Acta Technica 62 (2017), No. 7A, 1061–1072

Empirical study on motivation of college English learning based on maximum entropy self - efficacy theory

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Abstract. In order to improve the effectiveness of college English learning motivation analysis, this paper proposes an empirical study based on the theory of maximum entropy self-efficacy in college English learning motivation. First of all, this paper constructs a theoretical model of self-efficacy of college English learning motivation, and obtains a theoretical model of self-efficacy of college English learning motivation by questionnaire method. Secondly, it uses the statistical method based on maximum entropy to study the motivation model of college English learning And prediction. At the same time, in view of the large deviation of the traditional model estimation model, it is improved by using the method of weighted probability and moment to reduce the deviation of the algorithm. Finally, by the analysis on the numerical model and the empirical example, The Effectiveness of University English Learning Motivation Evaluation Algorithm.

Key words. Maximum entropy, My theory of effectiveness, College English, Motivation of learning.

1. Introduction

American psychologist Bentura put forward the concept of self-efficacy in his book "The Social Basis of Thought and Behavior" in the 1970s and gradually formed a framework of self-efficacy theory in his later works . Self-efficacy is accepted by people after a wide range of applications in education, psychology and management, and has achieved fruitful results. Over the years, people around the self-efficacy of this research topic carried out extensive research, and theory and practice reached a certain consensus. In their own teaching practice, self-efficacy also play a huge role. The good use of self-efficacy theory can have a positive impact on student learning and teacher's teaching.

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In his theory of social learning, Bandura paid special attention to the influence of human cognition on the regulation of learning and behavior. He believes that human cognition plays an important regulatory role in the mutual determination of behavioral, personal, and environmental factors The change in self-efficacy as a cognitive factor is considered as the psychological motivation for sustained self-regulation of the person. He pointed out that self-efficacy refers to people's beliefs or beliefs about their ability to achieve their goals in a particular area and is a concept in a particular area. Self-efficacy is not a skill nor is it a person's real ability, but an individual's level of confidence in the ability to perform certain tasks. Self-efficacy, as an individual's self-judgment on the subject's interaction with the environment, is based on certain experience or information. Self-efficacy is formed through these new cognitive processes. Western scholars, represented by Pandura Ravi, consider the sense of self-efficacy individuals have come from four types of experience. (1) previous successes that provide individuals with judgments and behavioral information that make sense of self-efficacy; (2) imitation or substitution, the accomplishment of models, behaviors that give observers the tactics needed to succeed, Provides a standard for comparing and judging one's own abilities, and at the same time gives it the conviction that if one tries hard, one can succeed. (3) Verbal or social persuasion is the individual's positive beliefs about his or her own abilities, that they should neither be self-deprecating, repressing and restricting their ability to exert their own abilities, nor produce unrealistically high expectations; (4) The state of emotions, the reduction of stressors in the context of the organization, and the improvement of physics are considered as effective ways to improve self-efficacy.

Self-efficacy determines the choice of behavior of teachers and students, determines the degree of perseverance and efforts to the behavior, but also affects the way of thinking and emotional response when dealing with the business model. In other words, the more self-efficacy a person has, the more likely he is to achieve his desired goal. By understanding the status of self-efficacy, you can find out the problems that exist in your sense of efficacy, and you can work hard to improve your sense of self-efficacy. This will not only have a better impact on your behavior and learning outcomes, but also improve the effectiveness of your behaviors, while also developing positive self-concepts that will make you more effective at doing anything.

2. Research methods

2.1. Literature review and assumptions made

(1) network self-efficacy and learning motivation. Internet self-efficacy refers to a person's subjective judgment that he or she can use computer network technology to achieve learning objectives and accomplish learning tasks. This belief will inspire students to motivate learning into practical action, which in turn will affect the student's academic performance, to complete the task of learning to judge and feedback in class. Learning motivation is based on one's belief in one's own abilities and on the environment. Proper learning motivation allows students to choose

