry substantially promotes economic growth. Secondly, there are still some obstacles to the development of the regional IoT-sensing manufacturing industry. For example, regional manufacturers only account for about 20% of the market share of the sensor industry, the lack of core intellectual property rights in the RFID industry, and the high cost. These impediments weaken the power of IoT-aware manufacturing to drive economic growth.

4.3. Regional Economic Cycle Gains. The regional economic cycle growth synergy factor graph can be regarded as a graphical representation of the rotated growth synergy factor loading matrix, and the variables in the graph are all

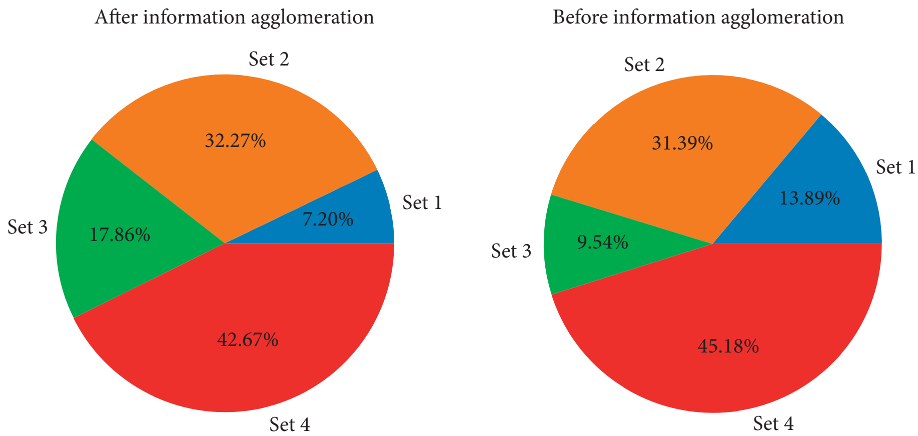

Figure 6: Shielding effect of industrial information agglomeration.

Table 1: Characteristics of regional economic cycle gains.

Regional economic cycle	Factor a	Factor b	Factor c
Synergy layer	60.557	32.078	0.865
	46.237	48.341	0.396
Converted layer	52.648	39.401	0.449
	2.258	46.608	0.770
Input layer	76.900	44.537	0.431
	10.942	28.231	0.113
Output layer	48.931	10.822	0.121
	42.908	22.793	0.004

logarithmic. It can be seen from the figure that WR and ER are relatively close, and AIR and TIP are relatively close. According to the nature of FA, FA is classified as pair, AIR, and TIP, and the same conclusion as the common growth synergistic factor extracted above can be seen. The abscissa is the serial number of the growth synergy factor, and the ordinate is the value of the corresponding characteristic root.

$$\overbrace{c(a) = 1 - \sqrt{a}, c(b) = 1 - \sqrt{b}, c = b - a}^{a+b<c} \longrightarrow c\{a, b\} = \max[a, b]. \quad (13)$$

It can be seen from the figure that the values of the two growth synergistic factors are generally high and connected into a steep line, while the eigenvalues after the third growth synergy factor in Table 1 are generally lower and connected into a gentle line. This further shows that it is more appropriate to extract two growth synergistic factors.

From the perspective of the Internet of things subsectors, the Internet of things communication industry has the highest correlation with per capita GDP, reaching 0.929, followed by perception manufacturing, with a correlation of 0.770, and finally the Internet of things service industry, with a correlation of 0.689. This is in line with the current development of various subsectors of the Internet of things in the region.

$$\frac{\Delta e(a,b)}{1 - \Delta e(a,b)} = \frac{1 - \Delta e(a,b)}{\Delta e(a,b) + 1}, \text{ for } \{\Delta e(a,b) < a + b\}. \quad (14)$$

It is inseparably related to the digital information industry and the Internet industry. Since the development of the digital information industry, a relatively complete digital information infrastructure has been established in the region, and the communication capability has been greatly improved.

5. Application and Analysis of the Collaborative Development Model of Industrial Agglomeration and Regional Economic Growth Based on Digital Information Growth Collaborative Technology

5.1. Preprocessing of Digital Information Data. The alpha coefficient of each variable in the digital information data is above 0.7, and the questionnaire has considerable reliability. Others are above 0.5, indicating that other variables have high validity. In terms of the price of the industrial agglomeration layer or service of the digital industry agglomeration, the average score is 3.76 points, and the standard deviation is 0.73, which is at the upper-middle level.

$$\begin{aligned}&\because \alpha \times x(n) + 1 - \alpha \times x(i-1) + 2 - \alpha \times x(n-2)\\&\quad = 1, \therefore \beta \times x(n) + 1 - \beta \times x(n-1) < 1.\end{aligned} \tag{15}$$

This shows that the price of digital industry agglomeration for digital industry agglomeration and the price of industrial agglomeration in the real economy market are between uncertain and agree that the price of digital industry agglomeration is lower than that of real economy industry agglomeration, which shows that the price factor is in people's decision to make digital industry agglomeration.

