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*Research Article*

# The Relationship between Social Entrepreneurship Capability of SOM Neural Network Algorithm and New Enterprise Performance

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As an important factor in the creation and growth of new enterprises, social entrepreneurship and new enterprise performance have attracted more and more attention from scholars in recent years. This research analyzes the network relationship of new companies on the basis of existing entrepreneurial network research. This paper proposes social entrepreneurial capabilities and new company performance based on the SOM neural network algorithm to solve these problems and then establishes entrepreneurial networks, organizational learning, and new business performance models. The method of this paper is to study the SOM neural network algorithm and then establish the entrepreneurial ability and enterprise performance evaluation system. The function of these methods is to put forward the meaning and research of venture capital. It also defines the meaning and research of innovation capabilities based on innovation theory, ensuring the scientific nature of the evaluation indicators, evaluation standards, and evaluation processes of innovative enterprises. In this survey, this paper conducted a field survey in Shanxi Province, China, and analyzed the internal impact of the network of social entrepreneurship and new companies on corporate performance. The survey results show that the value of the correlation $\beta$ between entrepreneurial orientation and entrepreneurial environment dynamics is 0.167 ($P < 0.05$). This shows that improving the entrepreneurial environment and enhancing social entrepreneurial capabilities have a positive impact on corporate performance.

## 1. Introduction

With the acceleration of economic globalization, the knowledge economy is developing rapidly. Countries all over the world are working hard to improve tolerance to adapt to the new trends and requirements of economic development. The spirit of innovation has played a vital role in promoting China's economic growth and development. In recent years, China's entrepreneurial activities have been very active, but the survival rate of new companies is very low. This research is based on the experience of entrepreneurs and knowledge management theory. Its purpose is to make China one of the world's powers at an early date and to enhance its independent innovation capabilities. This paper proposes a conceptual model of the relationship between dual opportunity awareness and new enterprise performance based on learning theory and organizational duality theory, and describes in detail the differences in the impact of different types of entrepreneurial experience on dual opportunity awareness.

Enterprise innovation has historical significance. Not all technologies in innovation activities mean that they are a single type of innovation, or can they be completed only within the enterprise. The enterprise establishes an enterprise scientific and technological innovation system to improve its independent innovation capability. This is vital to China's future economic and scientific development. This research improves the impact of political connections on corporate performance and provides theoretical support for startups to reduce the negative impact of political connections on companies and exert the beneficial effects of political connections on companies. This research further analyzes the mediating role played by internal knowledge sharing in entrepreneurship and the identification of dual opportunities between different types of entrepreneurial experiences. This provides some practical guidance for enterprises to avoid innovation risks.

In previous studies, scholars mainly used Chinese listed companies as samples—or industrial, agricultural, tourism, clothing, transportation, and other listed companies as samples—while research on innovative companies hardly existed. This article examines the moderating role of corporate growth, and whether there are significant differences in the relationship between innovation and corporate performance for companies of different growth levels. In this article, innovative companies will be selected for research. This article chooses entrepreneurial companies because there is less research on this type of company, and there is no research on the relationship between innovation and corporate performance. This article fills up the gaps in empirical research in this field through reasonable indicator selection, accurate data screening, and scientific empirical analysis techniques.

## 2. Related Work

As the trend of innovation and entrepreneurship gradually prevails, people are paying more and more attention to the role of social entrepreneurship, and there are more and more studies on this. Lai et al. conducted a graded waterlogging risk assessment on 56 low-lying spots in Beijing based on the self-organizing map. The results show that SOM-ANN is suitable for automatic quantitative assessment of risks related to waterlogging. It can effectively overcome the interference of subjective factors and produce more objective and accurate classification results [1]. Ni et al. proposed to use GAN-SOM as a new clustering architecture based on deep learning. The SOM-like network is designed to achieve the purpose of encoding and clustering data samples at the same time. The joint training of this network and GAN can optimize the newly defined clustering loss [2]. Suryani and Susilo aim to segment blood vessels using the main method of self-organizing map artificial neural networks. The segmentation method they proposed can effectively improve the test performance of medical machinery and increase the success rate of surgery [3]. Runst et al. proposed a novel classification scheme aimed at improving the identification of entrepreneurial companies in the microcensus. Policy changes are only aimed at entrepreneurial enterprises, and after the complete deregulation of trade, the proportion of enterprises entering the industry has increased significantly, and the innovation and entrepreneurship of enterprises have become stronger and stronger [4]. Hsieh and Wu investigate how entrepreneurs innovate the corporate ecosystem during the entrepreneurial process. He researched and discussed various platform-based enterprise innovations, and also discussed the worries and problems that the ecosystem of innovation platforms may bring to enterprises [5]. Rodriguez et al. aim to further explore the influencing factors of corporate performance through innovative concepts. His research results show that market orientation has a direct impact on organizational performance. He observes the specific ways in which innovation performance structure regulates market orientation [6]. Abushaikha et al. studied the relationship among warehouse operation performance, distribution performance, and business performance. He first used Delphi technology to develop relevant questionnaires, then used data to measure the degree of performance improvement in different warehouse activities, and tested his hypotheses. His conclusion is that there is a positive correlation between warehouse operation performance and distribution performance [7].

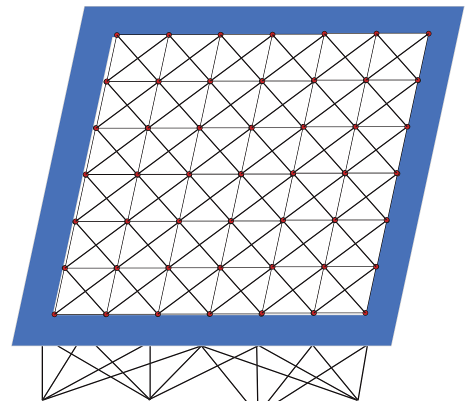

Figure 1: SOM neural network topology.

## 3. Social Entrepreneurship and Corporate Performance Evaluation Methods

*3.1. SOM Neural Network Research.* A self-organizing competitive neural network (SOM) was first proposed by Teuvo Kohonen [8]. OM neural network adjusts the weight of the network through self-organizing feature mapping so that the network converges to a stable state. Network learning is self-organized learning under unsupervised conditions. During the learning process, certain neurons are only sensitive to certain types of patterns. Because different neurons have different degrees of sensitivity to different input patterns through unsupervised competitive learning. The operator of the network can detect specific input patterns. Figure 1 shows the network topology of the SOM neural network.

This is a feedforward neural network composed of two layers of neurons. The number of neurons in the input layer is the same as the dimension of the input sample. The output layer, also called the conflict layer, arranges the nodes into a two-dimensional array. The connection between the input layer and the competing layer node is fully connected with variable weight [9].

