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Modeling and Simulation of Entrepreneur Individual Based on Dynamic and Complex System Computing

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There are disadvantages such as lack of resources and experience in college students' entrepreneurship and the current research belong to the investigation and research, lacking the prediction simulation model research. Based on the theory of individual learning and the theory of complex systems, this study analyzes the mechanism of college students' entrepreneurial process through dynamic learning theory, establishes the model of college students' entrepreneurial subject, studies the different learning styles of college students, and discusses the influence of environmental dynamics on college students' chance recognition. Through simulation and practice analysis, it is concluded that college students' entrepreneurship is the process of learning and development of an individual and enterprise subject. Simultaneously, this study finds that the improvement of learning efficiency, learning channels and vision can effectively promote the development of enterprises, and can provide new ideas for the theoretical research of college students' entrepreneurship.

Keywords: dynamic complex environment; entrepreneurship; college students; simulation

1. INTRODUCTION

There are not many current researches on college students' entrepreneurial modeling. Most of the modeling to date simulates the environment, and little has been done to model the individual college student. Multi-agent modeling is one of the most dynamic and influential modeling methods in the current research of complexity. It determines the interaction between the subject's behavior, attributes, subjects, and subject and environment by describing the subject's behavioral rules (Tao, 2015). It simulates the real world using a bottom-up approach and models complex systems as a multi-agent system. The reason why Pratt's proposed simulation method is suitable for the study of complex systems is that the simulation method establishes a microscopic model, simulates the interaction between microscopic individuals, and discovers complex behavior at the macro level to merge microscopic subjects and macroscopic behaviors. At the same time, the simulation method is process-oriented, can track the whole process of system evolution from a dynamic perspective and observe the state change and structural change of the system during the evolution process, analyze the decision logic and behavior mechanism of the micro individual, and achieve individual learning and evolution (Pratt, 2016).

The basic principle of the simulation method is to select individuals in the system, model individual attributes and interaction rules between individuals, simulate their interactions on a computer, and examine the emerging macro-level behavior patterns and attributes (Liao, 2015). A complex system is also a dynamic system that spontaneously generates new behavior

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patterns and features during its evolution. The entity can act autonomously while it is running, without requiring the intervention of others to achieve its goals. At the same time, the subject needs to interact with other subjects through some form of communication to achieve its goals, and the interaction between the subjects constitutes social behavior. According to Lamarck's theory, the subject does not wait for an ideal environment; rather, it is able to perceive itself and actively change its behavior and characteristics to cope with and adapt to environmental changes. In addition, the main body acts as the main actor in the simulation process and has the ability to make decisions independently. The subject's mental state which may involve intention, ability, responsibility, belief, desire, commitment, etc., also provides a path for the description of subject characteristics and the analysis of the subject's macro level behavior. Therefore, simulation modeling must define the characteristics of the subject clearly and in detail , including general system attributes and psychological characteristics of the subject (Martín, 2014).

Through the above discussion, it can be seen that the history of entrepreneurship education in colleges and universities has a long history, and colleges and universities have rich research material on the cultivation of college students' entrepreneurial ability. Moreover, most of the research conducted by colleges and universities is about the establishment of college-related entrepreneurship courses and teaching models, which basically form a complete set of theoretical systems for entrepreneurship education. However, the research on entrepreneurial ability started relatively late, and the amount of research literature on individual entrepreneurial ability is relatively small (Hughes, 2015). Previous studies have carried out some useful research on entrepreneurial ability and its influencing factors, but have not reached a consensus on the connotation and factors associated with entrepreneurial ability. In addition, the literature focuses on the impact of certain specific factors on entrepreneurial ability, and most of them use literature reviews or follow-up surveys based on entrepreneurial projects or entrepreneurial practice. There seems to be no comprehensive and systematic analysis of the factors affecting entrepreneurial ability, or in-depth systematic theoretical and empirical research on the relationship between entrepreneurial ability and its influencing factors (Baptista, 2014). Therefore, this study is intended to analyze various key factors and non-critical factors of entrepreneurial ability, reveal the interaction of various influencing factors and the comprehensive impact on entrepreneurial ability. At the same time, through the organic integration of entrepreneurial ability and its influencing factors, this study conducts an in-depth analysis of the role of influencing factors in the formation and promotion of entrepreneurial ability, and recommends ways by which to improve college students' entrepreneurial ability.

2. RESEARCH METHODS

2.1 Model Establishment

College students' entrepreneurship is part of the process of continuous learning and promotion, and enterprises are also learning and developing. Therefore, this study investigates the impact of different learning styles on the opportunity recognition efficiency of enterprises, and compares the impact of different learning methods on such efficiency when the enterprise is in a stable and highly dynamic environment. Based on the above analysis, this paper proposes the following hypotheses (Pando, 2016):

H1a: When the enterprise is in a stable environment and the cognitive learning efficiency of college entrepreneurs does not change, improving the experience learning of college entrepreneurs can in turn improve the ability of enterprises to identify opportunities.