The proportion of the choice of agglomeration is not as high as we usually think. There are other reasons why people choose the way of digital industry agglomeration.

From the perspective of the perceived usefulness of digital industry agglomeration and the ease of use of digital industry agglomeration, the average score of digital perceived usefulness in Figure 7 is 3.75 points, but the average score of digital ease of use is only 3.45 points, which shows that people generally believe that digital industrial agglomeration has brought convenience and improved efficiency to our lives, but in terms of ease of use of digital industrial agglomeration, the mastery of procedures and functions of digital industrial agglomeration need to be improved.

$$\begin{aligned}&\{[n,b], [x(n),b], [n,x(b)], [x(n),x(b)], \ldots, x[n]x[b]\}\\&\cup \{x[n]-x[b]\} = \varnothing.\end{aligned} \tag{16}$$

In terms of subjective speculation and purchase intention of digital industrial agglomeration, the average scores of the two questions are 3.69 and 3.62, both of which are in the upper-middle range, indicating that in the context of today's Internet age, people's recognition of digital industrial agglomeration and purchase of digital industrial agglomeration are like the tendency of tiers, it is at the middle and upper level, and merchants need to further improve the quality of the digital industry agglomeration layer so that the digital industry agglomerators can be recognized by more people.

5.2. Simulation of Coordinated Development of Regional Economic Growth. In this article, with the aid of the econometric analysis software EVIWS5.0, the ADF test method is used to test the LNRGDP, LNK, and LNL related data of the regional industry respectively for AIC and SC digital information minimum criteria to determine. The so-called cointegration relationship means that economic variables are nonstationary, but a certain linear combination of them may be stationary, that is, a group of variables maintains a set of linear relationship trends within a certain time interval, and there is a cointegration relationship

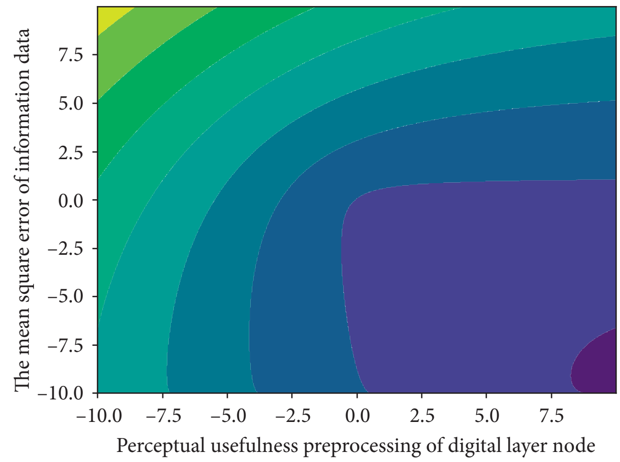

Figure 7: Perceptual usefulness preprocessing of digital information data.

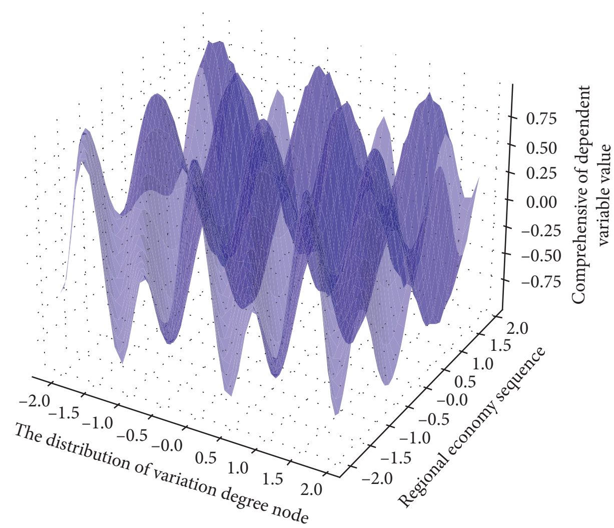

Figure 8: Distribution of variation degree of dependent variable explained by regional economy.

between the variables. The nonequilibrium error must be a stationary sequence, otherwise it must be an $I(1)$ sequence with a unit root. Therefore, only two variables are tested for cointegration, the single integer order of the two variables should be the same.

