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Research on Dynamic Adaptive Design of Mobile Application UI Based on Affective Computing

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Abstract A mental model is a collection of internal factors such as motivation, thought processes, emotions, and needs. It serves as the standard by which users evaluate products. This study investigates the process and methods for constructing a mental model of user behavior using an eye tracker, designs an eye-tracking experiment for interface interaction behavior, and analyzes and organizes the data. Eye-tracking metrics are used to calculate users' PAD emotional values and establish a user emotional prediction model. The relationship between eye-tracking data and PAD multi-dimensional emotional values is explored, and the model's validity is verified. The results show that the Sig. values of the emotional prediction model are all greater than 0.05, indicating high predictive capability and the ability to accurately predict users' emotional preferences for web interfaces. Then, a user behavior HMM model, a user emotional PAD dimension model, and a user UI interface mapping model were established, and a mobile adaptive UI was designed for application verification.

Index Terms PAD emotion, partial least squares regression, eye-tracking technology, emotion prediction

I. Introduction

In contemporary society, mobile applications have become deeply integrated into people's daily work and lives [1], [2]. These applications not only provide users with convenient services and entertainment but also have a profound impact on people's lifestyles. From social media, shopping, health management to learning and work, people have gradually become accustomed to using various applications to complete daily tasks and meet diverse needs [3]-[5]. With the rapid development of the mobile application market, the number of apps continues to grow [6]. Taking the renowned mobile app store Google Play as an example, statistics show that the number of apps available on the platform has grown from 15,000 in 2009 to 4 million in 2024, with the overall trend indicating a steady annual increase in app numbers [7].

In mobile applications, the user interface (UI) plays a crucial role as the bridge connecting the app to users, directly influencing their interaction experience with the app [8]-[10]. A well-designed UI interface can enhance user satisfaction and loyalty. A clear and concise layout, an intuitive navigation structure, and visually appealing effects can help users complete tasks more efficiently while increasing their trust in the application [11], [12]. Conversely, a cluttered and confusing interface may lead to user churn and negative word-of-mouth [13]. Therefore, UI is crucial to the sustainable development and success of an app.

UI development involves two important tasks: UI design and UI implementation [14]. UI design aims to create an intuitive, easy-to-understand, and attractive interface. During this phase, developers use various UI prototyping tools to create UI prototypes [15]. UI implementation involves converting the UI design into an actual, functional interface. During this phase, developers write code based on the UI prototypes [16]. To support the UI design process, extensive data mining efforts have been conducted around UI design, including UI design patterns, color evolution, UI accessibility, and page layout [17]-[20]. Li, T et al. [21] proposed a novel self-supervised algorithm (Screen2Vec), which utilizes UI text content, visual design, layout patterns, and application metadata to generate more comprehensive semantic embeddings for UI screens and components. Ali, A et al. [22] proposed a deep learning-based method named Mobile Application User Interface Repair (M-UI-R) to detect and locate UI display issues in mobile applications, and demonstrated its effectiveness in real-world scenarios through experiments and developer feedback. Krizhevsky, A et al. [23] proposed a deep learning-based style transfer algorithm that uses art to redesign UI styles, creating UI that integrates the aesthetic features of art with the functionality of the application. Chen, J et al. [24] proposed a convolutional neural network-based method for performing UI design search based on wireframes, which capture the types and layout information of visual components but ignore high-fidelity visual details in the UI.

To support the UI implementation process, many researchers have proposed different methods to assist developers in implementing UI. Chen, C et al. [25] proposed a deep learning architecture that extracts UI implementation knowledge from existing applications and can automatically generate UI frameworks based on input UI design images. Wang, W et al. [26] conducted a phased study aimed at developing mobile health (mHealth) applications, validating practical adaptive user interface (AUI) design guidelines, and providing evidence-based guidelines for software practitioners. Cai, B et al. [27] proposed an automatic UI code generator, GUICG, which combines deep neural networks and image processing techniques to effectively detect UI elements from UI images and generate front-end code. Samir, M et al. [28] proposed a new method based on deep learning technology, utilizing the YOLO v7 algorithm to detect UI elements in high-fidelity model images and generate cross-platform front-end code, achieving high accuracy in element detection and layout hierarchy construction. Moran, K et al. [29] proposed an automated method for converting graphical user interface (GUI) models into code, involving tasks such as detection, classification, and assembly. They demonstrated its effectiveness through the ReDraw system for Android and highlighted its potential to improve development workflows. Beltramelli, T et al. [30] proposed pix2code, a method based on convolutional and recurrent neural networks that takes a single UI screenshot as input to generate layout code. Existing research has primarily focused on the implementation of layout code for static UI design images, while studies on UI animations—a dynamic element—remain relatively scarce.

Dynamic elements have gradually become a common feature in mobile app UI, and many researchers have explored the impact of dynamic elements in mobile app UI on user interaction. Kraft, J, and Hurtienne, J [31] conducted an empirical study, which showed that animated UI interfaces can help users establish more accurate mental models of application structures and enhance gesture-based interactions. Vinod, A et al. [32] proposed a method for UI design based on dynamic principles in human-computer interaction systems, which includes selecting sensors and formulating problems as combinatorial optimization problems. Alipour, M et al. [33] proposed a user interface adaptation framework that covers specific dimensions of emotions and their temporal aspects, enabling adaptation based on different types of emotions and time. The above studies fully demonstrate the importance of dynamic adaptive design for mobile application UI. Although they provide useful insights into the motivation for research on dynamic adaptive design in mobile application UI, they do not offer specific solutions to help developers implement dynamic adaptive design.

