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A New Mental Experience Quantification and Emotion Prediction Model for E-Learning Users

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ABSTRACT
At present, there exists a lack of an in-depth study on the quality of service evaluation of computer systems from the perspective of user psychological experience. This paper proposes an overall model for prediction of user psychological experience which is based on the environmental analysis of E-learning, the quantitative evaluation of user psychological experience and emotion. First, this study analyzes the impact of usability, usefulness, emotion and other factors on the psychological experience of E-learning users. Next, we use the resource coverage rate, recommendation hit rate and other indicators to measure usability and usefulness that are to construct the feature weight matrix and then use the AHP to quantify the overall user psychological experience evaluation model. The partial least squares regression method is adopted to take the individual characteristics of the learners as independent variables, and the characteristics of negative emotion regulation strategies as the variables. The proposed model can effectively find the E-learning system experience in the shortcomings of user psychology through a practical application. The results of this study can be used to build a more suitable quantitative evaluation method of user psychological examination for further study the characteristics of emotions affecting the user's psychological experience.

Keywords: quantitative evaluation, emotion prediction, user psychological experience, partial least squares regression

INTRODUCTION

The speed and extent of service information development depends on the availability of Internet, computer technological and financial resources at this time, but in its essence development is a process that is determined by the response of user to their external environment. User experience is subjective, dynamic from time variations, environmental limited and different among individuals, which all demonstrate that there will never be identical user experiences (Calvo & D'Mello, 2010; Moridis & Economides, 2008). However, it is still possible to create similar user experience with certain designs when it comes to clear target customer groups, which requires in depth research and precise control to take all the circumstances of customers using the product into consideration.

Experience economy is a kind of subjective psychological feeling formed by users when they receive service. Researchers in computer science, psychology, sociology and other fields have studied user experience from their respective perspectives and applications. In the process of service acceptance, the user, computer system and objective environment will affect the quality of user experience (Broekens & Brinkman, 2013; Ortigosa, Martín, & Carro, 2014). The current research on the user experience becomes more focused on the research of the system but the lack of consideration of user psychological and cognitive factors. Therefore, the human thinking and mental aspects of the user experience to further research is a big issue to explore it.

Buchholz defined QoC (Quality of Context) as quantitative indicators to describe the information of quality for any user (Buchholz, Küpper, & Schiffers, 2003). They discussed what QoC is, what its most important parameters are and how QoC relates to QoS (Quality of Service) and QoD (Quality of Device). These three notions of quality

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Contribution of this paper to the literature

- This research helps to complete the quantitative assessment and psychological adjustment strategy prediction for e-Learning users' psychological experience.
- It is hoped that the results of this study can be used instead of expert assessment which can provide suggestions for studying the characteristics of users' psychological experience.
- This paper provides a reliable path for solving the quality problems of user experience when receiving services.

are unequal, but not unrelated. Based on several examples they showed the interdependence between them. Manzoor proposed the objective and subjective view of distinguishing QoC (Bellavista, Corradi, Fanelli, & Foschini, 2012). They pointed out that the evaluation of user experience quality should be defined and measured according to the consumer's needs and expectations. Bellavista presented a unified architectural model and a new taxonomy for context data distribution by considering and comparing a large number of solutions. In addition, Sheikh etc., identified and defined five quality-of-context indicators for context-aware middleware, and discuss different alternatives for their quantification (Sheikh, Wegdam, & Sinderen, 2007). These quality-of-context indicators are: precision, freshness, spatial resolution, temporal resolution and probability of correctness (Manzoor, 2010).

On the basis of previous research, this paper gives a quantitative analysis method from the perspective of user psychological experience, the key issues including E-learning application background (Harrati, Bouchrika, Tari, & Ladjailia, 2016):

1. The characteristics and factors that affect the psychological experience of E-learning users;
2. The quantitative measurement of features and elements;
3. The overall construction and experimental analysis of the quantitative model of user's psychological experience;
4. Construct a quantitative model of learners' personality and emotion regulation strategies.

The rest of this paper is organized as follows: Section 2 describes the related research work; Section 3 introduces the E-learning user psychological experience of the quantitative evaluation model; Section 4 introduces the E-learning user psychological emotion regulation strategy model. Section 5 the empirical quantitative evaluation model and emotion regulation prediction model of E-learning users' psychology were tested and analyzed. Finally, some conclusions and future works are drawn.

RELATED WORKS

Factors of Influencing Mental Experience for User

Researchers in psychology, sociology and computer science have made qualitative and quantitative research on the factors that influence the quality of user experience from different focuses (Aparicio, Bacao, & Oliveira, 2016; Chu, & Chen, 2016; Sinclair, Kable & Levettjones, 2016). In the qualitative aspects, some researchers believe that the influence factors of user experience can be divided into surface layer, frame layer, structure layer, layer and layer micro scope of strategic factors affect user experience is divided into service content, reconstruction and expression. In quantitative aspect, the researchers propose some quantitative indicators to measure the user experience, such as Lewis (1995) introduces a set of questionnaires for different phases of usability evaluation: one for collecting immediate user response after a task in a usability test (After Scenario Questionnaire ASQ), another for post-study evaluation for usability tests (Post Study System usability questionnaire PSSUQ) and the third for field studies (Computer System Usability Questionnaire CSUQ). The measurements have been developed by IBM. Two questionnaires were used to analysis of the effectiveness of information system quality, interface quality and overall satisfaction (Ortigosa et al., 2014). Arnie Lund designed effectiveness, satisfaction, learnability and usability questionnaire (USE) including 30 score items (Broekens & Brinkman, 2013).

The overall results show that the factors affecting the quality of user experience including:

1. It's easy to use, which can be further refined as the response speed and easy to learn, easy navigation, simple operation, favorable operation, visual appeal and other factors.
2. It can be further refined to meet the needs of users, improved the work efficiency of users and brought the value of user.
3. Some other factors can be used for user experience such as the character of the user, the user's personal information and the user emotional factors.

From the user's cognitive and emotional characteristics of the user experience has become a hot topic in this field, such as usability consideration of user cognition, behavior, psychology and qualitative research method of psychological measurement. But there is lack of quantitative evaluation methods and experimental verification in practice.

