Analysis of the Correlation between Emerging Industry Development and University Students’ Entrepreneurship Based on Big Data

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With the strong support of local governments for strategic emerging industries such as high-end equipment manufacturing, new materials, and new energy, strategic emerging industries are playing an increasingly important role in the economy and society. With the increasing enthusiasm of college graduates for independent entrepreneurship, college students’ entrepreneurship is constantly integrated with the development of strategic emerging industries. Based on this background, aiming at the practical problems of the development of strategic emerging industries, this study innovatively puts forward the method of using big data technology and GM model to realize the dynamic model analysis of the development of strategic emerging industries and college students’ entrepreneurial behavior. This article analyzes the correlation between dynamic big data such as industrial scale, industrial market, and industrial direction of local strategic emerging industries and university entrepreneurship, so as to provide theoretical support for the development strategy of strategic emerging industries. Through the neural network algorithm, this article evaluates the entrepreneurship of college students, so as to provide a digital basis for the layout of strategic emerging industries to attract talents and entrepreneurship. Experiments show that the big data integration system established by GM correlation analysis and ant colony Elman regression artificial neural network has high accuracy and can well identify the priority relevance of the industrial direction of strategic emerging industries to college students’ entrepreneurship. It provides theoretical support for regional policy makers to better formulate college students’ entrepreneurship strategy and the development plan of emerging industries.

1. Introduction

In recent years, as an important part of a powerful country in science and technology and learning, China has been vigorously supporting the development of strategic emerging industries [1]. Seven strategic emerging industries such as high-end equipment manufacturing, new energy, new materials, energy-saving industry, new information technology, biopharmaceutical, and new energy vehicles gradually play an important role in China’s economic structure [2]. At the same time, China’s major cities have also successively issued relevant talent policies to attract talents, and the combination of industry and talent, innovation, and entrepreneurship are the key to the use of talents [3]. At present, although scholars have put forward corresponding evaluation schemes for the development of strategic emerging industries and college students’ entrepreneurship [4], the research on the correlation between the development of strategic emerging industries and college students’ entrepreneurship is still blank [5]. In this context, this article studies the coupling correlation between the development of strategic emerging industries and college students’ entrepreneurship based on big data technology and analyzes the layout and configuration of local strategic emerging industries for the purpose of attracting college students’ entrepreneurship through the analysis model constructed by neural network algorithm.
Aiming at the problems of income uncertainty and poor quantifiable ability in the development of strategic emerging industries, this article uses big data technology to establish a complex dynamic discrete data analysis model based on the GM correlation algorithm and the artificial neural network algorithm and analyzes the coupling relationship between the development of strategic emerging industries and college students’ entrepreneurship. For the development and allocation of strategic emerging industries for college students’ entrepreneurship, it provides a solution for local strategic emerging industry policies. This article is divided into five sections according to the research focus of each section. Section 1 roughly summarizes the research background and the content planning of this article. Section 2 briefly introduces the research status of big data analysis technology, the development of strategic emerging industries, and college students’ entrepreneurship. Section 3 is mainly based on the integrated big data system to build the theory, model, and result analysis of the coupling correlation algorithm between the development of strategic emerging industries and college students’ entrepreneurship. Section 4 analyzes and calculates the layout optimization of strategic emerging industries by using artificial neural network algorithm. Section 5 briefly summarizes the full text.

Compared with the cluster evolution model based on the logistic model and the Lotka-Volterra model adopted in the mainstream research on the development of strategic emerging industries, the innovation of this article is to propose a GM correlation model as the blueprint to analyze the dynamic data of the development of strategic emerging industries and college students’ entrepreneurship. A coupling model of strategic emerging industries related to college students’ entrepreneurship is established. The model can make full use of the correlation characteristic information in the coupling process between the development of strategic emerging industries and college students’ entrepreneurship, dynamically analyze the relevant data, and realize the qualitative analysis of the impact of strategic emerging industries on college students’ entrepreneurship. Use Hadoop HDFS architecture combined with artificial neural network algorithm to analyze the relevant big data generated by strategic emerging industries, customize the personalized incentive plan for college students’ entrepreneurship, and realize a reasonable strategic emerging industry structure.

2. Related Work

Although researchers have studied the development of strategic emerging industries and college students’ entrepreneurship in their respective research fields for many years, there is no connection between them, and most studies only analyze them according to their appearance, and the models with quantitative index ability are often lacking [6].