First, we introduce discrete emotion models and dimensional emotion models, and select the Chinese version of the PAD emotion scale as the tool for emotion measurement. We establish an emotion prediction model linking eye-tracking metrics and PAD emotion using partial least squares regression analysis, and then conduct experimental designs to validate the model's effectiveness and applicability. Using the PAD emotion model, this study investigates the emotions associated with information visualization interactive interfaces. Emotional features are mapped to the user's emotional state in the PAD model for emotional mapping analysis, enabling the identification of emotional states during user experience based on the subjective emotions generated by users. Finally, a mobile UI adaptive design is established for application validation.

II. Methods for constructing user mental models based on affective computing

II. A. Emotion Description Model

II. A. 1) Discrete Emotion Model

Discrete emotion models typically describe emotions using discrete labels, such as sadness, anger, and happiness. Describing emotions using discrete labels is clear and straightforward, aligning with people's intuitive perceptions in daily life. This approach was widely adopted in early emotion-related research. However, due to the richness and complexity of language, linguists have identified over 300 common emotional states, presenting a significant challenge for computer recognition. Therefore, selecting more universal and representative emotion labels to describe emotions is a fundamental problem that researchers must address. Among the classifications proposed by numerous researchers, the six basic emotions identified by American psychologist Paul Ekman—happiness, anger, fear, sadness, surprise, and disgust—are the most well-known and widely used emotion model, also referred to as prototypical emotions [34].

Discrete emotion models based on classification cannot effectively express the rich emotions of humans. This is particularly evident in the following three aspects: first, for discrete emotion models that only cover a few basic emotions, their ability to describe and express emotions is also extremely limited; second, discrete emotion models also lack the ability to express the interrelationships between emotions; finally, even for a particular emotion, it can be divided based on different intensities, but discrete emotion models cannot effectively express these emotional intensities. For example, the emotion of sadness can be divided into general sadness, moderate sadness, and extreme sadness based on intensity.

II. A. 2) Dimensional Affective Model

Due to the complex mechanisms and blurred boundaries of emotional generation, there are significant individual differences in both the expression and perception of emotions. In recent years, many researchers in the field of affective computing both domestically and internationally have begun to focus on how to model and analyze the complexity, subtlety, and continuity of emotions through continuous dimensions, leading to the development of the dimensional affective model. Theoretically, any emotional state that exists in real life can be represented by a specific coordinate point in the dimensional affective space. In the dimensional emotion model, the real numbers used to describe emotions are uninterrupted and continuous, hence the dimensional description method is also known as the continuous description method. The dimensional emotion model's description method can overlook the complex process of emotion generation, treating different emotional states as smooth, gradual transitions [35].

II. A. 3) Calculation method for PAD spatial emotion

In this paper, emotion is a two-dimensional vector as shown in Formula (1):

$$E = (S, G) \tag{1}$$

Where S represents the emotional state, with values ranging from Ekman's basic emotion set. G represents the emotional intensity, with values ranging from [0, 1].

(1) Determining the emotional state

Based on the distribution characteristics of basic emotions in the mood space, it is known that basic emotions exist as discrete points in the mood space. During the encoding test of virtual dolls, it was found that the majority of PAD mood model vectors are discretely distributed around the basic emotion points. This means that to obtain the basic emotional state corresponding to the PAD mood model vector, it is necessary to perform clustering calculations on the PAD mood model vector to determine which emotional state it belongs to.

According to relevant literature, there are two main methods for determining emotional states in the PAD mood space: (a) determining emotional states by calculating the spatial distance between unknown emotional points and basic emotional points; (b) determining emotional states based on the correspondence table between PAD space quadrants and emotions.

As pointed out in the literature, the PAD space is not a uniformly Euclidean metric space. The measurement of the distance between two emotional points in the space is not only related to the emotional mean but also significantly influenced by the variance. Therefore, directly using the distance formula between two points in the space is inappropriate. It is necessary to consider the influence of emotional variance when calculating the distance between the PAD mood vector and the basic emotional points.

Therefore, the method selected in this paper for calculating emotional distance in the PAD mood space is the Euclidean distance metric method, as shown in Formula (2):

$$S(x_1 - x_2) = \frac{\| x_1^2 - x_2^2 \|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \tag{2}$$

where x_1, x_2 are the sample means of two emotional point vectors x in the PAD affective space, and σ_1, σ_2 are the sample variances of the two emotional points.

In the PAD space, S_p, S_A, S_D represent the dimension values of the two emotional points P, A, D, respectively. Since PAD is a three-dimensional Euclidean emotional measurement space, the final distance between the two emotional points is given by formula (3):

$$S = \sqrt{S_P^2 + S_A^2 + S_D^2} \tag{3}$$

Using formulas (2) and (3) to calculate distances, the distance values between the unknown emotional points and each basic emotional point are obtained.

The emotional points serve as the emotions of the unknown emotional points, thereby completing the emotional clustering calculation for the unknown emotional points.

(2) Determination of emotion intensity

Due to the complexity and ambiguity of human emotions, there is still some controversy regarding the calculation of emotion intensity. Considering the emotional significance of the PAD space, this paper adopts the method of measuring the emotion intensity of the unknown point using the spatial distance from the origin to the unknown point. Since the value range of emotion intensity is [0, 1], the specific calculation is as shown in Formula (4).

$$G = \frac{1}{\sqrt{3}} \sqrt{M_p^2 + M_a^2 + M_d^2} \tag{4}$$

In the equation, M_p, M_a, M_d are the PAD spatial coordinates.

II. B.Multi-dimensional emotion prediction for PAD users based on physiological signals

II. B. 1) PAD Emotional Scale and Partial Least Squares Regression Method

The Chinese version of the PAD Emotional Scale was selected as the emotional measurement tool, as this PAD scale demonstrates good reliability and structural validity. As a tool for assessing emotional responses across three dimensions, the entire emotional space is divided into eight distinct regions based on the positive or negative values of the P, A, and D dimensions, corresponding to eight distinct emotional categories. Specifically, +P+A+D represents happiness, -P-A-D represents boredom, +P+A-D represents dependency, -P-A+D represents contempt, +P-A+D represents relaxation, -P+A-D represents anxiety, +P-A-D represents docility, and -P+A+D represents hostility.