Quantitative Measurement of Factors

We can obtain user needs, habits and other information from man-machine interaction and interface by observation, interview, questionnaire survey, user role play simulation and other methods to analyze the psychological characteristics of the user. This method is relatively direct and easy to operate that is mostly used in qualitative measurement but they need to spend time, use a lot of manpower and is subject to the human subjective factors (Clark, & Wrona, 2016; Reyes-Aguilar, & Barrios, 2016).

The user experience is an individual behavior which can't be completely simulated and reproduced. But there are a lot of psychological characteristics in common from the user group. Most users can be reached satisfaction through psychological common characteristics and different application of user experience servicer.

Some quantitative methods have been generated through user experience research such as GOMS method, CPM-GOMS method and NGOMSL method which all focus on operating time.

Construction of User Experience Model

The comprehensive evaluation method of user experience quality mainly includes Grey Relational Analysis (GRA) and Analytic Hierarchy Process (AHP). Grey relational analysis (GRA) is one of the most widely used model in grey system theory. It is a method to judge the degree of correlation between factors based on the similarity degree of geometric shape of each factor (Li, Wen, & Xie, 2015; Lin & Lin, 2002; Malek, Ebrahimnejad & Tavakkoli-Moghaddam, 2017). The basic idea of grey relational analysis is to carry out dimensionless processing of the original number of evaluation indicators, calculate correlation coefficient and correlation degree, and rank the evaluation index according to the degree of correlation, so it is suitable for the comparative analysis of multiple versions of service system.

The AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology (Dong, & Herrera-Viedma, 2017; Wang, Sharkh, Chipperfield & Cruden, 2017; Zhou & Xu, 2016). Users of the AHP first decompose their decision problem into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently. Decision makers establish relative weight calculation and consistency check by establishing the hierarchical structure of analysis objectives and constructing the 22 comparison judgement matrix of element weights, and get the relative importance of each element. Therefore, the analytic hierarchy process (AHP) is suitable for single system analysis.

User Emotion Regulation Strategy

Emotion is any conscious experience characterized by intense mental activity and a high degree of pleasure or displeasure. Emotions are complex. According to some theories, they are states of feeling that result in physical and psychological changes that influence our behavior (Dyson & Renk, 2006; Hannigan, Edwards, & Burnard, 2004). The physiology of emotion is closely linked to arousal of the nervous system with various states and strengths of arousal relating, apparently, to particular emotions. Emotion is also linked to behavioral tendency. Extroverted people are more likely to be social and express their emotions, while introverted people are more likely to be more socially withdrawn and conceal their emotions. Emotion is often the driving force behind motivation, positive or negative. According to other theories, emotions are not causal forces but simply syndromes of components, which might include motivation, feeling, behavior, and physiological changes, but no one of these components is the emotion (Chang, Liang, Chou & Lin, 2017; Chen, Yen, & Hwang, 2012). Nor is the emotion an entity that causes these components. At present, the research based on the relationship between emotion regulation strategy and personality is mainly qualitative analysis of a character and strategy in personality. But past studies did not explain the qualitative research of the application background and emotion research mostly took western people as subjects.

QUANTITATIVE EVALUATION MODEL OF E-LEARNING USERS' PSYCHOLOGICAL EXPERIENCE

In this paper, user's psychological experience is defined as the degree of the psychological feeling of the user in receiving the service (Hwang, Al-Arabiat, Shin, & Lee, 2016; Kebritchi, Hirumi, & Bai, 2010; Lee, 2010; Liu & Huang, 2015). The overall framework of the quantitative evaluation method of user's psychological experience is shown in

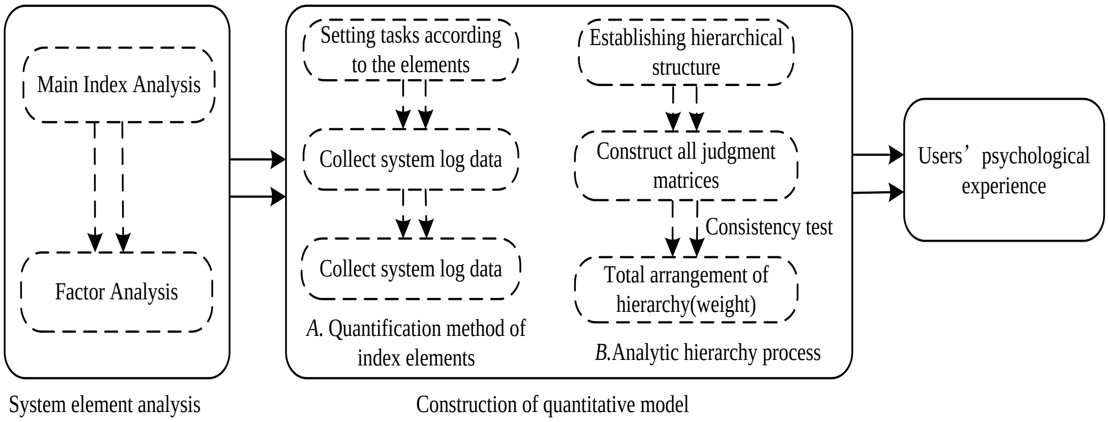

Figure 1. Overall framework of the quantitative evaluation method of user's psychological experience in E-learning

Figure 1. As shown in **Figure 1**, the overall idea of the quantitative evaluation method of user psychological experience is divided into three parts: (1) analysis of system elements. The main evaluation indexes are selected according to the psychological experience characteristics of the users, and the factors of the evaluation indexes are analyzed. (2) Quantitative model construction. First, according to the evaluation index, a hierarchical structure is established to determine the weight of each evaluation index. Secondly, set tasks according to the elements, collect log data and quantify the elements. (3) User psychological experience decision. Combined with the weight of each index, the quantitative results of the index factors evaluate the user's psychological experience.

Characteristic analysis and quantization method of the quality of user's experience (QoE)

From the analysis of the previous section we can see, there are many factors that affect the user's experience, among which the most important is the usefulness and usability.

Usefulness

The degree of satisfaction of users to the service provided and recommended by the system is called usefulness, also called validity, which has the following 3 characteristics:

1. Resource coverage rate. It means, to which extent the resources provided by the system can cover the domain of knowledge learned by the user.