In recent years, with the introduction of various new concepts of science and innovation industry, researchers gradually began to study the layout of strategic emerging industries [7]. Sun et al. selected 60 listed companies as samples and used logistic regression early warning model to analyze the impact of industrial development of new industries on ecological environment. The model successfully warned ecological problems and provided a theoretical basis for the sustainable development of strategic emerging industries [8]. Diner et al. put forward a comprehensive model for comprehensive evaluation of emerging industries through the Danp model and the Moora model. The model shows that when a strategic emerging industry is in the initial stage of development, enterprises need to pay attention to the ability to attract external investors, and this goal can be achieved by obtaining third-party recognition and improving human capital standards [9]. Wenge et al. analyzed the internality between strategic emerging industries and industry associations according to 2SLS program and found that industry associations had a positive impact on the innovation ability of emerging industries [10]. Through the unguided SBM and network DEA model, Zhong et al. analyzed the technological innovation efficiency of strategic emerging industries in China’s provinces from 2002 to 2013 and found that during this period the overall technological innovation efficiency continued to improve, and the efficiency of eastern provinces was higher than that of central and western provinces [11]. Ahia et al. analyzed 1272 Chinese emerging industry enterprises and put forward a sandwich model to explain the transmission between government subsidies, R & D, and innovation, indicating that government subsidies play a vital role in the development of strategic emerging industries [12]. At present, with all walks of life moving towards informatization, many traditional industries have introduced big data technology [13]. Aiming at the potential intrusion risk of nuclear power plant network, Sangdo et al. have developed a real-time monitoring system for nuclear power plant network intrusion based on big data. The system can make immediate response when nuclear power plant network is invaded, so as to ensure the safe operation of nuclear power plant control system [14]. Suh et al. aiming at the prevention of hearing impairment, combined the improved logistic regression analysis algorithm with the big data system as the framework, calculated the correlation between hearing loss and vestibular function impairment and found that low-frequency hearing threshold impairment may cause vestibular function impairment [15]. Aiming at the planning problem of air channel utilization, GUI et al used the big data system to collect the multisensor data built in the aircraft in real time, imported the collected data into the long-term and short-term memory algorithms, and effectively predicted the air traffic flow in different regions [16]. Zhang et al. combined big data technology with human resource management technology and proposed a theoretical framework of human resource data based on induction and deduction through clustering algorithm, which provides a new idea for human resource management mode in the new era [17]. For the research related to college students’ entrepreneurship, Barba-Sánchez et al. analyzed the challenges of college students’ entrepreneurship under the background of high unemployment rate and found that independence is an important factor determining college students’ engineering
entrepreneurship [18]. Spinuzzi et al. conducted differentiated iterative analysis on college students’ entrepreneurs based on the logic of commodity leading and service leading and summarized a new paradigm to improve entrepreneurs’ communication ability [19]. Wu and other scholars provided an 18-week entrepreneurship course for 22 college students and improved their entrepreneurial ability through classroom response system and mobile devices [20]. Öznur et al. tested the correlation between college students’ personality traits and career adaptation through questionnaire survey based on Pearson correlation analysis and multiple linear regression model and put forward the method of changing college students’ entrepreneurial characteristics with personality characteristics to support college students to adapt to their own work [21].

To sum up, the following points can be summarized: on the one hand, the diversification of the application fields and scope of big data technology, on the other hand, the employment and entrepreneurial behavior of college graduates is the focus affecting the national labor structure, and strategic emerging industries are the key link in the national structural reform [22, 23]. In terms of practical engineering problems, big data technology does not have a solution to the correlation between strategic emerging industries and college students’ entrepreneurship [24, 25]. Therefore, it is necessary to carry out research on the correlation between strategic emerging industries and college students’ entrepreneurship based on the big data framework.

