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Research Article

Analysis of Driving Factors of Innovation and Entrepreneurship Based on Time Series Analysis

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In order to analyze the driving factors of innovation and entrepreneurship, based on the time series analysis algorithm, this paper combines the analysis requirements of innovation and entrepreneurship driving factors to improve the time series, uses decomposition methods to decompose the complex original data into relatively simple components and reconstruct them, and predicts the reconstructed components to integrate the final predicted value. Moreover, this paper introduces entrepreneurial attitude as an intermediary variable and verifies it through data collection and statistical analysis, so that entrepreneurial traits influence entrepreneurial propensity through entrepreneurial attitude. The test results show that entrepreneurial attitude can better explain the influence of entrepreneurial traits on entrepreneurial propensity. In addition, this paper constructs an analysis model of driving factors for innovation and entrepreneurship, obtains experimental data through questionnaire survey methods, and conducts experimental research in combination with mathematical statistics. From the statistical results, it can be seen that the innovative and entrepreneurial driving factor analysis model based on time series analysis proposed in this paper is effective.

1. Introduction

From ancient times to the present, the phenomenon of entrepreneurship has always existed, but it has not received everyone's attention. In particular, it has never entered the research vision and research framework of mainstream economists. It was not until the emergence of the New Austrian School of Economics in the 1970s and 1980s that entrepreneurship became a hot topic for mainstream economists [1]. Moreover, due to the accelerated growth of the global economy, domestic and foreign researchers have begun to increase their efforts to study entrepreneurship issues. In the past two decades, entrepreneurship research has become the fastest growing field in management research. Why is entrepreneurial research so popular? The first point is that entrepreneurship provides a virgin field for research, which needs to be enriched by scholars. Second, entrepreneurship can weaken the inefficient mechanism of an economy and improve efficiency. Finally, entrepreneurship is an important source of social change and innovation.

Entrepreneurship activities are playing an increasingly important role in the economy and society and have aroused widespread concern in the academic community. At the same time, entrepreneurship involves management, cognitive theory, sociology, psychology, and other theories and methods. Therefore, it is not to study entrepreneurial activities as an independent discipline. At present, research results in entrepreneurship and related fields show a trend of diversification and diversification. In particular, the research on entrepreneurial cognition, entrepreneurial ability, entrepreneurial awareness, entrepreneur traits, entrepreneurial opportunity identification, entrepreneurial propensity, entrepreneurial decision-making, and entrepreneurial performance is constantly changing. Among them, the research on the concepts and issues related to entrepreneur traits and entrepreneurial inclination has attracted much attention [2].

Regardless of the content of entrepreneurship and related fields, the research on entrepreneurial activities has important practical significance. Entrepreneurship activities play a positive role in promoting economic progress, integrating resource allocation, and promoting social progress, and they also bring a variety of elements to active markets. At present, entrepreneurial theory still lacks localized research, and most of its research methods and models are borrowed from or based on western research results. In a small number of empirical studies in China, the subject is a group of college students. Because college students lack practical work experience and their cognition of entrepreneurial activities is mostly at the level of theoretical research, the results of the research have a low success rate. In view of the phenomenon that the selection of subjects may cause deviations in the research results, the subjects selected in this study are subjects with higher education, knowledge, and culture, rich work and practical experience, entrepreneurial capabilities, and mature thoughts, especially MBA. This will not only broaden the scope of research subjects, increase the accuracy of data, and make empirical research more convincing, but at the same time enrich the content of entrepreneurial theory and expand the scope of research on entrepreneurial theory. Innovation is essential to the development and progress of a country. Among them, entrepreneurship is a typical manifestation of innovation [3].

This paper analyzes the driving forces of innovation and entrepreneurship based on time series algorithms, and on this basis, it studies the problems of innovation and proposes relevant strategies.

2. Related Work

Literature [4] believed that for entrepreneurial companies, team members must have strong learning ability and knowledge absorption ability. Only in this way, when facing the dynamic market environment and the ever-changing competitive situation, the enterprise can face it calmly and flexibly.

For entrepreneurs, the importance of the three driving forces and the difficulty of obtaining them are not constant. As time changes, the effects of the environment and time will also change, and the importance of the three elements will also appear in a state of imbalance. At this time, successful entrepreneurs need to make flexible and dynamic balance arrangements for the three elements in accordance with external competitors and dynamic changes in the environment. Although the importance of the three major driving forces is dynamically changing, for enterprises, the three major driving forces are indispensable at any stage of development. Therefore, the process of entrepreneurship will not stop; it will continue in the process of constant adaptation and balance of the three driving forces [5].

Literature [6] shows that entrepreneurship and innovation have the same root and the same relationship, and the two are related to each other and complement each other. The source of entrepreneurship is innovation, and innovation can develop and flourish in entrepreneurial activities. Moreover, entrepreneurship ultimately transforms innovation into a commodity with social value and realizes the value of innovation. From the perspective of the transformation of scientific and technological achievements of enterprises, literature [7] analyzed the driving factors of innovation and entrepreneurship of Chinese enterprises through cases and summarizes 4 modes. Literature [8] regarded the driving forces of innovation and entrepreneurship as the same. Literature [9] tried to introduce Timmons' entrepreneurial model into the field of innovation. Literature [10] constructed a technological innovation cultivation model for technological enterprises based on the Timmons entrepreneurial management model.