2. Recommended hit rate. The hit rate is defined as the ratio of hit times and recommendation times in the process of login. And when the user finishes the content recommended by the system, the recommendation is considered to be a hit when the evaluation of the content is greater than the corresponding threshold. As for the recommended hit rate, it is the ratio of the total number of hits to the recommended content of the system and the total number of recommended content of the system, namely

$$\alpha_H = \frac{n_s}{n_r} \tag{1}$$

3. User loyalty. It is defined as the degree of willingness of users to reuse the system, and can be measured by the frequency of user visits. If the number of users using the system per week is n_u, and the number of loyalty benchmarks based on experts' experience is N, we have

$$\alpha_L = \begin{cases} 1 & n_u \geq N \\ \frac{n_u}{N} & n_u < N \end{cases} \tag{2}$$

Usability

When users master the operation, learning, navigation and use of the service provided by the system, the degree of difficulty in accordance with the user's habits is called usability. Usability of the E-learning system can be reflected by the following characteristics:

1. Response speed. The response time is a time interval between the user requests the service and the system render the request service, which can be obtained by analyzing the system log record

$$\upsilon = \begin{cases} 1 & \bar{t}_{re} \le t_{ts} \\ \frac{t_{ts}}{\bar{t}_{re}} & \bar{t}_{re} > t_{ts} \end{cases} \quad (3)$$

where, t_{re} is the response time, is the time of the user logging into the system control and loaded; t_{ts} denotes the reference response time. And user login system time is t_{in}, the time when system control is loaded is t_s, so

$$t_{re} = t_s - t_{in} \quad (4)$$

2. Navigation definition

$$\alpha_C = \frac{N_k}{M} \quad (5)$$

where, M is the number of knowledge items accessed by the user when the task is successfully completed; N_k means the number of knowledge items succeed in learning. If the user finds the target directly, the navigation definition will be 100%; if not, then the navigation definition will be 0%. Therefore, it can be seen that the smaller the system navigation, the better the user can directly and easily find the target knowledge items.

3. Task completion efficiency

$$E_T = \frac{\sum t_{ek}}{\sum t_{en}}, e_k \in E \quad (6)$$

where, t_{ek} is the length of learning time, namely, the time from the user clicks the k-th knowledge item $e_k$to the next knowledge. It is also the time of the user learning knowledge item e_k; t_{en} means the time spent by the user in learning the n-th knowledge of N knowledge items; E denotes the target knowledge item set, namely a collection of knowledge items that users need to learn in a learning task, $E = \{e_1, e_2, \ldots\}$.

In E-learning system, learning resources are provided to users by means of knowledge items. The minimum time of the user in learning the corresponding target knowledge item ist_{ekm}. If $t_{ek} < t_{ekm}$, it suggests that the user does not complete the learning task of the knowledge item. The minimum time is defined by the teacher expert or by referring to the average learning time of the user group.

If user's length of learning timet_{ek} is longer thant_{ekm}, namely $t_{ek} > t_{ekm}$, and the user thinks he/she has successfully learned the knowledge, namely the learning of knowledge item e_k is successful, the function assignment is 1; otherwise it is 0, namely

$$S_{ek} = \begin{cases} 1 & t_{ek} \ge t_{ekm} \\ 0 & t_{ek} \le t_{ekm} \end{cases} \quad (7)$$

If the user successfully learned the N knowledge item in E, then think that they completed the learning task, the function assignment is 1; otherwise it is 0, namely

$$T_{S_{ek}} = \begin{cases} 1 & \sum S_{ek} \ge N, e_k \in E \\ 0 & \sum S_{ek} < N, e_k \in E \end{cases} \quad (8)$$

The task time is a period from the task loaded to the completion of the task successfully, namely

$$t_T = \sum t_{en} \quad (9)$$

An Overall Quantitative Model of E-learning User's Psychological Experience

Analytic hierarchy process (AHP) is a decision making method for qualitative and quantitative analysis, which decomposes the elements related to decision-making into goals, criteria, plans and so on. It is a simple, practical and effective method for decision analysis and comprehensive evaluation of complex problems with multi objectives, criteria, factors and levels. Based on this, this paper applies the analytic hierarchy process (AHP) to the overall quantification of E-learning user's psychological experience.

Hierarchical structure of user's psychological experience

User's psychological experience is a kind of overall and subjective psychological feeling when users use E-learning system to study. From the above content can be seen, the overall user experience quality can be reflected in the usefulness, usability and other characteristics, which can be further refined. The hierarchical structure of the quality of mental experience in E-learning system is shown in **Figure 2**.

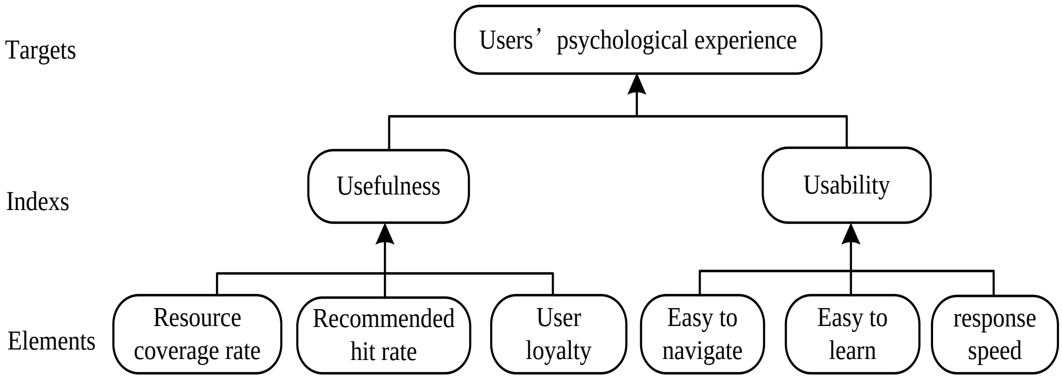

Figure 2. Hierarchical structure of user's psychological experience

Table 1. 1-9 scale method

Scale	Definition
1	equally important
3	slightly important
5	obvious important
7	strongly important
9	extremely important
2、4、6、8	Denote the median of 1-3, 3-5, 5-7, 7-9 adjacent judgments respectively

Table 2. Weight judgment matrix of each sub feature of usefulness index

Usability Index	Resource Coverage Rate	Recommended Hit Rate	Loyalty
Resource Coverage Rate	1	3	1/3
Recommended Hit Rate	1/3	1	1/5
User Loyalty	3	5	1

Table 3. Weight judgment matrix of each sub feature of usability index

Usability Index	Response Speed	Navigation Definition	Task Completion Rate
Response Speed	1	1/5	1/3
Navigation Definition	5	1	3
Task Completion Rate	3	1/3	1

Table 4. The relative weight matrix of the second level index to the first level target

Index	Usability	Usefulness
Usability	1	3
Usefulness	1/3	1

Constructing all judgment matrices at all levels

The discriminant matrix represents the relative importance between the underlying factor and its related elements in the upper layer, and determined by the mutual comparison between elements, namely, under a certain index, the feature of high weight is obtained by comparing 2 arbitrary features. And the scale of 1~9 is used to measure the comparison (**Table 1**).

