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RESEARCH ON ENTREPRENEURIAL ABILITY OF EMERGING TECHNOLOGY ENTERPRISES

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ABSTRACT

Emerging technologies are receiving more and more attention from the business community and academia. At present, the research on the entrepreneurial capabilities of emerging technology enterprises is still insufficient. In particular, how to improve the entrepreneurial capabilities of such enterprises in China, there is still no specific research. Therefore, this topic takes the emerging technology enterprises in Anshan as the starting point to study the mechanism and path of the entrepreneurial ability improvement of emerging technology enterprises and provides practical and feasible countermeasures for Liaoning Province and even related enterprises in China.

KEYWORDS

Entrepreneurial ability, Emerging technology enterprises, Improvement.

1. INTRODUCTION

Emerging industries are industries with intensive knowledge and technology, low consumption of material resources, large growth potential, and comprehensive benefits based on major technological breakthroughs and development needs. They have a significant tie-making effect on social and economic development. There is no emerging industry without emerging technologies, and there is no innovation and entrepreneurial activity of emerging technology companies. Naturally, there is no transformation of emerging technologies into emerging industries.

Obviously, improving the entrepreneurial ability of emerging technology enterprises is an important way to accelerate the evolution of emerging technologies to emerging industries and promote the development of emerging technology industries. The existing literature on entrepreneurial competence mainly focuses on dimensioning, Opportunity perspective, Dynamic ability, Performance framework. The framework aspect of entrepreneurial skills needs and research based on the perspective of relationships. In summary, the literature has discussed how to improve the entrepreneurial ability of enterprises, and laid the foundation for the research of this topic [1-3].

However, the literature has rarely studied the entrepreneurial capabilities of emerging technology companies. In fact, as a special type of enterprise, emerging technology enterprises are generally in line with the general law of entrepreneurial ability. However, since the core of emerging technology companies is to carry out emerging technology innovations, the characteristics of emerging technologies themselves have made the entrepreneurial capabilities of emerging technology companies unique. Emerging technologies are science-based, and it is possible to create a new industry or transform an innovation in an existing industry. It is highly uncertain and complex, with a strong era, commercialization, and creative reinvention of the traditional technology industry. Emerging technologies are high-tech technologies that have recently emerged or are developing that can have a major impact on economic structure and industrial development. It has three elements : 1) The technology is being formed or developing 2) High technology rather than general technology 3) Can have an important impact on economic structure or industry development. The development of emerging technologies requires

enterprises to continuously develop new capabilities. This will definitely lead to the dynamic evolution of entrepreneurial capabilities [4].

2. RESEARCH OBJECTIVES

In theory, to explore the mechanism between the factors that affect the promotion of entrepreneurial ability of emerging technology enterprises, and on this basis, to build a path for the improvement of entrepreneurial ability of emerging technology enterprises; In practice, in view of the uniqueness of emerging technology enterprises, this topic constructs a special conceptual model based on this, and uses the emerging technology enterprise entrepreneurial ability to enhance the path theory model to ensure that the model is scientific and reasonable. It provides practical suggestions for improving the entrepreneurial ability of related enterprises in China.

3. RESEARCH VALUE

Theoretical value : ①Comprehensively use multi-disciplinary, multi-theoretical and multi-method research paths to comprehensively excavate and deeply analyze the growth rules and development characteristics of emerging technology enterprises in Anshan City, and strive to establish an emerging technology enterprise in Anshan City by combing the contents of the research of different enterprise theory schools. The analysis framework of the influencing factors of capacity improvement, and then analyze the internal mechanism of different factors on the entrepreneurial ability of emerging technology enterprises in Anshan City, so as to construct the theory of sustainable entrepreneurship of emerging technology enterprises, in order to guide and promote their sustainable growth. ②The problem of improving the entrepreneurial ability of emerging technology enterprises in Anshan City, through clarifying the influencing factors of the entrepreneurial ability of emerging technology enterprises in Anshan City, and exploring its improvement path, is conducive to clarifying the entrepreneurial ability of emerging technology enterprises in Anshan City, and helping to enrich the entrepreneurial management of emerging technology enterprises. Relevant theories realize the organic integration of entrepreneurial theory and enterprise management theory; clarify the key influence of market orientation, entrepreneurial learning and innovative methods on entrepreneurial ability, which is beneficial to fundamentally break through the bottleneck of entrepreneurial ability and enhance the entrepreneurial ability of

emerging technology enterprises in Anshan City The promotion provides a new path [5].