Literature [11] believed that the identification of innovation opportunities is essential to the continuous innovation of enterprises, and the decision-making behavior preferences of corporate decision-makers play a moderating role in the identification of major corporate opportunities. This literature formally emphasizes the two driving factors of opportunity and team. Literature [12] studied the impact of corporate absorptive capacity and knowledge integration capacity on corporate innovation performance and found that the team's absorptive capacity and knowledge integration resource acquisition capacity improved corporate innovation performance to a certain extent. Literature [13] further pointed out that entrepreneurial opportunities can be a new product/service, new material, or even a new organization method, but it must finally enter the mass production stage and obtain revenue through market sales. Literature [14] adopted Schumpeter's classic definition and believed that opportunity is a possibility for creative integration of resources to meet market demand and realize value. Therefore, opportunity recognition refers to the behavior of companies identifying new ideas and transforming ideas into business concepts that can create value through resource integration. The concept of opportunity recognition originated in the field of entrepreneurship. Existing research also specifically emphasized the concept of opportunity recognition in the field of innovation. Literature [15] studied the impact of cultural differences on the ability to identify innovation opportunities. The definition of opportunity recognition is the ability of individuals to associate changes, events, and trends to produce new products or services. It can be found that the definition of opportunity identification has transitioned from the field of entrepreneurship to the field of innovation. Literature [16] defined opportunity recognition as the behavior of individuals or organizations linking changes, events, and trends to identify new ideas and generate new products or services through resource integration to create value.

Regarding the research on the relationship between opportunity recognition and innovation, most scholars agree that opportunity recognition is the front-end process of innovation. Some scholars have found that opportunity identification has a positive effect on corporate performance, comprehensive innovation, business model innovation, and open innovation. In addition, there are studies that specifically emphasize the relationship between opportunity identification and exploratory/breakthrough innovation [17]. Literature [18] found in case analysis that only disruptive innovation can build a company's competitive advantage, and opportunity identification is an important part of it. Breakthrough innovation is usually the result of the integration of various new technologies after the identification of corporate opportunities. However, few studies have explored the relationship between opportunity identification and incremental innovation/utilization innovation. The conclusion of the relationship between opportunity recognition and exploitative innovation is not clear, and further exploration is needed. Before literature [19] clearly proposed the concept of resource patchwork, resource patchwork was often confused with improvisation. This shows that resource patchwork and improvisation have similarities, and they are mostly temporary solutions. Literature [20] believed that patchwork is a "loose coupling between intention, plan, behavior, and performance," that is, patchwork can have a certain degree of planning, but the plan is not strong. Literature [21] believed that resource patchwork has the attributes of rapid response, low planning, and action preferences, and companies often use this to deal with opportunities and problems that require rapid response.

Literature [22] divided the patchwork into "the exploration of the creative layer" patchwork and the "utilization of the resource layer" patchwork. On the one hand, resource patchwork is dedicated to the creative reorganization of resources, which is exploratory. On the other hand, it also follows the "satisfaction model," emphasizing temporary quick response, which in turn makes the resource patchwork less innovative and easy to form utilization innovation.

3. Time Series Analysis

The first step of MFCM is to decompose the complex original FTS, which can effectively reduce the complexity of the original data and the difficulty of predictive modeling. Therefore, the decomposition effect will greatly affect the analysis and prediction of FTS. At present, the widely used decomposition method with good effect is the empirical mode decomposition series model. As early as more than 30 years ago, literature [23] proposed an epoch-making signal analysis method called Hilbert-Huang Transform (HHT). The core part of the algorithm is empirical mode decomposition (EMD). Essentially, the EMD method is to smooth the original data and obtain the time-frequency-energy characteristics of the signal. This signal analysis method has been widely used, including various fields in many industries, such as the following: in the medical field, it can be used to detect arrhythmia, the spread of dengue fever, and blood pressure changes; in the transportation field, it can be used to detect the safety of highways and bridges; in the security field, it can be used to identify the speaker's identity; in the geographic field, it can be used in earthquake engineering; in the aerospace field, it can be used in satellite data analysis, etc. This method has made a great contribution to the development of these fields. Later, this analysis method was also applied to the financial field.

The basic goal of the EMD algorithm is to adaptively decompose the original signal into components with different frequencies and a residual term (trend component). These different frequency components are called eigenmode functions (IMFs). IMF is defined as a function that satisfies the following conditions: (a) in the entire time series, the number of local extreme points of the data and the number of zero-crossing points of the data should not be much different, and the difference should not exceed 1; (b) anything in the entire data for a time, the local upper and lower envelopes are symmetrical, where the upper (lower) envelope refers to the envelope of the local maximum (small) value, that is, the average value of the two envelopes is equal to zero. Among the two conditions, the former requirement is similar to the narrowband requirement of Gauss signal. Item (b) is a new requirement, which reduces the previous global requirement to a local requirement, so that the fluctuation of the asymmetric waveform does not affect the instantaneous frequency. For nonstationary FTS, calculating the local mean involves a local time scale that is difficult to determine. Therefore, in condition (b), the local mean value of the two envelopes is required to be zero, so that the signal waveform is locally symmetric. Under normal circumstances, using this method, the instantaneous frequency will still conform to the physical meaning of the research system. IMF represents the inherent vibration mode of the sequence. Since most of the FTS studied are not IMF, in any time dimension, FTS often contains many fluctuation patterns. Because of such a simple Hilbert transform cannot fully characterize the frequency characteristics of FTS, further EMD decomposition of FTS is a better choice.