This paper selects partial least squares regression as the regression modeling method for eye movement indicators and PAD emotional values. Compared to traditional regression analysis, the advantage of this method lies in its ability to simultaneously perform regression modeling for multiple independent variables and multiple dependent variables. This advantage becomes particularly evident when the number of variables in two groups is large, or when the sample size is small and most variables exhibit multiple correlations [36].

II. B. 2) Process of establishing a model for the relationship between eye movement indicators and emotional values

The process of establishing a mathematical model for eye movement indicators and PAD emotional values primarily consists of two parts: eye movement indicator selection and mathematical model establishment. Since eye movement indicators include dozens of metrics such as blink duration and fixation duration, it is necessary to screen the eye movement data to better and more accurately predict emotions. This is achieved through one-way analysis of variance (ANOVA) to identify eye movement indicators suitable for emotional prediction. After obtaining the eye tracking metrics, the PAD emotional value is used as the dependent variable and the eye tracking metrics as the independent variable to establish a mathematical model linking eye tracking metrics and emotional values. To verify whether the mathematical model can effectively reflect human emotions, an experimental design is conducted to obtain users' PAD emotional values, and the obtained PAD emotional values are compared with the predicted values to validate the model's reliability and accuracy.

II. B. 3) Multivariate regression mathematical model of eye movement indicators and emotional values

Using eye movement metrics as the independent variable x and PAD emotional values as the dependent variable y, with q dependent variables and p independent variables, to study the statistical relationship between the dependent and independent variables, we select n sample points, thereby forming the data table of independent and dependent variables $X = \lfloor x_1, x_2, ..., x_p \rfloor_{m\times p}$ and $Y = \lfloor y_1, y_2, ..., y_q \rfloor_{n\times q}$. For the convenience of mathematical derivation, the data is first standardized. The standardized data matrix for X is denoted as $E_0 = (E_{01}, ..., E_{0p})_{n\times p}$; the standardized data matrix of Y is denoted as $F_0 = (F_{01}, ..., F_{0q})_{n\times q}$.

In the first step, let t_1 be the first component of E_0, where $t_1 = E_0 w_1$, and w_1 is the first axis of E_0, which is a unit vector, i.e., $\| w_1 \| = 1$. Let u_1 be the first component of F_0, $u_1 = F_0 c_1$, where c_1 is the first axis of F_0, and $\| c_1 \| = 1$. If t_1 and u_1 can respectively represent the data variation information in X and Y well, according to the principle of principal component analysis, the following should hold:

$$Var(t_1) \to \max \quad Va(r_1 u) \to m \tag{5}$$

On the other hand, due to the need for regression modeling, t_1 is required to have the greatest explanatory power for u_1. Based on the idea of typical correlation analysis, the correlation coefficient between t_1 and u_1 should reach the maximum value, that is:

$$r(t_1, u_1) \to \max \tag{6}$$

Therefore, in summary, in partial least squares regression, we require the covariance between t_1 and u_1 to be maximized. The formal mathematical expression should be to solve the following optimization problem, namely:

$$\max_{w_1 c_1} \langle E_0 w_1, F_0 c_1 \rangle \tag{7}$$

Therefore, we will find $\langle E_0 w_1, F_0 c_1 \rangle$ under the $\| w_1 \|^2 = 1$ and $\| c_1 \|^2 = 1$.

After obtaining the first axis w_1 and c_1 using the Lagrange method, we can obtain the components: $t_1 = E_0 w_1, t_1 = E_0 w_1$. w_1 is the unit eigenvector corresponding to the maximum eigenvalue of the matrix $E_0 F_0 F_0 E_0$ and c_1 is the unit eigenvector corresponding to the maximum eigenvalue of the matrix $F_0 E_0 E_0 F_0$. Then, we separately solve the three regression equations of E_0, F_0 with respect to t_1 and u_1.

$$\begin{aligned} E_0 &= t_1 p_1 + E_1 \\ F_0 &= u_1 q_1 + F_1^* \\ F_0 &= t_1 r_1 + F_1 \end{aligned} \tag{8}$$

In the equation, the regression coefficients are $p_1 = \frac{E_0' t_1}{\|t\|^2}$, $q_1 = \frac{F_0' u_1}{\|u\|^2}$ and $r_1 = \frac{F_0' t_1}{\|t\|^2}$. The matrices E_1, F_1, F_1^* are the missing matrices of the three regression equations, respectively.

In the second step, replace E_0, F_0 with the missing matrices E_1 and F_1. Then, calculate the second axis w_2 and c_2 as well as the second component t_2 and u_2.

Continue this calculation. If the rank of X is A, then we have $E_0 = tp' + ... + t_\lambda p_\lambda'$, and $F_0 = t_1 r_1' + ... + t_A r_A' + F_A$ Since $t_1, ... t_R$ can be expressed as a linear combination of $E_{01}, ... E_{0i}$, therefore $F_0 = t_1 r_1' + ... + t_A r_A' + F_A$ can also be reduced to the regression equation $y_k^* = F_{0k}$ with respect to $x_j^* = E_{0j}$ as shown in equation (9):

$$y_k^* = a_{k1} x_1^* + ... + a_{kp} x_p^* + F_{Ak}, k = 1, 2, ..., q \tag{9}$$

The partial least squares regression equation converted back to the original variables, i.e., the mathematical relationship model between eye movement indicators and PAD emotional values, is shown in Equation (10):

$$\hat{y}_k = \left[E(y_k) - \sum_{i=1}^{p} a_{ki} \frac{S_{y_k}}{S_{x_i}} E(x_i) \right] + a_{k1} \frac{S_{y_k}}{S_{x_i}} x_1 + ... + a_{kp} \frac{S_{y_k}}{S_{x_p}} x_p \tag{10}$$

$E(y_k), E(x_i)$ are the sample means of y_k and x_i, respectively; S_{yk}, S_{v_i} are the sample standard deviations of y_k and x_i, respectively.