As for usefulness, the weighting matrix is shown in **Table 2**.

As for usability, the weighting matrix is shown in **Table 3**.

The relative weight matrix of the second level index to the first level target is shown in **Table 4**.

Hierarchical single ordering and its consistency check

The solution W of the eigenvalue problem $AW = \lambda_{\max}$ of the judgment matrix B, after normalization, it is the rank weight of the relative factors of the same level to the relative importance of the upper level. The process is called the hierarchical single order.

Table 5. The relationship between random consistency index and matrix order

n_A	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Table 6. Hierarchical total ordering

	Usefulness	Usability	Total Ordering Weight
	0.75	0.25	
Resource Coverage Rate	0.2583	0	0.1937
Recommended Hit Rate	0.1047	0	0.0785
User Loyalty	0.6371	0	0.4775
Response Speed	0	0.1047	0.0262
Navigation Definition	0	0.6371	0.1592
Task Completion Rate	0	0.2583	0.0646

The judgment matrix needs to be acquired by the expert's experience. Because of their different views, the weight judgment matrix needs to be checked by consistency. When the judgment matrix cannot be guaranteed to be completely consistent, the eigenvalue of the corresponding judgment matrix will change, and the consistency of the judgment can be checked by the change of the eigenvalue of the judgment matrix. Therefore, in the analytic hierarchy process, the consistency index of the judgment matrix check is

$$C = \frac{\lambda_{max} - n_A}{n_A - 1} \tag{10}$$

where, λ_{max} is the largest eigenvalue of matrix A; n_A denotes the order of matrix. When the matrix is inconsistent, $\lambda_{max} > n_A$, the greater the difference $\lambda_{max} - n_A$, the greater the error, that is, the greater the n_A, the poorer the consistency. In order to eliminate the influence of order on consistency test, the random consistency index R is introduced, as shown in **Table 5**.

When the order is greater than 2, the ratio of the consistency index of the judgment matrix C and the average random consistency index RI of the same order is called the random consistency ratio, which is denoted as CR. When $CR = \frac{C}{RI} < 0.1$, it is believed that the judgment matrix has satisfactory consistency, otherwise, the elements in the matrix need to be modified so that the importance of the elements is relatively balanced. After the consistency test, the relative weight of each feature can be obtained by normalizing the corresponding eigenvectors of λ_{max}.

As for the usability index, $\lambda_{\max} = 3.0386$, $C = 0.0192$, corresponding to **Table 2**, $R = 0.52$, corresponding to **Table 5**, then $CR = 0.036 < 0.1$, which shows that the matrix has passed the consistency test. Eigenvectors $W' = [0.3715, 0.1506, 0.9161]$ corresponding to λ_{max}, the normalized eigenvector $W_1 = [0.2583, 0.1047, 0.6371]$, where the numerical value corresponds respectively to the relative weight of the resource coverage rate, the recommended hit rate and user loyalty of the usefulness index. Similarly, as for the usability index, $CR = 0.037 < 0.1$, satisfying consistency test, the normalized eigenvector $W_2 = [0.1047, 0.6371, 0.2583]$, the numerical values correspond respectively to the relative weight of the response speed, the navigation definition and the task completion efficiency of the usability index. Similarly, in **Table 4**, the relative weight of the second layer index layer relative to the first layer target layer is $W_3 = [0.75, 0.25]$.

Hierarchical total ordering and its consistency test

From the previous section, the relative weight of all the elements in each layer of the hierarchy to the total target is obtained, as shown in **Table 6**.

Next, with

$$CR = \frac{\sum_{j=1}^{m} CI(j) a_j}{\sum_{j=1}^{m} RI(j) a_j}, j = 1,2 \tag{11}$$

The consistency check of the total rank weight matrix is further carried out. It can be seen from the last section, $CI(1) = 0.01925$, $CI(2) = 0.01925$, $RI(1) = 0.52$, $RI(2) = 0.52$, by(11), $CR = 0.037 < 0.1$ can be got, which shows that the quality feature weight matrix of the whole user mental experience is tested and has satisfactory consistency.

PREDICTION MODEL OF E-LEARNING USER'S PSYCHOLOGICAL EMOTION REGULATION STRATEGY

The relationship between learners' personality and emotion regulation strategies can be expressed by 6 tuple

$$L = \langle U, V, W, X, Y, f \rangle \tag{12}$$

where, U symbolizes the whole set of learners; X means the attribute set of learners' personality characteristics; Y denotes the set of learners' emotion regulation strategies; W represents learner's feature set, and $W = X \cup Y$; V is the predicted emotion regulation strategy set, $V = \bigcup_{y \in Y} v_y$, in which v_y is the value of $y \in Y$; $f: U \times W \to V$ refers to the feature mapping function of learners, and any entity $w \in W$ in U corresponds uniquely to V.

An Overview of Partial Least Squares Regression (PLS)

In the general multivariate linear regression model, there is a set of dependent variable $Y = \{y_1, y_2, \cdots, y_q\}$ (q is the number of dependent variables) and independent variable $X = \{x_1, x_2, \cdots, x_m\}$ (m is the number of independent variables), when the data satisfies the Gauss Mark off theorem, according to the least square method, we have

$$B = X(X^T X)^{-1} X^T Y \tag{13}$$

where, B is the estimated regression coefficient. When the variables in X have serious multiple correlations (the physical meaning of variables determines their correlation, or is caused by the insufficient number of sample points), determinant $(X^T X)$ in formula 13 is close to zero. Therefore, there will be serious rounding errors when solving $(X^T X)^{-1}$, making the sampling variability of the estimation of regression coefficient increase significantly. What is more, when the variables in X are completely correlated, $(X^T X)$ will be an irreversible matrix, unable to solve regression coefficient. At the same time, if the least square method is used to fit the regression model, there will be many abnormal phenomena in the regression result, which will not guarantee the accuracy and reliability. In practical work, the multiple correlations of variables are universal. Partial least square (PLS) method can solve this kind of problem better.