The EMD decomposition method has three assumptions, which are explained below. (a) There are at least two extreme values, namely, at least one maximum value and at least one minimum value. (b) The time scale between extreme points uniquely determines the local time domain characteristics of the data. (c) If there is no extreme point in the sequence, but there is an inflection point, the extreme value can be obtained by differentiating the data n times and then integrating to obtain the decomposition result. This process can be vividly called "sifting." After the "sifting" process, IMFs with different frequencies and a monotonic residual term that can no longer be decomposed are obtained, which is also called the trend term $R(t)$. IMF is selected from high frequency to low frequency in order, and there is no direct connection between them. The decomposition result can be expressed as the following formula:

$$X(t) = \sum_{i=1}^{n} \mathrm{IMF}_i(t) + R(t). \tag{1}$$

Next, we will introduce the specific decomposition steps of the EMD method.

(1) The algorithm finds all the local extreme points of the data $X(t)$

(2) The algorithm uses cubic spline interpolation to fit the maximum and minimum points, respectively, and construct the upper envelope $u(t)$ and the lower envelope $l(t)$

(3) After obtaining $u(t), l(t)$, the algorithm calculates its mean value, obtains the mean value curve, and records it as $m_1(t)$. The expression is as follows:

$$m_1(t) = \frac{1}{2}(u(t) + l(t)) \tag{2}$$

(4) The algorithm sifts out $m_1(t)$ from the original data $X(t)$ and denotes the remaining part as $h_1(t)$:

$$h_1(t) = X(t) - m_1(t) \tag{3}$$

(5) The algorithm judges whether $h_1(t)$ is IMF, that is, whether it meets the two basic conditions of IMF. In an ideal situation, $h_1(t)$ should be the IMF, because the $h_1(t)$ obtained through the above process seems to have met all the requirements of the IMF. However, in reality, new extreme values are usually generated, and existing extreme values are shifted or exaggerated. Therefore, under normal circumstances, the screening process needs to be repeated many times to achieve a true eigenmode function. If $h_1(t)$ is not IMF, the algorithm continues to replace $X(t)$ with $h_1(t)$ and repeat the above steps until the remaining part meets the two conditions of IMF. Specifically, the algorithm repeats the process from 1 to 5 k times until ${h_1}^k(t)$ is IMF. So far, the first eigenmode component $\mathrm{IMF}_1(t)$ is obtained, where

$$h_1^k(t) = h_1^{k-1}(t) - m_1^k(t) \tag{4}$$

In particular, the criteria for stopping the screening process can be limited to a certain range based on the value of the standard deviation (SD) of two adjacent results in order to retain sufficient physical information of the IMF. The following conditions must be met:

$$\mathrm{SD} = \sum_{t=0}^{T} \left[\frac{\left| h_1^{k-1}(t) - h_1^k(t) \right|^2}{\left(h_1^{k-1}(t) \right)^2} \right] \leq \alpha. \tag{5}$$

Among them, α represents the screening threshold, and a value between 0.2 and 0.3 is often used in operation.

(6) The algorithm replaces $X(t)$ with $X(t) - \mathrm{IMF}_1(t)$ and repeats the above steps 1 to 5 in the next screening process to continue to find the next IMF until all IMFs are screened out. At this time, there is only one monotonic residual sequence left, which is denoted as $R(t)$, that is, the trend component. The flow chart of the EMD algorithm is summarized as Figure 1