As described above, a mathematical relationship model between PAD emotional values and eye-tracking metrics can be derived. Subsequent research can utilize eye-tracking data from users in experiments to infer their PAD emotional values, thereby reducing the inaccuracies in mental model construction caused by subjective factors in methods such as interviews and verbal reporting.

II. C. Relationship between eye movement information indicators and PAD multidimensional emotional values

II. C. 1) Experimental Preparation

(1) Experimental subjects and materials

The 20 volunteers recruited for this experiment were aged between 20 and 27 and were all capable of performing basic computer operations. All participants agreed to the entire research protocol and signed informed consent forms. The experimental instrument used was the REDn Scientific desktop eye tracker produced by German company SMI. The experimental materials consisted of two images of homepage layouts from portal websites with the greatest visual design differences, specifically the Phoenix News and Hexun News websites.

(2) Experimental Procedure

The experimental procedure was pre-set in Experiment. The primary task was for the 20 participants to browse the experimental pages without any specific destination, with browsing time controlled by the participants themselves. After browsing, participants completed the PAD Emotional Scale regarding their perceptions of the visual design elements in the stimulus materials, followed by a 5-minute rest period. After the rest period, participants continued to complete the browsing task for the second stimulus material following the same procedure and completed the PAD Emotional Scale.

II. C. 2) Emotion classification table and eye movement signal indicator screening

Label the emotional spaces in the PAD emotional categories as "1, 2, 3, 4, 5, 6, 7, 8." Based on the experimental results, the PAD emotional values for different webpages from 20 participants can be obtained. According to the eight emotional spaces, the emotional values are classified into positive and negative states. The classification results are shown in Table 1.

Table 1: classification of emotions

Number	Phoenix			Emotional categories	Hexun.com			Emotional categories
	P	A	D		P	A	D	
1	1.78	1.31	0.78	1	-3.78	-2.28	-2.28	2
2	2.78	1.31	-1.53	3	2.53	2.78	1.53	1

3	0.53	1.78	0.28	1	-2.53	-0.18	3.28	4
4	2.53	2.53	-2.28	1	-1.28	-2.53	-1.78	2
5	1.78	2.05	-2.28	3	-2.53	-1.78	-1.78	2
6	1.78	2.05	2.53	1	-2.03	-2.78	-0.53	2
7	1.55	0.28	1.78	1	-1.53	1.78	-2.28	6
8	3.28	3.28	3.53	1	-3.03	-1.03	-1.28	22
9	2.05	1.78	1.53	1	-2.28	-2.78	-1.78	
10	0.53	2.53	0.53	1	0.78	-0.53	1.03	5
11	-1.05	-2.80	1.78	4	1.28	2.53	1.78	1
12	3.52	-3.28	-3.53	7	2.53	1.28	0.53	1
13	0.53	2.78	1.28	1	-0.78	-0.78	-1.53	2
14	3.78	3.53	0.53	1	-2.53	-1.03	-1.53	2
15	1.78	1.28	1.78	1	-0.53	0.53	-1.03	6
16	2.28	1.78	1.78	1	-1.28	-2.53	-0.53	2
17	3.78	-3.78	2.03	5	-1.03	1.28	-1.78	6
18	1.53	-0.28	0.78	7	-0.28	-1.53	-2.03	2
19	1.53	1.53	1.78	1	-2.28	-1.78	-2.03	2
20	2.28	0.28	2.28	1	-2.03	-1.78	-2.03	2

Remove abnormal experimental data to ensure the accuracy of the experimental results. First, conduct a test of variance homogeneity for eye movement information indicators, using emotional category as the factor, and eliminate variables with a significance p-value less than 0.05. The remaining eye movement information indicators with a significance p-value greater than 0.05 can be further analyzed. Second, further analysis yields the results of the one-way ANOVA for eye movement information indicators. The results of the one-way ANOVA for eye movement information indicators are shown in Table 2. It can be seen that the p-values for the significance levels of 10 eye movement information indicators, including fixation rate, minimum blink duration, and average saccade amplitude, are all less than 0.05, making them suitable for use in establishing an emotion prediction model.

Table 2: One-way ANOVA for eye movement indexes

Item	F	P	Item	F	P
Fixation rate[count/s]	3.347	0.013	Maximum viewing time[ms]	0.293	0.939
Average fixation time[ms]	2.934	0.022	Minimum fixation time[ms]	1.015	0.437
Minimum fixation point dispersion [px]	3.776	0.008	Mean of focal point dispersion[px]	0.741	0.626
Viewing rates[count/s]	4.618	0.005	Maximum saccadic amplitude[°]	3.005	0.022
Average saccade time[ms]	8.841	0.001	Minimum sweep amplitude[°]	0.415	0.869
Minimum blink time[ms]	4.047	0.006	Scan the average speed[°/s]	0.831	0.562
Minimum saccade time[ms]	3.092	0.018	Maximum saccadic speed[°/s]	2.409	0.051
Average saccadic amplitude[°]	3.637	0.008	Minimum scanning speed[°/s]	0.410	0.871
Blink rate[count/s]	0.571	0.758	Average saccadic latency[ms]	0.999	0.442
Longest saccade time[ms]	1.709	0.153	Maximum pupil size[mm]	0.745	0.622
Average blink time[ms]	4.882	0.002	Average pupil size[mm]	0.663	0.685
Longest blink time[ms]	1.908	0.111	Minimum pupil size[mm]	1.189	0.341