Practical value : How to support the emerging technology enterprises in Anshan City to get rid of the predicament of "short life and high mortality", promote their sound and rapid development and sustained growth, maintain stable and rapid growth of Anshan's economy, and realize the "Outline of the 13th Five-Year Plan" established goals have important strategic importance. Therefore, On the basis of trying to enrich the theoretical research on the entrepreneurial ability of emerging technology enterprises, this paper summarizes the entrepreneurial ability path and experience of emerging technology enterprises in Anshan City, aiming to provide realistic suggestions and method guidance for the formulation of Anshan macroeconomic policy and enterprise management. Furthermore, through empirical research, the factors of entrepreneurial ability of emerging technology enterprises in Anshan City are clarified, and the internal mechanism of different factors acting on the entrepreneurial ability of enterprises is revealed. It is beneficial to provide reference and reference for enterprises of the same type in Liaoning Province and even in China, so as to better to promote the healthy development of emerging technology companies [6,7].

4. THE MECHANISM OF UPGRADING THE ENTREPRENEURIAL ABILITY OF EMERGING TECHNOLOGY ENTERPRISES

This topic believes that the entrepreneurial ability of emerging technology enterprises is a very complex and multi-dimensional ambiguity concept. This topic defines entrepreneurial ability refers to the self-efficacy circle that successfully completes multiple tasks and assumes multiple roles in the process of entrepreneurship. The aforementioned research only focuses on one aspect of entrepreneurial ability. From the perspective of entrepreneurial process, it is not conducive to guiding entrepreneurial practice, especially for emerging technology companies with special, highly uncertain and complex technologies. Because the realization of entrepreneurial success requires multiple capabilities at the same time, this topic will re-construct the conceptual dimension of entrepreneurial competence from a more integrated perspective, pointing out that entrepreneurial competence should include two dimensions and 11 dimensions, namely related opportunity capabilities and related management capabilities. Two first-order dimensions, and 11 second-order dimensions such as relationship, learning, knowledge sharing, innovation, opportunity identification and development and management,

organization, coordination, risk management, strategy, and conceptual ability under the first-order dimension opportunity [8-10].

Emerging Technology Enterprise Entrepreneurship Path: Companies will anticipate the evolving needs of the market and respond with innovative products and services that will drive entrepreneurial learning and increase innovation through entrepreneurial learning, especially knowledge-intensive Innovations led by industry, individual and team learning have become the only source of sustained competitive advantage in the enterprise. Different market-oriented facets will drive different types of entrepreneurial learning. Different forms of entrepreneurial learning will inevitably lead to different forms of innovation. Different forms of innovation will evolve different entrepreneurial capabilities, and different entrepreneurial capabilities will lead to different corporate performance [11].

5. TYPICAL CASE STUDY

5.1 Data collection

Investigate 100 emerging technology companies in four areas including Taian County, Haicheng City, Xiuyan County and Anshan City in Anshan City to collect first-hand data. To ensure the universality of evidence in sample data, sample horizontal difference measures are required. This study refers to the measure of the difference in the level of entrepreneurship of emerging technology companies in different regions of Anshan City.

This survey conducted statistics on the collected questionnaires. This time, a total of 760 questionnaires were distributed, and the feedback rate of the returned questionnaires reached 698. In the questionnaires collected, 24 invalid questionnaires were selected without some choices or all questions were filled out. The final number of valid questionnaires was 674. The details are shown in Table 1:

Table 1: Questionnaire recovery

category	Issue questionnaire	Recycling questionnaire	valid questionnaire	Recovery rate	Efficient
Quantity	760	698	674	91.84	96.56

5.2 Analysis method

5.2.1 Descriptive statistical analysis

The basic characteristics analysis of the sample is to analyze and analyze the basic information of the sample enterprise (such as the size of the enterprise, the time of establishment, the industry, etc.), describe the distribution table of the mean, percentage, and frequency of each variable, and to analyze the characteristics and categories of the sample and the status of the proportional distribution. At the same time, the sample data should be descriptively counted, and the minimum, maximum, mean, standard deviation, skewness and kurtosis of each observed variable should be calculated by statistical software.

5.2.2 Trust level analysis

Reliability refers to the reliability of the measurement data results, that is, the consistency and stability of the measured values. Consistency mainly reflects the relationship between internal problems and whether the various topics verified have consistency or internal isomorphism. Stability refers to the repeated measurement of the same thing or human reliability factor at different points in time with a measurement tool. What faith does not mean is all or nothing, but a degree of problem. If the results are very close after repeated measurements in the test, it can be said that the reliability of the measurement results is the opposite. When the variation of the results of each measurement is large, the reliability is low.