SOM neural network training steps are as follows:

First, the network is initialized, the network weight is initialized to $w_{nm}(n = 1, 2 \ldots n, m = 1, 2 \ldots m)$, $n$ is the number of neurons in the input layer, and $m$ is the number of neurons in the competition layer. The weights can be initialized randomly. It sets the maximum number of cycles $T$, inputs training samples, and normalizes them. Then, it calculates the distance $D$ between the normalized input vector $X = (x_1, x_2 \ldots x_n)$ and the neuron $j$ of the competition layer as follows:

$$D_j = \sqrt{\sum_{n=1}^{m} \left(x_n - w_{mn}\right)^2}. \quad (1)$$

It looks for the winning neuron. The neuron $C$ of the competition layer with the smallest distance from the input vector is selected as the winning neuron. One needs to remember that the class label of the input vector is $C_x$; if $C_x = C_i$, then adjust the weight as follows:

$$w_{mn} = w_{mn} + n\left(x - w_{mn}\right). \quad (2)$$

Otherwise, adjust as follows:

$$w_{mn} = w_{mn} - n\left(x - w_{mn}\right). \quad (3)$$

If neuron $i$ and $j$ belong to different categories, the distance $di$ and $dj$ between neuron $i$ and $j$ and the current input vector satisfy

$$\min\left\{\frac{di}{dj}, \frac{dj}{di}\right\} > p. \quad (4)$$

Among them, $p$ is the width of the window near the center section of the two vectors that the input vector may contain, usually about two-third. The learning rules of the SOM neural network are derived from the lateral inhibition of neuronal cells. The flowchart is shown in Figure 2.

The adjustment weight, the update formula is as follows:

$$w_{mn} = w_{(m+1)(n+1)} + N(n)h(n)\left(x_n - w_{mn}\right). \quad (5)$$

In the formula, $N(n)$ is the learning rate function, and its value range is $0 < N(n) < 1$, and $h(c)$ is the neighborhood function, which gradually decreases with time. Their learning rules are as follows:

$$h(n) = \exp\left(-\frac{d_{cm}^2}{2r^2(n)}\right),$$
$$r(n+1) = \mathrm{INT}\left(\left(r(n) - 1\right)\left(1 - \frac{n}{T}\right)\right) + 1, \quad (6)$$
$$N(n+1) = N(n) - \frac{N(0)}{T}.$$

In the formula, $d_{cm}$ is the distance between neuron $c$ and neuron $m$, $r(n)$ is the radius of the neighborhood, INT is the rounding function, and $T$ is the total number of learning times. Let $n = n + 1$, return to perform random initialization processing on the weights until the maximum number of iterations or the learning rate reaches a set value [10].

In order to verify the validity and correctness of the established model, it is necessary to ensure that the sample data provided for fault diagnosis are true and reliable. For multidimensional features, the correlation coefficient method is used for feature extraction. By analyzing the relevant characteristics of different features, the features with lower discrimination are removed and the features with higher discrimination are retained. In the end, only the extracted features are used to train the neural network, and the same feature compression is performed on the test data.

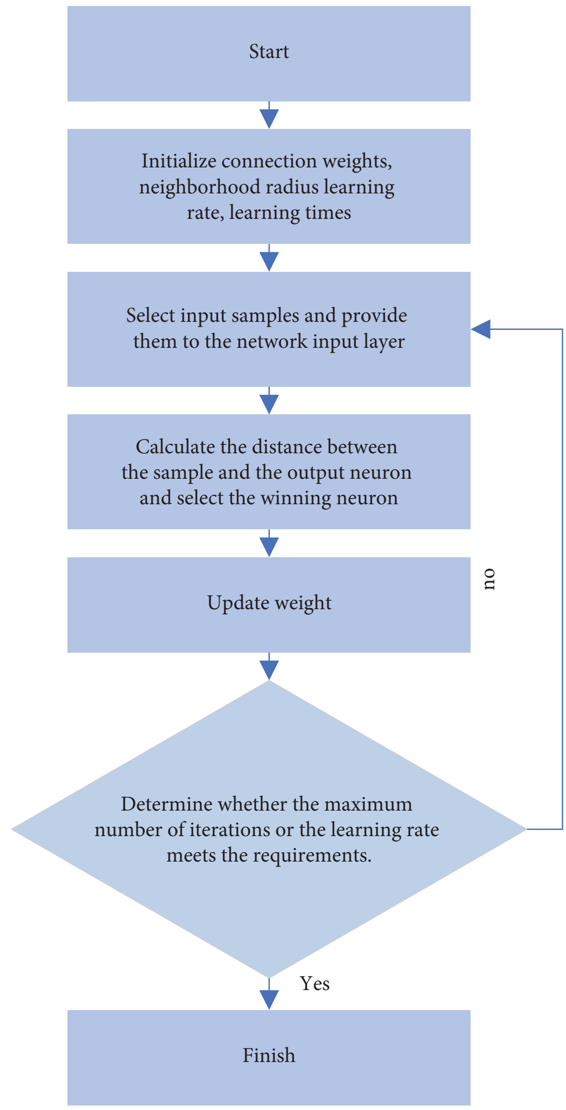


Figure 2: SOM neural network algorithm flowchart.

The calculation formula of the correlation coefficient between different features is as follows:

$$p\left(f, x_m\right) = \frac{\sum_{n=1}^{N}\left(f_n - \overline{f}\right)\left(x_{nm} - \overline{x}_m\right)}{\sqrt{\sum_{n=1}^{N}\left(f_n - f\right)^2 - \sum_{1=n}^{N}\left(x_{nm} - x_m\right)^2}}. \quad (7)$$

In the formula, $f$ is the target value, $x_m$ is the feature, $N$ is the sample size, and $\overline{x}_m$ is the mean value of the feature. The larger the correlation coefficient, the more obvious this feature distinguishes the failure mode [11].

The SOM network can automatically classify the input mode. It is based on the simultaneous response of multiple neurons to the classification results and does not require a large amount of sample data. Moreover, its network structure is simple, and the algorithm process is relatively easy to implement. However, it also has shortcomings. Before training, the user needs to initialize the number of clusters and the initial weight matrix. That is to say, the number of clusters and the network structure are fixed and cannot be adjusted during the training process. During the training process, some neurons never win in the competition, forming dead neurons. And some neurons are overused in the learning process, which will affect the training performance of the network. During training, if a new type is added to the training sample, it must be relearned [12].