II. C. 3) Model Establishment

By applying the PLS method, the regression equation was converted into a non-standardized regression equation, and a mathematical model was constructed to describe the relationship between the multivariate values of eye movement information indicators and the multidimensional emotions of PAD:

$$\overline{y}_j = \left[A(y_j) - \sum_{k-1}^{n} c_{jk} \frac{S_{y_j}}{S_{x_k}} A(x_k) \right] + c_{j1} \frac{S_{y_j}}{S_{x_1}} x_1 + c_{j2} \frac{S_{y_j}}{S_{x_2}} x_2 + \cdots + c_{jn} \frac{S_{y_j}}{S_{x_n}} x_n \tag{11}$$

Select the eye movement information indicators screened from Table 2 as independent variables $x_k, k = 1, 2, \cdots, 8$, and select the PAD multidimensional emotional values as dependent variables $y_j, j = 1, 2, \cdots, 8$. $A(x_k)$ is the sample mean of the k th independent variable x_k; $A(y_j)$ is the sample mean of the j th dependent variable y_j;

S_{xk} is the sample standard deviation of the k th independent variable x_k; S_{yj} is the sample standard deviation of the j th dependent variable y_j. Standardize the variable Coefficient and restore it to the original data's variable Coefficient and Constant terms, ultimately obtaining the restored regression equations for the three dependent variables:

$$P = -1.987 + 0.437x_1 - 0.009x_2 + 0.065x_3 - 0.662x_4 - 0.027x_5 \\ +0.015x_6 + 0.431x_7 - 0.144x_8 + 0.002x_9 + 0.001x_{10} + 0.003x_{11} \tag{12}$$

$$A = 10.653 + 0.051x_1 - 0.023x_2 - 0.066x_3 + 0.359x_4 - 0.113x_5 \\ -0.006x_6 - 0.235x_7 + 0.064x_8 + 0.002x_9 - 0.005x_{10} + 0.001x_{11} \tag{13}$$

$$D = 7.288 + 0.497x_1 - 0.031x_2 + 0.004x_3 + 1.342x_4 - 0.045x_5 \\ +0.002x_6 - 0.530x_7 - 0.389x_8 + 0.001x_9 + 0.013x_{10} - 0.003x_{11} \tag{14}$$

Among these: x_1 is the fixation rate; x_2 is the average fixation time; x_3 is the minimum fixation point dispersion value; x_4 is the saccade rate; x_5 is the average saccade time; x_6 is the shortest blink duration; x_7 is the shortest saccade duration; x_8 is the average saccade amplitude; x_9 is the average blink duration; x_{10} is the maximum saccade amplitude; x_{11} is the maximum saccade velocity.

II. C. 4) Model Validation

Three additional sets of experimental data not used in the aforementioned experiments were selected for supplementary experiments to validate the predictive validity of the relationship model. By incorporating the three sets of eye-tracking signal data into the calculation formula using the relationship model, predictive values for the three sets of PAD multidimensional emotions can be obtained. A paired-sample t-test was conducted using SPSS analysis software to compare the predictive values of the three sets of PAD multidimensional emotions with the actual observed values. The results of the analysis are shown in Table 3.

From the analysis results in the table, it can be seen that the two-tailed Sig. values for all three sets of data are greater than 0.05, indicating that there is no significant difference between the model's predicted values and the actual observed values. This demonstrates the validity of the predictive capability of the relational model between eye movement information indicators and PAD multidimensional emotional values, i.e., the relational model can effectively predict users' multidimensional emotions during interaction with web interfaces through eye movement information indicators.

Table 3: results of paired t-test analysis

Pairwise differences						t	Freedom	Sig.
Group	Dimension	standard deviations	Standard error mean	Lower limit of 95% confidence interval	Upper confidence interval			
Pair 1	P	0.008	0.042	0.025	-0.091	0.275	2	0.815
Pair 2	A	0.021	0.035	0.022	-0.067	0.925	2	0.451
Pair 3	D	-0.118	0.083	0.049	0.324	-2.641	2	0.127

To validate the applicability of this relational model, supplementary experiments were conducted. Images from the homepage of Tencent News, which differed from the materials used in the aforementioned experiments, were selected as test materials. Additionally, 10 participants were selected to repeat the emotional measurement experiment following the same experimental procedures as before. After collecting the data, the experimental data was processed, and the eye-tracking signal data was incorporated into the aforementioned regression equation for calculation, yielding the predicted values of PAD. Then, by combining the predicted values with the actual values, a line chart was plotted for comparative analysis. If the line fitting exhibited consistency, it indicated that the model's predictive results were valid; if the line fitting was inconsistent, it indicated that the two sets of data were unrelated, and the model's predictive results were invalid. The comparison results of P-values, A-values, and D-values are shown in Figures 1 to 3, respectively.