3. Methodology

3.1. Application of Relevance Coupling Model in the Correlation between the Development of Strategic Emerging Industries and College Students’ Entrepreneurship. The emergence of relevance coupling method provides an effective solution for the quantitative research of relevance between various problems. In order to conduct intermechanism quantitative research on the relevant data of the development of local strategic emerging industries and the entrepreneurship of college students, this study introduces GM relevance method as the analysis model. The full name of GM is grey model. This means that the known content and unknown content coexist in the GM system, which makes the internal system have great uncertainty. The mechanism of looking for the change of one subattribute and the change of other attributes is discussed by GM correlation method. This makes the GM correlation method very suitable for analyzing the multiattribute dynamic process, and the data related to the development of strategic emerging industries and college students’ entrepreneurship have the typical characteristics of multiattribute coupling, which is very suitable for analysis combined with the GM correlation method. Figure 1 shows the schematic diagram of strategic emerging industry development and college students’ entrepreneurship analysis system based on GM correlation method. This study collects and imports the collected stream data related to strategic emerging industry development into Hadoop HDFS in real time. Hadoop HDFS is compiled by Java architecture. After importing into the system, the GM analysis module compiled by Python analyzes and processes the stream data.

3.2. Dynamic Analysis Process of GM Correlation Model between the Development of Strategic Emerging Industries and College Students’ Entrepreneurship. When using the GM correlation model based on the development of strategic emerging industries, its core is to judge whether there are close similarities between them by calculating the sequence shape of the data related to the development of strategic emerging industries and the data related to the entrepreneurship of college students.

In order to solve the problem of weak overall robustness of GM correlation model in dealing with dynamic discrete data, this article introduces the newly obtained sample data into the dynamic training sample database based on integrated big data system. The GM correlation model is used to calculate the correlation coefficient between the comparison sequence and the reference sequence, and the relevant attribute characterization data of strategic emerging industries are used as the comparison sequence. The correlation coefficient is designed to calculate the correlation between the development of strategic emerging industries and college students’ entrepreneurship. The calculation process of data correlation GM correlation model is shown in Figure 2.

The construction method of GM correlation coupling model is as follows: first, $\Omega$ is defined as the correlation coefficient, $\Theta$ as the correlation degree, $y$ as the mean image of each sequence, $Y$ as the matrix of the mean image, $\Delta$ as the matrix of the difference sequence, and $m$ and $M$ as the minimum difference and maximum difference between the maximum and minimum values. In order to calculate the values of $\alpha$ and $\Psi$, the following steps need to be performed

$$
Y'_i = \frac{1}{i+1} \sum_{k=0}^{n} y'_i(k), \quad i = 0, 1, 2, \ldots, m
$$

$$
\Delta_i(k) = \frac{1}{i+1} \sum_{k=0}^{n} y'_i(k) - y'_i(k),
$$

$$
M = \chi \sqrt{\max_i \left( \max_k \Delta_i(k) \right)},
$$

$$
m = \chi \sqrt{\min_i \left( \min_k \Delta_i(k) \right)},
$$

where $\tau$ is the influencing factor related to $i$ and $\chi$ is a composite factor ranging from 0 to 1. Through equations (1) to (4), the value of correlation coefficient $\Omega$ can be directly calculated as
\[ \Omega_{0i}(k) = \chi^2 \left( \frac{m + \beta M}{\Delta_i(k) + \beta M} \right) \quad k = 1, 2, \ldots, n, \quad i = 1, 2, \ldots, n. \]  

(5)

In equation (5), \( \beta \) is a parameter greater than or equal to 0 and less than or equal to 1. Finally, the correlation coefficient \( \Theta \) can be obtained:

\[ \Theta_{0i} = \frac{1}{n} \sum_{k=1}^{n} r_{0i}(k), \quad k = 1, 2, \ldots, n, \quad i = 1, 2, \ldots, n. \]  

(6)

When the correlation coefficient is greater than 0.8, there is a strong correlation between the defined reference attribute and the comparison attribute. When the correlation coefficient is less than 0.8 and greater than or equal to 0.5, the
correlation between the defined reference attribute and the comparison attribute is medium. When the correlation coefficient is less than 0.5 and greater than or equal to 0.3, there is a weak correlation between the defined reference attribute and the comparison attribute. When the correlation coefficient is less than 0.3, there is almost no correlation between the reference attribute and the comparison attribute. According to the calculated correlation coefficient, the correlation between the development of strategic emerging industries and college students' entrepreneurship can be analyzed. First, the data of three groups of known strategic emerging industries in the development process of regional science and technology index, regional tax, and regional corporate social responsibility index are simulated and analyzed. The three groups of known data are analyzed under 10 different threshold settings under the GM correlation algorithm. The simulation analysis results are shown in Figure 3.

