Journal of Intelligent & Fuzzy Systems xx (20xx) x–xx
DOI:10.3233/JIFS-179061
IOS Press

Data mining-based competency model of innovation and entrepreneurship

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Abstract. Data mining technology is a complex process of extracting or mining people's interest from a large number of data. After more than 20 years of development, the research of data mining has made remarkable progress and has been applied to many fields. The process of entrepreneurship is not an individual entrepreneurial activity. It needs all kinds of resources and opportunities in the process of entrepreneurship. Combining with data mining technology, this paper constructs a competency model of innovative entrepreneurship team, regards entrepreneurship orientation as a critical dimension of entrepreneurial team competence, and adopts descriptive statistical analysis, regression analysis, and structural analysis. Cheng examines the factors that influence entrepreneurial performance. The study found that the eight dimensions of entrepreneurial team competency structure have a positive impact on entrepreneurial performance. Different entrepreneurial environments (dynamic, competitive, heterogeneous) and organizational factors (enterprise size, entrepreneurial spirit, and industry type) play different roles in regulating the relationship between entrepreneurial team competence and entrepreneurial performance. Controlling variables of entrepreneurial orientation and leadership behavior also have significant effects on entrepreneurial performance.

Keywords: Data mining technology, entrepreneurial team, competency model

1. Introduction

Today's society is a people-oriented society. Its hallmark is to make everyone's autonomy, creativity and potential wholly profound [1]. To entirely put these characteristics to good use, it must be closely connected with entrepreneurship. The value of entrepreneurship is that it gives individuals the opportunity to exert these characteristics [2]. With the development of the market, the renewal of technology, the diversification of products, and the diversification of lifestyles, many companies are undergoing tremendous changes. As new companies continue to join in the trend, entrepreneurship has become an essential way for human economic and social life [3]. In such a pioneering environment, enterprises must rationally use and allocate their disposable resources according to the surrounding environment to make their business successful [4]. Therefore, the process of starting a business is not an individual's entrepreneurial activity. It requires a variety of resources and opportunities in the process of entrepreneurship. It is difficult to satisfy these conditions by individual entrepreneurship alone [5].

The entrepreneurial company is the goal of this study. This paper constructs a competency model of innovative entrepreneurial team based on data mining technology. Entrepreneurial orientation is regarded as a critical dimension of entrepreneurial team competence. Descriptive statistical analysis, regression

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analysis, and structural equation are used to test the Factors Affecting Entrepreneurial performance. □

Through validation, it is found that the impact of entrepreneurial orientation on entrepreneurial performance is not the most important. Before this factor, there is the ability to promise, learn and cooperate. The results of this study can help entrepreneurial team members understand the impact of team competency on entrepreneurial performance. This paper is divided into five parts. In the first part, the background and significance of this paper are introduced. In the second part, the previous literature is reviewed, which lays a theoretical foundation for the writing of this article. In the third part, the research methods are discussed, including data mining algorithms and multi-dimensional association algorithms. In the fourth part, the above algorithm is verified, and the evaluation result is obtained. The full text is summarized in the fifth part.

2. State of the art

Before the entrepreneurial team competence was not put forward, competency research mainly revolved around research on individual competency. A small number of related studies focused on organizational competency, and some scholars studied entrepreneurial competency. Both the entrepreneurial skill and the organizational competency provide the basis for the research on entrepreneurial team competence [6]. In the process of entrepreneurship, two or more people are usually required to be involved in. Strictly speaking, entrepreneurial activities should all exist in the form of teams. Therefore, the main contribution to the competency of entrepreneurial organizations is the entrepreneurial team competency [7]. Some scholars in China have begun to study the competency of entrepreneurial teams, but they are still at the stage of theoretical research. Scholars believe that the skill of the entrepreneurial team is first and foremost a kind of ability, and it is the essential ability to maintain the normal operation of the entire entrepreneurial activity; secondly, it is a system that integrates entrepreneurs, entrepreneurial resources and entrepreneurial teams. What's more, it is a kind of strategic view. It expands the field of competition and raises competition to confront the overall strength of the entrepreneurial team. Therefore, to be successful, the entrepreneurial team must have competence resources with competitive advantages and be good at increasing entrepreneurial performance with the help of a reasonable competence structure [8].