H1b: When the enterprise is in a stable environment and the learning efficiency of the college entrepreneurs does not change, improving the cognitive learning of the entrepreneurs can in turn improve the ability of enterprises to identify opportunities.

H1c: When the enterprise is in a stable environment, the improvement of the experience learning and cognitive learning efficiency is better than the equal-level improvement of the individual learning method.

H2a: When the enterprise is in a highly dynamic environment, and the cognitive learning efficiency of the college entrepreneurs does not change, improving the experience learning of the college entrepreneurs can in turn improve the ability of enterprises to identify opportunities.

H2b: When the enterprise is in a highly dynamic environment, and the cognitive learning efficiency of the college entrepreneurs does not change, improving the experience learning of the college entrepreneurs can in turn improve the ability of enterprises to identify opportunities.

H2c: When the company is in a highly dynamic environment, improving the efficiency of empirical learning and cognitive learning is better than the same level of improvement in individual learning.

H3a: When the company is in a stable environment rather than a highly dynamic environment, the same degree of improvement in the experience of college student entrepreneurs has a more significant impact on the efficiency of enterprise opportunity recognition.

H3b: When the company is in a stable environment, compared with the highly dynamic environment, the same degree of improvement in the cognitive learning of college entrepreneurs has a more significant impact on the efficiency of enterprise opportunity recognition.

H3c: When the company is in a stable environment rather than a highly dynamic environment, the same degree of simultaneous improvement in the efficiency of learning and cognitive learning has a more significant impact on the efficiency of entrepreneurial opportunity recognition.

Based on the above assumptions, the conceptual model of this paper is established as shown in Figure 1.

In order to simplify the model, this paper assumes that there is a certain, fixed period of opportunity. The degree of

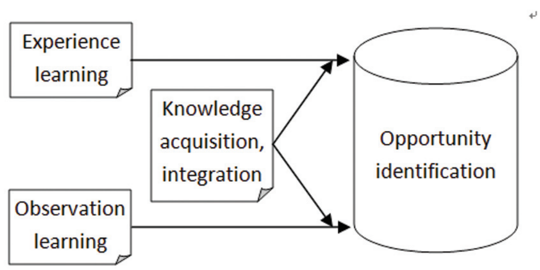


Figure 1 Conceptual framework of the relationship between individual learning and opportunity identification.

change in opportunity is affected by the level of environmental dynamics. The higher the environmental dynamics, the higher the probability that the knowledge dimension that constitutes the opportunity will change. The relevant variables of the model are as follows (Olive, 2015):

This paper defines the opportunity as an m-dimensional knowledge vector, and each dimension (ej) represents a type of knowledge.

$$\mathrm{e} = \mathrm{e}_1\mathrm{e}_2 \ldots \mathrm{e}_m \tag{1}$$

$$\mathrm{e}_j = \{-1, +1\},\ j = 1, \ldots, m \tag{2}$$

The values of the above elements take 1 or -1 with the same probability. The larger the value of m, the more complex is the organization's environment, and the more complex are the types of opportunities outside the organization.

In the process of organizational development, the values of the dimensions in the m-dimensional knowledge representing the opportunity will change with time. In this study, the probability of the change of the knowledge dimension contained in the opportunity is set to p3. When the enterprise is in a stable environment, the value of p3 is small, and the enterprise can effectively identify the opportunities existing in the environment based on the original knowledge. When a company's environment is in a state of turbulence, the types of opportunities that exist in this environment change rapidly, and the types of knowledge involved in the opportunities change; hence, p3 has a great value at this time.

For the m-dimensional knowledge existing in the external environment, the correct knowledge that the college entrepreneurs may have (that is, the corresponding dimension) is the same as the knowledge vector value of the opportunity expressed in the external environment. However, incorrect knowledge is different from the knowledge vector associated with the opportunity. When college entrepreneurs do not have this knowledge, they are represented by 0; b represents the knowledge vector of college entrepreneurs. Then the following formula can be derived:

$$\mathrm{b} = \mathrm{b}_1\mathrm{b}_2 \ldots \mathrm{b}_m \tag{3}$$

$$\mathrm{b}_j = \{-1, 0, 1\} \tag{4}$$

where b_j represents the value of the j-dimensional knowledge vector of college entrepreneurs. The higher the consistency of the knowledge vector level of the undergraduate entrepreneurs with the opportunity vector, the higher is the level of knowledge they have. In the simulation initialization phase, the knowledge level of college entrepreneurs is randomly assigned, and can be expressed as:

$$\mathrm{KL} = \sum_{j=1}^{m} b_j e_j \tag{5}$$

When A is equal to 1, this indicates that it is consistent in the required knowledge dimension. However, when A is equal to -1, this means that there is inconsistency in the required knowledge dimension, and inconsistent knowledge prevents an enterprise from identifying opportunities.