The reliability analysis of this study uses *Cronbach'a* internal consistency

coefficient values to verify the reliability of each latent variable and its observed variables. The reliability of the latent variable is composed of the reliability of all its observed variables. When the general coefficient is greater than 0.7, the reliability of the data can be considered to be high. If it is lower than this limit, the set of indicators and variables will be deleted or modified. If the latent variable exhibits higher reliability, it indicates that the observed variable can test the latent variable.

Based on the internal consistency coefficient method for variable reliability analysis, the reliability coefficient of a single index can be evaluated by the total correlation coefficient CITC (Corrected Item---Total Correlation), where the CITC coefficient is required to be greater than 0.5, if the indicator If the value is less than its limit, it means that the indicator needs to be deleted or modified.

5.2.3 Exploratory factor analysis

Validity refers to correctness and validity. It refers to the closeness of the measured value measured by the measurement tool and the true value. If the validity of the measured value is higher, it indicates that the more the measured result indicates the true characteristic of the object to be measured. Validity is mainly divided into content validity and construction validity. Content validity is mainly used to reflect the extent to which the content of the scale fits the theme. If the measurement content covers all the research plans, it can be said to have good content validity. Content validity is mainly tested by expert evaluation method.

Construct validity is mainly used to test the fact that the scale truly measures the variables to be measured. It is mainly divided into two types: convergent validity and discriminate validity. For the determination of the construct validity, the factor analysis method is mainly used, and the factor load of 0.5 is usually used as the criterion. In the facet of the same factor, if the factor load of the item is larger, the more effective the convergence is. If the item is in a non-affiliated factor facet, the smaller the factor load is, the more discriminant the validity is.

5.2.4 Confirmatory factor analysis

The confirmatory factor analysis is used to test whether the factor structure model of the scale fits the actual collected data, and whether the indicator variable can be effectively used as a measurement variable for the factor construct. In the confirmatory factor analysis, the factor load, the reliability coefficient, the measurement error, the construction reliability, and the mean variance extraction (AVE) are usually used as criteria for whether the factor structure model of the test scale matches the actually collected data. The factor load and reliability coefficient are obtained by running AMOS 17.0 software, where the factor load is a standardized path coefficient, which is generally between 0.50 and 0.95. The larger the value, the more effective it is to reflect the traits to be measured. The reliability coefficient is the square of the multivariate correlation, which indicates the variation of the individual observed variables explained by their latent variables. If the value is higher than 0.5, the internal quality of the model is good. The measurement error is 1 minus the coefficient of confidence, the smaller the value, the better. The calculation formula for constructing reliability:

$$\rho_c = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum (\theta)}$$

Wherein the composite reliability factor; indicator variable for the standardized parameter estimate on the latent variables, namely factor loading; measurement error of observed variables. Generally, the construction reliability should be greater than 0.6, which means that the inherent quality of the model is ideal. The calculation formula of AVE:

$$\rho_v = \frac{(\sum \lambda^2)}{(\sum \lambda^2) + \sum (\theta)}$$

Wherein the average variation quantity extraction; indicator variable for the load factor on the latent variables; measurement error of observed variables. The average variance extraction can be used to directly show how much of the variance explained by the potential construct is from the measurement error. The larger the AVE, the larger the percentage of the variance that the indicator variable is explained by the latent variable construct, and the smaller the relative measurement error. The general criterion is that AVE is greater than 0.5, indicating that it is acceptable.

Since the measure of structural equation modeling has many different methods, according to the present study Wuming Long (2009) et al., Suggested that the development of the following test index: the ratio of the degree of freedom chi-square (χ^2/df), the root mean square error of approximation (the RMSEA), goodness of fit index (the GFI), and root mean square residual error (the RMR), standard fit index (NFI), the correction fit index (IFI) and relative fit index (CFI).

5.3 Structural equation model

5.3.1 Overview of structural equation modeling

Structural equation modeling is a very good statistical analysis method in social science research. This method was matured in the 1980s. The structural equation model develops rapidly and makes up for the shortcomings of traditional statistical methods. It can not only study observables, but also study latent variables that cannot be directly observed. It can not only study the direct effects between variables, but also study the indirect effects between variables. The graph visually shows the relationship between variables. Through the structural equation model, the researcher can construct the relationship between the latent variables and verify whether the structural relationship is reasonable. The structural equation model can study the relationship between latent variables by setting observation variables for latent variables that are difficult to measure directly and using the relationships between the observed variables that can be used for statistical analysis.