Partial least squares regression (PLS) is the integration and development of multiple linear regression, canonical correlation analysis and principal component analysis. This method first extracts component t_h $h = (1,2,\cdots)$from the independent variable set X, each component is independent of each other. Next, establish regression equations between these components and independent variable X, the key to which is the extraction of components. Different from the principal component regression, the components extracted by partial least squares regression can not only generalize the information in independent variable system, but also explain the dependent variable best and eliminate the noise interference in the system. Therefore, the model of regression modeling is effectively solved under the condition of multiple correlations between independent variables.

Emotion Regulation Strategy Prediction Model

At present, there are many categories of personality characteristics. Considering the age distribution of learners, and combining the mature evaluation technology with existing research results, 16 personality characteristics defined by the cartel is adopted in this paper, and the learner's personality is divided into 16 attributes, they are sociability, intelligence, stability, strength, excitability, perseverance, social boldness, sensitivity, suspicion, fantasy, sophistication, anxiety, experiment, independence, self-discipline and tension, which are defined as $P = [A_1, A_2, \cdots, A_{16}]$, the elements in the vector represent the 16 dimensions of the above characters respectively. At the same time, this paper adopts Gross strategies of emotion regulation and divides emotion regulation strategies into depressed expression and cognitive reappraisal, which can be shown as $T = [R, S]$, the Chinese version of CERQ has been proved to have good applicability.

The collected data were standardized, and the personality characteristics of learners and the emotion regulation strategies of learners are independent variables and dependent variables respectively, which are presented as $X = [x_1, x_2, \cdots, x_{16}]$ and $Y = [y_1, y_2]$. Using partial least squares regression method, the algorithm of emotional strategy modeling based on personality strategy is as follows

Input: Learner personality matrix $X = [x_1, x_2, \cdots, x_{16}]$ and he emotion regulation strategy of learners $Y = [y_1, y_2]$.

Output: Prediction model of learners' emotional strategies $y = \alpha + \beta_i x$.

(1) Standardize the matrix of the individual personality X and the emotion adjustment strategy Y, and obtain the standardized independent variable matrix E_0 and dependent variable matrix F_0.

(2) Based on the maximum eigenvalue θ_1^2 of the matrix $E_0^T F_0 F_0^T E_0$ and the corresponding eigenvector ω_1, the components representing the learner's individuality $t_1 = \omega_1^T X$, the score vector $\hat{t}_1$ ($\hat{t}_1 = E_0 \omega_1$) and the residual matrix $E_1 = E_0 - \hat{t}_1 \chi_1^T, \chi_1 = \frac{E_0^T \hat{t}_1}{\|\hat{t}_1\|^2}$ are obtained. Meanwhile, the eigenvector ω_2 corresponding to matrix $E_0^T F_0 F_0^T E_0$, the component of the emotion strategy γ_1 ($\hat{\gamma}_1 = F_0 \omega_2$), the score vector $\hat{\gamma}_1$ and the residual matrix $F_1 = F_0 - \hat{\gamma}_1 \beta_1^T$, $\beta_1 = \frac{E_0^T \hat{\gamma}_1}{\|\hat{\gamma}_1\|^2}$ are also gained.

(3) Cross validation test, when $Q_h^2 < 0.0975$ meets the precision requirements, the algorithm terminates, otherwise it continues.

Table 7. The minimum time length of the learners to complete the target knowledge item

	Knowledge Unit	$t_{ekm}(s)$	$\hat{t}_{ek}$ (s)		Knowledge Unit	$t_{ekm}(s)$	$\hat{t}_{ek}$ (s)
1	equivalent transformation of circuit	3	6	**9**	2 equivalent transformation of real circuit	8	16
2	series and parallel connection of resistance	1	3	**10**	circuit diagram	8	16
3	Y circuit of resistance	6	12	**11**	KCL independent equation	6	16
4	△delta circuit of resistance	6	3	**12**	KVL independent equation	10	20
5	series connection of voltage source	3	7	**13**	branch current method	11	22
6	parallel connection of voltage source	5	11	**14**	mesh current method	12	24
7	series connection of current source	3	7	**15**	loop current method	12	25
8	parallel connection of current source	6	13	**16**	node voltage method	14	28

Table 8. The learner log results of the E-learning system

ID number	2013
User identification	324
User name	1601082014
Knowledge unit	branch current method
Log in time	2017-09-04,19:12:34
Log out time	2017-09-04,19:13:37
Time Length/s	63

(4) Because of the rank r of E_0, $r \leq \min(n-1, m)$, there may exist r components $t_1, t_2, \cdots t_r$, residual matrix E_1 and F_1 replace E_0 and F_0, and repeat the steps above.

(5) Regress of r' components $t_1, t_2, \cdots t'_r$ extracted in F_0, and get ordinary least square regression equation $F_0 = \hat{t}_1\beta_1^T + \hat{t}_2\beta_2^T + \cdots + \hat{t}_{r'}\beta_{r'}^T + F_{r'}$.

(6) As $\omega'_k = \prod_{j=1}^{h-1}(I - \omega_j\alpha_j^T)\omega_h$, $t_k = \omega'_{k1}x_1 + \omega'_{k2}x_2 + \cdots + \omega'_{km}x_m (k = 1,2,\cdots,r')$, plug $Y = t_1\beta_1 + t_2\beta_2 + \cdots + t_{r'}\beta_{r'}$, and the partial least squares regression equation $y_j = \alpha_{j1}x_1 + \alpha_{j2}x_2 + \cdots + \alpha_{jm}x_m$ of emotion regulation strategy dependent variables of p was obtained, the algorithm terminates.

EXAMPLE VERIFICATION AND ANALYSIS

Quantitative Analysis of E-learning User's Psychological Experience

By using this method, this paper analyzes the user's psychological experience of E-learning system in the course of the third grade of a university, in which 113 learners are randomly sampled. In the experiment, the learning task required by participants is to learn 2 equivalent knowledge units: equivalent transformation of resistance circuit and general analysis of resistance circuit in E-learning system.

Definition of successful completion of learning tasks

To complete the 2 learning tasks above, it is necessary to learn the target knowledge item set E, E=[Equivalent transformation of circuit, series and parallel connection of resistance, Y circuit of resistance, delta circuit of resistance, series connection of voltage source, parallel connection of voltage source, series and parallel connection of current source, two equivalent transformations of real circuit, circuit diagram, KCL independent equation, KVL independent equation, branch current method, mesh current method, loop current method, and node voltage method].