3. Methodology

3.1. Data mining algorithm

Let A and B be the attribute values sets of the attributes A_i and A_j, respectively. These two attributes can produce $p * R$' item pairs. Firstly, let the following theorem be true. Theorem: For any $u_k \in V_i$, it forms a pair of q items with the consisting elements in Vj, denoted by $(u_k v_1)(u_k v_2), ..., (u_k v_q)$, where $(u_k v_q)$ is satisfied with $\sup(u_k v_1) \geq \frac{\sup(u_k)}{q}$. Proof: Since $\sup(u_k) = \sup(u_k v_1) + \sup(u_k v_2) + ... + \sup(u_k v_q)$ is true so that anti-evidence method can be adopted.

Proof: Since $\sup(u_k) = \sup(u_k v_1) + \sup(u_k v_2) + ... + \sup(u_k v_q)$ is true so that anti-evidence method can be utilized. If the values in C are sorted according to the order of large and small amounts, the largest k in C is set as Ck,there should be at least k items in the collection of project pairs that are not less than Ck when θ is set as Ck.

$$|C| = \sum_{i=1}^{m} p_i * (m - i) \tag{1}$$

Proof: The conclusion (1) can naturally be derived from the theorem. The verification process for Conclusion (2) is as follows. For the set C, the i-th attribute is given p, *(m i) elements. All the attributes are accumulated, and the conclusion (2) is obtained. The theorem has been proved theoretically. In the excavation of Top-K strongly correlated item pairs, as long as θ is set as Cx, it can be ensured that there are at least K item pairs in the obtained result. Besides, in practical applications, the value of K is generally relatively small, as in the (100, 500) interval. Because the range of the result set will increase as the value of K increases, if the value of K is too significant, there is no point in researching the mining of Top-K strong related items. Due to most of the mining data is high dimensional data in practical applications, (the value of m is tremendous), dozens of attributes are very common, and even hundreds or even thousands of attributes' relationship table need to be handled. Therefore, the corresponding $|C| = \sum_{i=1}^{m} p_i * (m - i)$ ould be a more significant value, and the validity of the method is guaranteed, that is to say, Ck can be obtained.

The top-k strong correlation project pair mining algorithm based on threshold estimation. In the second step, since the θ calculated by the algorithm based on threshold estimation must be greater than 0, the resulting set must be relatively small. From this, it can be seen that its execution efficiency is higher than what can be directly achieved with the Taper R method. Also, at the beginning of a threshold based estimation algorithm, an additional limit must be estimated, which also increases the computational cost [9]. However, effective pruning at the completion of the threshold estimation has greater efficiency gains. Therefore, in general, the first step can achieve higher efficiency than directly using the TaperR method in the implementation efficiency [10]. Based on the above analysis, the algorithm used the Top-K robust correlation project mining algorithm estimated by the threshold is efficiently and it can quickly and effectively obtain mining results. This is also confirmed in the following experiments. Experiments are used to verify the algorithm [11]. The comparison between the algorithm proposed in this paper and the mining of the algorithm directly using TaperR is compared in the running time, and then the verification of the mining algorithm nature based on the Top-K strong correlation project estimation is performed. Experimental results show that the algorithm based on threshold estimation is effective and superior to other algorithms.

The two algorithms given above are based on the Java language programming. Besides, the hardware environment is similar to the environment described above, but the configuration is changed to WindowsXP Professional PC with 42.8 G, 512 M running memory. In the experiment, the two datasets previously used are still addressed: the mushroom dataset and the soybean dataset, which would not be repeated here [12].