2.2 Simulation Rule Setting

In this paper, the efficiency of college student entrepreneurs to learn explicit knowledge is p1, and the efficiency of learning tacit knowledge is p2. Drawing on the existing research conclusions, the proportion of college students who use empirical learning and observation learning in the learning process is different. The knowledge obtained through observation and learning is explicit knowledge. Explicit knowledge is more efficient for knowledge acquisition because of its coded characteristics; that is, p1 is concentrated above 0.7. However, the knowledge acquired through empirical learning is mostly tacit knowledge. Due to the viscous nature of tacit knowledge and carrier dependence, the efficiency of acquiring knowledge is low; that is, p2 is concentrated below 0.3. In the knowledge vector, the explicit knowledge part is represented by XXZSbi, $i \in (1, n)$, and the tacit knowledge part is represented by YXZSbi, $i \in (n+1, m)$. Through different learning methods, organizations can acquire new knowledge and update knowledge within the organization. The updated knowledge storage capacity is (Zhang, 2015):

$$\mathrm{b}_t = \mathrm{XXZSb}_j\mathrm{p}_1 + \mathrm{YXZSb}_j\mathrm{jp}_2 + \mathrm{b}_{t-1} \tag{6}$$

$\mathrm{b}_{(t-1)}$ is the knowledge vector of the college entrepreneurs in the $t-1$ cycle, and b_t is the knowledge vector of the t-cycle of the college entrepreneurs after a running cycle.

In the initialization phase, the relevant parameter values of the simulation are set. The specific settings are shown in Table 1. The $-1, 0, 1$ is randomly assigned to the m-dimensional knowledge vector to represent the opportunity and, over time, the knowledge vector combination representing the opportunity changes. At the same time, college entrepreneurs are given different knowledge vectors and adopt different learning methods in the process of acquiring knowledge. Only those individuals with relevant knowledge can discover the opportunities existing in the external environment. Individuals acquire explicit knowledge at the speed of p1 and learn tacit knowledge at the speed of p2. Undergraduate entrepreneurs

Table 1 Related parameter settings.

Parameter setting	Meaning	Parameter value
m	Opportunity, number of knowledge dimensions of college entrepreneurs	500
p1	Learning rate of observe learning	0.6/0.9
p2	Learning rate of empirical learning	0.1/0.4
p3	Matching degree of individual and opportunity knowledge	0.5
KL	Probability of opportunity change	0.20.9
D	Number of opportunity identification	

learn according to the learning rules of college entrepreneurs mentioned above, and different learning methods have different knowledge stocks. After a certain period of study, the knowledge level of college entrepreneurs is updated, and the degree of matching (KL $= \sum_{j=1}^{m} b_j e_j$) between the knowledge level of entrepreneurship and the external environment knowledge vector is calculated. When the degree of matching between the knowledge vector representing the opportunity and the knowledge vector of the opportunity existing in the external environment reaches a certain degree, this indicates that the college entrepreneur has successfully identified the opportunity, which is defined as 0.5 in this paper. Moreover, the effect of the final corporate opportunity identification is measured by the number of opportunities that can be identified. In the model hypothesis stage, this paper has pointed out that opportunities change with time. When the chance of matching has not reached a certain level, it is assumed that the enterprise failed to seize this opportunity. When the initial matching degree does not satisfy 0.5, there may be several possible reasons for this. One is that college entrepreneurs lack corresponding knowledge, and the other is that opportunities are different from those of college entrepreneurs, and the attraction of college entrepreneurs cannot be correspondingly attractive. At the same time, environmental dynamics has a certain impact on the change of opportunity, which causes the opportunity to change with the probability of p3. In the case of different degrees of opportunity change, the number of chance recognition is different in a certain period (Mulenga, 2014).