Therefore, the main advantages are: First, it can demonstrate driving force analysis at multiple levels. This display of causality is more in line with human thinking habits, which is what traditional regression analysis cannot do. The attributes are divided into multiple layers for analysis based on the degree of abstraction of the different attributes. Second, analysis can include attributes that cannot be directly measured, such as consumer loyalty. This will increase the scope of data analysis, especially for some of the more abstract inductive properties. Third, the analysis can quantify the causal relationship between attributes so that they can be compared at the same level, and the same model can be used to compare each market segment or competitor. Factor structure and factor relationships are also estimated. Let's take an example to see the difference between traditional statistical analysis and structural equation methods.

Suppose that in the new study, the same group of participants also considered the relationship between self-confidence and gregariousness, that is, a total of two confidence and extroversion, self-confidence and gregarious correlation coefficients were calculated. With traditional analytical methods, the structure and relationships within the original factors of the new study remain unchanged. That is to say, the relationship between the self-confidence problem and the self-confidence factor, the relationship between the extrovert topic and the extroversion factor is exactly the same as the original relationship. This means that the structure within each factor does not change due to the presence of other factors. However, in the structural equation analysis, the structure of the self-confidence factor will be adjusted and changed in consideration of other simultaneous variables.

That is to say, other coexisting factors and their structures in the same study will affect each other, affecting not only the relationship between factors, but also the relationship between the internal structure of the factor and the index. Structural Equation Modeling (SEM) is a more practical method in social science research. It can be applied to many research fields such as social sciences, economics and management. It can also calculate the relationship between multiple reasons and multiple results, and even calculate variables (latent variables) that cannot be directly measured. Traditional calculation methods such as multiple regression, covariance analysis, and factor analysis can be replaced by structural equation models, and can accurately analyze how much individual indicators play a role in the overall indicators, and predict the relationship between multiple individual indicators. The structural equation model is a method of constructing a model, estimating an indicator, and verifying the test result. The model contains both explicit variables that can be directly observed, and potential variables that cannot be directly observed. The widespread use of structural equation models in recent years avoids the problems that cannot be dealt with due to the limitations of traditional statistical methods. This method plays a very important role as a tool in multivariate data analysis.

5.3.2 Structure of structural equation model

The structural equation model consists of a measurement equation and a structural equation. The measurement equation is responsible for interpreting the relationship between the latent variable and the indicator variable, and the structural equation is responsible for explaining the interrelationship between the various latent variables.

The measurement equation is usually written in the form of a relationship between the indicator and the latent variable:

$$\begin{aligned}x &= \Lambda_x \xi + \delta \\y &= \Lambda_y \eta + \varepsilon\end{aligned}$$

Where x is a vector of exogenous indicators, y is a vector of endogenous indicators, ξ represents a vector of exogenous latent variables, η represents a vector of endogenous latent variables, and is an exogenous indicator on an exogenous latent variable. Factor load matrix, describing the relationship between exogenous indicators and exogenous latent variables, is the factor loading matrix of endogenous indicators on endogenous latent variables, describing the relationship between endogenous indicators and endogenous latent variables, is outside The error term of the source indicator x is the error term of the endogenous indicator. The structural model, which is the relationship between latent variables, is usually represented by the following structural equation:

$$\eta = B\eta + \Gamma\xi + \zeta$$

In the formula, it is an endogenous latent variable, which is an exogenous latent variable, B is the relationship between endogenous latent variables, and is the influence of exogenous latent variables on endogenous latent variables. It is the residual term of the structural equation and is used to reflect the part of the equation that could not be explained.

The measurement model consists of a latent variable and an observed variable (also called a measured variable). In terms of mathematical definition, a measured model is a linear function of a set of observed variables, which are sometimes referred to as latent variables. Explicit variables (Manifest variables are also called linear variables) or measured indicators (Measured indicators) or indicator variables. The so-called observation variable is the data obtained by measuring tools such as a scale or a questionnaire. The latent variable is the trait or abstract concept formed between the observed variables. This trait or abstract concept cannot be directly measured but is reflected by the data measured by the observed variable.

The measurement model analysis verifies the fitness of internal structure of model, which is mainly to evaluate the reliability and validity of the measurement index variable and the latent variable, and the significant level of the estimated parameter. The intrinsic quality of the model is tested, so the measurement model can verify the Convergent validity and Discriminant validity of the constructs of the various factors in the model. The so-called convergence validity means that the test indicators that measure the same potential traits (constructs) will fall on the same common factor, while the difference validity means that the test indicators that measure different potential traits (constructs) will fall on different common factors on. The structural model is the description of the causal relationship model between potential variables. Structural models can also be called causal models, latent variable models, or linear structural relationships.