Assume that the minimum time length of a learner to complete a target knowledge item is equal to half of the average length of time that the learner group studies the knowledge item, as shown in Table 7. According to the expert experience, if the learners successfully learn 4 knowledge items in E, the learning task is completed successfully. N=3 is the frequency of learners using E-learning system per week, the reference response time is 10s.

Quantitative evaluation of data acquisition and user's psychological experience

Based on the above learning tasks, the learner log results of the E-learning system are collected, as shown in Table 8.

Next, using the above-mentioned analytic hierarchy process, and starting from the usefulness and usability, we construct the overall quantitative evaluation model of user psychological experience quality, so as to obtain the

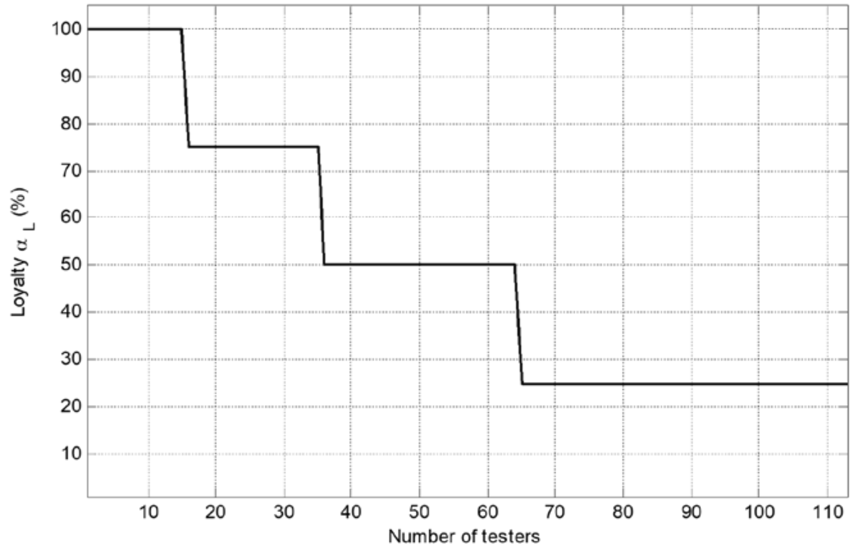

Figure 3. User loyalty

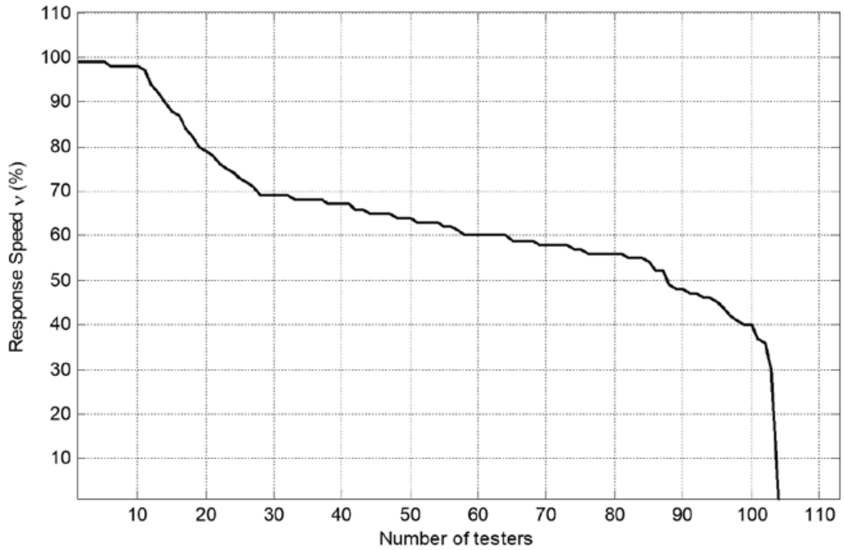

Figure 4. Response speed

resource coverage rate, recommended hit rate, user loyalty, response order weight speed, navigation definition and task completion efficiency, which were 0.1937, 0.0785, 0.4775, 0.0262, 0.1592, 0.0646 respectively, and by the combination of consistency test, It can be seen that the feature weight matrix has satisfactory consistency.

Experimental results and analysis

The key point of the experiment is to analyze and discuss the indexes such as user loyalty, response speed, navigation definition and task completion rate, and the total index of the user's psychological experience.

Loyalty is shown in **Figure 3**. From **Figure 3**, the average value of loyalty is 50.2%, which indicates that the system is less attractive to learners, and few users are willing to continue to use the system.

The response speed is shown in **Figure 4**. Seen from **Figure 4**, affected by the network environment, the average response time is from 35s to 80s, the mean value of the response speed is 59.8%, the system response speed for 9% users is 0%. This shows that the user has taken a shutdown measure while waiting for the system to load, so the response time cannot be obtained.

Navigation definition is shown in **Figure 5**. From **Figure 5**, the average navigation definition is 37.1%, and the navigation definition of the system for 20% users is 0%, that is, it is difficult for 20% users to find the learning knowledge items while using the system.