According to the results in Figure 8, the adjusted R^2 value is about 0.9908, indicating that the regression model can explain 99.08% of the variation of the dependent variable, and the fitting degree is excellent. Then the results of the t-test of each explanatory variable are compared. The explanatory variable $x1$ cannot pass the t-test, indicating that the Internet penetration rate has no impact on the regional per capita network industry agglomeration, while the explanatory variables $x2$ and $x3$ have passed the t-test, indicating that the per capita urban resident income and higher education level have a significant impact on regional per capita digital industry agglomeration.

According to the model results, when the Internet penetration rate increases by 1%, the regional per capita

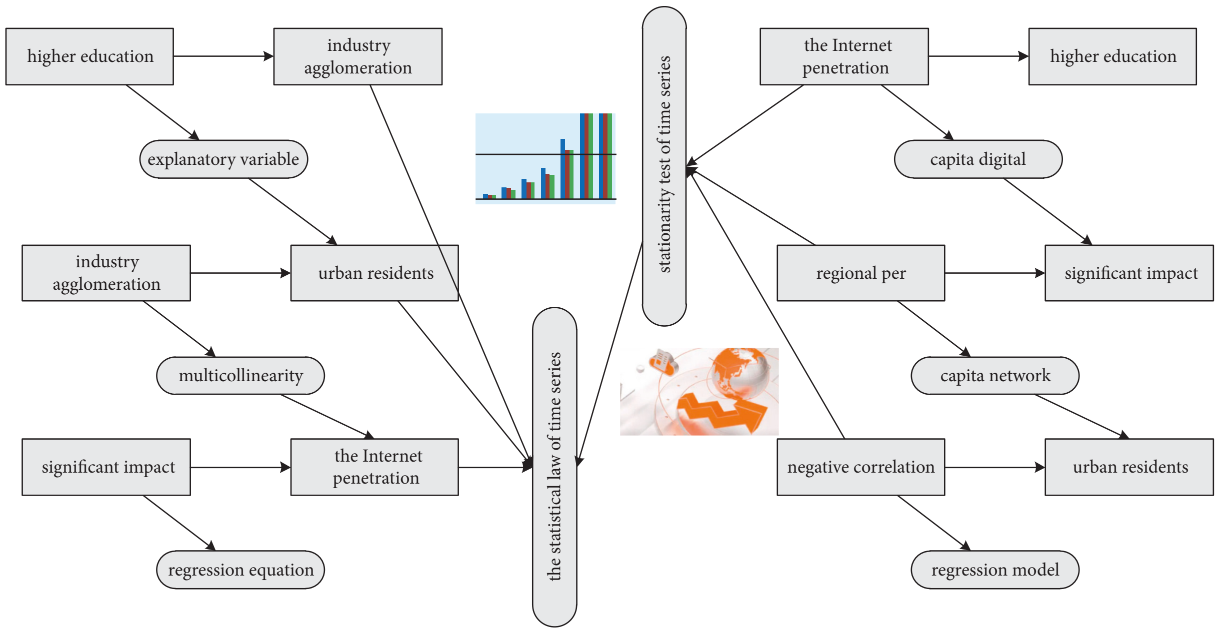

Figure 9: Process of coordinated development of regional economic growth.

Table 2: Null hypothesis realization of digital information data.

Null hypothesis case	Digital information value	Agglomeration data
The subindustries of the Internet of things	0.743	
Digital industrial agglomeration	0.022	13.94
The perceived usefulness and ease	0.594	
Quality of the industrial agglomeration	0.375	
Two populations are not the same	0.382	32.27
The surveyed equal variance	0.128	
The measurement indicators	0.013	
The perceived usefulness	0.865	18.31
The development level	0.429	

digital industry agglomeration increases by 0.7% on average; when the level of higher education increases by 1%, the regional per capita digital industry agglomeration decreases on average by 2.45% when the per capita urban income increases by 1%. At the same time, the regional per capita network industry agglomeration increased by about 4.60% on average. Although the regression model is significant, the explanatory variable $x1$ is not significant, and there is a negative correlation between the level of higher education and the level of per capita network industry agglomeration, so there may be multicollinearity in the regression equation.

The stationarity test of it is necessary to test the stationarity of the observed time-series data in Figure 9. If the original data are stable after analysis, we can directly carry out regression and other analysis; if the data are not stable, we cannot directly carry out regression and other analysis on the original data, and we need to deal with the original data accordingly before continuing to carry out relevant economic analysis.