3. RESULTS

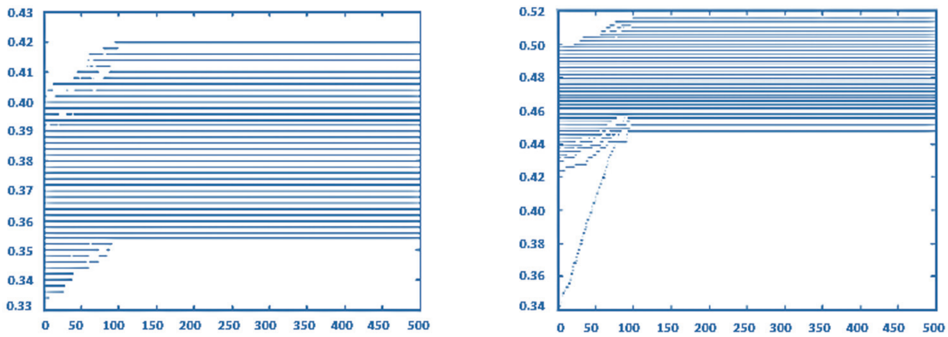
When the enterprise is in a stable environment, that is, the probability that the knowledge dimension constituting the environment changes is small, according to the relevant research conclusions, the dynamics of the environment are quantified, and the probability of defining environmental changes under a steady state is 0.2, that is, in each cycle, each dimension of the constituent opportunities changes with a probability of 0.2. According to hypotheses 1a, 1b, and 1c, when the rate of different learning modes is changed, the impact on enterprise opportunity recognition is analyzed. It is analyzed mainly from the matching degree of the knowledge required by the subject knowledge and the opportunity and the equilibrium level reached by the matching.

When the enterprise is in a highly dynamic environment, that is, the probability that the knowledge dimension constituting the environment changes is large, the probability of defining environmental changes is 0.5; that is, in each cycle, each dimension that constitutes an opportunity changes with a probability of 0.5. Hypotheses 2a, 2b, 2c are analyzed and tested (Mayangsari, 2015).

Environmental dynamics has a greater impact on the opportunity recognition efficiency of new ventures, and places greater demands on the flexibility and learning efficiency of enterprises. The comparison and analysis of the opportunity recognition efficiency under different environmental dynamics are of great significance if enterprises are to cope with a dynamic environment and improve their recognition of business opportunities.

When the enterprise is in a stable environment with a cognitive learning rate of 0.6 and an empirical learning rate of 0.2, the chance matching and final recognition effect are as shown in Figure 2(a). When the cognitive learning rate of college entrepreneurs is increased from 0.6 to 0.8, and the empirical learning rate does not change, the chance matching and final recognition effect are as shown in Figure 2(b). It can be concluded from Figures 2 (a) and (b) that when companies find that their knowledge is inadequate for identifying opportunities in the environment, they will adopt different learning methods to acquire new knowledge from different sources, thereby improving their ability to identify opportunities (Khefacha, 2015).

A comparative analysis of Figure 2(a) and Figure 2(b) finds that when the cognitive learning rate of the enterprise is increased, the level of final matching can be significantly improved. Under the condition of Figure 2(a), the chance matching is lower than 0.45, $D = 0$, that is, under the



p3=0.2, p1=0.6, p2=0.2; D=0 p3=0.2, p1=0.8, p2=0.2; D=41

Figure 2 Analysis mode 1 of enterprise opportunity recognition efficiency under a stable environment.

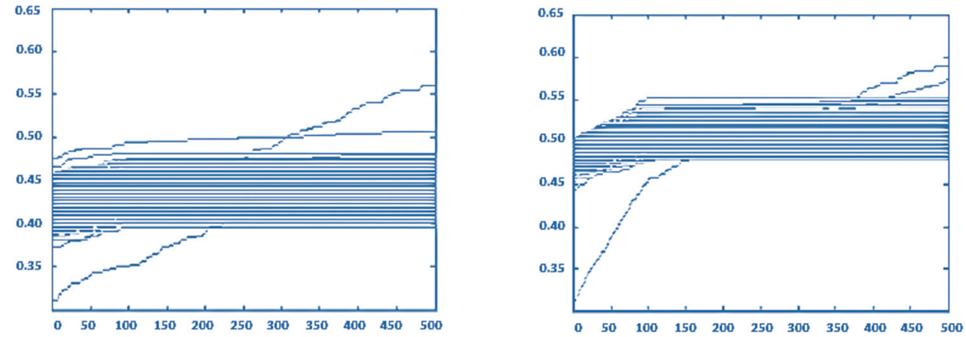
condition of Figure 2(a), the opportunity in the environment cannot be successfully identified. However, under Figure (b) conditions, the chance matching degree exceeds the requirement of opportunity identification, $D = 41$, that is, among the 500 different opportunities, 41 opportunities can be successfully identified by adopting different learning rates under Figure (b) conditions. Therefore, hypothesis 1a is verified. At the same time, under the condition of b, the level of final matching is more concentrated, further indicating that increasing the rate of cognitive learning plays an important role in the acquisition of knowledge and the identification of opportunities (Costa, 2012).