*3.2. Evaluation of Entrepreneurial Ability.* There are many indicators to measure enterprise performance. This article will measure the performance of SMEs from two aspects: short-term profitability and long-term growth ability. This article uses the variable return on assets (ROA) used by most scholars to measure the short-term profitability of enterprises.

$$\mathrm{ROA} = \frac{\mathrm{NOPAT}}{TA}. \tag{8}$$

In the formula, ROA represents the rate of return on total assets, NOPAT represents net operating profit after tax, and TA represents total assets. This article adopts Tobin's $Q$ index used by most scholars to measure the growth performance of SMEs. The calculation formula is as follows:

$$\mathrm{Tobin's}Q = \frac{(EV + \mathrm{BVL})}{TA}. \tag{9}$$

In the formula, BVL represents the book value of liabilities, and EV represents the value of equity. Multiple linear regression is a statistical method to study a linear relationship between a dependent variable and multiple independent variables. The basic idea is a statistical method that can estimate the dependent variable and its influence on its variability by using the value of more than one independent variable. Therefore, it is the continuation and promotion of simple regression analysis and correlation analysis [13]. In this study, panel data will be used for multiple regression analysis. The regression formula of panel data is as follows:

$$y_i = b_0 + x_i b_i + z_i r + v_i + E_i. \tag{10}$$

Among them, $y_i$ is the dependent variable, and $x_i$ is the independent variable that varies with the individual and time. $z_i$ is an individual characteristic that does not change over time, such as gender. $v_i + E_i$ constitutes an interference term, $v_i$ is an individual characteristic that is unobservable and does not change with time, $E_i$ is a perturbation term that changes with the individual and time, and hypotheses $E_i$ and $v_i$ are not correlated. The formula (10) is processed, and the two sides are averaged to obtain

$$\overline{y}_i = b_0 + \overline{x}_i' b_i + z_i' r + v_i + \overline{E}_i. \tag{11}$$

Performing OLS on formula (11) can get the intergroup estimator, but this requires that it cannot be correlated with all explanatory variables, otherwise the estimation will be invalid. When individuals are related to explanatory variables, this article calls the panel data model a fixed-effects model. At this time, OLS estimates are inconsistent. But this article can be processed to turn it into a consistency estimate [14]. Specifically, it is obtained by formula (10) and formula (11):

$$y_i - \overline{y}_i = x_i - \overline{x}_i' b_i + \overline{E}_i - \overline{E}_i. \tag{12}$$

If the errors in the panel data are autocorrelated, then the commonly used standard errors are also incorrect. Because it is derived under the false assumption that autocorrelation does not exist. Furthermore, panel data have potentially nonuniform variance that may be associated with different temporal conditions for a particular individual. This article also uses the Xtgls command to analyze the impact of entrepreneurial social capital ($S$) on the performance of SMEs. The design of the following multiple regression analysis formulae is as follows:

$$\begin{aligned} F = {} & A + B_1 S + B_2 L + B_3 G + B_4 Sc + B_5 Ag \\ & + \sum_1^t \delta_i Y + \sum_1^t \gamma_k I + E_i. \end{aligned} \tag{13}$$

Formula (13) shows the impact of three main aspects of entrepreneurial social capital ($S$), political connections (POL), industry association relations (BAN), and technology association relations (TAN) on enterprise performance. Due to political relations, trade association relations, and the three technical association relations, there is an important positive relationship. To avoid the problem of multicollinearity, each of the three variables is assigned to the model. In addition, the factors that affect the performance of SMEs ($F$) are more complex, so this article introduces a set of variables. The debt-to-asset ratio ($L$) is measured by the company's total debt-to-asset ratio, that is, the company's total liabilities divided by its total assets. Sales growth rate ($G$) is the company's sales growth rate for the year. Company size (Sc) is measured by the natural logarithm of total assets for the year. The company life (Ag) is calculated from the company registration year as the starting year to the number of years set in the survey sample. In addition, this article adds an industry ($I$) dummy variable (i.e., $K = 20$) and a year ($Y$) dummy variable (i.e., $I = 5$) to the model control. This article hopes to satisfy the assumption that the political relationship between entrepreneurs, the relationship between industry associations, and the relationship between technical associations have a significant positive impact on the performance of SMEs.

In order to intuitively understand the relationship among entrepreneurial political relations, industry group relations, technical group relations, and the performance of SMEs, this paper uses grouping techniques to conduct $T$-tests. This study tests whether there is a significant difference between the two. For example, does the existence of entrepreneurial social capital have a significant impact on company performance? When testing whether there is a significant difference in the mean of the two groups of variables, it can be distinguished by using the $T$-test command in Stata.

$$\overline{x}_1 - \overline{x}_2 = u_1 - u_2 + \overline{E}_1 - \overline{E}_2. \tag{14}$$

This article proposes the meaning and research aspects of entrepreneurial social capital by investigating and combining relevant theories, and defines the meaning and research aspects of innovation ability based on innovation theory.

*3.3. Corporate Performance Evaluation.* The Herfindahl index ($H$) is used to measure the degree of diversification of a company. The Herfindahl index was originally used to measure industrial concentration in the theory of industrial organization. It can be used to reflect the relative weight of different business units at a single SIC classification level.

$$H = \sum_{i=1}^{n} (p_i)^2. \quad (15)$$

Among them, $p_i$ represents the proportion of the operating income of the different industries that the company produces or the industry involved in the business belongs to the total income of the company, and $n$ represents the number of businesses operated by the enterprise. $H$ has an inverse relationship with the degree of corporate diversification. The larger the $H$, the lower the degree of diversification. In the process of application, many scholars deform $H$ and use the difference of 1 minus $H$ to express the degree of enterprise diversification. This makes $H$ have a positive correlation with the degree of corporate diversification, and the greater the $H$, the higher the degree of corporate diversification. When the enterprise is a single business, $H$ is equal to 0 [15].

$$H = 1 - \sum_{i=1}^{n} (p_i)^2. \quad (16)$$

Using entropy measurement to measure the level of diversification:

$$H = \sum_{i=1}^{n} p_i \ln\left(\frac{1}{p_i}\right). \quad (17)$$

According to the different meanings of $p_i$ and $n$, the "entropy" index can be used to calculate three indicators of enterprise diversification, that is, the degree of overall diversification, unrelated diversification, and related diversification. When $p_i$ and $n$ represent business indicators belonging to the four-code industry, the "entropy" index calculates overall diversification. When $p_i$ and $n$ represent business indicators belonging to the two-code industry, the entropy index calculates noncorrelated diversification. $H$ is positively correlated with the degree of diversification of the enterprise. The larger the $H$, the higher the degree of diversification of the enterprise. When $H$ is 0, the enterprise conducts a professional operation.

For an innovative enterprise that integrates technological innovation, brand innovation, system and mechanism innovation, business management innovation, concept and cultural innovation, etc., related performance evaluation theories must also consider social and company benefits.