As can be seen from Figure 3, in the analysis results of three groups of data groups with different correlation degrees (regional corporate social responsibility index = 0.3/regional tax = 0.6/regional science and technology index = 0.9), the corresponding chaotic reference value index also changes with the increase of the number of iterative calculations of the coupling analysis method in the GM correlation algorithm. The main reason for this effect is that after many iterations, the GM correlation model can not only predict the new data based on the previous training data but also use the new dynamic data to better optimize the overall correlation analysis. After several cycles of the GM model, the relevant information finally obtains the strategic emerging industry evaluation model according to the needs of the degree of relevance, that is, the relevance analysis is carried out for the development of strategic emerging industries and their target attributes, which can approach the evaluation value of the coupling between the development of strategic emerging industries and the target attributes in the real situation, and take college students' entrepreneurship as a target attribute. It can quantitatively analyze the relationship between the development of strategic emerging industries and college students' entrepreneurship in a dynamic environment.

3.3. Construction of GM Correlation Model Prototype Platform for the Development of Strategic Emerging Industries and College Students' Entrepreneurship. The big data integration system based on GM association model is built by Java software, which is mainly composed of input component, analysis component, and management component. The analysis component based on the GM correlation method is the core of the system. The simulation analysis process of the analysis component of the big data system integration system designed in this study is shown in Figure 4. The test samples are still three groups of data with known correlation coefficients (regional corporate social responsibility index = 0.3/regional tax = 0.6/regional science and technology index = 0.9). The abscissa in the figure is the analysis completion degree, and the ordinate is the correlation coefficient.

As can be seen from Figure 4, with the increase of analysis times in GM association algorithm, the corresponding association degree is also gradually increasing (first increasing, then decreasing, then increasing). The import component extracts the relevant data behaviors of strategic emerging industries and imports them into the SQL database to provide data support for the analysis component. Then, it classifies the target attributes of strategic emerging industries, and the analysis component analyzes and calculates different attributes. As the completion degree of GM correlation analysis program tends to 1, the corresponding correlation coefficient also tends to remain unchanged. When the analysis component completes the analysis, the larger the correlation coefficient, the higher the correlation. In this study, Python version 3.6 software is used as the development software of the data analysis module. The development ide uses the open-source pycharm framework to build the scene, so as to complete the algorithmic analysis of dynamic discrete data such as the development of strategic emerging industries and the entrepreneurship of college students.

3.4. Simulation Experiment and Discussion of GM Correlation Model between the Development of Strategic Emerging Industries and College Students' Entrepreneurship. This study selects the entrepreneurship of college students in a region of China from 2011 to 2020 as the reference sequence and takes the relevant data of the number of industries, industrial revenue, industrial scale, and industrial proportion of strategic emerging industries in the region as the reference sequence, so as to make the correlation analysis between the development of strategic emerging industries and college students' entrepreneurship quantifiable. The above data are imported into the GM correlation analysis model constructed earlier, and the results of correlation coefficients are shown in Table 1.

As a control experiment, the core program of the analysis component is replaced by the experimental simulation of the mainstream logistic model analysis strategy, Lotka-Volterra model analysis strategy, and GM correlation analysis strategy as a comparative analysis. The analysis results are shown in Figure 5.

According to Table 1 and Figure 5, in the data analysis of three different groups, in the experimental simulation analysis results of mainstream logistic model analysis strategy, Lotka-Volterra model analysis strategy, and GM correlation analysis strategy, the accuracy of correlation calculation of GM correlation analysis strategy is higher than that of the other two mainstream models. Investigate the reason because the GM correlation analysis method has iterated the data attributes before analyzing the data, and the data have an adaptive function in attribute correlation analysis, so as to obtain a high accuracy.
students are used for calculation, the data analysis results are shown in Figure 6. As can be seen from Figure 6, in the experimental simulation analysis results of mainstream logistic model analysis strategy, Lotka-Volterra model analysis strategy, and GM relevance analysis strategy, the industrial scale and industrial quantity proportion of strategic emerging industries calculated by GM relevance analysis strategy are higher than those of the other two mainstream models. Therefore, it can be explained to a certain extent that the industrial scale and number of strategic emerging industries are highly correlated with college students’
entrepreneurship, which reflects that with the scale and diversification of strategic emerging industries, college students’ enthusiasm for entrepreneurship and innovation is extremely high. The industrial revenue of strategic emerging industries has a low correlation with college students’ entrepreneurship, which reflects that the amount of temporary income has little impact on college students’ entrepreneurship. The proportion of regional total industries in strategic emerging industries is moderately correlated with college students’ entrepreneurship, which shows that the differentiation of industrial structure has a high impact on college students’ entrepreneurship. Overall, strategic emerging industries have a certain correlation with college students’ entrepreneurship, which is consistent with the research expectation of this study. On the other hand, if a place hopes to attract more high-tech talents represented by college students to innovate and start businesses, the development of local strategic emerging industries is an important part to achieve this goal.

