Modeling of Learners' Interest in Blended Learning: Insights from Emotional Cognition

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Abstract. In blended learning, how to explore and evaluate the learner's interest is very important. In this paper, we study on modeling of learners' interest from the perspective of cognitive neuroscience. Emotional cognitive theory and brain cognitive process for situational learning interest were introduced. In addition, in order to solve the problem of quantitative assessment of interest, learner's online operation behaviour was summarized through data mining methods, and the learners' interest regression model was built. Experimental results show that the accuracy of the model is more than 91% and it has good applicability in blended learning.

1 Introduction

In recent years, profound changes have occurred in teaching methods with the development of information technology. In particular, E-learning method emerged the end of twentieth century, which makes it possible to learn at any time and at any place. Although E-learning method provides a lot of convenience in learning, but also it has some shortcomings. For example, it is lack of face-to-face communication between teacher and student, and depends on digital teaching too much, especially, it faces to high drop-out rate and low completion rate. It was reported that there are more than 50,000 registered students selected software engineering course of UC Berkley on Coursera platform, but only 7% of them passed the exam [1]. As another example, MOOCs has developed rapidly in recent years, but the data indicated that the number of learners who can finish MOOCs was only 6% in China [2]. Therefore, in order to improve the above situation, the blended teaching is put forward, which combines the advantages of traditional teaching and E-learning [3]. Because blended teaching includes the advantages of previous teaching method, then this kind of learning is deeply loved by the learners.

Because learner's interest seriously affects completion of his studies, the study of learner interest has been concerned by scholars, and there are a lot of research results. However, learners in blended teaching have different social experiences and educational background, which make research of learners' interest show a lot of complexity. Previous research methods are often ineffective, such as learning path analysis, web log mining. It is well known that online learning process often involves a large number of text, pictures, semi-structured and unstructured data, which is very closed related to learner's interest and difficult to analyse. Taking into account the above difficulties, we adopt cognitive neuroscience as theory basis to research above issue, which has proven to be successful in the study of emotions, advertising and marketing [4]-[6].

2 Theories and Methodology

2.1 Emotion classification theory

Emotion is a kind of attitude experience of people toward the objective matters [7]. Although emotions have long been known, however, the classifications and the descriptions of emotions have not reached consensus in scholars for a long time. Relatively speaking, the classification from the perspective of psychology is generally accepted by most of scholars. From psychological point of view, human emotions are divided into two categories, one is basic emotion, and the other is dimensional emotion [8].

2.1.1 The basic emotion theory

The basic emotion theory thought that human emotions are composed of body experience, physiological arousal and external expression. And typical classification of basic emotion is concluded by American scholar Orthony (1990), which is shown in Table 1 [9].

Table 1. Classifications of Emotions

Scholars	Classifications
Arnold	Anger, aversion, courage, desire, despair, hate, hope, love, etc.
Ekman, Friesen & Ellsworth	Anger, joy, sadness, surprise, etc.
Frijda	Desire, happiness, interest, surprise, wonder, sorrow
Gray	Rage and terror, anxiety, joy
Izard	Anger, disgust, distress, fear, interest, shame, surprise, etc.
James	Fear, grief, love, rage
McDougall	Anger, disgust, fear, subjection, wonder, etc.
Mowrer	Pain, pleasure
Oatley & Johnson-laird	Anger, disgust, anxiety, happiness, sadness
Panksepp	Expectancy, fear, rage, panic
Plutchik	Ecstacy, admiration, terror, amazement, grief, loathing, rage, vigilance
Tomkins	Anger, interest, disgust, fear, joy, shame, surprise, etc.
Watson	Fear, love, rage
Weiner & Graham	Happiness, sadness

2.1.2 The dimensional emotion theory

The dimensional theory thinks that all human emotions are composed of multiple dimensions, and every kind of emotion is not independent, it is continuous. On the method of dimensional division, wheel of emotions is proposed by Plutchik (1980). In Plutchik´s wheel of emotions, eight kinds of emotion were divided. That is, ecstacy, admiration, terror, amazement, grief, loathing, rage and vigilance. These emotions are in a round structure centred on the original point. All emotions can be obtained based on the above eight emotions. For example, contempt is composed of loathing and rage.