If there are $n$ decision-making units (DMU), each decision-making unit has m-type input and s-type output. Then, the resource input of the decision-making unit is represented by $x$ as the input of the DMU, and the output of the decision-making unit is represented by $y$ as the output quantity of the DMU. The weight vectors $v$ and $u$ are allocated, and the efficiency evaluation index of each DMU is as follows:

$$h = \frac{u^T y_i}{w^T x_j} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} w_r x_{rj}}. \quad (18)$$

The weight coefficients $w$ and $u$ can be appropriately obtained, so that $h \le 1$. Usually, fishbone diagram analysis is used to reflect the formation process of innovative enterprise performance, and to clarify the formation process of innovative enterprise performance. Let us take the decomposition of enterprise performance maximization goal as an example to explain, as shown in Figure 3.

After establishing the strategic goal of maximizing corporate performance, the fishbone diagram can be used to decompose the strategic goals of the enterprise layer by layer in accordance with the method of causality. The scientific nature of the performance evaluation system is the basis for ensuring the accuracy and reasonableness of the performance evaluation results of innovative enterprises. The scientific nature of a performance evaluation activity depends on the scientific nature of various aspects such as evaluation indicators, evaluation standards, and evaluation processes. Compared with the characteristics of traditional enterprise performance evaluation and strategic performance evaluation, the innovation performance evaluation system of innovative enterprises takes into account the actual situation of enterprise strategic innovation. It needs to combine the performance evaluation content of various levels of innovative enterprises to ensure the rationality of the overall structure of the performance evaluation system. In addition, the innovative performance system of innovative enterprises captures the main aspects of the innovation of corporate strategic objectives. Considering the difference between the strategic innovation of innovative enterprises and traditional original enterprise strategies, a certain flexible innovation interval is designed. This can highlight the focus of innovation performance evaluation, and carry out a longitudinal comparison before and after the evaluation of strategic innovation performance of innovative enterprises and at each stage of the innovation process. This will be horizontally compared with similar innovative companies outside, and finally, combined with multilevel performance appraisal content. In this way, it uses a multifaceted performance evaluation system that includes indicators of innovation for innovative enterprises, and finally, forms an efficient and innovative performance evaluation system [16].

## 4. Experiment and Analysis of the Correlation between Social Entrepreneurship and Corporate Performance

*4.1. The Integration of Entrepreneurship Capability.* Flexible and efficient knowledge integration represent two completely different combinations of entrepreneurial knowledge integration methods. In the actual entrepreneurial process, new ventures will use these two types of

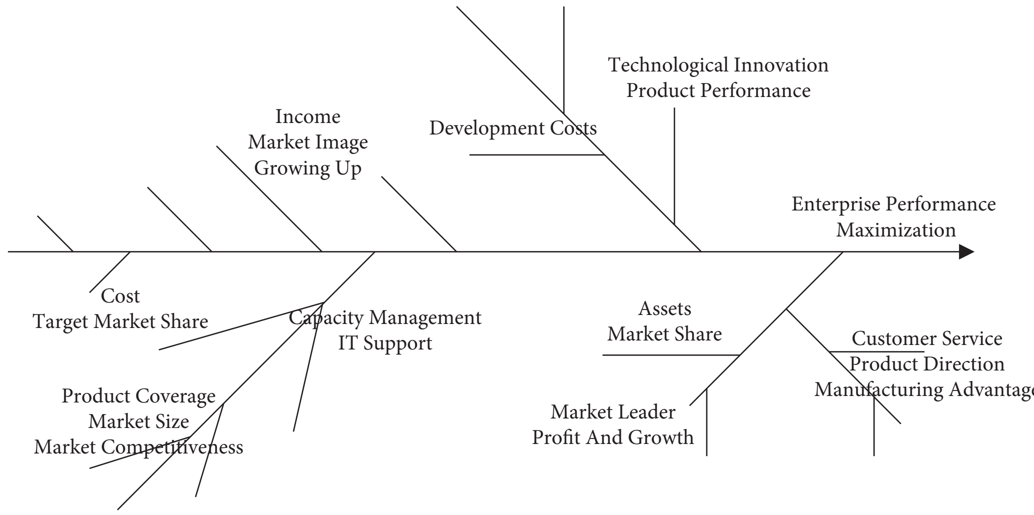


Figure 3: The goal decomposition of innovative enterprise performance formation.

Table 1: Descriptive statistical analysis of measurement items for flexible knowledge integration.

| Item | Mean | Standard deviation |
|---|---|---|
| E1 combines market feedback to establish new strategic goals | 3.880 | 0.747 |
| E2 combines new technologies to establish new strategic goals | 3.900 | 0.390 |
| O1 stakeholders promote corporate development | 3.400 | 0.499 |
| O2 cooperate to promote product/service innovation | 3.930 | 0.184 |
| C1 rewards employees for sharing experience | 3.300 | 0.743 |
| C2 provides a resting place for employees | 3.850 | 0.796 |

entrepreneurial knowledge integration to varying degrees. This helps explain the reasons for the difference in the performance of startups. Based on the above theoretical analysis, this article summarizes the characteristics of the flexible and efficient knowledge integration of the case enterprises.

It assumes that enterprise A has strong performance in both flexible and efficient knowledge integration. It is embodied in the strategic dimension as both emergency and planned knowledge integration. It is embodied in the cultural dimension as both extroverted and introverted knowledge integration. In the institutional dimension, it is embodied as an equal emphasis on coordinated and systematic knowledge integration. Enterprise B focuses on flexible knowledge integration. That is, it is mainly embodied as emergency knowledge integration in the strategic dimension, outward-oriented knowledge integration in the cultural dimension, and coordinated knowledge integration in the institutional dimension. And C enterprise mainly focuses on efficient knowledge integration. That is, in the strategic dimension, it is mainly reflected in planned knowledge integration; in the cultural dimension, it is mainly reflected in introverted knowledge integration; and in the institutional dimension, it is mainly reflected in systematic knowledge integration. As mentioned earlier, it is different from A, B, and C enterprises, and D enterprise has no outstanding performance in strategic, cultural, and institutional knowledge integration. Therefore, the company has weak performance in both flexible and efficient knowledge integration [17]. The average number and standard deviation of each measurement item of flexible knowledge integration are shown in Table 1.

Factor analysis is an important method to test the validity of the Likert scale, but not all data are suitable for factor analysis. In order to test whether the flexible knowledge integration scale is suitable for factor analysis, this study first performed KMO and Bartlett on the data. The result of the sphere test shows that the KMO coefficient is 0.747, which is much greater than 0.5. The Barlett sphere test passed ($P < 0.001$), indicating that the scale meets the factor analysis standard, as shown in Table 2.