When the enterprise is in a stable environment, the empirical learning rate of college entrepreneurs is increased from 0.2 to 0.3, and the cognitive learning rate does not change, the chance matching and final recognition effect are shown in Figure 3(a). Comparative analysis of Figure 2(a), Figure 3(a) found that when the company's empirical learning rate is increased, the level of final matching can be significantly improved. Under the condition of Figure 2(a), the number of matches for the opportunity D is 0, which means that the opportunity in the environment cannot be successfully identified. However, under the condition of Figure 3(a), the matching degree of the opportunity partially exceeds the requirement of opportunity recognition, $D = 2$. At the same time, under the condition of Figure 3(a), the concentration of the matching level is strong, which further demonstrates that increasing the rate of empirical learning plays an important role in the acquisition of knowledge and the identification of opportunities. Therefore, Hypothesis 1b is supported (Eggers, 2014).

When the enterprise is in a stable environment with a cognitive learning rate of 0.6 and an empirical learning rate of 0.2, the chance matching and final recognition effect are as shown in Figure 3(b). When the cognitive learning rate of college entrepreneurs is increased from 0.6 to 0.8 and the empirical learning rate is increased from 0.2 to 0.3, the chance matching and final recognition effect are shown in Figure 2(d). Comparative analysis of Figures 2(a) and (d) indicates that when the cognitive learning rate and the empirical learning rate of the enterprise are improved, the opportunity recognition level can be significantly improved. Under the condition of Figure 3(a), $D = 0$, the enterprise cannot successfully identify the opportunities in the environment. However, under the condition of Figure 3(d), $D = 443$, that is, among the 500 different opportunities generated, by acquiring the learning rate under the condition of d, the 443 opportunities can be successfully identified. At the same time, after comparing Figure 2(b) and Figure 3(a), it is concluded that simultaneously improving the cognitive learning rate and the learning rate of the enterprise plays a positive role in the enterprise's recognition of opportunity. Therefore, hypothesis 1c is verified; that is, when the enterprise is in a stable environment, the effect of improving the experience learning and cognitive learning efficiency on the identification of entrepreneurial opportunities is better than the equal opportunity to enhance the opportunity recognition effect of the individual learning methods.

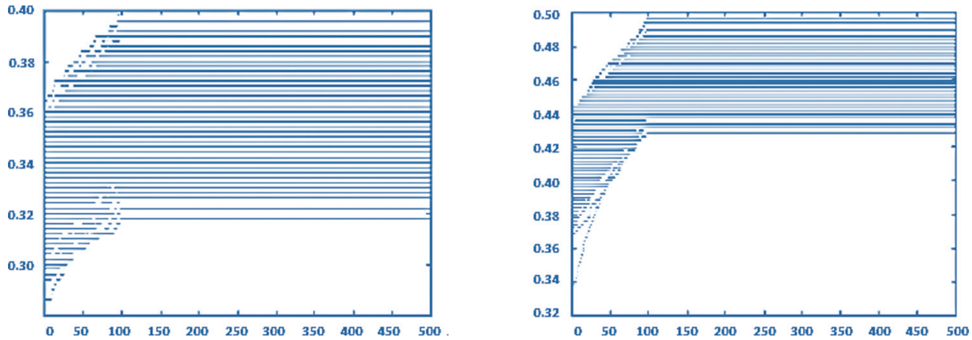
When the enterprise is in a highly dynamic environment, the cognitive learning rate is 0.6, and the empirical learning rate is 0.2. The chance matching and final recognition effect are shown in Figure 4(a). When the cognitive learning rate of college entrepreneurs is increased from 0.6 to 0.8, and the empirical learning rate does not change, the chance matching and final recognition effect are shown in Figure 4(b). Comparative analysis of Figures 4(a) and 4(b) found that under two different conditions, the final identified number of 500 different opportunities is 0, but the matching degree of (b) is obviously concentrated, and the mean is higher than that in Figure 4(a). Therefore, it can be concluded that improving the cognitive learning level of enterprises can increase the matching degree. However, due to the high degree of environmental dynamics, the opportunities in the environment are more likely to change, the existing knowledge of the enterprise does not meet the needs of future opportunities, and the individual learning ability is limited, and cannot adapt to changes in the environment quickly. Even if the cognitive learning rate is increased and the original knowledge storage can be improved, the efficiency of enterprise opportunity recognition cannot be significantly improved. Therefore, Hypothesis 2a is not fully supported (Yuan, 2015).