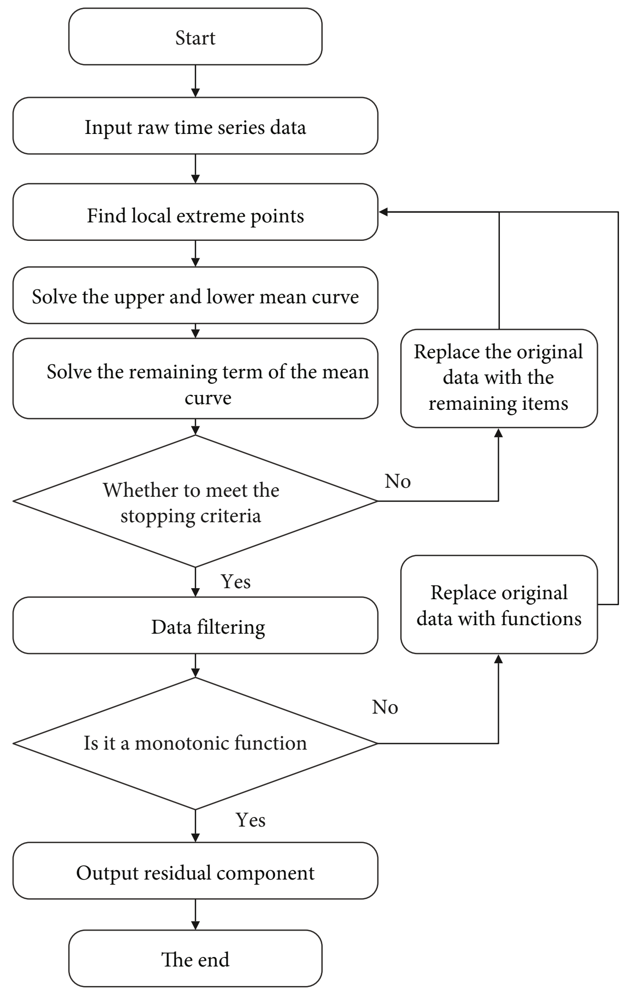

Figure 1: Flow chart of the EMD algorithm.

The EMD algorithm has some good characteristics, such as decomposition adaptability, completeness, and subsignal orthogonality. The adaptability is embodied in three aspects, namely, the adaptive basis function, frequency, and filtering process, which can automatically decompose the components with decreasing frequency according to the characteristics of FTS itself; completeness refers to the decomposition of the original data through the EMD algorithm. Each IMF and trend item can be added together to form the original data, and the original book order data can be completely recovered from the decomposed components with small errors. Therefore, the EMD algorithm has high completeness; the orthogonality of the subsignals is obvious. It means that the decomposed components are orthogonal to each other.

At the same time, the EMD algorithm also has some unavoidable shortcomings, including the error accumulation of the decomposition results and the aliasing of submodes. In response to the above problems, relevant scholars continue to study and put forward some improvement methods.

Add Gaussian white noise with uniform spectrum distribution to the original data. In the subsequent averaging process, the added white noise can basically cancel each other through multiple integrations and at the same time solve the problem of modal aliasing in EMD decomposition. The effective realization of data decomposition is an important improvement of EMD.

The following describes the specific decomposition steps of EEMD on the basis of EMD:

(1) The algorithm adds the Gaussian white noise sequence $\varepsilon_m(t)$ to the original data $X(t)$ to obtain the mixed time series data, denoted as $X_m(t)$, and the expression is as follows:

$$X_m(t) = X(t) + \varepsilon_m(t) \quad (6)$$

Among them, m represents the number of times of mixing, and $m = 1, 2, 3, \cdots, N$, and N represents the total number of times of mixing white noise in the original data.

(2) The algorithm implements the EMD method on the mixed data $X_m(t)$ to obtain n IMF components and 1 residual component $R_{mn}(t)$. The expression is as follows:

$$X_m(t) = \sum_{j=1}^{n} \mathrm{IMF}_{mj}(t) + R_{mn}(t) \quad (7)$$

(3) The algorithm repeats the above process until $m = N$, that is, N times of EMD decomposition is performed

(4) The algorithm, respectively, averages the IMF components and remainders obtained by N times of EMD decomposition, and the result is used as the output of EEMD. The expression is as follows:

$$X(t) = \sum_{j=1}^{n} \overline{\mathrm{IMF}}_j(t) + \bar{R}(t) \quad (8)$$

Among them, n indicates that a total of n IMFs are decomposed, and $\overline{\mathrm{IMF}}_j(t)$ and $\bar{R}(t)$ indicate the mean value of the decomposition results of m noise data. The flow chart of the EEMD method is shown in Figure 2.

The EEMD method improves the inherent defects of EMD modal aliasing by adding Gaussian white noise with uniform spectral distribution to the original data. Under the premise of ensuring the original characteristics of the data, it improves the accuracy of the decomposition and in turn makes the application of EMD-like methods more extensive and more valuable. However, the introduced Gaussian white noise will cause some pollution to the original data, and the increased integration times will also cause serious calculation time.

For FTS with complex nature, the decomposition effect will greatly affect the analysis and prediction of FTS, so the improvement of decomposition method is of great significance to model optimization.

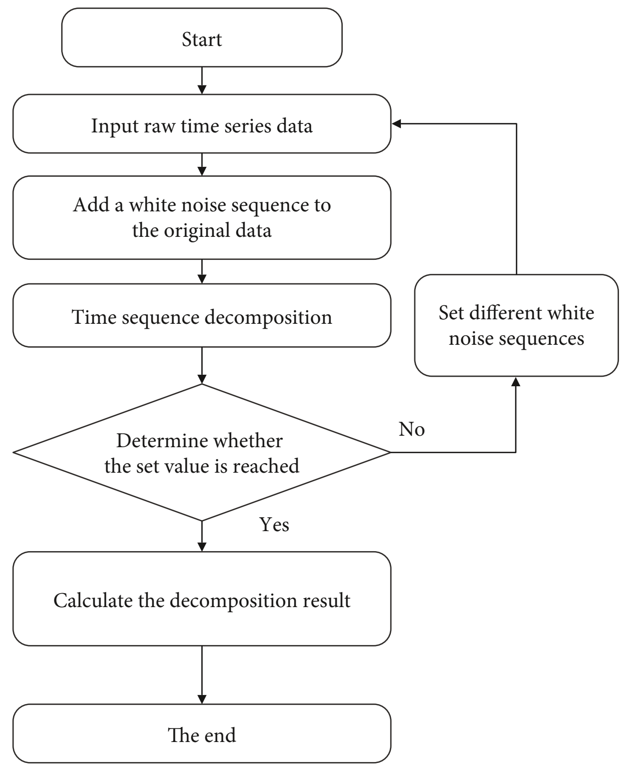

Figure 2: EEMD algorithm flow chart.