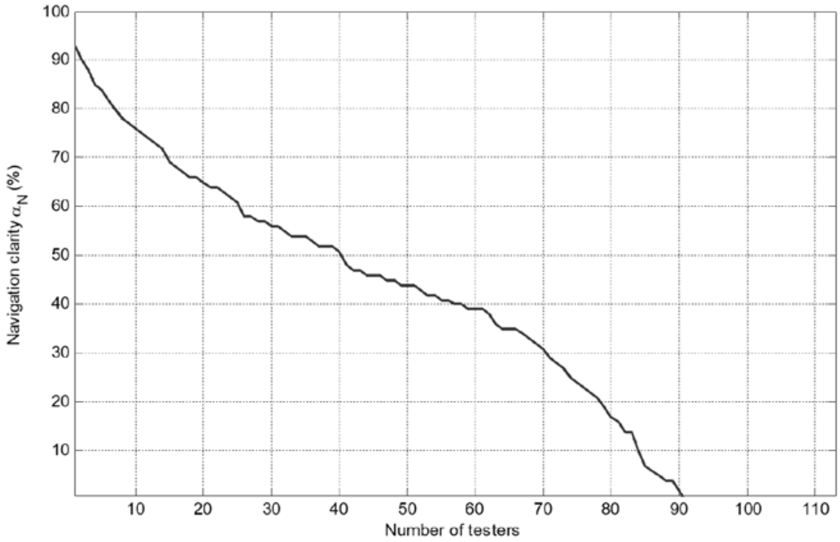

Figure 5. Navigation definition

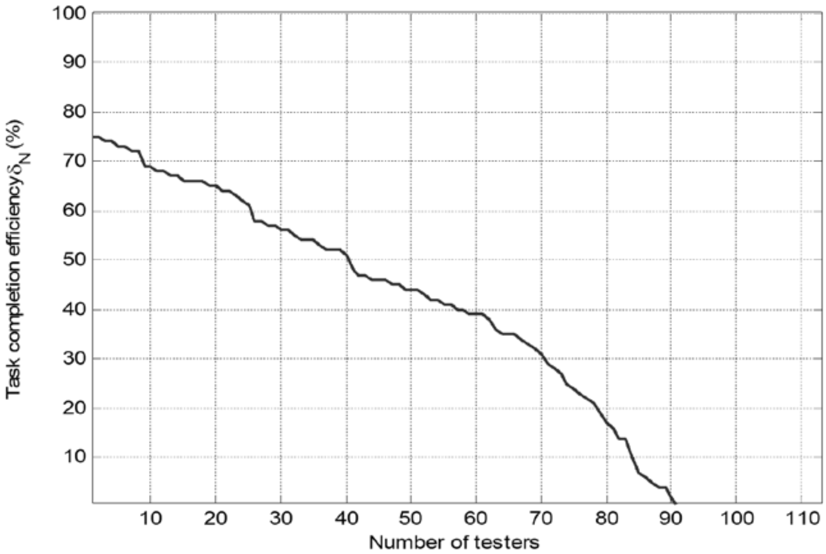

Figure 6. Task completion rate

The task completion efficiency is shown in **Figure 6**. From **Figure 6**, the average task completion rate of users when using the system is 36%, the maximum task completion rate is 75%, which shows that some users can effectively complete the learning task, but 20% users can not complete the learning task.

The overall user's psychological experience quality that E-learning system brings to the learners is shown in **Figure 7**. According to **Figure 7**, the highest experience quality is 72%; the lowest is 27%; the average is 37.5%, which indicates that the quality of user psychological experience of E-learning system needs to be further improved.

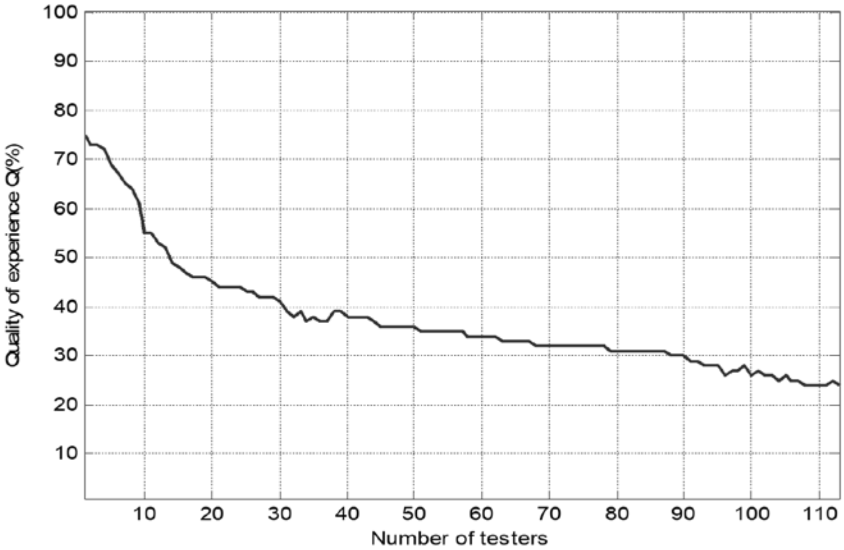

Figure 7. User experience quality

Table 9. The correlation coefficient between learners' personality and emotion regulation strategies

Attribute	correlation coefficient		Attribute	correlation coefficient	
	Repressed expression	Cognitive reappraisal		Repressed expression	Cognitive reappraisal
A_1	-0.470**	0.529**	A_9	0.202	0.523**
A_2	0.219	0.227	A_{10}	0.421**	-0.080
A_3	0.116	0.258	A_{11}	0.152	0.218
A_4	-0.429**	0.228	A_{12}	-0.144	0.276
A_5	-0.582**	0.237	A_{13}	-0.003	0.088
A_6	0.127	0.078	A_{14}	0.461**	-0.219
A_7	-0.302*	0.336	A_{15}	-0.092	0.105
A_8	-0.112	0.261	A_{16-}	-0.159	-0.019

Notes: Data strip * means p <0. 05, data strip ** in table denotes p <0. 01

E-learning User's Emotion Prediction Analysis

In order to study the relationship between learners' personality and emotion regulation strategies, this paper observed 113 learners, and form a table of the independent variable and dependent variable. The partial least squares regression is used to extract the required components on X and Y, and the emotion prediction model of personality and emotion regulation strategies are established.

Data preprocessing

In this paper, 113 valid samples are collected, of which 83 samples are used to establish the data set of the prediction model, and the other 30 samples are used as the sample set of the analysis and prediction model to verify the effect of the model fitting. First of all, data like personality characteristics, learners' emotion regulation strategies are preprocessed respectively, so as to gain the corresponding values. Then, the person coefficient is used to determine whether the independent variable and the dependent variable are related, and the correlation coefficient matrix is used to get the correlation between the emotion regulation strategy and the character attribute, as shown in **Table 9**.

From the research above and relevant data analysis, it is can be seen that in the learners' individual data, high attribute features lie in intelligence (6.084), perseverance (6.126) and self-discipline (5.978), which proves their wisdom, abstract thinking, quick thinking, responsibility, self-discipline and preciseness. The mean values of two types of emotion regulation strategies (depressive expression and cognitive reappraisal) are 2.51 and 3.168, respectively, which shows the personality and emotion regulation strategies of the learners are in line with those of the college students.