The first experiment is to compare the running time of the two algorithms. In the case of the method based on the TaperR algorithm and the proposed algorithm with the increasing number of K, the comparison of running time between the Mushroom Dataset and the Soybean Dataset are given. The running time of the two algorithms increases with the number of K. However, at any time, the running time of the proposed algorithm is much smaller than the method based on the TaperR algorithm [13]. Therefore, it can be seen that the algorithm proposed in this paper is very efficient. Based on the estimation ability of the threshold estimation algorithm, the relationship between the estimated threshold value of the algorithm and the actual optimal threshold value, that is, the ratio of the optimal threshold value and the determined threshold value can be used to verify. From the comparison between the Mushroom dataset and the Soybean dataset, it can be seen that the ratio of the estimated threshold to the optimal threshold increases with increasing K number. Although the expected effect is not very good, it is closer to the actual value. Therefore, it can be concluded that the algorithm proposed in this paper is sufficient [14]. The algorithm based on threshold estimation has a good effect on the strongest Top-K related items pairs in the relational database and can be well extended to the actual relational database system.

3.2. Multidimensional association algorithm

A two-dimensional structured database D includes a set of triplets $elemnt =< ID, data_m, data_n >$, where ID is the identifier and $data_j$, $j = \{m, n\}$ is the structured data of an attribute Attributej, such as a tree or a graph. The symbol PTN_j, $j = \{m, n\}$ is used to indicate a type of pattern to be extracted in the attribute Attribute. There may be several classes that will be removed in a structured database. For example, if mining from a graphical database, not only the graphics mode will be extracted, but also the route or tree mode will be extracted. Besides, it is necessary to determine which containment relationships should be used, such as export subgraphs and embedded subgraphs. Therefore, the pattern type to be extracted needs to be specified in advance. Assumed that PTN defines a general ordering that satisfies the following conditions: For two modes $A, B \in PTN_j$, if A is more general than B, then $A \prec= B$, then for any p, $B \prec= p \rightarrow A \prec= p$ is true. Supposed that a two-dimensional structured database D and a pair of modes $(ptn_m, pt_n) \in \mathrm{PTN}_m \times \mathrm{PTN}_n$ have a joint support degree of $\sup p(ptn_m, ptn_n)$, and (ptn_m, ptn_n) has a correlation coefficient of $\phi(ptn_m, ptn_n)$ in D. The definitions are as follows:

$$\sup\ p(ptn_m, ptn_n) = \frac{|\{\langle ID, data_m, data_n\rangle \in D | ptn_m \prec= data_m|, ptn_n \prec= data_n\}|}{|D|} \tag{2}$$

$$\phi(ptn_m, ptn_n) = \frac{\sup p(ptn_m, ptn_n) - \sup p(ptn_m, ptn_n)}{\sqrt{\sup p(ptn_m) \sup p(ptn_n)(1 - supp(ptn_m))(1 - \sup p(ptn_n))}} \tag{3}$$

In the formula:

$$\sup\ p(ptn_j) = \frac{|\{\langle ID, data_m, data_n\rangle \in D | ptn_m \prec= data_m\}|}{|D|} \quad (4)$$

Assumed that the two user-defined thresholds are $\sigma(1/|D| \leq \sigma \leq 1)$ and $\theta(0 < \theta \leq 1)$. If $\sup\ p(ptn_m, ptn_n) \geq \sigma$ is true, it is considered that the pattern pairs (ptn_m, ptn_n) in D is frequent. If $\phi(ptn_m, ptn_n) \geq \theta$ is true, it means that (ptn_m, ptn_n) is related — worthy mention that only positive correlations were focused on here. □

According to the definition, if the pattern pair (ptn_m, ptn_n) is true, then (ptn^*_m, ptn^*_n) may be redundant.