This paper conducts exploratory factor analysis (EFA) on the scale. The factor load is the value obtained by the orthogonal rotation method. Most of the factor loads on the three common factors exceed 0.7, and are consistent with the dimensions measured in advance. This shows that the scale has high validity, with a cumulative contribution rate of 62.922%. In order to test the reliability of the scale, this study uses Cronbach's alpha coefficient method (abbreviated as "a" coefficient method) to test the reliability of each dimension of the scale and its overall items. The "*a*" coefficient of each item after deletion is lower than the existing a coefficient, and the "*a*" coefficient of each dimension is higher than 0.7, and the "*a*" coefficient of the overall item is 1.353. In summary, the scale has good reliability and validity. This article will use these 10 items to measure flexible knowledge integration.

Entrepreneurship opportunities emerge and entrepreneurial activities also emerge one after another. The process

Table 2: Reliability and validity test of the flexible knowledge integration scale.

| Dimension | Item | Factor 1 | Variance contribution rate (%) | $a$ coefficient after deletion | $a$ coefficient |
|---|---|---|---|---|---|
| Emergency | E1 | 0.749 | 69.014 | 0.508 | 0.608 |
| | E2 | 0.061 | | 0.146 | |
| Extroverted | O1 | 0.923 | 6.586 | 0.513 | 0.613 |
| | O2 | 0.447 | | 0.626 | |
| Coordinated | C1 | 0.542 | 87.322 | 0.031 | 0.131 |
| | C2 | 0.092 | | 0.413 | |
| Total table | | | 62.922 | | 1.353 |

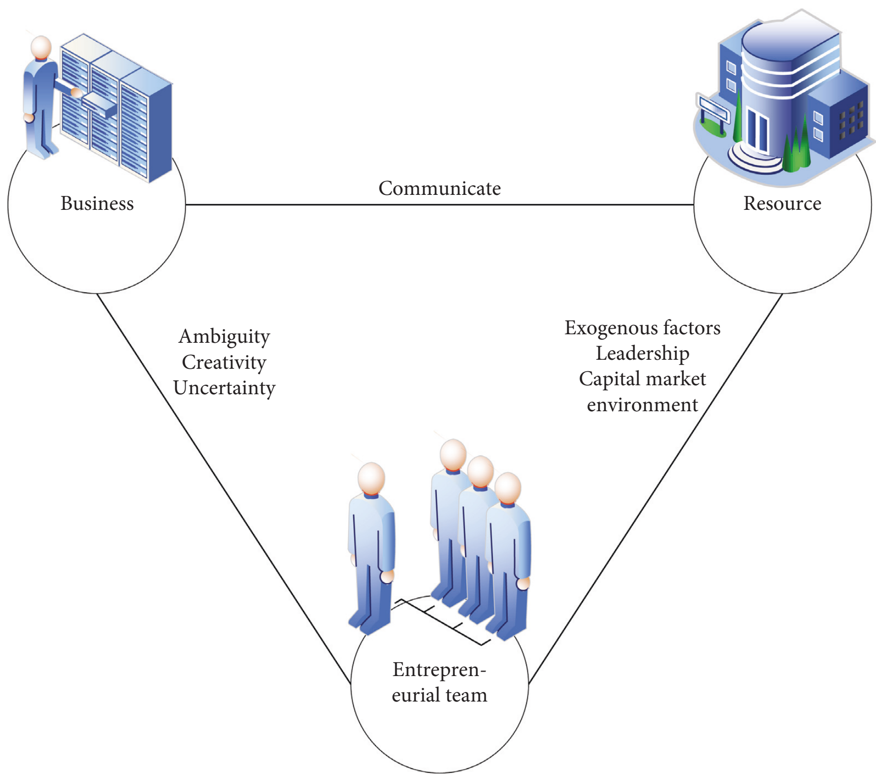


Figure 4: Timmons entrepreneurial model.

of continuous integration of entrepreneurial opportunities, entrepreneurial teams, and related entrepreneurial resources is a manifestation of entrepreneurial activities. In this process, various factors in the external environment have an effect on each stage of entrepreneurial activities all the time [18].

The entrepreneurial model is shown in Figure 4. The model is considered that the core position of entrepreneurship should be environmental factors. The model believes that the key elements of entrepreneurship are entrepreneurial resources, entrepreneurial opportunities, entrepreneurial spirit, entrepreneurial transaction behavior, and the external environment of entrepreneurship. The external environment affects and restricts all activities and behaviors involved in the entrepreneurial process.

*4.2. Corporate Performance Data Collection.* On the basis of the assumptions in Section 4.1, adding a balanced market dual opportunity to construct Mode1, the data results show that the impact of balanced dual opportunities on the performance of the new company is not significant. The Model 1 in Table 3 is used to test the relationship between market duality and new enterprise performance in a sample of non-high-tech industries [19].

The data analysis results in the table show that in non-high-tech industries, only pursuing market exploration and market utilization opportunities will have a significant positive impact on the performance of the new company. The coefficient of influence of market exploration opportunities on business performance is $0.585^{**}$, which is higher than the regression coefficient of market utilization opportunities $-0.328^{*}$. Like nontech companies, the dual opportunities of pursuing a balanced market will have a positive impact on the performance of the new company.

Based on social network theory and organizational learning theory, this paper constructs a research framework for the relationship among entrepreneurial networks, organizational learning, and new corporate performance. The relationship among entrepreneurial networks,

Table 3: Regression analysis results of the relationship between the recognition of dual opportunities in the market and the performance of new companies.

| Explanatory variables | Explained variable: New enterprise performance | | | |
|---|---|---|---|---|
| | High-tech industry | | Non-high-tech industries | |
| | Model 1 | Model 2 | Model 1 | Model 2 |
| Business age | 0.145 | −0.347 | −0.959 | 0.373** |
| Enterprise size | 0.418** | −0.935 | −0.706 | −0.561 |
| Education level | −0.213 | −0.911 | −0.627 | 0.374 |
| Age of entrepreneur | 0.438 | −0.955 | −0.216 | 0.160 |
| Gender of entrepreneur | −0.370 | −0.761 | 0.340 | 0.160 |
| Market exploratory opportunities | 0.578 | 0.934** | 0.585** | −0.084 |
| Market exploitable opportunity | −0.809 | 0.073 | −0.328* | 0.853 |
| Balanced market dual | 0.319 | −0.812 | 0.783 | −0.822 |
| $R^2$ | 0.822 | −0.121 | −0.389 | 0.690 |
| Adjust $R^2$ | −0.350 | 0.688 | −0.973 | −0.982 |
| F-value | 0.211** | −0.746 | 0.269** | 0.397** |

*Note.* *** indicates the significance level $P < 0.01$ (two-tailed detection), ** indicates the significance level $P < 0.05$ (two-tailed detection), * indicates the significance level $P < 0.1$ (two-tailed detection).