Reconstructing component prediction is the most critical step of the MFCM model, and the result of component prediction will directly affect the final model effect. At present, the prediction part of MFCM usually uses the support vector regression (SVR) model with good effect. The application of this method in the field of FTS has been fully studied by scholars, and it has been successfully applied to the prediction of reconstructed components after decomposition, and certain results have been achieved.

Among the existing MFCM models, the support vector regression model (SVR) has been successfully applied to the prediction of reconstruction components and has good performance due to its relatively simple structure, fast learning rate, and strong generalization ability. Support vector machine (SVM) starts from a certain amount of sample data, based on the VC dimension theory, and follows the principle of structural risk minimization. At the same time, it takes into account the two aspects of ensuring the accuracy of the model and reducing the complexity to solve the global optimal solution, thereby constructing the optimal learner. SVM is usually suitable for classification problems. After the original SVM model was researched and developed by related scholars, a support vector regression model (SVR) suitable for regression problems was derived. In this paper, we mainly focus on Least Squares Support Vector Regression (LS-SVR), which is widely used and faster to solve in MFCM.

We set a set of training data $\{(x_0, y_0), \cdots, (x_l, y_l)\}$, where x_i is an input and y_i is the target output, and for $i = 0, 1, \cdots,$

$l, x_i \in R^d, y_i \in R$. The core idea of SVR is to determine the function $f(x, w)$, and its predicted value can be accurately close to the actual value in the future, which can be expressed as follows:

$$y = f(x, w) = w\varphi(x) + b. \tag{9}$$

Among them, w and b represent the weight vector and the deviation, respectively, $w \in R^{n_k}$, $b \in R$ and the input vector x will be mapped to the high-dimensional feature space through a certain nonlinear function $\varphi : R^d \longrightarrow R^{n_k}$.

LS-SVR solves the regression problem by minimizing the following constrained objective function to solve w and b.

$$\begin{gathered}\min_{w\in R^{n_k}, b\in R} J(w, \xi) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \xi^T \xi, \\ s.t.\, y = z^T w + b1_l + \xi.\end{gathered} \tag{10}$$

Among them, $Z = (\varphi(x_1), \varphi(x_2), \cdots, \varphi(x_l)) \in R^{n_k \times l}$, and $\xi = (\xi_1, \xi_2, \cdots, \xi_l)^T \in R^l$ contain the relaxation variable, $\gamma \in R_+$ is a positive real regularization parameter, and $1_l = [1, 1, \cdots, 1]^T \in R^l$. The Lagrange function of the above formula is as follows:

$$L(w, b, \xi, \alpha) = J(w, \xi) - \alpha^T \left(z^T w + b1_l + \xi - y\right). \tag{11}$$

Among them, $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_l) \in R^l$ is a vector composed of Lagrange multipliers. The KKT condition of the optimization problem is as follows:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \Rightarrow w = Z\alpha, \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \alpha^T 1_l = 0, \\ \dfrac{\partial L}{\partial \xi} = 0 \Rightarrow \alpha = \gamma\xi, \\ \dfrac{\partial L}{\partial \alpha} = 0 \Rightarrow z^T w + b1_n + \xi - y = 0_l. \end{cases} \tag{12}$$

By offsetting w and ξ, the following linear system can be obtained:

$$\begin{bmatrix} 0 & 1_l^T \\ 1_l & H \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}. \tag{13}$$

Among them, $H = K + \gamma^{-1} I_l \in R^{l \times l}$ is a positive definite matrix, where $K = Z^T Z \in R^{l \times l}$, and the elements are

$$K_{i,j} = \varphi(x_i)^T \varphi(x_j) = K\left(x_i, x_j\right). \tag{14}$$

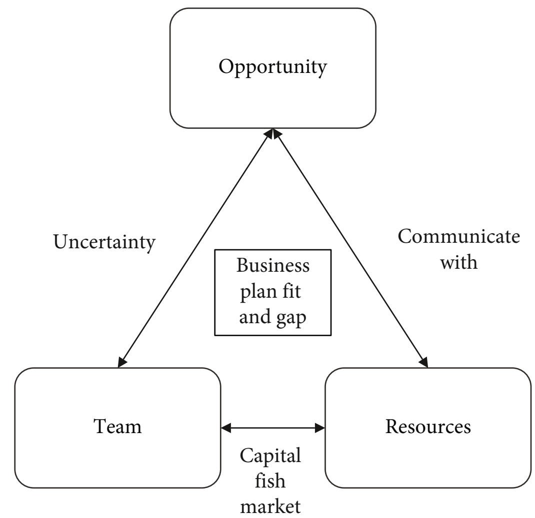

Figure 3: Timmons entrepreneurial model.