In addition, the three-dimensional theory of emotion was put forth by Wundt. And it was developed after that. Especially, PAD (Pleasure-Arousal-Dominance) three dimensional emotions model has great effect on related research, which was proposed by Mahrabian and Russell. Among their model, P dimension reflects individual positive emotion or negative emotion. A dimension means level of individual physiological activation. D dimension refers to individual control state for situation or other people [6].

2.2 Autonomous Learning Theory

In the concept of autonomous learning, different researchers give different opinions, for example, Holee think it is a kind of ability, Pintrich think it is a process of active construction of learning, Yu et al., think it is a way of learning [1]. No matter what kind of definition is, it is identical in essence, that is, learner autonomy determines learning style and learning behaviour in autonomous learning. From the perspective of research, the theory of autonomous learning can be divided into behavioural perspective [10] and Humanism perspective [11]. From behavioural perspective of view, it is considered that the nature of autonomous learning is a kind of learning behaviours of ‘stimulus response’, which is based on the response of reinforcement.

From humanism perspective of view, it emphasizes learners' autonomous learning ability, and it is believed that autonomous learning needs to play their own initiative and combine learning activities with their own requirement to carry out meaningful learning. The learning process of autonomous learning involves many aspects, such as mental, emotion, motivation, demand and so on. The process of autonomous learning is shown as Figure 1.

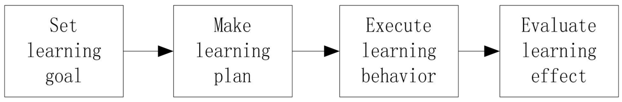

Figure 1. Process of Autonomous Learning

3 Brain cognitive mechanism for context learning interest

3.1 Brain cognitive activity for interest

Human emotion is produced by the interaction of three factors, that is, stimulation, physiology and cognition. Among them, cognitive factor is the key factor [12]. When learners logged on online learning platform, web page will firstly arouse their attention. Web information was delivered to learner’s limbic system by selective attention mechanism and sensory pathway, and then produced first emotional information. Due to first emotion come from the superficial information of stimulus signal. Therefore, it is very important to how to design an attractive web course interface to arouse learners’ first interest in online learning platform.

Based on the first emotional response, the content of stimulus signal will generate the second response, which comes from advanced cerebral cortex cognitive activities respond to semantic information. As a result, it is equally important to provide attractive course content for online learning platform. If online learning platform can provide attractive web pages and course, which is easy to arouse learner's selective attention, and make his brain produce first emotional response and second emotional response, and can arouse learner's independent learning interest and good learning behaviour.

Overall, brain cognitive process of context interest can be seen as three parts, context generation, cognitive neural activities and emotional experience. The brain cognitive process of context learning interest is shown as Figure 2.

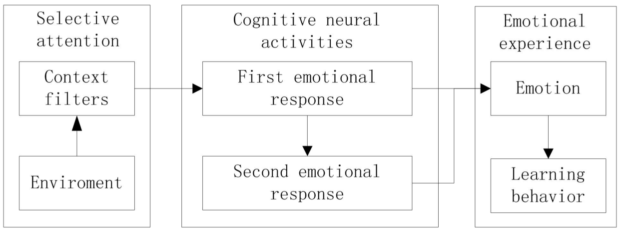

Figure 2. Brain Cognitive Process of Context Learning Interest

As we known, learners' brain constructs the emotional symbol system for the specific stimulus symbols under the action of memory based on the first and the second emotional experience. Once a familiar semantic symbol occurs, the learner will give selective attention according to emotional experience in memory, and adjust the distribution of cognitive time on visual and hearing sense. According to the above analysis, we know if pleasant learning experience was provided in blended learning, it will help learners to form their own learning habits and behaviours, and awaken their learning interest. At the same time, the memory stored in the brain will be more profound, and interest is also easy to be perceived.

3.2 EEG experiment for context interest

In recent years, EEG (Electroencephalography) method has been applied to much research [13], such as the research of marketing strategy and advertising effectiveness. In our study, EEG method was used in study of learners' interest.

3.2.1 Experimental subjects

Our experiment includes eighteen participants, and all of them come from learners of 'Shanghai study website'. Among them, eleven were male and seven were female, average age was 22.7 years old. All subjects were physically and mentally healthy, right hand in hand, normal vision or corrected visual acuity, and had signed the informed consent before testing.