the learning task and learning environment appropriate to their abilities. In the process of online learning, network self-efficacy will affect the students' choice of courses and learning efficiency. A high level of self-efficacy accelerates the conversion of learning motivation into learning hope. If students are interested in using a computer, his online self-efficacy can be improved by training. The literature generally considered learning motivation (motivation) is the main factor affecting the learning outcomes. ARCS four-factor model as a well-known academic achievement motivation study, has been widely recognized academics. Kydd found that students' willingness to learn, satisfaction and attention were the main factors that motivated their learning. Liu et al. Applied the ARCS model to the curriculum design and found that students' satisfaction with the curriculum improved. Therefore, we believe that network self-efficacy can affect learning motivation. To sum up, this paper puts forward the following assumptions: Hypothesis 1: Different levels of network self-efficacy have significant differences in learning motivation.

(2) Network self - efficacy and academic performance. Social cognition believes that students' self-efficacy can affect their performance. Students with a higher level of self-efficacy tend to achieve better grades. Liaw study shows that college students self-improvement network will enhance the students' willingness to use the Internet to learn, but also improve academic performance. Similarly, Tsai et al. Reached similar conclusions, believing that self-efficacy students performed better than self-efficacy students in using online learning. However, some scholars believe that when college students use the Internet to study, self-efficacy and academic performance have nothing to do. To sum up, this paper puts forward the following assumptions: Hypothesis 2: Different levels of network self-efficacy have significant differences on academic performance.

Network self-efficacy and gender differences. Gender difference is an important field in pedagogy, psychology and sociology. Boys and girls in the learning process of the great differences have long been widespread concern. Similarly, in the online learning process, motivation, academic performance, etc. also reflect the gender differences. Wu & Tsai et al. Found that men are more active, open-minded and more frequently using computers than their counterparts in the Internet. Foreign scholars reached controversial conclusions on this issue. Sullivan pointed out through research that male and female college students show huge differences in online learning, such as their personality, self-discipline and motivation. Studies have shown that boys are more adept at using the Internet to learn and network self-efficacy is also higher. Boys are more confident and decisive than girls. They are also more enthusiastic about learning, but often have poor self-discipline. However, some scholars think that girls are better at learning than boys because girls listen more carefully. The conclusions drawn from previous studies failed to reach an agreement. Therefore, this study also continued to study this issue. To sum up, this article puts forward the following assumptions: Hypothesis 3: boys and girls online self-efficacy, motivation and academic performance significantly different.

2.2. Questionnaire

This study mainly uses the questionnaire survey method, each participant needs to complete three questionnaires.

(1) self-efficacy comprehensive scale. Including three parts: the first part is the general self-efficacy scale, the second part is the academic self-efficacy scale, the third part is the self-regulation efficacy scale.

(2) adult college students English learning motivation point questionnaire. A total of 55 questions. Including the aggressive, extroverted, interest-seeking, avoidance or excitement, social services and social relations and other six related issues.

(3) English learning motivation intensity questionnaire. A total of 40 questions. In addition, some open questions have been set up for a total of 3 questions to understand the students' specific interest in English teaching and classroom teaching and their reasons.

The main survey for college students, at the level of specialist and undergraduate, a total of 60 people. 60 questionnaires were distributed and 48 valid questionnaires were collected. The survey subjects are all English majors. Among them there are 18 boys and 30 girls.

3. Maximum entropy weight probability moment statistics

3.1. Maximum entropy method

The concept of entropy was originally derived from thermodynamics. Its main function is to measure the instability of the system. It has broad prospects for engineering and theory. If the parameter x is a random variable defined in space R and has a probability distribution $P(X = X_k) = p_k, k = 1, 2, 3, \cdots, n$, then The entropy of parameter x is calculated as [11-12]:

$$H = -\sum_{k\geq 1} p_k \ln p_k \,. \tag{1}$$

Similar to the above definition of the concept of discrete variables, if variable x is a random variable defined on space R, which is continuous and has a form of probability density $f(x)$, the variable x entropy is calculated as follows:

$$H = \int_R f(x) \ln f(x) dx \,. \tag{2}$$

In equation (2), if $f(x) = 0$,the equation form can be defined $f(x) \ln f(x) = 0$ if it is satisfied.