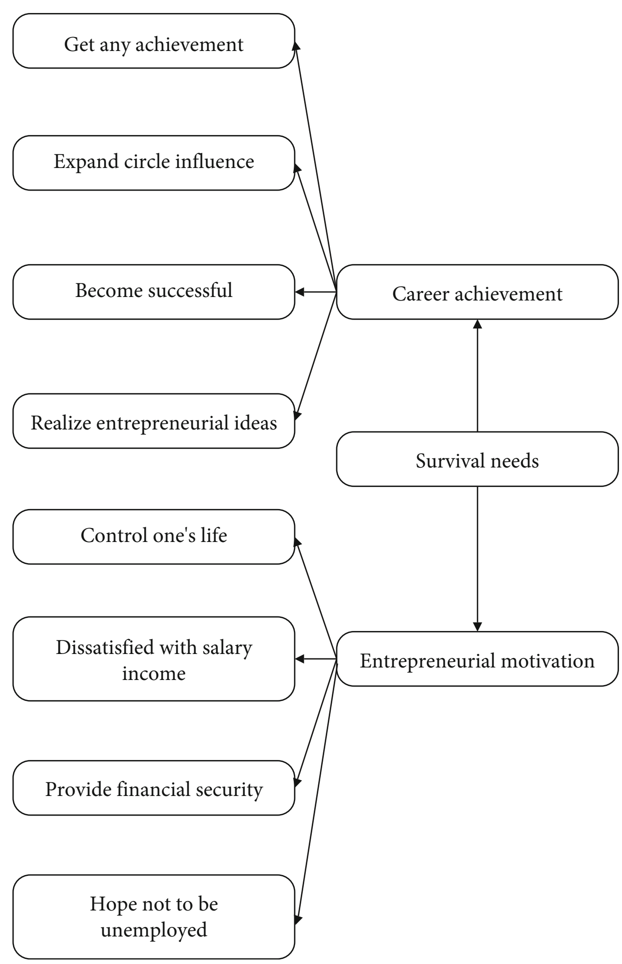

Figure 4: Two-factor model of entrepreneurial motivation.

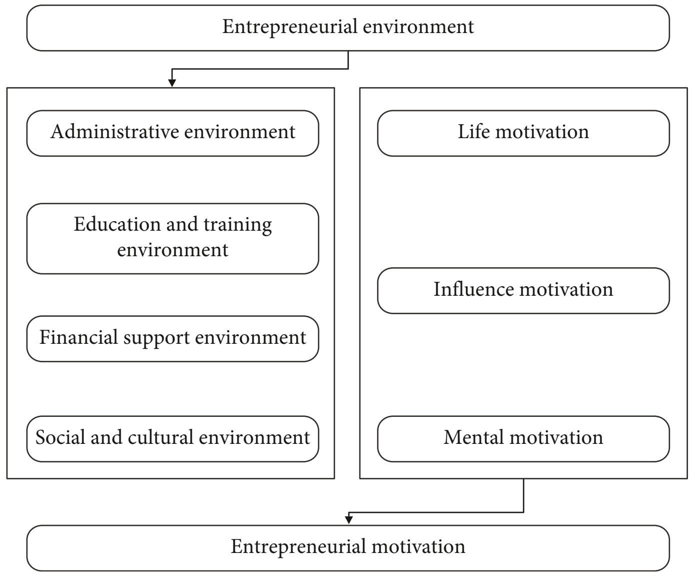

Figure 5: Theoretical structure diagram.

$K(\cdot,\cdot)$ is the kernel function. For $\forall(i,j)\in N_l\times N_l$, if the solution of formula (13) is $\alpha^*=(\alpha_1^*,\alpha_2^*,\cdots,\alpha_1^*)^T$ and b^*, then the corresponding decision function is as follows:

$$\begin{aligned} y=f(x,w^*)&=\varphi(x)^T w^*+b^*=\varphi(x)^T Z\alpha^*+b^* \\ &=\sum_{i=1}^{l}\alpha_i^*\varphi(x)^T\varphi(x_i)+b^*=\sum_{i=1}^{l}\alpha_i^*K(x,x_i)+b^*. \end{aligned} \quad (15)$$

4. Model Building

Successful entrepreneurial activities require constant matching and adaptation of resources, business opportunities, and teams, so that the three can maintain a dynamic balance. Among them, business opportunities are the core and origin of the entire entrepreneurial activity. Therefore, in the early stage of entrepreneurship, the discovery and selection of opportunities is crucial, and companies should identify as many business opportunities as possible to help improve the performance of entrepreneurial activities. At the same time, resources are the supporting elements of the entrepreneurial process, and they are important for the identification and development of opportunities. Therefore, entrepreneurs need to try to develop and establish multiple channels to obtain abundant resources. Figure 3 shows the Timmons entrepreneurial model.