3.2.2 Experimental design

In order to study on learners' interest in blended learning, we designed two test tasks, task 1 is material browsing, Task 2 is designed to test human cognition for symbolic information, and test material is composed of variety of content material, include animation, colour, voice, picture and text. Among them, text material preparation is as follows.

Firstly, we visit some teachers and collect one hundred related words. Then, fifty words were selected by field experts and were used in experiment. Each word is classified the degree of relevance of the level of judgment (0-5), among which, 0 refers to no relationship, 5 refers to the highest correlation. At the same time, fifty families living words were selected as neutral word materials. Finally, the above words consist of stimulus and neutral words.

3.2.3 Experimental procedure

The experiment of EEG is shown as Figure 3. It includes signal collection, signal processing and EEG analysis etc. Among them, the methods of signal processing include Support Vector Machine, Bayesian method, Back-Propagation neural network etc. In our study, Wavelet Transform were used.

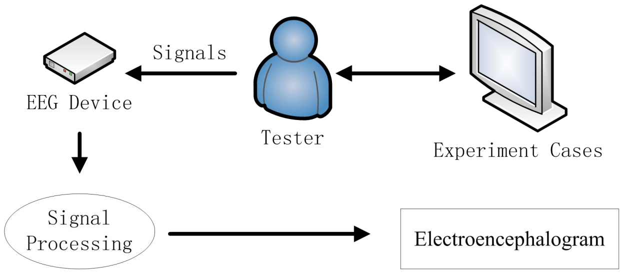

Figure 3. Process of EEG Experiment

3.2.4 Analysis of experiment

The data of four categories of brainwaves (α , β , δ , θ) is collected after subjects finished experiment. Previous studies have shown that when the human brain is thinking or excited, a large number of beta waves will appear [14]. Our experiment show that when the content of interest appears, learners often express more attention or mood-swings, and it is easy to cause beta rhythm. Then the relative energy of the beta rhythm wave is used to analyse the different cognitive load of the learner. The results of EEG experiment show that the relative energy ratio of beta rhythm wave is higher when executing the stimulus words. And Mann-Whitney U test shows P value below 0.05, which means the difference of relative energy are significant between stimulus and neutral words.

In the above of EEG experiment, we also found that human brain's cognitive time is different when it faces to different material. The human brain's cognitive time for text information is more than animation, which is very important for us to research interest.

4 Representation of online learning interests

4.1 Learning interest parameters

Learners' online operation behaviours reflect their mental state, which is an important representation of interest. After reference to previous studies, we divide online operation behaviours of learners' interests into six categories, and the following sets were used to represent online learning interest.

$$I = (T0, T1, T2, T3, T4, T5) \qquad (1)$$

In (1), *T0* means the type of displaying interest behaviour, *T1* is the type of marked interest behaviour, *T2* is the type of interest behaviour of course link, *T3* is the type of learning time, *T4* is the type of rolling span of page, and *T5* is the type of text interest. Expand to say, *T0* is obtained through feedback of interest questions on the web page, which indicates learners' interest. *T1* is obtained by calculating the behaviours of all these online operations, such as add tag, add bookmark, save page etc. *T2* implies that more times the course resources are clicked and the more learners' interest is shown. Similarly, *T3* implies that the longer the accumulated learning time and the more learners' interests it shows. *T4* is also can be regarded as the longer the distance of rolling and the more learners' interest is shown. *T5* is obtained by calculating the learner's interest from his online text.

According to the results of previous EEG experiments, human brain's cognitive time is different. When learner studies on the Internet, his brain's cognitive time is closely related to the symbol information. If learner's operation time is significantly different from normal threshold, this operation will be filtered out.

5 Modeling of learners' interest

5.1 Selection of parameters

Due to learners' behaviour on online learning platform is closely related to their psychological activities. That's to say, learning behaviour is the external expression of mentality. If learner likes one course, then he will learn it seriously and give feedback on time. According to previous theoretical analysis, some behaviour can reflect the actual interest of learner toward this kind of resource, such as learning frequency, time, collection, questionnaire, information of focus, answering process, evaluation, etc. In our study reading and operation behaviours were selected as represent learners' interest.