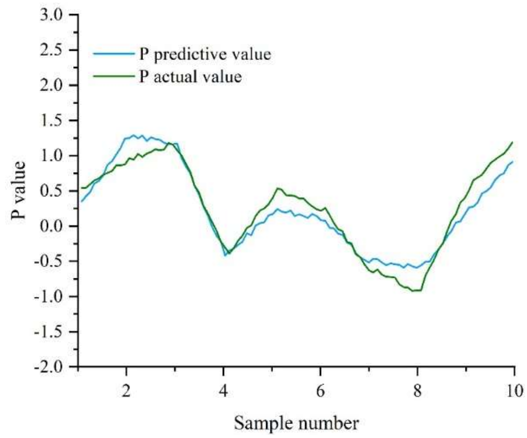

Figure 1: Comparison line graph of predicted and actual values of P

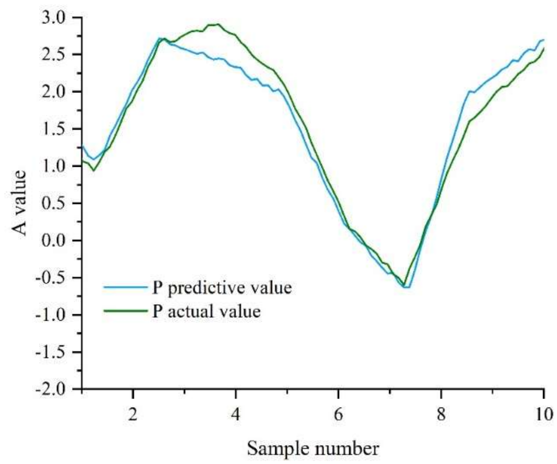

Figure 2: Comparison line graph of predicted and actual values of A

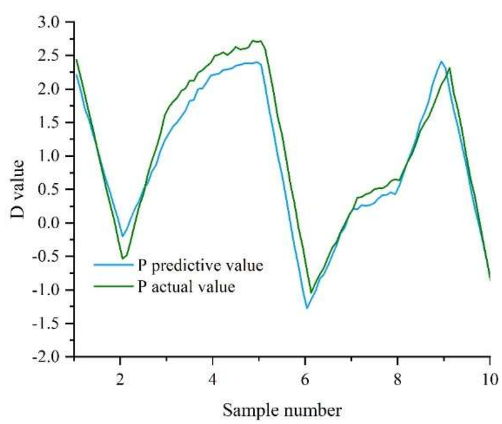

Figure 3: Comparison line graph of predicted and actual values of D

In the above three comparison plots, the y-axis represents the P-value, A-value, and D-value, respectively, while the x-axis denotes the sample numbers of the 10 participants. The blue solid line in the comparison plots indicates the predicted values, and the green solid line represents the actual values. The analysis results of the line charts comparing the three dimensional values show that the differences between the model's predicted values and actual values for the P, A, and D dimensions are small, their polarities are consistent, and the trends of the two sets of numerical line charts are generally aligned. This indicates that the line charts exhibit consistency in fitting, suggesting that the model achieves good performance in emotional prediction and is generally effective.

III. Adaptive interactive interface based on emotional models

III. A. PAD Value and Information Visualization Association Strategy

Eye-tracking experiments are used to assess emotions. Physiological behaviors are composed of various physiological indicators, and the regular movement processes of these physiological behaviors constitute the external manifestation of psychological emotions. In this experiment, multiple physiological indicators were selected, and the PAD emotional model was used to study the emotions of information visualization interactive interfaces.

For information visualization interaction interfaces, we can select physiological behavior indicators to form the feature vector space I of the information visualization interaction interface. As shown in formulas (16), (17), and (18).

$$I = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}\} \tag{15}$$

Calculation method for PAD value:

P dimension:

$$\begin{aligned} P = {} & Constant + Coefficient\ x_1 + Coefficient\ x_2 + Coefficient\ x_3 \\ & + Coefficient\ x_4 + Coefficient\ x_5 + Coefficient\ x_6 + Coefficient\ x_6 \\ & + Coefficient\ x_7 + Coefficient\ x_8 + Coefficient\ x_9 + Coefficient\ x_{10} \\ & + Coefficient\ x_{11} + Coefficient\ x_{12} \end{aligned} \tag{16}$$

A Dimension:

$$\begin{aligned} A = {} & Constant + Coefficient\ x_1 + Coefficient\ x_2 + Coefficient\ x_3 \\ & + Coefficient\ x_4 + Coefficient\ x_5 + Coefficient\ x_6 + Coefficient\ x_6 \\ & + Coefficient\ x_7 + Coefficient\ x_8 + Coefficient\ x_9 + Coefficient\ x_{10} \\ & + Coefficient\ x_{11} + Coefficient\ x_{12} \end{aligned} \tag{17}$$

D dimension:

$$\begin{aligned} D = {} & Constant + Coefficient\ x_1 + Coefficient\ x_2 + Coefficient\ x_3 \\ & + Coefficient\ x_4 + Coefficient\ x_5 + Coefficient\ x_6 + Coefficient\ x_6 \\ & + Coefficient\ x_7 + Coefficient\ x_8 + Coefficient\ x_9 + Coefficient\ x_{10} \\ & + Coefficient\ x_{11} + Coefficient\ x_{12} \end{aligned} \tag{18}$$

Among these: x_1 is the time to first fixation metric data, x_2 is the fixation before metric data, x_3 is the first fixation duration metric data, x_4 is the total fixation metric data, x_5 is the total fixation duration% metric data, x_6 is the fixation count metric data, x_7 is the fixation count% , x_8 is the visit count metric data, x_9 is the visit duration metric data, x_{10} is the total visit duration metric data, x_{11} is the total visit duration% metric data, and x_{12} is the fixation duration metric data. To validate the accuracy of the formula, multiple specific interaction interfaces were selected for verification. First, 30 test subjects were selected for PAD testing, and physiological feature metric data were extracted. The PAD emotional model formula was used to calculate the PAD value, and the best experimental results were compared and screened to draw conclusions. As shown in Formula (19).

$$\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x_i})^2 \tag{19}$$

In the formula, $\overline{x_i}$ represents the PAD value calculated from the eye-tracking test experiment, x_i refers to the PAD value calculated from the offline questionnaire survey, and the error value is calculated precisely. Specifically, it is as follows:

$$\begin{gathered} P0.0136 \\ A0.0081 \\ D0.0129 \end{gathered} \tag{20}$$

III. B. Mapping of emotions

III. B. 1) User Behavior-Emotional Influence Model

In terms of obtaining user emotions, existing methods mainly use multi-channel technology to collect and gather information related to user emotions, which is then comprehensively processed to measure user emotions. This paper will primarily use user behavior as a basis to model the user's emotional process and obtain the user's current emotional state through questionnaires. This will be combined with the capture of user facial expressions during usability testing as a reference to measure user emotions.