For arbitrary

$$(ptn^*_m, ptn^*_n) \in S_m(ptn_m) \times S_n(ptn_n) \quad (5)$$

$$[\sup p(ptn_m, ptn_n) = \sup p(ptn^*_m, ptn^*_n) \wedge \varphi(ptn_m, ptn_n) = \varphi(ptn^*_m, ptn^*_n)) \quad (6)$$

Where,

$$S_j(A) = \{B \in PTN_j | \forall \langle ID, data_m, data_n\rangle \in D[A \prec= data_j \leftrightarrow B = data_j]\} \quad (7)$$

To reduce the generation of redundant mode pairs, the Meta pairs in the mode pair are limited to the closed mode. That is, about the maximal mode of general ordering, there is a set of ways with the same support value in database D. A set of frequent closed patterns in Attribute is denoted as $F_j = \{A \in PTN_j | \sup p(A) \geq \sigma\}$ and A is closed. Based on the above theory, the data mining problem is formally defined. Assumed that in a two-dimensional structured database D, the extracted model class is PTN_j, $j = \{m, n\}$, the minimum support value is $\sigma(1/|D| \leq \sigma \leq 1)$, and the minimum correlation value is $\theta(0 < \theta \leq 1)$. So the problem of "mining the frequent association pattern pair (MFA)" is to find all the closed pattern pairs of $(ptn_m, ptn_n) \in F_m \times F_n$ in database D. In this way, (ptn_m, ptn_n) is frequently associated.

The main task of this paper focuses on solving two difficulties in this problem is (1) determining the minimum support value; (2) mining frequent association pattern pairs. Firstly, an efficient mining algorithm [21–26] for top-k strong association project pair is proposed [15]. The algorithm essentially used the technique based on correlation graph matrix to capture the support frequency of all 1- and 2-member item sets then used those support frequencies to calculate the correlation coefficient of all the project pairs, and finally extracted the strongest associated k project pairs. The algorithm can generate top-k strong association items by scanning the database once [16]. The simplified logic structure implements the technology more attractive. Another advantage of this algorithm is that it also supports interactive mining. Experiments show that this algorithm is faster than the Tkcp algorithm and TAPER algorithm [17]. At the same time, a Top-K strong correlation project mining algorithm is proposed based on threshold estimation, which can effectively solve this problem. The algorithm converted the mining problem of the minimum correlation threshold B into the mining problem of the Top-K strong correlation project pair, that is, sought K project pairs with the largest Pearson coefficient. A large number of experimental results show that the new method is useful, not only approaching the actual value at the threshold but also effectively reducing the mining execution time [18].

4. Result analysis and discussion

4.1. Comparison of mining execution time of different algorithms

This section experiments are used to verify the algorithm and compare the proposed algorithm with the TaperR algorithm at operation time. Then, the verification of the nature of the Top-K strong correlation project pairs mining algorithm is made based on threshold estimation. Experimental results show that the algorithm based on threshold estimation is effective and superior to other algorithms [19]. The two algorithms given above are based on the Java language for programming. Besides, the hardware environment is similar to the environment described above, but the configuration is changed to WindowsXP Professional PC with 42.8 G, 512 M running memory. In this experiment, the two datasets previously used are still addressed: the mushroom dataset and the soybean dataset, which would not be repeated here. The first experiment is to compare the running time of the two algorithms. The figure shows the comparison between the Mushroom Dataset and the Soybean Dataset at the running time, based on the TaperR algorithm and the proposed algorithm in the case of an increase in the number of K. Obviously, the running time of the two algorithms increases with the number of K. However, at any time, the running

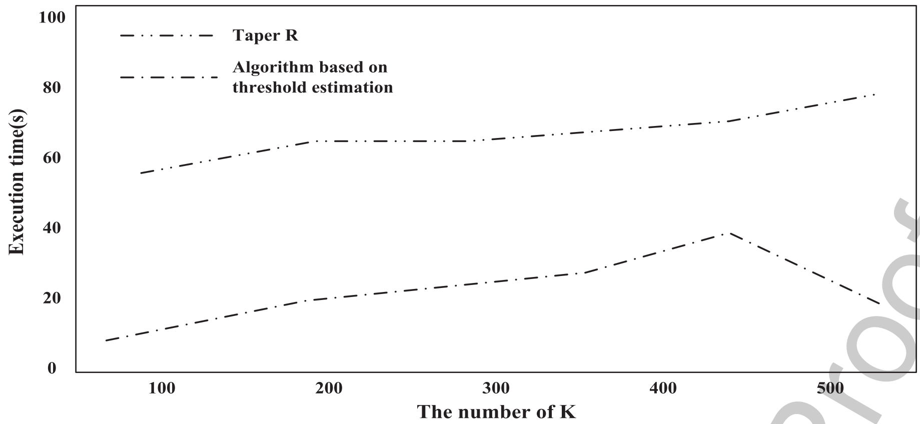

Fig. 1. Comparison of execution duration in the mushroom dataset.