When the enterprise is in a highly dynamic environment, the empirical learning rate of college entrepreneurs increases from 0.2 to 0.3; when the cognitive learning rate does not change, the chance matching and final recognition effect are shown in Figure 5(a). A comparative analysis of Figure 4(a) and Figure 5(a) shows that under two different conditions, the final identification number of 500 different opportunities is 0, but the matching degree of Figure 5(a) is obviously concentrated, and the mean of the matching degree is higher than that in Figure 4(a). Therefore, it is concluded that an improvement in the level of experience and learning of enterprises can improve the matching level. However, due to the high degree of environmental dynamics,



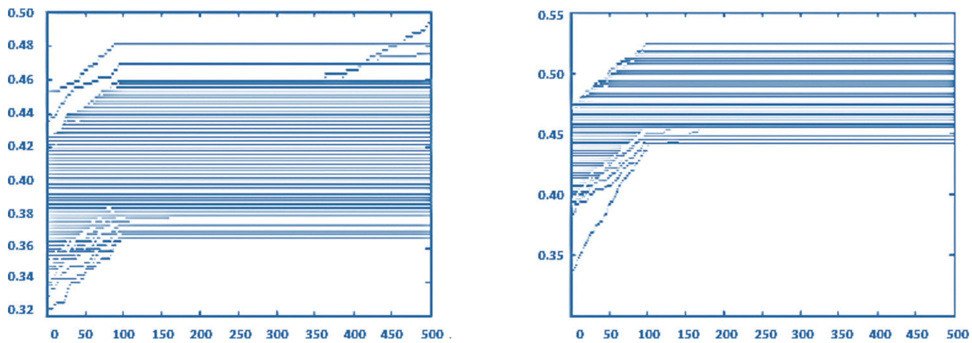
p3 = 0.2, p1 = 0.6, p2 =0.3; D = 2 p3 = 0.2, p1 = 0.8, p2 =0.3; D = 453

Figure 3 Analysis mode 2 of enterprise opportunity recognition efficiency under stable environment.



p3 = 0.5, p1 = 0.6, p2 =0.2; D = 0 p3 = 0.5, p1 = 0.8, p2 =0.2; D = 0

Figure 4 Analysis mode 1 of enterprise opportunity recognition efficiency in a highly dynamic environment.



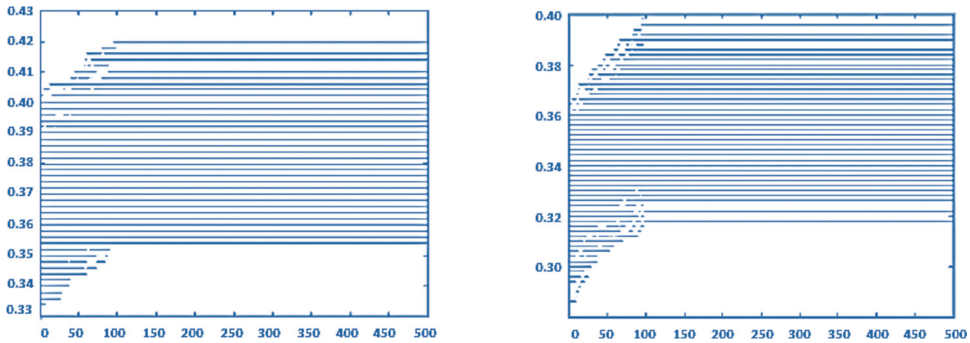
p3 = 0.5, p1 = 0.6, p2 =0.3; D = 0 p3 = 0.5, p1 = 0.8, p2 =0.3; D = 70

Figure 5 Analysis mode 2 of enterprise opportunity recognition efficiency in a highly dynamic environment.

the opportunities in the environment are more likely to change, the existing knowledge of the enterprise does not meet the needs of future opportunities, and the individual learning ability is limited and cannot adapt to changes in the environment quickly. Even if the cognitive learning rate is increased and the original knowledge storage can be improved, the efficiency of enterprise opportunity recognition cannot be significantly improved. Therefore, Hypothesis 2b is not fully supported.

When the enterprise is in a highly dynamic environment, the cognitive learning rate of college entrepreneurs increases from 0.6 to 0.8, and the empirical learning rate is increased from 0.2 to 0.3, the chance matching and final recognition effect are shown in Figure 5(b). Comparative analysis of Figure 4(a) and Figure 4(d) show that when the cognitive learning rate and the empirical learning rate of the enterprise are improved, the level of opportunity recognition can be significantly improved. Under the condition of Figure 4(a), $D = 0$, the enterprise cannot successfully identify the opportunities in the environment. However, under the condition of Figure 5(b), $D = 70$, almost all opportunities can be identified. At the same time, after comparing Figure 4(b) with Figure 5(a), it is concluded that an improvement in the cognitive learning rate and experience learning rate of enterprises will have a positive effect on the opportunity recognition of enterprises. Hence, Hypothesis 2c is validated; that is, when the enterprise is in a highly dynamic environment, improving the efficiency of empirical learning and cognitive learning at the same time is better than the equal opportunity to enhance the chance of individual learning.