Due to individual differences among users, different users experience varying emotional changes in response to the nine basic behaviors. Therefore, it is necessary to classify users based on their individual characteristics and identify the influencing factors of user behavior for different types of users. During the research process, we used personality questionnaires to match users based on their individual characteristics, categorizing them into several groups. By statistically analyzing and studying the data on behavioral influence factors for users of the same type, we fitted a set of optimal factors as the behavioral influence factors for that category of users and established a user personalized model library, which can be defined as:

$$U = \{u_m, sn(\Delta p, \Delta a, \Delta d)\} \tag{21}$$

Among them, U_m represents the user group of category m ; Sn represents the basic behavior n ; $\Delta P_n, \Delta A_n, \Delta D_n$ represent the influencing factors of user behavior Sn .

III. B. 2) Emotion PAD model based on HMM

Psychology suggests that when people receive stimuli, they experience a process of emotional accumulation, followed by a process of attenuation, with emotions gradually returning to a calm state.

Emotional accumulation: The current intensity of a user's emotions can be defined as the sum of the emotional intensity at the past t moments and the current emotional change parameter.

The theory regarding external stimuli and users' psychological perceptions is one of the fundamental theories established by cognitive psychology, with key theories including:

Psychology indicates that the relationship between stimulus intensity and sensory intensity follows Weber's Law, which states that the ratio of the increase in stimulus intensity to the stimulus intensity itself is a constant, i.e.:

$$\Delta I / I = Km \tag{22}$$

This law was first derived from studies on the sensitivity of the human eye to light waves. Later, it was discovered that the sensitivity of other human organs to stimuli also follows this law, and finally, it was found that the sensitivity of the entire biological world to stimuli follows this law. Therefore, Weber's law is actually a basic biological law. If this law is transformed mathematically, we can obtain:

Fechner's law: The intensity of sensation is linearly related to the logarithm of the intensity of the stimulus, that is:

$$\mu = KmLogI + C \tag{23}$$

Among them, Km and C are constants, μ is the sensation intensity, and I is the stimulus intensity.

This establishes a model based on user behavior that combines emotional superposition and attenuation for the calculation of emotions during usability testing, as shown in Figure 4.

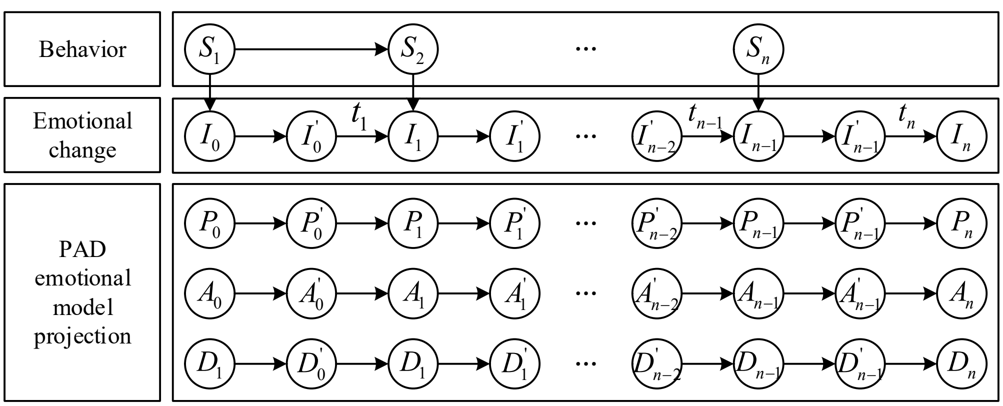

Figure 4: Pad projection model based on user behavior

Among these, S1 to Sn represent one of the nine behaviors exhibited by users during usability testing. The stimuli associated with these behaviors act on the user's initial state, causing their emotions to transition from I to I'. After an emotional decay period of time t before the next behavior begins, this state serves as the initial state for the next stimulus. The state I is composed of three dimensions: P, A, and D, and changes in I can be represented by changes in P, A, and D.

For software users, user emotions can be viewed as a continuous and interrelated process. Past emotional states have a significant impact on current emotional states. The correlation between emotions is mainly reflected in the superposition and attenuation of emotions.

User behavior when operating software conforms to the continuous random variation process of the HMM model, which can be used to describe this behavioral process.

III. C. Emotional Mapping Analysis

The three-dimensional emotional values of the PAD were obtained by having participants label the PAD emotional scale under different emotional states. The results of the four emotional states were then mapped onto the PAD three-dimensional emotional space. Figure 5 shows the distribution of subjective emotional PAD three-dimensional data in the PAD three-dimensional emotional space.

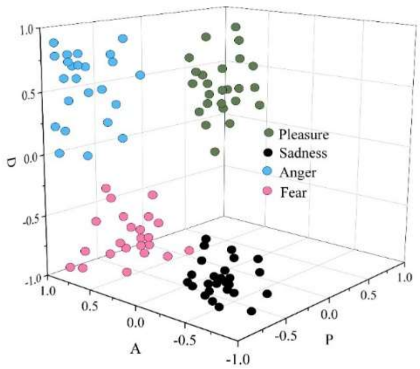

Figure 5: Four types of emotional state data are distributed in the 3D space of the PAD

At the same time, taking “fear” emotional data as an example, we output the average normplot of its annotations in the three dimensions of P, A, and D, as shown in Figure 6.