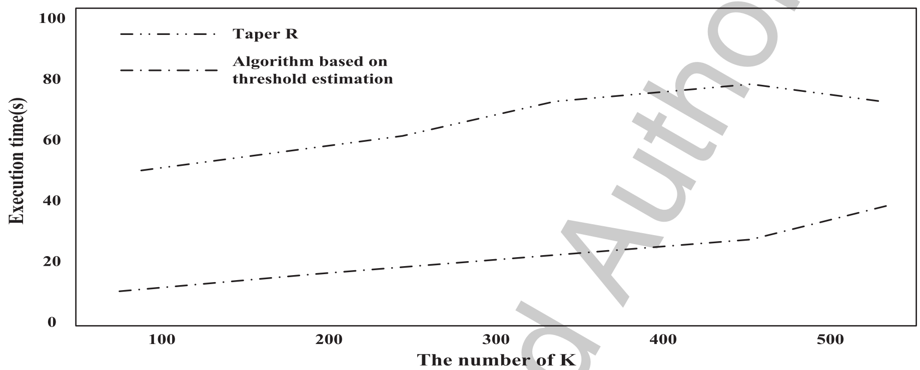

Fig. 2. Comparison of execution duration in soybean dataset.

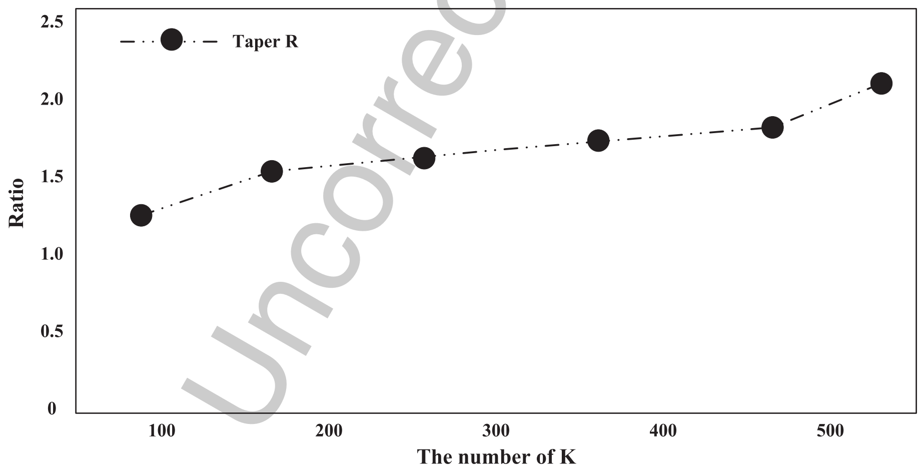

Fig. 3. The ratio between the optimal threshold and estimated threshold in the mushroom dataset.