The construction of the structural equation model of this project is divided into two stages: ①The measurement model is constructed according to the theoretical analysis and the questionnaire, and the data collected by the questionnaire is tested, that is, the confirmatory factor analysis. ②Firstly, construct a structural model based on theoretical analysis, and then combine the tested measurement model to construct a structural equation model and test it.

5.3.3 Analysis process of structural equation model

There are four main steps to establish and statistically analyze the structural equation model: 1) Construction of the model. Based on relevant theories and previous research results, the researchers construct theoretical models and analyze the relationship of variables according to the structural equation model. The construction of the model mainly includes: the relationship between the observed variable and the latent variable; observing the relationship between the latent variables; when the model is more complicated, the parameters such as the coefficient between the factor load and the factor can be restricted. 2) Estimation of the model. Different methods are used to estimate the model parameters, generalized least squares method, maximum likelihood method, unweighted least square method, and so on. At present, the maximum likelihood method is the most widely used parameter estimation method. 3) Evaluation of the model. When evaluating a newly constructed model, it is important to evaluate that the structural equation is not suitable, including whether the estimated values of each parameter are reasonable, whether the iterative estimation is convergent, etc.; whether the relationship between the parameters and the preset model is reasonable; The fitting between the data is evaluated, and the fitting index of the surrogate model is also compared. 4) Correction of the model. When the model does not fit well with the data, you need to correct or reset the model. You need to decide how to add, delete, and modify the parameters of the model. The degree of fit of the model can be enhanced by resetting the parameters. Taking into account the above factors, the structural equation model can analyze the problems raised by this project. ①The structural equation model can not only reflect the individual relationship between the various elements in the model, but also reflect the interaction between the elements. ②This project mainly uses the analysis to make good use of the multi-path analysis of the method to directly or indirectly affect the characteristics of the variables. The clear path can realize the understanding of the structural equation model, and can also avoid the error caused by the variable measurement error interference.

Structural equations can generally be analyzed with reference to five

major steps: model construction, model identification, model fitting analysis, model evaluation, and model correction.

First, the construction of the model. ①The model construction process includes: the relationship between observed variables and latent variables, that is, the relationship between indicators and factors; ②the relationship between each latent variable; ③ in a relatively complex structural model, several factor correlation coefficient values or several Factor load value and other parameters

Second, model recognition. The identification of the model plays an important role in the modeling process of structural equations. If the model itself is unrecognizable, the model cannot be estimated, and the structural equation model constructed is meaningless. But the model can be identified does not mean that the model being built is reasonable. A necessary and insufficient condition that the model can identify is that the number of parameters is less than the variance of the observed variables and the total number of covariances. What kind of structural equation model is a identifiable model? There is no conclusion about this problem, but if the model can be identified, at least the following conditions must be met: First, the total number of variances and covariances between observed variables should be greater than the number of free parameters; the latent variable needs to make some measure settings. For example, the variance of the latent variable can be set to a fixed value. If it is set to 1, it is a standardized setting. In addition, the factor load of a certain factor to the latent variable can be set. For a specific value, it is usually set to 1.

Third, the fit of the model. After the new model is constructed, it is necessary to find an estimate of the model parameters. This process is also the model fitting process. In the structural equation model analysis, the goal of the analysis is to find the parameters to minimize the "gap" between the covariance matrix and the sample covariance matrix that are not apparent in the model. Different methods are used to estimate the model parameters, generalized least squares method, maximum likelihood method, unweighted least square method, and so on. At present, the maximum likelihood method is the most widely used parameter estimation method.

Fourth, the evaluation of the model. When evaluating a model, the researcher needs to check: ① whether the solution of the structural equation is appropriate; ②whether the relationship between the preset model and the parameters is reasonable; ③and the fitting index of the entire model of different types, such as CFI, NNFI and RMSEA, etc.

Fifth, the revision of the model. The steps of model modification: ① based on relevant theoretical assumptions, propose one or more reasonable prior models; ② check the relationship between indicators and latent variables, construct a measurement model, and may recombine the topics according to actual needs or increase the deletion. ③ If the model contains many factors, you can check the model with fewer factors each time to determine the rationality of the small part, and then combine all the involved factors into the original designed test model; ④ To test the standard error, correction index and different types of fitting index, etc. Then modify the preset model and repeat step 3 and step 4; the final model is modified according to a certain sample data, preferably with other multiple independent the samples are used for mutual verification.