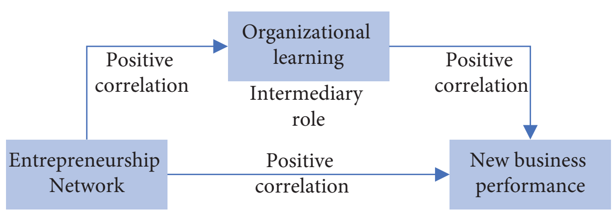


Figure 5: The relationship between entrepreneurial networks, organizational learning, and new company performance.

organizational learning, and new company performance is shown in Figure 5.

*4.3. Examples of Entrepreneurial Ability and Corporate Performance.* Based on theoretical research on knowledge management, experiential learning, organizational duality, entrepreneurial learning, etc., this research constructs a conceptual model of the relationship among entrepreneurial experience, dual opportunity awareness, and new business performance. It further understands the differences in the impact of different types of entrepreneurial experience on the identification of dual opportunities, and the mitigation effect of knowledge sharing between the two. Combining the framework of the technology market, this paper analyzes the difference in the impact of dual opportunity perception on the performance of new companies in the background of different technology-intensive industries [20].

In order to increase the questionnaire response rate, this article will give priority to collecting paper questionnaire data. This article combines the characteristics of Shanxi's small- and medium-sized enterprises based on previous questionnaire surveys in related fields, designed a questionnaire to collect the data needed for the survey, and distributed paper questionnaires.

In this survey, a total of 300 paper questionnaires and online questionnaires were distributed, and 296 paper questionnaires were recovered. Because some survey items were incomplete and could not accurately reflect the actual situation of the interviewees, 14 invalid surveys were excluded. There were 282 valid paper surveys, the survey recovery rate was 98%, and the survey effective recovery rate was 94%. The specific situation is shown in Figure 6.

The regional distribution of sample data is shown in the figure. Among them, enterprises in the western region accounted for 21%, manufacturing accounted for 25.7%, service industry accounted for 31.9%, and commerce accounted for 12.9%. These three industries accounted for more than 70% of the total sample size, and the remaining industries, including high-tech, finance, and real estate, accounted for less than 20%. This can reflect the concentration and imbalance of Shanxi's small- and medium-sized enterprises in industry selection.

This uneven distribution can reflect to a certain extent the concentration and imbalance of the development of small- and medium-sized enterprises in Shanxi Province. The distribution of the sample data in the industry is shown in Figure 7:

The following are the descriptive statistics of the return on assets, return on net assets, R&D density, engineer ratio, capital investment ratio, patent variables, asset-liability ratio, and company size of the eastern and central western samples. As shown in Figure 8.

In terms of corporate performance, the average corporate performance of the sample of companies in the eastern and western regions is 6.316 and 7.756. The average corporate performance of the sample of enterprises in the central and western regions is 5.770 and 7.296. This can preliminarily judge that enterprises in the eastern region have better corporate performance than those in the central and western regions [21]. According to the clustering results obtained by the P-SOM neural network model, a statistical graph of the results shown in Figure 9is drawn.

It can be found that among the six management system levels, the first-level company A management system performs well in three aspects: safety performance, social contribution performance, and service performance. All of these have made it difficult for Company A to catch up in

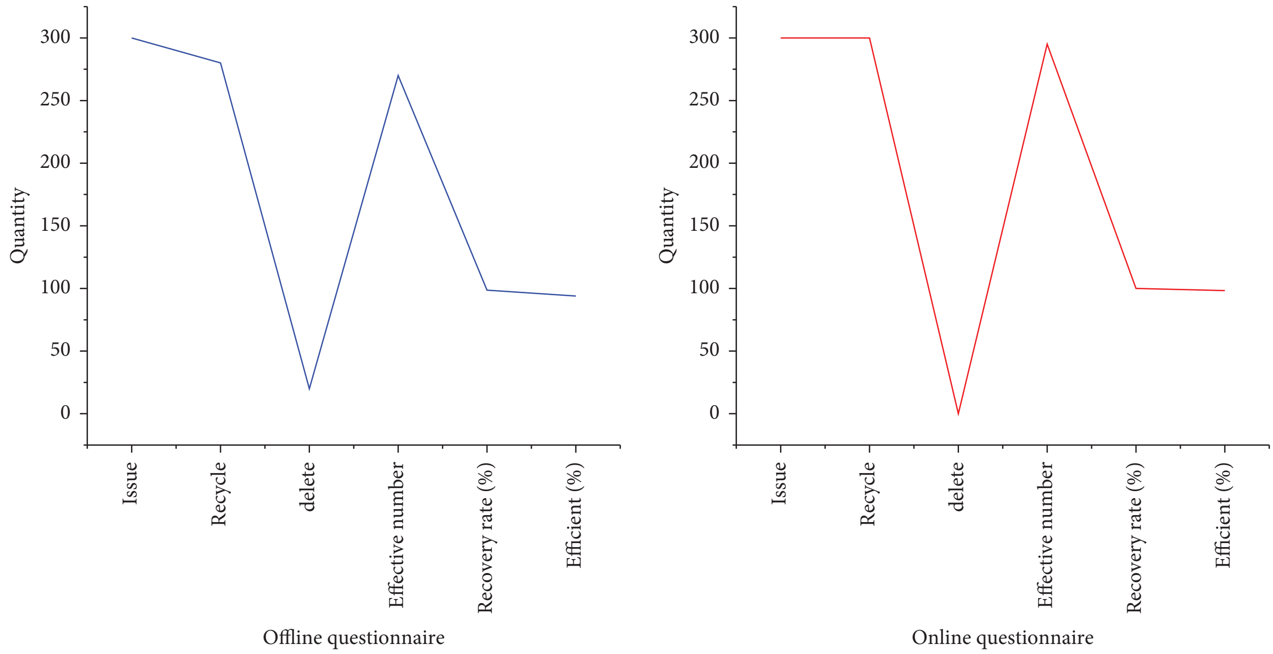


Figure 6: Questionnaire distribution and recovery.