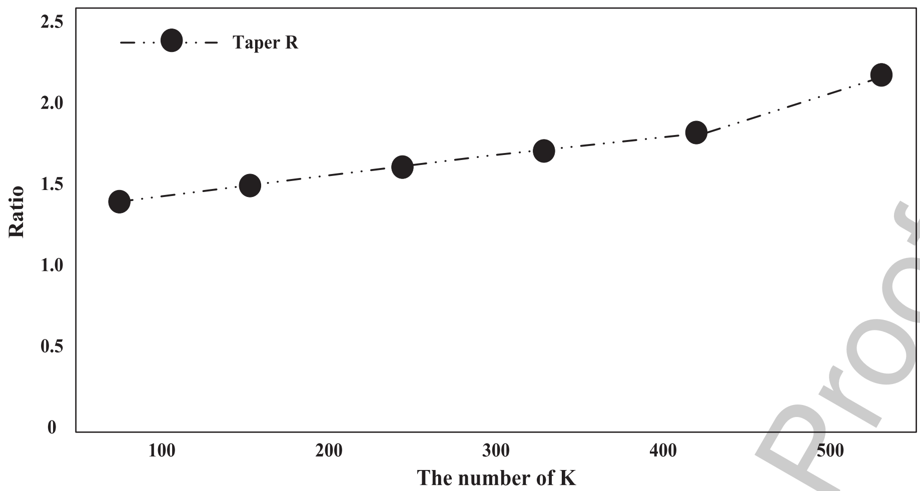

Fig. 4. The ratio between the optimal threshold and estimated threshold in soybean dataset.

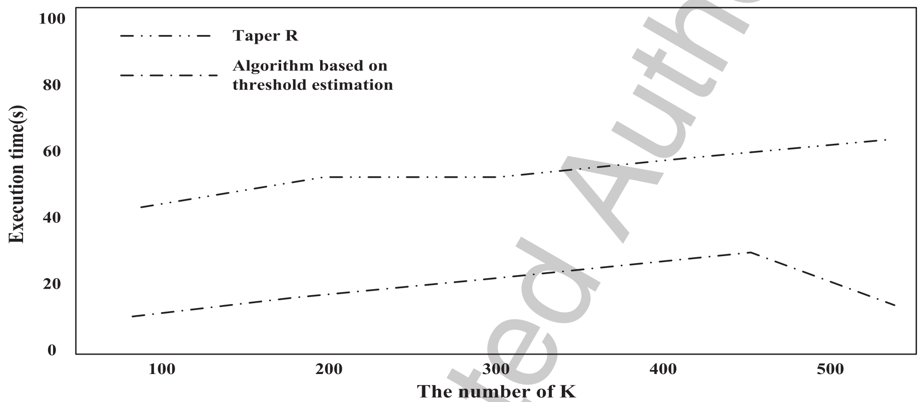

Fig. 5. Comparison of execution duration in the mushroom dataset.

Table 1
Effects of entrepreneurial team competency dimensions on Entrepreneurial Performance

Model	B	Standard error	*T* value	R^2	Adj.R^2	*F* value
(Constant)	2.734	0.21	13.092**	0.45	0.42	42.61**
Entrepreneurial strategy	0.14	0.03	4.13**			
Transformational leadership	0.16	0.03	5.02**			
Paternalistic leadership	0.13	0.06	2.36*			
Opportunity ability	0.04	0.05	3.28**			
Relationship collaboration	0.01	0.01	3.46**			
learning ability	0.10	0.00	2.16*			
Knowledge sharing	0.09	0.05	2.06*			
Innovation ability	0.05	0.03	2.88**			
Organization skills	0.03	0.01	2.62**			
Commitment capacity	0.08	0.01	2.46*			
Entrepreneurial orientation	2.734	0.02	3.46**			

time of the proposed algorithm is much smaller than that based on the TaperR algorithm. Therefore, it can be seen that the algorithm proposed in this paper is very efficient [20].

4.2. Verification of the nature of mining algorithms by top-K strong related projects based on threshold estimation

Based on the estimation ability of the threshold estimation algorithm, the relationship between the estimated threshold value of the algorithm and the actual optimal threshold value, that is, the ratio of the optimal threshold value and the determined threshold value can be proved. The comparison results on the Mushroom dataset and the Soybean dataset are shown in the figure.

It can be seen that the ratio of the estimated threshold to the optimal threshold increases with the number of K. Although the estimated effect is not very good, it is closer to the actual value. Therefore, it can be concluded that the algorithm proposed in this paper is effective. The above experimental results show that the mining algorithm based on threshold estimation has a good effect in relation to the strongest Top-K related project of the relational database and can be well extended to the actual relational database system. In this part of the study, the regression analysis of entrepreneurial team competency on entrepreneurial performance is conducted first, and then the regression analysis of each factor of the entrepreneurial team to competence entrepreneurial performance is carried out.