6. EMPIRICAL ANALYSIS

6.1 Description of sample data

6.1.1 Sample basic feature analysis

The number of valid questionnaires surveyed in this questionnaire was 674. For the measurement of the corresponding variables of each dimension of the project, in order to consider other factors that may have an impact, the data analysis is more comprehensive, reasonable and accurate, such as the age of the subjects, education, position, nature of the company, number of employees, main areas of technology, etc. Then descriptive statistical analysis of sample features by SPSS statistical software, the corresponding situation is as follows:

6.1.1.1 Questionnaire age

The age distribution of the participants in this questionnaire is detailed in Table 2:

Table 2: Descriptive statistical analysis of the age of the questionnaire (N=674)

age	frequency	percentage	Cumulative percentage
20-30 years old	54	8	8
31-40 years old	223	33.1	41.1
41-50 years old	328	48.7	89.8
Over 50 years old	69	10.2	100
total	674		

As can be seen from Table 5.1 above, the technology-based small and micro enterprise executives are mainly distributed between 31-50 years old. The proportion of people in this age group accounts for 81.7% of the total sample size, of which the proportion of 41-50 years old is 48.6%. The proportion of people aged 31-40 years old, accounting for 33.1% of the total; less than 50 years old, only 10.3% of the total; enterprises aged 20-

30 accounted for the least, accounting for only 8% of the total.

6.1.1.2 The educational background of the subjects

The education level of the participants in this questionnaire is detailed in Table 3:

Table 3: Descriptive statistical analysis of the education of the questionnaire participants (N=674)

Education	frequency	percentage	Cumulative percentage
Master degree and above	201	35.8	35.8
Bachelor	296	52.7	88.5
College	55	9.79	98.3
High school or secondary school	10	1.7	100
Junior high school and below	0	0	100
total	674	100	

From the perspective of the degree of education received by the respondents, most of the entrepreneurs engaged in high-tech have a good educational background, with 35.8% of the master's degree or above, and more than half of the undergraduate degree questionnaires. 52.7%; undergraduate education accounting for 11.49%. Through statistical analysis, it can be concluded that technology-based small and micro enterprises are technology-intensive enterprises, and business leaders often have certain professional and technical backgrounds, and the overall

education level is relatively high, which indicates that the new technology is a high-end talent innovative business.

6.1.1.3 The position of the questionnaire applicant

This survey fills out the questionnaire for the chairman, general manager and senior managers of the new technology-based enterprises. For details, see Table 4:

Table 4: Descriptive statistical analysis of the position of the questionnaire

Position	frequency	percentage	Cumulative percentage
Chairman	93	16.5	16.5
General manager	117	20.8	37.3
Technicians and core backbone	64	11.4	48.7
Senior management	288	51.3	100
total	674	100	

As can be seen from Table 5 above, the subjects were in the top management ranks, accounting for 51.3%; the subjects were 16.5% of the chairman; the candidates were 20.8%; the subjects were the proportion of scientific and technical personnel and core backbone is very small, accounting for 11.4%. The above personnel are in line with the scope of this research, and the subjects have certain cognitive ability to the basic operations of the company.

6.1.1.4 Nature of the company

The scope of this survey is aimed at technology-based small and micro enterprises. For the nature of their own enterprises, see Table 5.4:

Table 5: Descriptive statistical analysis of the nature of the enterprise

Nature of business	frequency	percentage	Cumulative percentage
State-owned or state-owned	129	23	23
Sino-foreign joint venture	103	18.3	41.3
Foreign-owned	48	8.5	49.8
Collective ownership	35	6.2	56
Private (private)	234	41.6	97.6
other	13	2.4	100
total	674	100	

It can be seen that the state-owned or state-controlled enterprises of this questionnaire feedback accounted for 23%; followed by Sino-foreign joint ventures with 18.3%; private (private) enterprises accounted for 41.6%; and foreign-owned enterprises were 8.5%; collectively owned enterprises were 6.2%.

6.1.1.5 Enterprise main business technology field

The 110 companies in this survey are distributed in the main business technology areas. For details, see Table 6:

Table 6: Descriptive statistical analysis of the technical field of the main business of the enterprise (N=674)

Main business technology field	frequency	percentage	Cumulative percentage
Electronics and information	103	18.5	18.5
Biology and medicine	131	23.4	41.9
new material	84	15	56.9
New energy and energy efficiency	83	14.8	71.7
High-tech service	71	12.7	84.4
Aviation and aerospace	52	9.4	93.8
Earth, space, ocean engineering	30	5.1	98.9
other	8	1.1	100
total	674	100	

In this survey, the main business of the sample enterprises in the technical field of biology and medicine is relatively large, accounting for 23.4%; electronics and information second, accounting for 18.5%, new materials accounted for 15%; new energy and energy efficiency ratio 14.8%, the technical service industry accounted for 12.7%, aviation and aerospace accounted for 9.4%, and earth, space and ocean engineering accounted for 5.1%.