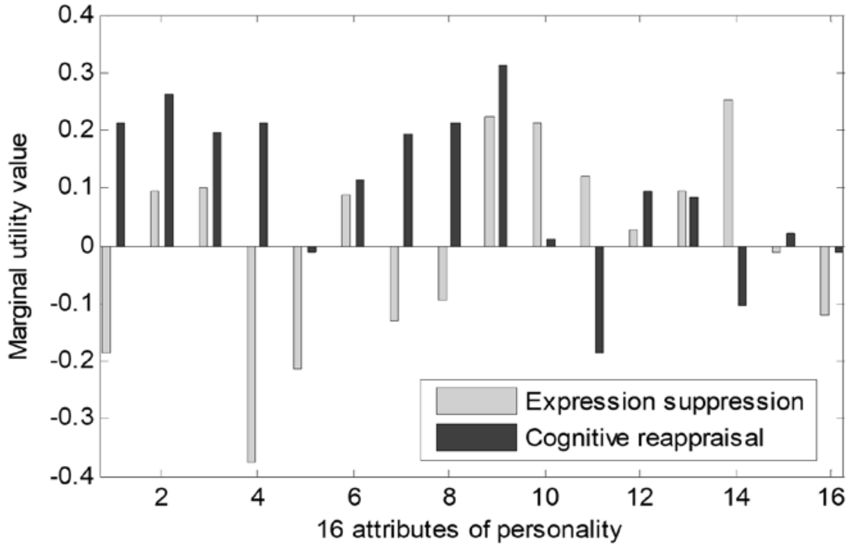

Figure 8. Regression coefficients of standardized data

Data analysis

Based on the above data preprocessing results, the 83 samples of the effective sample set are used as the data set, and the program of partial least squares algorithm is run under the matlab2012a environment. In order to evaluate the predictive ability of the model, the cross validity is used to evaluate the model. Suppose $Q_h^2 = -0.0178$, According to the rule of $Q_h^2 \geq 0.0974$, finally, 3 components were extracted to fit, and then the depressive expression and cognitive reappraisal standardized prediction regression equation were obtained

$$\begin{aligned} y_r &= 0.352 + 0.075x_1 + 0.097x_2 + 0.088x_3 \cdots - 0.038x_{14} + 0.019x_{15} - 0.006x_{16} \\ y_s &= 1.667 - 0.061x_1 + 0.041x_2 + 0.057x_3 + \cdots + 0.017x_{14} - 0.0131x_{15} - 0.0622x_{16} \end{aligned} \tag{14}$$

where, y_r and y_s denotes the value of repressed expression and cognitive reappraisal, the greater the value, the greater the tendency of using this emotion regulation strategy, and the value range is $y \in [1,5]$; $x_1, x_2, \cdots, x_{16}$ represents the 16 dimension attributes of learners' personality in turn, Its value range is [1,10]. In this prediction model, the explanatory power of personality attributes to expression suppression and cognitive reappraisal is 72.049% and 67.862% respectively, and good accuracy is achieved.

In addition, in order to observe the importance of personality attributes in explaining emotion regulation strategies more intuitively, the histogram of regression coefficients is drawn, as shown in **Figure 8**, which shows, sociability, intelligence, stability, strength, sensitivity and suspicion is of great influence in cognitive reappraisal strategy; aggressiveness, suspicion, fantasy plays an important role in the interpretation of repressed expression; while experiment and self-discipline almost do not affect emotion regulation.

Forecast analysis

Using the prediction equation set (14) established by PLS and the other 30 samples as the data set, the cognitive reappraisal and repression expression in the emotion regulation strategy are predicted. The fitting prediction based on PLS forecast values are compared with the observed values, as shown in **Figure 9**, we can see that all the sample points are near the diagonal distribution, prediction of the equation and the observed value are smaller, so the equation fitting effect is satisfactory.

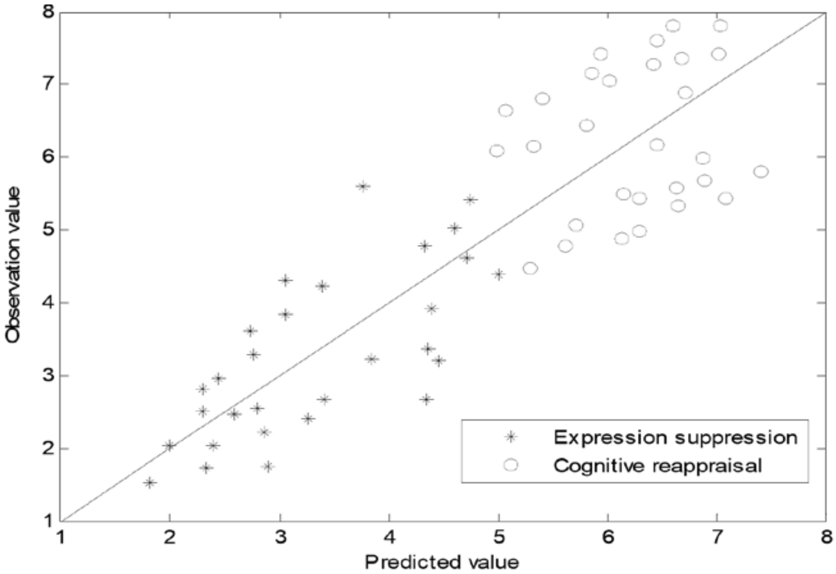

Figure 9. Predictive value and observational value of emotion regulation strategies

CONCLUSIONS AND FUTURE WORKS

User experience research mostly focuses on the research of computer application system, which results in a research blank of user psychology, emotion, cognition and so on. This paper analyzes the characteristics of user psychological experience quality and the measurement method of selection feature quantification. Meantime, we also analyze the correlation between variables and establish the quantitative relationship between personality and emotion regulation strategies. Two conclusions have been made as following: (1) A quantitative evaluation method of user psychological experience can effectively analyze the factors that affect the quality of psychological experience of E-learning users. (2) A predictive model of emotion regulation strategy lays a theoretical foundation for designing and implementing emotion compensation system in personalized E-learning environment.

In the next step, we will continue to study other factors, such as age, family background, and so on, and establish a more perfect user experience quantitative evaluation method and emotion regulation strategy prediction model. The drawback is that this paper uses analytic hierarchy process to calculate the weight between each index. However, when there is an excessive index, the method needs to construct a deeper, larger number and larger judgement matrix, which is not conducive to consistency checking, and the exact solution of eigenvalues and eigenvectors is more complicated. In addition, the determination of judgement matrix is mostly based on the subjective experience of experts, and cannot objectively and accurately depict the fuzziness and randomness of importance among indicators.

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