Using the above definition of maximum entropy, the minimum deviation distribution model of variable x in space R is defined:

$$\begin{cases} \max H = -\int_R f(x)\ln f(x)dx \\ s.t. \int_R x^n f(x)dx = \mu_n, x = 0, 1, 2, \cdots, N \end{cases} \tag{3}$$

In equation (3), N is the largest sample probability moment of the order; μ_n is the probability of the sample; m is the number of training data related to the process; x_i is variable i. Sample probability moments have the following definitions:

$$\mu_n = \frac{1}{m}\sum_{i=1}^{m} x_i^n \,. \tag{4}$$

$$c_n = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_1)^n \,. \tag{5}$$

In Eqs. (4-5), the parameter c_n is the n centripetal moment, which can be transformed with the traditional origin moment μ_n, and the transformation form is binomial transformation. The Lagrange method [13-14] is incorporated here to solve the probability density based on the principle of maximum entropy based on the traditional variational method:

$$f(x, \lambda_0, \lambda_1, \cdots, \lambda_n) = \exp(\lambda_0 + \sum_{n=1}^{N} \lambda_n x^n) \,. \tag{6}$$

In Eq. (6), the parameter $\lambda_i, i = 0, 1, \cdots, N$ represents the i-th moment of Lagrange constraint [10]. Using equation (13), we can see that after the determination $\lambda_i, i = 0, 1, \cdots, N$ is made, the calculation result $f(x)$ of the probability density can be completely obtained.

3.2. Weight probability moment

If the variable x is defined on the space R, the weight probability moment of the above function can be calculated as follows [15] if the cumulative function associated with it has a distribution form $F(x) = P(X \leq x)$ and the inverse function of the sub-function $x = x(F)$ is available:

$$M_{i,n,k} = \int_0^1 [x(F)]^i F^n (1-F)^k dF \,. \tag{7}$$

In equation (7), the subscript i,n, k is a real number. It can be seen that the moment of the value of the weight is an extension of the evolution on the basis of the classical moment. The classical moment can be used as a special case of the probability moment of the adopted weight. There are mainly two types of probability moments that are commonly used:

$$\text{Type 1: } \alpha_k = M_{1,0,k} = \int_0^1 x(F)(1-F)^k dF : \tag{8}$$

$$\text{Type 2: } \beta_n = M_{1,n,0} = \int_0^1 [x(F)]F^n dF \,. \tag{9}$$

Sort samples by sampling, available in order form $x_1 \leq x_2 \leq \cdots \leq x_{m-1} \leq x_m$, then exact estimate a_k and b_n are in the form:

$$a_k = \frac{1}{m}\sum_{i=1}^{m}\left\{\left[\begin{array}{c} m-1 \\ k \end{array}\right] x_i \middle/ \left[\begin{array}{c} m-1 \\ k \end{array}\right]\right\}. \tag{10}$$

$$b_n = \frac{1}{m}\sum_{i=1}^{m}\left\{\left[\begin{array}{c} i-1 \\ n \end{array}\right] x_i \middle/ \left[\begin{array}{c} m-1 \\ n \end{array}\right]\right\}. \tag{11}$$

In equation (10~11), $k = 0, 1, \cdots, m-1$,$n = 0, 1, \cdots, m-1 \left[\begin{array}{c} i \\ n \end{array}\right] = \frac{i!}{(i-n)!n!}$.

Because the method of parameter estimation based on the probability of weight moment is not sensitive to small sample applications, it is applied to small samples with respect to classical moments and has higher robustness, Poor evaluation.

3.3. Weight probability moment and inverse cumulative distribution function

If the variables x in the study are non-negative and random, then the parameter β_n can be regarded as the inverse cumulative moment of the distribution model. According to this argument, the relation formula can be obtained as follows:

$$E[X^n] = \int_R x^n f(x)dx = \int_0^1 [x(u)]^n du \,. \tag{12}$$

In equation (12), $du = dF(x) = \frac{f(x)}{\int f(x)dx}$, compared with the parametric model β_n, combining (12) $x(u)uf(x)$ shows that they can establish a certain degree of similarity correlation between the conversion model with the following:

$$dT(u) = \frac{x(u)du}{\int_0^1 x(u)du} = \frac{x(u)du}{\beta_0} \,. \tag{13}$$

The use of parameters dT can be transformed to form the probability β_n of moment weight derived:

$$\beta_n = \beta_0 \int_0^1 u^n dT(u), n = 1, 2, \cdots, N \,. \tag{14}$$

In Eq. (14), we use the β_0 as sample mean value. β_n/β_0 Is the inverse of the $x\,(u)$ cumulative moment n moments. By the same token, the inverse cumulative n-th order form of $x(1-u)$ the function is α_k/α_0. For the standard,$\beta_0=1$,β_n is the n-th order inverse cumulative distribution $x(u)$. To sum up, the following form of distribution of maximum cumulative entropy of inverse accumulation is as follows:

$$\begin{cases} maxH = -\displaystyle\int_0^1 x(u)\ln x(u)du \\ s.t. \displaystyle\int_0^1 u^n x(u)du = b_n, n=0,1,2,\cdots,N \end{cases} \tag{15}$$

Solving for the model (15) yields:

$$x(u,\lambda_0,\lambda_1,\cdots,\lambda_n) = \exp(\lambda_0 + \sum_{n=1}^{N}\lambda_n u^n)\,. \tag{16}$$

Comparing (3) with (16) shows that if we modify the original domain of the model, the constraint in the model (16) is the same as that presented by the classical moment, then Eq. (11) We need to obtain the probability density value, which has the constraint is the weight of the design of the moment here, then Eq. (11) is the distribution function of the inverse cumulative form.

4. Parameter Estimation

4.1. Calculation formula

It is necessary to determine the above-mentioned multiplier parameters $\lambda_i, i=0,1,\cdots,N$ first, according to the equivalent relationship between the mean value of the samples and the zero-order moments of the inverse cumulative function distribution, we can get:

$$\int_0^1 \exp(\lambda_0 + \sum_{n=1}^{N}\lambda_n u^n)du = b_0\,. \tag{17}$$

On both sides of (17) multiplication factor $e^{-\lambda_0}$

$$\int_0^1 \exp(\sum_{n=1}^{N}\lambda_n u^n)du = e^{-\lambda_0}b_0\,. \tag{18}$$

Differential operation on λ_n

$$e^{-\lambda_0}b_0\frac{\partial\lambda_0}{\partial\lambda_n} = \int_0^1 u^n \exp\left(\sum_{n=1}^{N}\lambda_n u^n\right)du\,. \tag{19}$$

hence we get :

$$\frac{\partial \lambda_0}{\partial \lambda_n} = -\frac{b_n}{b_0} \,. \tag{20}$$

$$\frac{\partial \lambda_0}{\partial \lambda_n} = \frac{\int_0^1 u^n \exp\left(\sum\limits_{n=1}^{N} \lambda_n u^n\right) du}{\int_0^1 \exp\left(\sum\limits_{n=1}^{N} \lambda_n u^n\right)} \,. \tag{21}$$

According formula(21∼22) , we can get

$$b_n = b_0 \frac{\int_0^1 u^n \exp(\sum\limits_{n=1}^{N} \lambda_n u^n) du}{\int_0^1 \exp(\sum\limits_{n=1}^{N} \lambda_n u^n) du} \,. \tag{22}$$

Equation (22) is a set of N equations constructed from the relative parameters. $\lambda_i, i = 0, 1, \cdots, N$ In order to facilitate the numerical calculation, formula (17) is modified as follows:

$$Q_n = 1 - b_0 \frac{\int_0^1 u^n \exp(\sum\limits_{n=1}^{N} \lambda_n u^n) du}{b_n \int_0^1 \exp(\sum\limits_{n=1}^{N} \lambda_n u^n) du} \,. \tag{23}$$

Solve the optimization goal:

$$\min Q = \sum_{n=1}^{N} Q_n^2 \,. \tag{24}$$

Based on the Giacobot computing strategy, we write the calculation software code to perform the corresponding iterative solution to equation (24), can get $\lambda_i, i = 0, 1, \cdots, N$

4.2. Algorithm steps

Step 1: Sort the data samples of motivation of college English learning;

Step 2: Use the data of historical university English learning motivation to conduct different order samples of weight probability moments, and in order to ensure the consistency, set the 6th order moment as its upper limit;

Step 3: Build goal (31), which is the model residual and set its initial value;

Step 4: Call the program to optimize the algorithm;

Step 5: Discrimination of the target convergence, if convergence can be achieved, go to step 7, unconverted then go to step 6;

Step 6: Recalculate with other initial values and go to Step 4;

Step 7: Calculate the value $\lambda_i, i = 0, 1, \cdots, N$ and output it as the final result;

Step 8: End the calculation.