6.1.1.6 Years of establishment of the company

The survey is a small-scale technology-based enterprise, so the establishment time of the company is relatively short. The project is divided into five time periods, as shown in Table 7:

Table 7: Descriptive statistical analysis of the establishment period of the enterprise

Year of establishment	frequency	percentage	Cumulative percentage
Less than 1 year	22	3.9	3.9
Within 1-3 years	114	20.3	24.2
Within 3-5 years	183	32.6	56.8
Within 5-8 years	142	25.2	82
8-10 years	101	18	100
	674	100	

6.2 Descriptive statistical analysis

By analyzing the minimum, maximum, mean, standard deviation, skewness and kurtosis of each observed variable, the project can grasp the quality and attributes of the data as a whole, and clarify the responses of each measurement indicator in the questionnaire. The degree of difference, so as to better grasp the information contained in the data. The average number of observed variables can be used to explain the degree of consent of the respondents to each indicator. The standard deviation can be used to explain whether all respondents have similar knowledge of the problem, and the smaller the standard deviation, the more investigated. The views of the people tend to be more consistent. This project uses the maximum likelihood method for parameter estimation. The premise of using this method is that the variables obey the multivariate normal distribution. Therefore, it is necessary to perform a

normality test on the observed indicators before conducting the demonstration. In general, when the skewness coefficient and the kurtosis coefficient are 0, it has good normality. Some scholars believe that the skewness and kurtosis coefficient are not 0, but the absolute value is not greater than 1, it can be approximated as obeying the normal distribution, otherwise it will affect the estimation result. This project considers that in practical applications, the value of the skewness coefficient is less than 3 and the value of the kurtosis coefficient is less than 8, which can be approximated as a normal distribution. It can be seen from Table 5.7 that the absolute values of the skewness and kurtosis of the data of this project are less than 1.0, so such sample data basically obeys the normal distribution. In the research model of this project, the average values of the 10 variables are all between 4.78 and 5.92, indicating that the respondents' evaluation of these indicators is at the upper-middle level. As shown in Table 8.

Table 8: Descriptive analysis

Descriptive statistics								
variable	N	Minimum value	maximum	Mean	Standard deviation	variance	Skewness	Kurtosis
A1	674	3	7	5.58	1.036	1.073	-.456	-.284
A2	674	3	7	5.62	.913	.833	-.271	-.403
A3	674	3	7	5.46	1.035	1.072	-.296	-.457
B1	674	3	7	5.66	1.113	1.239	-.697	-.168
B2	674	3	7	5.42	1.092	1.192	-.330	-.604
B3	674	3	7	5.21	1.035	1.072	-.209	-.657
B4	674	3	7	5.19	1.104	1.219	-.337	-.449
B5	674	3	7	5.14	.970	.941	-.315	-.341
B6	674	3	7	5.11	1.086	1.179	-.490	-.592
B7	674	3	7	4.85	1.036	1.073	-.227	-.900
Valid N(list state)	674							

6.3 Reliability and validity analysis

6.3.1 Reliability analysis

The Cronbach parameters for each latent variable are calculated by SPSS 17.0, as shown in Table 9. The overall value is 0.960, indicating that the

reliability of the survey data is very good. The Cronbach's coefficients of the study variables of the project were 0.845 and 0.938, respectively, which were above 0.7, indicating that the stability and consistency of the questionnaire were high. It can be seen that the collected questionnaire data can meet the research requirements.

Table 9: Reliability Analysis Data

variable	Partial scale Cronbach's Alpha value	Overall scale Cronbach's Alpha value	Item	Corrected item total relevance	Item deleted Cronbach's Alpha
Business learning	0.867	0.962	A1	.596	.962
			A2	.638	.961
			A3	.582	.962
Entrepreneurship	0.942		B1	.694	.961
			B2	.714	.961
			B3	.732	.961
			B4	.772	.960
			B5	.741	.961
			B6	.798	.960
			B7	.653	.961

6.3.2 Validity analysis

The validity of the questionnaire is generally measured by factor analysis. This project analyzes the validity of the questionnaire through exploratory factor analysis and confirmatory factor analysis. In the pre-test of the scale or questionnaire preparation, the exploratory factor analysis will be carried out first, and the trial will continue to try to establish the optimal factor structure of the scale to establish the construct validity of the questionnaire. In the pre-test of the scale or questionnaire preparation, the exploratory factor analysis will be carried out first, and the best attempt will be made. The SPSS17.0 software of this project divided the 674 questionnaires into 210 and 464 for exploratory factor analysis and confirmatory factor analysis. First, before performing factor analysis, it is necessary to test whether the obtained data is suitable for factor analysis, and generally by KMO and Bartlett sphericity test. KMO is a sampling suitability measure of Kaiser-Meyer-Olkin. When KMO is larger, the more