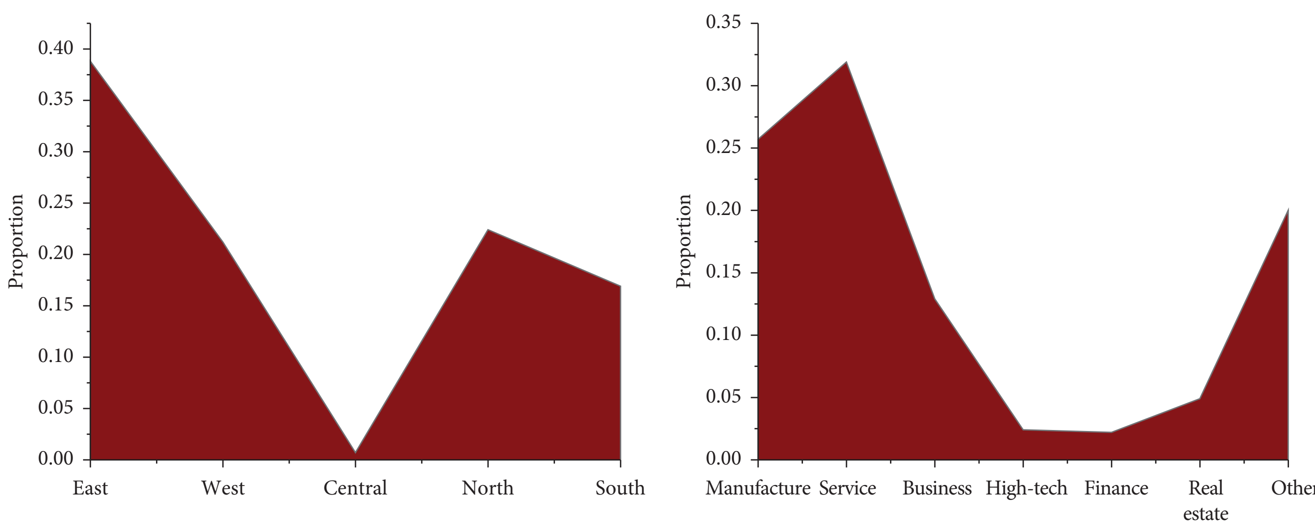


Figure 7: Regional distribution and industry category of companies.

financial terms in the following years. In recent years, Company A has actively carried out technological innovation, developed its own ATM system, and sold it. At the same time, it has built a new financing platform, so that its financial performance has a steady and positive trend. On the basis of these studies, if the company's investment in scientific research and innovation is increased, the changes in the company's financial performance are shown in Figure 10. This shows that there is a positive correlation between the spirit of social innovation and the performance of new enterprises.

The $t$ value of the interaction term "entrepreneurship orientation $x$ entrepreneurial environment hostility" is 0.260 ($P > 0.05$). The definition of the entrepreneurial environment of Shanxi SMEs shows that it does not regulate the relationship between entrepreneurial orientation and corporate performance. Therefore, the hypothesis that "the definition of the entrepreneurial environment of small and medium-sized enterprises in Shanxi Province plays an intermediate role in the relationship between entrepreneurial orientation and corporate performance" does not hold. The $t$ value of the interaction term "entrepreneurship $\times$ entrepreneurial environment dynamics" is $2.698^{**}$ ($P < 0.05$). The dynamics of the entrepreneurial environment of SMEs in Shanxi Province are entrepreneurial orientation and corporate performance. Therefore, it is assumed that "the dynamics of the entrepreneurial environment of small and medium-sized enterprises in Shanxi Province play a

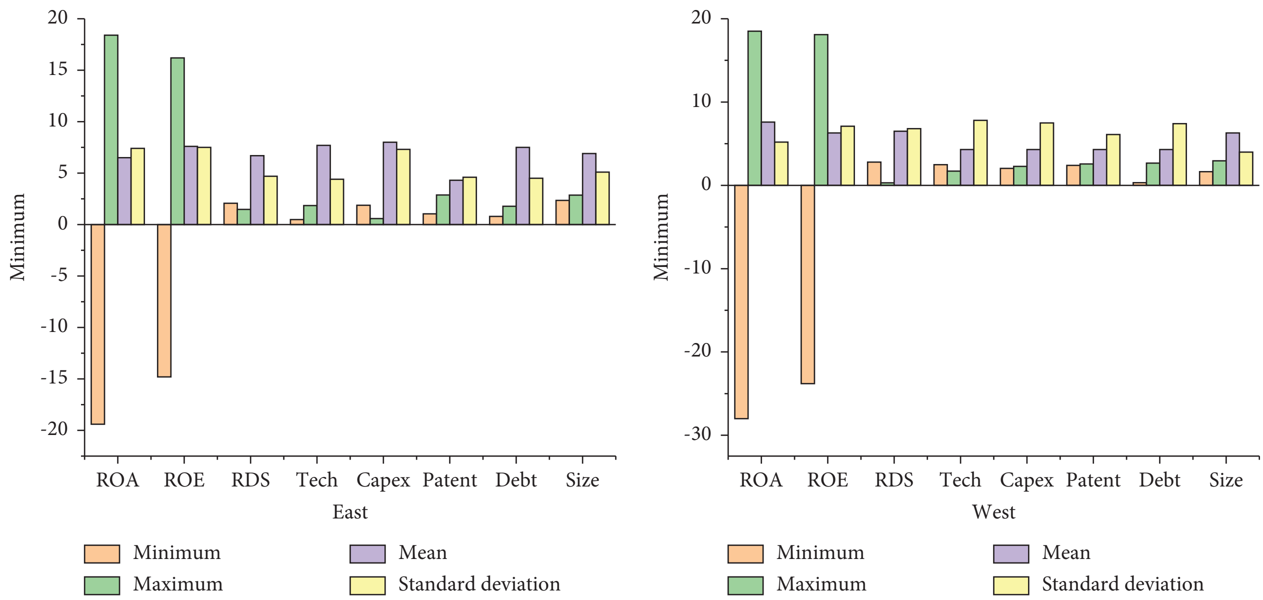


FIGURE 8: Descriptive statistics of samples from east and west regions.

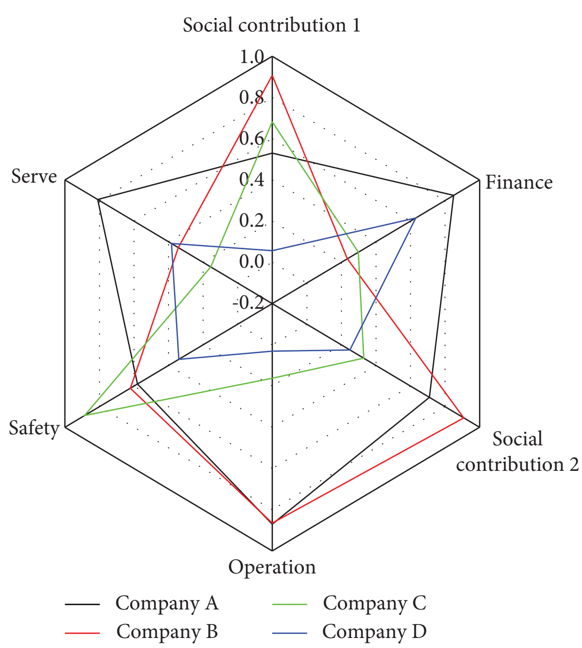


FIGURE 9: Performance factor radar chart.

moderate role in the relationship between entrepreneur-oriented risk-taking and corporate performance." The specific relationship table is shown in Table 4.