4. Result Analysis and Discussion

4.1. An Experimental Model of the Correlation between the Development of Strategic Emerging Industries and College Students’ Entrepreneurship. According to the conclusion drawn in the third section of this article, the development of strategic emerging industries has a certain correlation with college students’ entrepreneurship. In order to better attract innovative and entrepreneurial talents, it is necessary to optimize the industrial structure of strategic emerging industries in the region. In order to better control the network and avoid network congestion, improve the quality of network services. According to the real-time requirements of the network, an Elman regression artificial neural network is
adopted in this article. Elman neural network has the advantages of good real-time performance and no need for accurate mathematical modeling of the network. The simulation results show that the network can accurately predict the network traffic. Based on ant colony Elman recurrent artificial neural network algorithm, this section constructs a big data integration system with the function of industrial structure improvement analysis, which is used to optimize the layout strategy of the industrial structure of strategic emerging industries. The construction method of the big data integration system is combined with the model architecture proposed in Section 3.3 of this article.

Among them, the formula of ant colony Elman recurrent artificial neural network algorithm is as follows:

\[ A(t) = \left( \frac{\theta(wx(t) + jB(t) + \phi_1)}{wx(t) + jB(t)} \right)^2, \]

\[ y(t) = \left( \frac{\phi_1S(t) + \phi_2}{\phi S(t)} \right)^2, \tag{7} \]

\[ B(t) = \left( \frac{A(t - 1) + \phi_3}{A(t - 1)} \right)^2. \]

The activation function of the network is the traditional sigmoid function

\[ n(c) = \frac{1}{1 + e^{-c}}, \tag{8} \]

where \( x(t) \) is the representation function of the input layer, \( A(t) \) is the representation function of the hidden layer, \( y(t) \) is the representation function of the output layer, \( B(t) \) is the representation function of the feedback layer, \( \theta \) and \( \phi \), respectively, represent the transfer function between their corresponding layers, \( w, \phi, \) and \( j \) are the weights between their corresponding layers, and \( \phi_1, \phi_2, \) and \( \phi_3 \) are the thresholds of their corresponding layers. According to the correlation between the industrial direction of strategic emerging industries and college students’ entrepreneurship, \( e(t) \) is defined as the error function, and the objective function is the sum of squares of error \( E(t) \).

\[ e(t) = \frac{y(t)}{y_1(t)}(y_1(t) - y(t)), \tag{9} \]

\[ E(t) = \frac{1}{2n} \sum_{t=1}^{T} [e(t)]^2, \tag{10} \]

where \( n \) is the number of samples, and the ant colony Elman recurrent artificial neural network algorithm achieves enough small \( E(t) \) through continuous iterative calculation. The preliminary results obtained by combining the data of three experimental models of logistic model analysis strategy, Lotka-Volterra model analysis strategy, and GM correlation analysis with ant colony Elman recurrent artificial neural network are shown in Figure 7.

When grey correlation analysis is carried out in combination with ant colony Elman recurrent artificial neural network, it is necessary to calculate the optimization weight and optimization threshold of the whole network and continuously iterate until the error is reduced below the minimum accuracy or reaches the maximum number of iterations, complete the training, and minimize the square sum of the error between the actual output and the expected output of ant colony Elman recurrent artificial neural network. According to the calculation results of equation (9), the fitness function in the iterative process is defined as

\[ J(t) = \frac{1}{2n} \sum_{t=1}^{T} [e(t)]^2. \tag{11} \]

Then the ant colony Elman recurrent artificial neural network is normalized

\[ Z = \frac{0.6(x - x_{\text{min}})}{x_{\text{max}} - x_{\text{min}}} + 0.5. \tag{12} \]

After prediction, inverse normalization shall be carried out

\[ x = x_{\text{min}} + \frac{(Z - 0.5)(x_{\text{max}} - x_{\text{min}})}{0.6}, \tag{13} \]

where \( x \) represents the original data, \( x_{\text{min}} \) represents the minimum value in the original data, and \( x_{\text{max}} \) represents the maximum value in the original data. For the GM correlation analysis strategy, the overall error will change with the increase of the number of iterations. With the increase of the number of iterations, the error change of the model is shown in Figure 8.