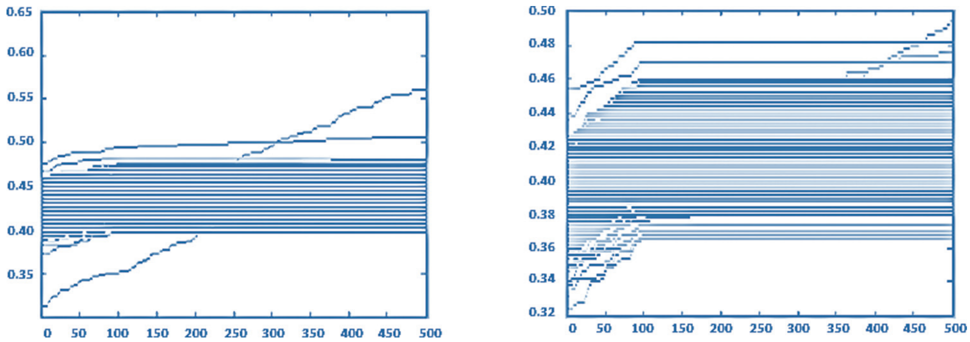
A comparative analysis of Figure 6(a) and Figure 6(b) shows that when the rates of cognitive learning and empirical learning are kept at a low level, the stable environment is more conducive to the accumulation of individual knowledge, and enables



p3 = 0.2, p1 = 0.6, p2 = 0.2; D = 0

p3 = 0.5, p1 = 0.6, p2 = 0.2; D = 0

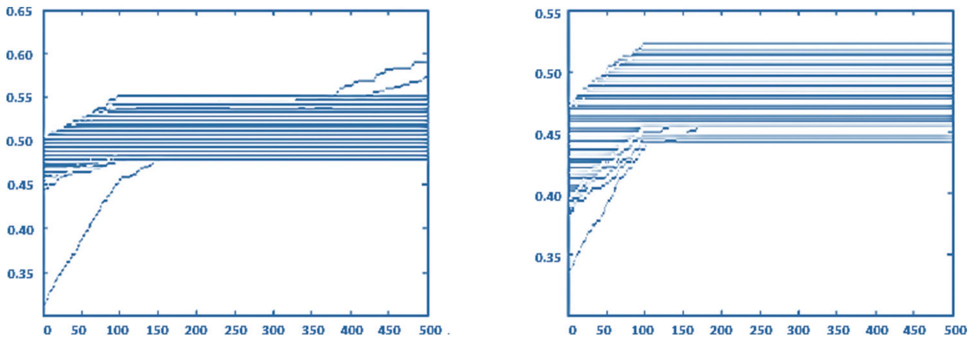
Figure 6 Comparative analysis mode 1 of enterprise opportunity recognition efficiency under different environmental dynamics.



p3 = 0.2, p1 = 0.6, p2 = 0.3; D = 2

p3 = 0.5, p1 = 0.6, p2 = 0.3; D = 0

Figure 7 Comparative analysis mode 2 of enterprise opportunity recognition efficiency under different environmental dynamics.



p3 = 0.2, p1 = 0.8, p2 = 0.3; D = 453

p3 = 0.5, p1 = 0.8, p2 = 0.3; D = 140

Figure 8 Comparative analysis mode 3 of enterprise opportunity recognition efficiency under different environmental dynamics.

individuals to have the potential to identify opportunities, and to improve the individual's knowledge level and the matching of enterprise knowledge and knowledge needed to identify opportunities. However, due to the limited ability of individuals to learn and the ability of enterprises to acquire knowledge, improving the learning rate of individuals in a stable environment can improve their knowledge matching and provide a possibility for enterprises to identify opportunities. However, ultimately, it may not improve the efficiency of identifying corporate opportunities.

A comparative analysis of Figure 5(a), Figure 5(b), Figure 6(a), Figure 6(b), Figure 7(a), Figure 7(b), it can be concluded that when the efficiency of different learning methods is improved to the same extent, the efficiency of enterprise opportunity recognition is more enhanced in a stable environment, and the matching concentration is more obvious. This result supports Hypotheses 3a and 3b. That is, compared with a highly dynamic environment, when the enterprise is in a stable environment, the same degree of improvement in the experience of college students' entrepreneurs has a more significant impact on the opportunity recognition efficiency of enterprises. The same degree of improvement in the cognitive learning of college entrepreneurs has a more significant impact on the efficiency of corporate opportunity recognition.