5.1.1 Reading behaviour of learners' interest

In learning process, the main behaviour is reading, including browse text and watch video. Learning is accompanied by click operation (For example: drag the scroll bar, turn the page, and click back). According to our analysis, if learner often drags mouse which indicates he browse carefully. Forward and backward operation indicates that the learner is not very interested in this part of content or he thinks it too simple to learn.

5.1.2 Operation behaviour of learners' interest

In learning process, if interest content encounters, learner will do some operations, such as collect, copy, concern, save, print, add bookmarks, share, etc. These behaviours often represent learner's interest. For example, online star rating, if the evaluation is one star, which indicates learner isn't interested in this content. Conversely, if the evaluation is five stars means learners are very interested in the resources or knowledge.

5.2 Modeling

5.2.1 Sample data collection

In our study, sample data were collected from the registered learners of website (http://www.shlll.net), and the date from August 2013 to August 2015. The learning behaviours of 33 learners are selected as samples and the learner interest sample data after unification as shown in Table 2.

Table 2. Sample Data for Learners' Interest

Stu ID	Course	A_0	A_1	A_2	A_3	A_4	A_5
201301	08001	0.556	0.067	0.778	0.022	0.744	0.042
201302	08001	1.000	0.111	0.754	0.062	0.744	0.050
...	...	...	...	...	...	...	...

5.2.2 Modeling of course interest

According to collected data, regression equation was established and obtained regression coefficient as following. β_0=0.0844, β_1=0.4347, β_2=0.0938, β_3=0.1607, β_4=0.1772, β_5=0.0492. Therefore, regression equation of the course interest is as follows.

$$Y = 0.4347x_1 + 0.0938x_2 + 0.1607x_3 + 0.1772x_4 + 0.0492x_5 + 0.0844 \quad (2)$$

Among which, X_1 is the set of marked interest behaviour coefficient. X_2 is the set of course linked interest behaviour. X_3 is the set of learning time interest behaviour. X_4 is the set of moving span interest behaviour. X_5 is the set of text interest behaviour.

In (2), we can see the coefficients of X_1 and X_4 are great, which suggests that these two kinds of behaviours are important to leaners' interests. The coefficient of X_5 is less, and the explanation for this is most of online learners are not very much involved in text discussion. Then the effectiveness of this model is tested, and R^2=0.9132, which suggests the fitting effect is good. Besides, P value of every coefficient is below 0.05, means the regression coefficient is significant. Then this model is used to predict learner interest for other ten learners. The result is shown as Figure 4.

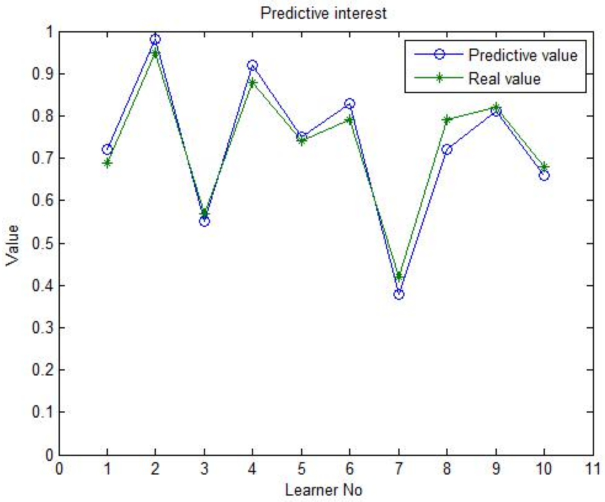

Figure 4. Compare Predictive Interest to Real Interest

It can be seen from Figure 4, the value of predicitive interest is close to the value of real interest. Calculation results show that the overall accuracy of ten learners is 91.04%, then it can be used to estimate interest.

6 Conclusions

Based on the characteristics of blended learning education, this paper studies the learners' interest modeling from the perspective of emotional cognition. We investigate the learning interests by observing the brain cognition experiment and data mining of learning behaviours. Our study contributes is to provide brain mechanism model for context learning interest, and put forward quantitative evaluation learning interest for six kinds of online operation behaviour. In addition, learners' interest regression model is established. The experiment suggests this model can represent effectively the learners' interests in blended learning.

In general, the future study can use eye tracker or other wearable devices and analyse the learning interest behaviour from the perspective of physiological features, which can improve the accuracy of our model.

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