5. Experiment analysis

5.1. Numerical examples

The commonly used Pareto distribution is taken as the numerical object of the test. The difference between the characteristic moments existing in the moments of the classical moments and the weights used in this paper is verified by experiments. The simulation is carried out by an example.

$$F\left(x\right)=u=\begin{cases}1-\left[1-c\dfrac{x}{d}\right]^{\frac{1}{c}},c\neq 0\\ 1-\exp\left(-\dfrac{x}{d}\right),c=0\end{cases}\tag{25}$$

The cumulative probability of inverse cumulative functions of the model shown in Eq. (25) has two forms, as mentioned above, type 1 and type 2. So available:

$$x\left(u\right)=\begin{cases}\dfrac{d}{c}\left[1-\left(1-u\right)^{c}\right],c\neq 0\\ -d\log\left(1-u\right),c=0\end{cases}\tag{26}$$

According to the characteristics of statistical data, the Lagrange parameters under the maximum entropy setting conditions can be calculated for different orders k, and the different characteristics between the theoretical calculation data and the statistical data are shown in Figs. 1 to 2. In the calculation of the theoretical data, the confidence level is 95%, which is essentially the hypothesis test of χ^2.

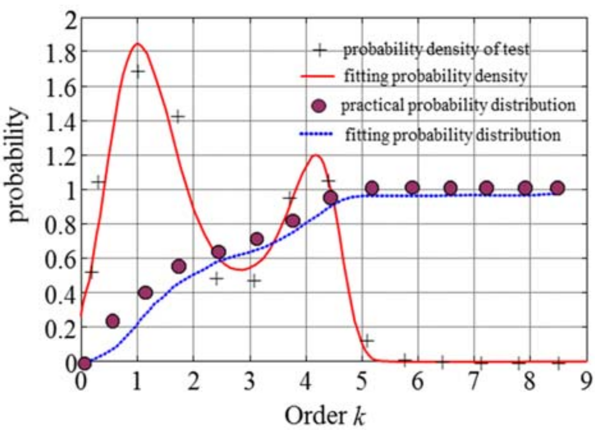

Fig. 1. Type 1 probability density function

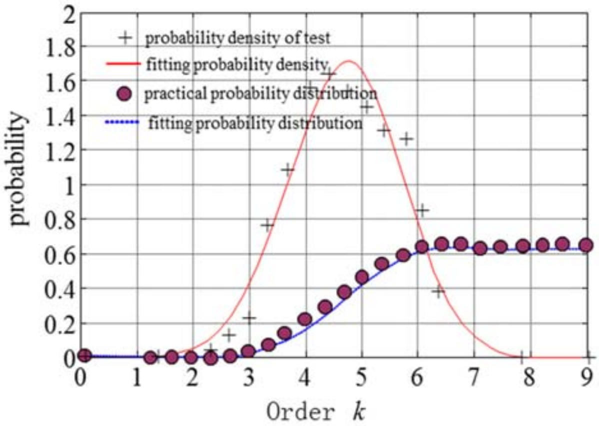

Fig. 2. Type 2 probability density function

5.2. Correlation analysis of college English learning motivation

Relevant statistics are shown in Table 1. Statistics show that:

(1) There is a positive correlation between gender and academic self-efficacy and self-regulation efficacy.

(2) There was a significant positive correlation between general self-efficacy and academic self-efficacy and self-adjusting efficacy.

(3) There was a significant positive correlation between general self-efficacy and interest-seeking motivation, which was related to the avoidance or motivation.