In summary, this survey mainly examines the relationship among the entrepreneurial environment, entrepreneurial orientation, and corporate performance of Shanxi SMEs. However, the unfounded research hypothesis reflects to a certain extent that a large part of the development of small- and medium-sized enterprises in Shanxi Province still relies on the power of the government. The government-led influence on the growth of enterprises is to a certain extent greater than the influence of the market on the growth of enterprises. This makes certain assumptions fail the verification, but the relationship among the three is basically verified.

This survey examines the impact of the entrepreneurial environment on corporate performance. It also confirmed that the hostility of the entrepreneurial environment of SMEs has a negative impact on corporate performance ($\beta = 0.167$, $P < 0.05$), and the dynamics of the entrepreneurial environment have a positive impact on corporate performance. This article uses Shanxi Province companies as an alternative sample to study the relationship between technological innovation and corporate performance. Therefore, the research conclusions have certain limitations.

## 5. Discussion

Based on previous theoretical research and empirical analysis, this paper summarizes the research conclusions on the relationship among entrepreneurial network relationships, technological innovation, and the performance of new ventures as well as research conclusions and the theoretical contributions of entrepreneurs, and proposes future research directions. This article will help entrepreneurs understand the specific role of interpersonal relationships in the performance of new startups and make better use of network resources. With the rapid development of China's economy, there are more and more business opportunities. With the improvement in social norms and legal systems, the benefits of interpersonal relationships do not appear as quickly or directly as before. However, entrepreneurs need to have some patience and pay attention to the impact that plays a role between network relationships and performance. Due to the characteristics of high risk, small scale, and strong innovation ability of entrepreneurial enterprises, the research results of this paper are only applicable to the

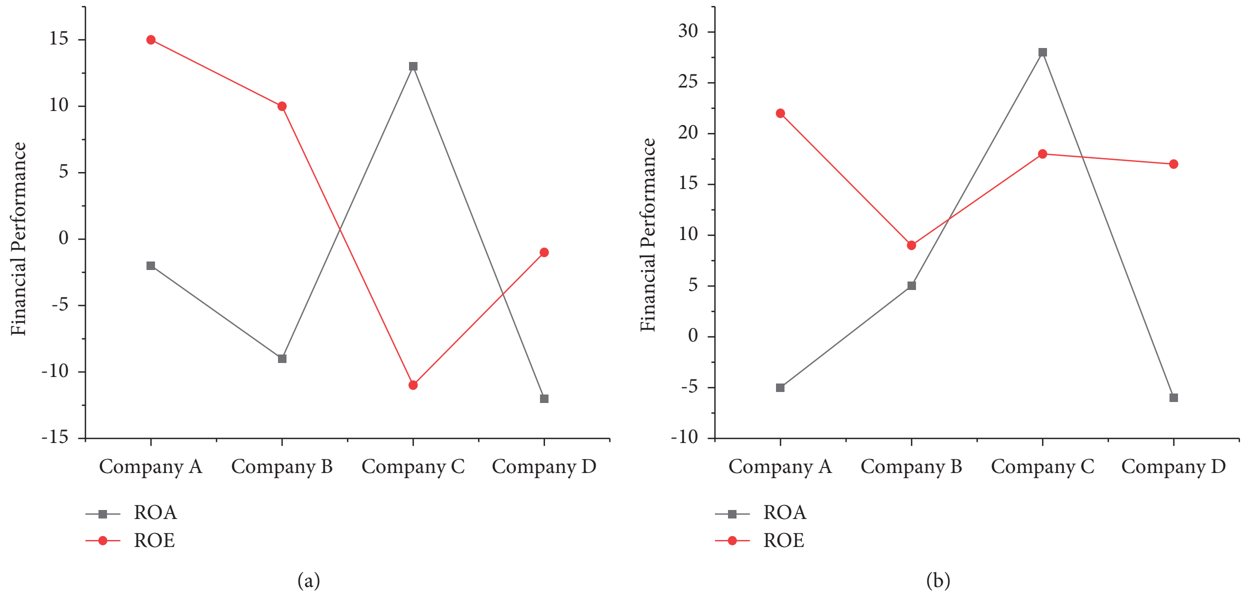


Figure 10: Changes in financial performance. (a) Change in financial performance prior to increased investment. (b) Change in financial performance following increased investment.

Table 4: The moderating effect of the entrepreneurial environment on the company's entrepreneurial orientation and corporate performance.

| Variable | Model 1 Business performance | | Model 2 Business performance | |
|---|---|---|---|---|
| | $\beta$ | $t$ | $\beta$ | $t$ |
| Independent variable | | | | |
| A: Entrepreneurial orientation | 0.117 | 6.258 | 0.621** | 8.169** |
| B: Dynamics of entrepreneurial environment | 0.220 | 0.440 | 0.738** | 3.285** |
| C: Entrepreneurship hostility | 0.023 | 0.079 | 0.866 | 0.124 |
| Interactive item | | | | |
| A × B | | | 0.167 | 2.698** |
| A × C | | | 0.832 | 0.630 |
| $R$ square | 0.545 | | 0.784 | |
| Adi. $R$ square | 0.031 | | 0.429 | |
| $F$ | 36.569 | | 22.647 | |
| $\triangle R$ square | 0.530 | | | |
| Partial $F$ | 12.983 | | | |
| $N$ | 99.786 | | | |

research of enterprises in this industry. This does not have general applicability, or can it explain the overall technological innovation status of Chinese enterprises taking into account the representativeness of the sample, the comprehensiveness and standardization of information disclosure, and the availability of relevant data.

## 6. Conclusions

This article is based on industry linkage theory, innovation theory, and core competitiveness theory. It also uses GEM-listed companies as samples to study the relationship between entrepreneurial innovation and corporate performance. It focuses on the research and development efforts and the impact of innovation investment on corporate performance. In addition, this article classified the entire sample by region and examined the relationship between innovation and corporate performance of sample companies in eastern Shanxi and central and western regions. Finally, in order to investigate the impact of corporate growth on the relationship between innovation and corporate performance, this paper also uses corporate growth as a slow-release variable to perform regression analysis.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The author declares that there are no conflicts of interest in this study.

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