According to Figures 7 and 8, with the increase of experimental analysis times, the strategy model based on GM correlation analysis proposed in this study has the advantage of smaller error rate compared with other mainstream comparison methods in the process of calculating the correlation between the development of strategic emerging industries and college students’ entrepreneurship. It can be seen from Figure 8 that with the increase of the number of experiments, the error of the experimental model will eventually be reduced to the allowable range with the increase of the number of iterations.

4.2. Analysis of Experimental Results. Strategic emerging industry refers to an industry with great growth potential based on major technological breakthroughs and major development needs, which plays a major leading role in the overall and long-term development of economy and society. It is a deep integration of emerging science and technology and emerging industries. It represents not only the direction of scientific and technological innovation but also the direction of industrial development. It has high scientific and technological content, large market potential, strong driving ability, and good comprehensive benefits.

The data related to the development of strategic emerging industries in a region of China from 2011 to 2020 and the data related to college students’ entrepreneurship are imported into ant colony Elman recurrent artificial neural network for analysis after correlation calculation. The data related to the development of strategic emerging industries
are the local high-end equipment manufacturing industry scale, new material industry scale, new energy automobile industry scale, biopharmaceutical industry scale, new generation information technology industry scale, new energy industry scale, and energy-saving industry scale. At the same time, the number of input layer nodes is 18, the maximum number of iterations is 5000, and the center value of ant colony is set to be the same as that of hidden layer. Figure 9 shows the analysis results of the mainstream logistic model analysis strategy, Lotka-Volterra model analysis strategy, and GM correlation analysis strategy on the correlation between the development of strategic emerging industries and college students’ entrepreneurship in the region.

As can be seen from Figure 9, according to the calculation results, the GM correlation model, logistic model, and Lotka-Volterra model have roughly the same analysis results on the development of regional strategic emerging industries and entrepreneurship of college students with the intervention of ant colony Elman recurrent artificial neural network. Among the strategic emerging industries, new
energy automobile industry, new generation information technology industry, and new material industry are highly related to college students’ entrepreneurship. The development of relevant industries can effectively promote the gathering and entrepreneurship of high-end talents represented by college students. The correlation between high-end equipment manufacturing industry and new energy industry and college students’ entrepreneurship is medium, while the correlation between biopharmaceutical industry and energy-saving industry and college students’ entrepreneurship is low.

5. Conclusion

How to combine the suitability of big data technology with practical problems to solve engineering problems is the key point of big data technology research. Based on this, aiming at the correlation between the development of strategic emerging industries and college students’ entrepreneurship, this article establishes a dynamic model system based on integrated big data system combined with GM correlation model and artificial neural network. This article introduces the development status and shortcomings of relevant research on the development of strategic emerging industries, college students’ entrepreneurship, and big data technology. A dynamic GM correlation model for the correlation between the development of strategic emerging industries and college students’ entrepreneurship is proposed. Second, it briefly describes the construction of big data model based on GM correlation model. The model can analyze the complex discrete dynamic strategic emerging industry data with high accuracy and robustness to a certain extent and calculate the correlation between these data and college students’ entrepreneurship. Finally, aiming at the development strategy of regional customized strategic emerging industries, a dynamic model based on ant colony Elman recurrent artificial neural network is proposed to iteratively calculate the correlation between each industrial direction of strategic emerging industries and college students’ entrepreneurship and obtain the lowest error rate. Experiments show that the big data integration system established by GM association analysis and ant colony Elman recurrent artificial neural network has high accuracy and can well identify the priority relevance of the industrial direction of strategic emerging industries to college students’ entrepreneurship. It provides theoretical support for regional policy makers to better formulate the development of strategic emerging industries for college students’ entrepreneurship. However, the dynamic model algorithm based on ant colony Elman regression artificial neural network needs further simulation verification. There are some errors between computer numerical analysis and practice. Therefore, the algorithm content of this article needs further research.

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 they have no conflicts of interest.

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