The theoretical model is obtained by exploratory factor analysis method, and the confirmatory factor analysis is carried out, and finally, a two-factor model is obtained. The model is shown in Figure 4.

On the basis of studying the results of domestic and foreign scholars, this paper combines the influence mechanism of entrepreneurial environment and entrepreneurial motivation, takes entrepreneurial environment as an independent variable, and divides entrepreneurial environment into four dimensions. At the same time, this paper takes entrepreneurial motivation as the dependent variable, which includes three dimensions: life-type motivation, influence-type motivation, and spiritual-type motivation. In order to explore the mechanism of entrepreneurial environment on motivation,

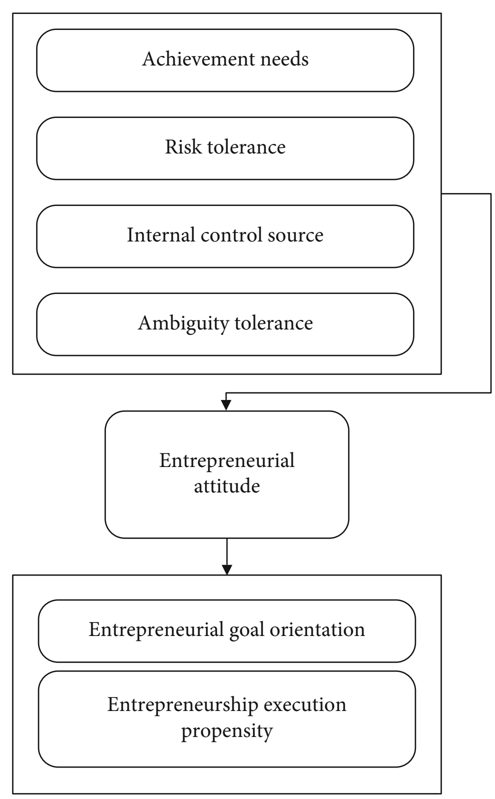

Figure 6: The relationship model of entrepreneur traits, entrepreneurial attitude, and entrepreneurial propensity.

Table 1: Statistical table of data mining effect.

Number	Data mining	Number	Data mining	Number	Data mining
1	82.4	28	90.7	55	85.5
2	91.3	29	83.9	56	80.8
3	84.0	30	82.9	57	85.8
4	89.2	31	81.9	58	80.4
5	85.0	32	87.3	59	80.8
6	86.5	33	86.3	60	88.0
7	80.8	34	80.6	61	80.0
8	85.9	35	79.1	62	87.5
9	93.4	36	94.0	63	82.2
10	90.5	37	82.6	64	79.5
11	86.1	38	83.0	65	86.7
12	79.9	39	88.4	66	86.8
13	81.3	40	83.3	67	89.3
14	87.7	41	93.8	68	80.3
15	80.3	42	83.5	69	84.2
16	89.2	43	81.8	70	82.5
17	90.4	44	91.5	71	85.4
18	85.1	45	92.1	72	86.7
19	90.7	46	82.3	73	82.7
20	80.7	47	83.1	74	86.2
21	92.0	48	93.4	75	88.7
22	92.4	49	85.0	76	87.3
23	81.6	50	88.2	77	85.3
24	92.0	51	83.0	78	80.6
25	81.4	52	84.1	79	90.6
26	86.3	53	84.6	80	88.9
27	82.5	54	92.8	81	81.0

Table 2: Statistical table of the evaluation of the decision-making effect of innovation and entrepreneurship.

Number	Decision effect	Number	Decision effect	Number	Decision effect
1	85.1	28	90.0	55	74.4
2	80.1	29	82.0	56	86.4
3	71.5	30	69.8	57	88.0
4	80.4	31	86.3	58	80.9
5	89.0	32	71.5	59	75.1
6	86.0	33	73.3	60	77.8
7	70.1	34	82.0	61	69.9
8	90.2	35	75.1	62	69.1
9	90.2	36	85.2	63	83.8
10	75.7	37	88.0	64	69.2
11	72.9	38	84.1	65	75.2
12	69.9	39	90.4	66	84.9
13	77.7	40	73.0	67	71.9
14	80.5	41	86.7	68	81.5
15	89.7	42	78.2	69	75.3
16	82.4	43	71.2	70	75.1
17	78.2	44	77.6	71	83.0
18	73.2	45	84.5	72	77.0
19	85.9	46	83.1	73	69.4
20	83.3	47	70.6	74	90.5
21	77.8	48	82.0	75	68.3
22	83.3	49	72.9	76	74.5
23	72.4	50	73.5	77	86.9
24	90.6	51	77.8	78	88.5
25	75.5	52	69.7	79	73.2
26	89.2	53	82.3	80	83.8
27	73.6	54	89.0	81	88.8