A comparative analysis of Figure 8(a) and Figure 8(b) draw the following conclusions. When the enterprise has a high level of cognitive learning and experience learning, the stable environment is more concentrated than the highly dynamic environment, which is more conducive to the opportunity identification of the enterprise. In the actual business process of the enterprise, there is no obvious division of learning methods, and there is no particular limit to the sources of enterprise knowledge. In order to improve the ability of opportunity identification, enterprises will improve their own learning speed as much as possible, gain knowledge from more diverse channels, and increase their knowledge reserves. Compared with the highly dynamic environment, the stable environment has less change in knowledge requirements, and the enterprise can achieve the equilibrium of its knowledge level through learning, and improve the efficiency of its opportunity recognition.

4. CONCLUSION

Based on the theory of complex systems, this study constructs a conceptual model and simulation model for the opportunity identification of new ventures, proposes research hypotheses, and obtains simulation results through program design. The specific conclusions are as follows: Through simulation research, it is found that when enterprises have high learning efficiency, they actively adopt different learning methods to acquire different types of knowledge using various means and sources, add to their store of knowledge, and then improve the ability of individuals to identify potential opportunities and promote the efficiency of opportunity recognition. For the subject, there is no clear restriction and definition of the type of learning and the source of knowledge. Promoting a particular type of learning can help the subject acquire a specific type of knowledge. Moreover, when the subject can simultaneously improve the way of acquiring various knowledge, it can fully exert the learning potential of the enterprise and maximize the knowledge acquisition and opportunity identification of the enterprise. In order to seize business opportunities, companies need to actively learn, acquire new knowledge, adapt to changes in the environment, focus on universal knowledge, and acquire implicit and difficult-to-reach key knowledge from their experiences and their experiences. Improving the effectiveness of different learning methods can effectively promote the opportunity recognition behavior of enterprises, and environmental dynamics affect the improvement of opportunity recognition.

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REFERENCES

1. Tao Y. H., Yeh C. R., Hung K. C. Validating the Learning Cycle Models of Business Simulation Games via Student Perceived Gains in Skills and Knowledge[J]. Journal of Educational Technology & Society, 2015, 18(1):77–90.
2. Pratt M. A., Hahn S. Enhancing hospitality student learning through the use of a business simulation[J]. Journal of Hospitality Leisure Sport & Tourism Education, 2016, 19:10–18.
3. Liao Y. W., Huang Y. M., Wang Y. S. Factors Affecting Students' Continued Usage Intention Toward Business Simulation Games: An Empirical Study[J]. Journal of Educational Computing Research, 2015, 53(2).
4. Martín-Cruz N., Martín-Pérez V., Pérez-Ríos J. M., et al. Team Syntegrity®; as a Tool for Efficient Teamwork: An Experimental Evaluation in a Business Simulation[J]. Systems Research & Behavioral Science, 2014, 31(2):215–226.
5. Hughes S., Scholtz F. Increasing the impact of a business simulation: The role of reflection[J]. International Journal of Management Education, 2015, 13(3):350–361.
6. Baptista M., Prendinger H., Santos P., et al. Improving Learning in Business Simulations with an Agent-Based Approach[J]. Journal of Artificial Societies & Social Simulation, 2014, 17 (3):7.
7. Pando-Garcia J., Periañez-Cañadillas I., Charterina J. Business simulation games with and without supervision: An analysis based on the TAM model [J]. Journal of Business Research, 2016, 69(5):1731–1736.
8. Olive A., Carre M., Cuadros J., et al. Tracking the Behavior of Players in a Finance Simulation and Identifying Work Patterns ⋆ [J]. Procedia - Social and Behavioral Sciences, 2015, 182:203–212.
9. Zhang M. J. Using login data to monitor student involvement in a business simulation game[J]. International Journal of Management Education, 2015, 13(2):154–162.
10. Mulenga J., Wardaszko M. Simulation Game as a Live Case Integrated into Two Modules[J]. Lecture Notes in Computer Science, 2014, 8264:102–109.
11. Mayangsari L., Novani S., Hermawan P. Batik Solo Industrial Cluster Analysis as Entrepreneurial System: A Viable Co-creation Model Perspective [J]. Procedia - Social and Behavioral Sciences, 2015, 169:281–288.
12. Khefacha I., Belkacem L. Modeling entrepreneurial decision-making process using concepts from fuzzy set theory[J]. Journal of Global Entrepreneurship Research, 2015, 5(1):1–21.
13. Costa E. A reference model perspective for conventional business narrative analysis: An essay on an entrepreneurial narrative[J]. African Journal of Business Management, 2012, 6(27):8199–8219.
14. Eggers F., Eggers F., Kraus S. Entrepreneurial branding: measuring consumer preferences through choice-based conjoint analysis[J]. International Entrepreneurship & Management Journal, 2014, 12:1–18.
15. Yuan K. H. Multiple-Group Analysis for Structural Equation Modeling with Dependent Samples[J]. Structural Equation Modeling A Multidisciplinary Journal, 2015, 22(4):552–567.