5.3. Example Application and Analysis. In digital information data technology, there are null hypothesis and substitution hypothesis. The calculation results show that the standard deviation of the surveyed male industry agglomeration's perceived ease of use of digital industry agglomeration is about 0.868, while that of women is 0.778. Therefore, it is believed that in terms of the perceived ease of use of digital industry agglomeration, the variance of the two populations is not the same and so on; and in the perceived usefulness of digital industrial agglomeration, the standard deviation of male industrial agglomeration satisfaction is 0.701, and that of women is 0.697, which is relatively close, so it is considered that the surveyed men and women have equal variance in the perceived usefulness of digital industrial agglomeration. Then, the independent samples t-test in Table 2 was carried out on the perceived ease of use and usefulness of digital industrial agglomeration through SPSS.

Firstly, it may set the total output value of the IoT industry as the parent sequence, denoted as $x0$, and set the per capita GDP and the added value of the primary, secondary, and tertiary industries as the comparison sequence, denoted as $X1$, $X2$, $X3$, and may use the gray correlation model to calculate the correlation between the Internet of things industry and the three industries. Secondly, it may set the measurement indicators of the development level of the three subindustries of the Internet of things as the parent

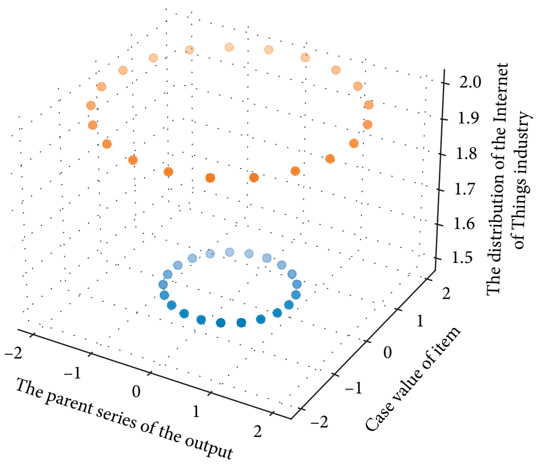

Figure 10: The distribution of the output value of the Internet of things industry.

sequence and set the per capita GDP and the added value of the three industries as the comparison sequence and may use the gray correlation model to calculate the correlation between the subindustries of the Internet of things and the three industries; the digital industrial agglomeration have a significant useful case with the price of the industrial agglomeration layer or service. When the perceived usefulness and ease of use of digital industrial agglomeration increase, the price of the service will also go up. The quality of the industrial agglomeration layer has a significant useful case with the perceived ease of use of digital industrial agglomeration ($p = 0.02 < 0.05$), but has no significant correlation with the perceived usefulness of digital industrial agglomeration ($p = 0.772 > 0.05$). The better the quality of the purchased industrial agglomeration layer, the more people will use the Internet for industrial agglomeration, but the purchased high-quality industrial agglomeration layer may not be needed in life.

The regression results of the three models are all significantly positive, and the individual fixed effect model in Figure 10 has the highest goodness of fit R^2 ($R^2 = 0.9779$), indicating that the model has the best explanatory power. By comparing this article, we choose to use the individual fixed effect model for regression. The D-W statistic in the individual fixed effect model is 0.4625, which is greater than 0 and less than 2, indicating that the model has no significant autocorrelation and the estimated result is stable. The individual fixed effects (IFE) of the 11 provinces, autonomous regions, and municipalities in the region were obtained by regression of individual fixed effects, the coefficient value of t is 0.7501, indicating that the direct contribution of the digital information industry sector to economic growth is significantly positive, that is, the contribution of the direct economic growth synergistic development of the digital information industry to economic growth is 0.7501, assuming that other factors remain unchanged, if the output of the digital information industry increases by one yuan, the digital information industry will effectively drive the economic growth by 0.7501 yuan.

6. Conclusion

Digital information industry is a digital information service industry and digital information equipment manufacturing industry integrating collection, processing, storage, and circulation. Firstly, this article combs the basic theories of the development of digital information industry, including industrial correlation theory and new economic growth theory. Then, it analyzes the coordinated development mechanism of economic growth that digital information industry promotes economic growth as well as the coordinated development mechanism and path mechanism of economic growth that affect economic growth. In addition, this article also establishes a gray correlation model from an empirical perspective to preliminarily explore the correlation between industry and economic growth. For the industrial networks of 40 industries, including the Internet of things industry, the social network analysis method is used to measure the impact of the Internet of things industry on the optimization of industrial structure. Finally, on the basis of theoretical and empirical analysis, this article puts forward relevant policy suggestions to vigorously develop the Internet of things industry and promote economic growth. In addition, the further work of this article is to study the impact of different factors in industrial agglomeration on the coordination of regional economic growth.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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