4.3. Regression analysis of the influence of entrepreneurial team competency dimensions on entrepreneurial performance

The competency of the entrepreneurial team consisting of the eight factors of opportunity ability, relationship collaboration ability, learning ability, knowledge sharing, innovation ability, organizational ability, commitment ability, and entrepreneur orientation is taken as the independent variable. The overall entrepreneurial performance is used as a dependent variable; the entrepreneurial strategy and leadership behavior are used as control variables in the regression equation to obtain results. The regression analysis results show that the impact of entrepreneurial team competency on entrepreneurial performance is significant as (β=0.13, $p < 0.0l$). Therefore, the direct influence of entrepreneurial team competency composed of eight factors such as opportunity capacity on entrepreneurial performance has been verified. Thus, the Hl hypothesis is proved. The regression analysis results show that entrepreneurial orientation has a significant impact on overall entrepreneurial performance (β=0.08, $p < 0.0l$). Therefore, the direct influence of entrepreneurial orientation on entrepreneurial performance has been verified, and the Hla hypothesis has been verified. □

The regression analysis results show that the impact of opportunity ability on entrepreneurial performance is significant (β=0.15, $p < 0.01$). Therefore, the direct influence of opportunity ability on entrepreneurial performance and the Hlb hypothesis have been verified. □

Regression analysis results show that the relationship collaboration ability has a significant impact on entrepreneurial performance (β=0.04, $p < 0.01$). Therefore, the direct influence of relational collaboration ability on entrepreneurial performance and the Hlc hypothesis have been verified. The overall impact of organizational ability on entrepreneurial performance is significant (β=0.05, $p < 0.001$). The impact of commitment ability on overall entrepreneurial performance is also significant (β=0.03, $p < 0.05$). Therefore, the direct influence of commitment ability on entrepreneurial performance has been verified, and the Hle hypothesis has been verified. The effect of learning ability on entrepreneurial performance is significant (β=0.01, $p < 0.05$). Therefore, the direct influence of learning ability on entrepreneurial performance has been verified, and the Hlf hypothesis has been verified. Knowledge sharing has a significant impact on entrepreneurial performance (β=0.10, $p < 0.05$). So, the direct influence of knowledge sharing on entrepreneurial performance has been verified, and the Hlg hypothesis has been verified. Innovation ability has a significant impact on entrepreneurial performance (β=0.09, $p < 0.0l$). So, the direct effect of innovation ability on entrepreneurial performance has been verified, and the Hlh hypothesis has been verified.

5. Conclusion

The dimensions of entrepreneurial team competency (entrepreneurial orientation, opportunity ability, relationship collaboration ability, organizational ability, commitment ability, learning ability, knowledge sharing, and innovation ability) have a positive effect on entrepreneurial performance. The degree of influence from low to high is innovation ability (8.9%), knowledge sharing (11%), organizational ability (11.4%), opportunity ability (12.3%), entrepreneurial orientation (15.1%), commitment ability (16.9%), learning ability (17%) and relationship collaboration ability (20%). From these data, it can be seen that in either the entrepreneurial team or the general team, the relationship collaboration capability has the most significant influence on the team's competence. This is the reason why entrepreneurs in China and other countries have always regarded team cooperation as the cornerstone. The entrepreneurial companies are the targeted research objectives, but it can be found that the obtained conclusions here are inconsistent with previous studies. When the predecessors researched entrepreneurial issues, they thought that the influence of entrepreneurial orientation on entrepreneurial performance was evident. However, this paper treats entrepreneurial orientation as a critical dimension in the competency of entrepreneurial teams. However, it finds that the impact of entrepreneurial orientation on entrepreneurial performance is not the most important. Before this factor, there is also commitment, learning and relationship cooperation ability. The results of this study can help entrepreneurial team members understand which team competency influences entrepreneurial performance is more important. In combination with the characteristics of the company itself, a sound and effective team incentive system can be established, the entrepreneurial performance by entrepreneurial team members during the entrepreneurial process can be improved.

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