common factors between variables, the more suitable for factor analysis. When $KMO \geq 0.90$, it is very suitable for factor analysis; $0.8 \leq KMO < 0.9$ indicates that it is suitable for factor analysis; $0.7 \leq KMO < 0.8$ indicates that factor analysis is still possible; $0.5 \leq KMO < 0.7$ indicates that factor analysis is barely performed; $KMO < 0.5$ Indicates that it is not suitable for factor analysis. The data of this project is obtained by running SPSS17.0, and the KMO value is 0.943, which is greater than 0.90, which indicates that the data is very suitable for factor analysis. At the same time, the Bartlett sphericity test can also be used to test whether the correlation coefficient matrix is suitable for factor analysis. When the statistic of the Bartlett spheroid test is less than 0.001, the correlation matrix representing the parent group has a common factor, which is suitable for factor analysis. According to SPSS 17.0, the statistical significance of the Bartlett sphericity test is 0.000, less than 0.001, indicating that the data is suitable for factor analysis.

Exploratory Factor Analysis (EFA) generally uses exploratory factor analysis to measure the construct validity of the questionnaire. From the data sampled by the randomly sampled respondents, statistical analysis is performed to construct the factor level, which is intended to explain

The largest total variation at the least level under the condition that the common factor is not limited, two factors are extracted. The cumulative explanatory variation of the two factors is 72.732%, which satisfies the condition of more than 60%. When the factor is extracted, the element

with the characteristic value greater than 1 is retained.

The rotated component matrix is shown in Table 10. The factor scores of each item are greater than 0.4, indicating that each factor extracted has the commonality of the items, that is, the observed variables of each latent variable better represent the commonality of latent variables.

Table 10: Component matrix after rotation

Rotation component matrix a		
	Ingredients	
	1	2
A1	.116	.199
A2	.117	.156
A3	.133	.110
B1	.739	.105
B2	.675	.156
B3	.746	.241
B4	.782	.275
B5	.728	.243
B6	.791	.241
B7	.662	.176

Confirmatory Factor Analysis (CFA) after the above exploratory factor analysis, the scale is composed of two different levels of factors. In order to confirm whether the factors included in the scale are the same as the original construct, the remaining 464 is needed. The samples were used

for confirmatory factor analysis to test whether the factor structure model of the scale fits the actual collected data, and whether the indicator variable can be effectively used as a measurement variable for the factor construct, as shown in Table 11.

Table 11: Confirmatory Factor Analysis

Potential variable	Measuring variable	Factor load	Reliability coefficient	Measurement error	Combination reliability	Average variance extraction
Business learning	A1	0.851	0.701	0.299	0.8654	0.6819
	A2	0.844	0.724	0.276		
	A3	0.818	0.712	0.288		
Entrepreneurship	B1	0.829	0.687	0.313	0.9466	0.7175
	B2	0.807	0.651	0.349		
	B3	0.855	0.731	0.269		
	B4	0.889	0.790	0.210		
	B5	0.859	0.738	0.262		
	B6	0.918	0.843	0.157		
	B7	0.763	0.582	0.418		

Table 12: Measurement indicators for each variable measurement model

Factor name	Measurement model	χ^2/Df	GFI	RMR	RMSEA	NFI	RFI	IFI	CFI
Entrepreneurship	Verification model	1.992	0.983	0.015	0.046	0.99	0.985	0.995	0.995
Business learning	Verification model	When there are only 3 measurement indicators for each concept, AMOS 17.0 cannot display the goodness of fit of the measurement model, and the validity can be judged by the factor load factor.							

As can be seen from Table 12, the confirmatory factor analysis value of the variable is less than 3, indicating that the confirmatory factor analysis can be performed on the variable. Other indicators such as RMSEA, GFI, AGFI, NFI, IFI and CFI values have reached the CFA adaptation criteria, so the fitting indicators of each variable have reached the goodness of fit.

7. THE EMPIRICAL RESULTS

It can be seen from the results of the fitting test that entrepreneurial learning has an impact on entrepreneurial ability. At the same time, entrepreneurial learning has a positive and significant impact on entrepreneurial ability. It can be seen from the above analysis that the

higher the entrepreneurial learning ability, the stronger the entrepreneurial ability, that is, the enterprise can consolidate and enhance the entrepreneurial ability of the small and micro enterprises of Anshan Technology by adopting appropriate entrepreneurial learning and enhance the enterprise by enhancing the entrepreneurial ability.

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