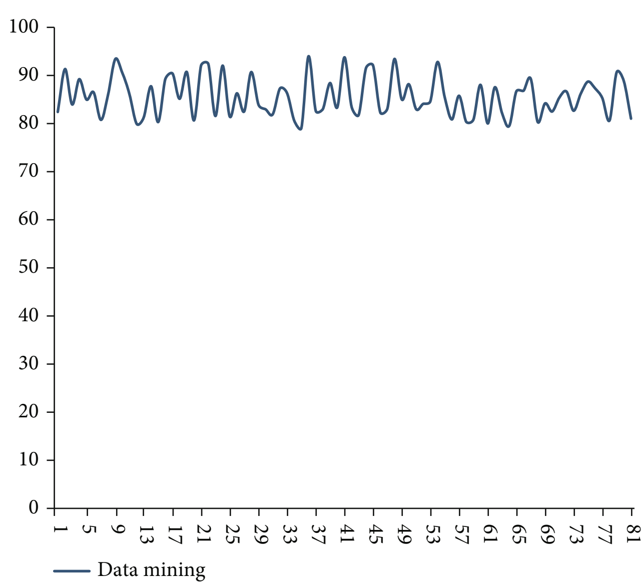

Figure 7: Statistical diagram of data mining effect.

this paper constructs the theoretical model of this paper by reading a large number of documents, as shown in Figure 5.

The purpose of this paper is to explore the relationship between entrepreneurial traits, entrepreneurial attitude, and entrepreneurial propensity. Through the analysis and combing of relevant literature, it is not difficult to find that the characteristics of entrepreneurs have an impact on entrepreneurial propensity. However, there are few empirical studies that show that the traits of entrepreneurs are directly related to entrepreneurial propensity, and when the personal traits of entrepreneurs or potential entrepreneurs are regarded as the only cause of entrepreneurial propensity, the research results will be one-sided. This article introduces entrepreneurial attitude as an intermediary variable and validates it through data collection and statistical analysis, so that entrepreneurial traits influence entrepreneurial propensity through entrepreneurial attitude. The test results found that entrepreneurial attitude can better explain the influence of entrepreneurial traits on entrepreneurial propensity. In summary, this paper constructs a conceptual model of the research, as shown in Figure 6.

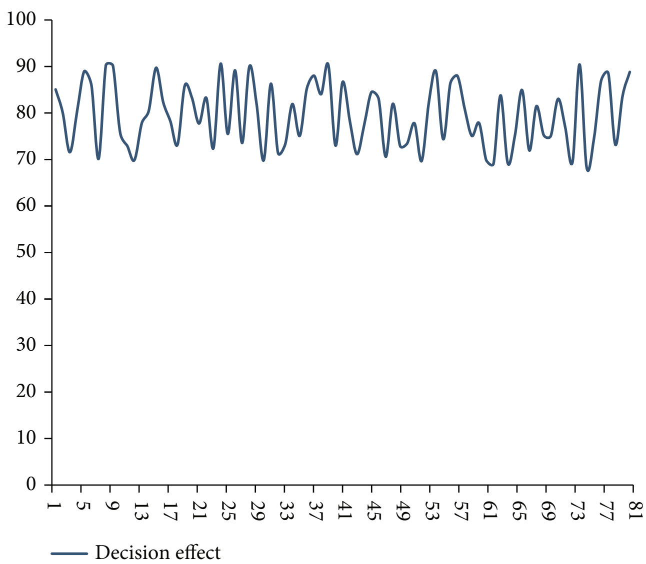

Figure 8: Statistical diagram of the evaluation of the decision-making effect of innovation and entrepreneurship.

5. Analysis of Driving Factors for Innovation and Entrepreneurship Based on Time Series Analysis

In order to test the effect of the model proposed in this paper, this paper will obtain data by issuing questionnaires and collect the questionnaires within a certain time limit. The questionnaire is mainly distributed by means of two-dimensional code sharing and web links, and the coverage is expanded through communication platforms such as WeChat, Weibo, and Qzone.

After obtaining the data, this paper examines the data mining effect of the innovative and entrepreneurial driving factor analysis model based on time series analysis proposed in this paper. The results are shown in Table 1 and Figure 7.

From the above research results, the innovative and entrepreneurial driving factor analysis model based on time series analysis proposed in this paper has a certain effect. On this basis, the effect of system innovation and entrepreneurship decision-making is evaluated, as shown in Table 2 and Figure 8 below.

Through experimental research, we can see that the innovative and entrepreneurial driving factor analysis model based on time series analysis proposed in this paper has a certain effect.

6. Conclusion

China's economy has entered a new normal, and Chinese companies are gradually moving from past imitative innovation to independent innovation. In this context, the voice of the business community for improving innovation performance is even higher, and entrepreneurs hope to develop more exploratory innovation while maintaining utilization innovation. Based on the time series analysis algorithm, this paper introduces the concept of resource patchwork on the basis of the Timmons entrepreneurial model and its three major elements (opportunities, resources, and teams). Moreover, this paper believes that resource patchwork, as an informal innovation hidden in the daily work of an enterprise, can quickly respond to identified opportunities through the rational development and recombination of resources at hand. In addition, this paper constructs an analysis model of innovation and entrepreneurship driving factors based on time series analysis and validates the model in this paper through case analysis. The research results show that the model constructed in this paper has a certain effect.

Data Availability

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

Conflicts of Interest

The author declares no competing interests.

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