Table 1. self-efficacy and motivation type of correlation analysis

	General perform-ance	Academic Perform-ance	Career Motiv-ation	External Expectations Motiv-ation	Awareness of Interest Motiv-ation	Escaping Motiv-ation	Social Services Motiva-tion	Social Relations Motiva-tion
Sex	0.091	0.481	0.293	0.148	0.487	0.375	0.284	-0.064
English Basis	-0.148	-0.257	-0.461	-0.032	0.057	-0.027	-0.154	-0.138
Work Application	-0.337	-0.103	-0.481	-0.229	-0.213	-0.170	-0.448	-0.243
General performance	1	0.701	0.403	0.031	0.609	0.532	0.487	-0.114
Academic Performance	0.701	1	0.548	-0.014	0.504	0.381	0.345	-0.393
Self-regulating efficiency	0.555	0.765	0.457	0.244	0.674	0.479	0.501	-0.191

(4) There is a significant positive correlation between academic self-efficacy and self-regulating efficacy.

(5) Academic self-efficacy was positively correlated with career motivation and positively correlated with motivation to seek knowledge.

(6) There was a positive correlation between self-regulation efficacy and motivation of career advancement, positive correlation with motivation of seeking interest, and positive correlation with motivation and social motivation of escape.

6. Conclusion

(1) Interest is a key factor that motivates students to learn. Because girls' academic performance, general self-efficacy and self-regulating efficacy are higher than boys, and gender is positively correlated with academic self-efficacy and self-regulating efficacy. Therefore, in English teaching, teachers should adopt a gender-sensitive teaching method, pay more attention to cultivating the sense of self-efficacy of boys, and enhance their self-confidence in English learning through various means such as strengthening and model motivation. From the collection and collation of open-ended questions in this study, the researchers also found the corresponding conclusion that girls generally expressed their interest in listening, speaking and intensive reading in the question "Which course did you learn more confident?" More confident, while boys said "no self-confidence course"; and asked "do you think you complete the English course which tasks more freely?", Girls are more inclined to hear and intensive reading, while boys think it is reading Text; When asked "which part of English teaching you are more interested in?", Both boys and girls think it is English listening and speaking. Here, boys in the hearing of the interest and not confidence formed a departure. Interest is a key factor in stimulating students' learning. If they can better enhance the self-efficacy of boys in English learning and keep them in line with their good learning interests, they are bound to be able to achieve better motivation to stimulate the effect. This is worth serious consideration of English teachers.

(2) Practicality has a direct effect on self-efficacy as an external motivation. The practical value of English and the linguistic environment make it significantly different for students' needs for English. This may be the main reason that all kinds of self-efficacy of students who need English in their work are higher than those who do not need English in their work. Students who use English frequently in their work are significantly more likely to practice English, especially in speaking and listening, than those who do not need English at work. It can be seen that the practicality of English as an external motivation has a direct impact on learners' self-efficacy. For students who do not need to use English in their work, teachers should give more practice opportunities, create a better language learning atmosphere for them, and integrate the teaching and living activities.

(3) Interest seeking motivation and general self-efficacy, academic self-efficacy and self-regulation effectiveness were positively correlated. This shows that motivating and cultivating students' interest-seeking motivation is of great importance to enhancing self-efficacy. The motivation of occupational motivation is positively correlated with academic self-efficacy and self-regulating effectiveness. The mutual promotion between work and study can help students to better Into the study of

English, the purpose of a more distinctive, higher English learning enthusiasm.

(4) The internal motivation of English learning is significantly and positively related to general self-efficacy, academic self-efficacy and self-regulating efficacy. This conclusion is consistent with that of Chi Liping and Xin Ziqiang (2006). The higher the efficacy of the subjects, the higher the internal motivation. The highly motivated subjects were full of self-confidence about their abilities and the results of their activities. As a result, they showed strong endogenous motivation. They dared to meet the challenges and were full of enthusiasm and enjoyment without being subjected to external factors. Noels et al.'s study of L2 learners also found similar results, ie individuals with high endogenous motivation are usually those with higher self-efficacy, and their anxiety levels are lower, regardless of the evaluation and reflection of others.

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Received May 7, 2017