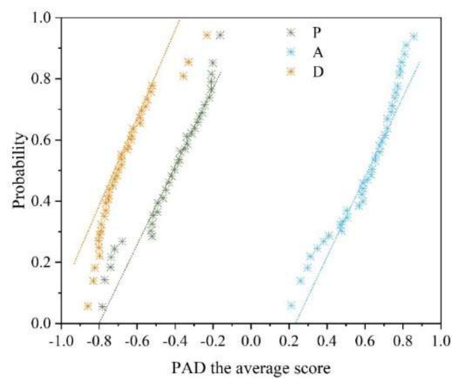

Figure 6: The probability distribution of fear emotion data

Observing Figures 5 and 6, it can be seen that the PAD annotation data for the four emotions can be clearly separated in the three-dimensional emotional space, and the annotation results are almost linearly distributed in all three dimensions. This indicates that the subjective emotional data we obtained follows a normal distribution and is valid. Additionally, the test average values for each emotion are shown in Table 4. From the data comparison provided in the table, it can be seen that the test results for the four emotions obtained generally align with the mapping relationship of emotional states in the PAD three-dimensional emotional space.

Table 4: Subjective emotional labeling results

The annotation results of the pad scale				
		Average value		
Feeling	PAD	P	A	D
Glad	P+A+D	0.68	0.67	0.33
Sad	-P-A-D	-0.59	-0.37	-0.81
Indignation	-P+A+D	-0.92	0.72	0.94
Fear	-P+A-D	-0.41	0.68	-0.76

IV. Mobile UI Design and Evaluation

IV. A. UI Design

(1) The shift from static to interactive interfaces

Modern UI interfaces are a series of static screens with interactive elements. Interactive design is an enhancement to static pages, adding more interesting interactive sections to better engage users. Creativity and novelty are essential to prevent users from feeling bored. Modern UI interfaces are no longer purely static displays; they utilize the dimension of time to bring the UI interface to life. This bridges the gap between human cognition and the software itself, making it easier for users to understand and use the software. When an app's animations are highly innovative, they can quickly capture users' attention and create a pleasant visual experience. Users will feel joyful each time they open the app, as it brings them a good mood. However, animations can do more than just this.

They not only allow users to experience real-life scenarios but also effectively "control" users' visual focus through interactive animations, guiding them into the functionality. The animation design for liking is another touchpoint that further enhances users' emotional engagement. This presentation style reflects the thoughtfulness of an app.

Most users face the limitations of space and the challenges of complex operations. It is essential to maximize space utilization, simplify product complexity, and use animations to present the interface in a logical and intuitive manner.

(2) Transitioning from rational to emotional interface design

Every product design begins as a story. The development of a story must be vivid and engaging, which is why understanding user psychology is essential for design. Designs that rely solely on rational thinking cannot meet user needs; they must incorporate emotional elements.

Why does design need to "tell a story"? Storytelling evokes emotions in the audience, sparking imagination and immersion. Mastering this form can enhance the design's presence in users' memories.

Product emotionalization must address the following questions: Is it useful? Does it meet expectations? Next is reliability—does it operate reliably, quickly, and without errors? Then comes usability—is it usable, easy to use, and user-driven? Finally, the last two, and most challenging, are: interesting and meaningful. Is the experience user-friendly? Does it bring joy to users? Is it operable and enjoyable? Meaningful refers to whether the services provided by the product are meaningful and can evoke emotional resonance with users.

When designing a product, one should adopt the mindset of a product person, placing the product at a certain level of importance within oneself and designing it with emotion. From the foundational understanding of the product, its commercialization, and promotion, to delving into the lifecycle of the product experience, one should ask whether both oneself and the users feel passionate about it, and approach the product with the attitude of a product person, repeatedly exploring and refining it.

IV. B. Application Verification

This study investigates the visual design of mobile UI dynamic design from the perspective of user emotions. A scale was established to analyze users' emotional evaluations of websites, followed by further analysis of the relationship between emotional evaluations and user emotions, as well as the relationship between website interface design elements and user emotions. To further expand the scope of the study and propose a method for analyzing mobile UI dynamic design from the perspective of user emotions and suggesting improvements, an example verification was conducted.

Design elements for mobile UI dynamic design were coded, with results shown in Table 5. Subsequently, the quantified 0-1 coded values of design elements were input into the PLS regression model, yielding emotional scores predicted based on design elements, as shown in Table 6. In the second step, the emotional evaluation scores of 20 participants on mobile UI dynamic design were organized and input into the PLS regression model, yielding emotional scores predicted based on user emotional evaluation data, as shown in Table 7. The results in the table show that the mobile UI dynamic design effectively presents rich product information to users when needed while maintaining a clean webpage layout. In contrast, the other two websites only use standard link methods, requiring users to click further to view specific product information, which increases cognitive difficulty and may cause frustration for users.

Table 5: 0-1 Responding scores of ad. samples

Variable sample	A11	A12	A21	A22	A31	A32	A33	A34	A41	A42	A43	B11	B12	B13	B21	B22
1	1	0	0	1	0	1	1	0	0	0	1	0	0	0	0	1
2	1	1	0	1	0	1	1	1	0	0	1	0	0	1	1	0
3	1	0	0	0	0	1	0	1	0	0	1	0	0	1	0	1
Variable sample	B23	C11	C12	C13	D11	D12	D21	D22	E11	E12	E21	E22	E31	E32	E33	

1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	0	
2	0	1	1	0	1	0	1	0	1	1	0	0	1	0	0	
3	0	0	0	0	1	0	1	0	0	0	0	1	0	1	0	

Table 6: Web design elements of the emotional score prediction

Website / Affective dimension	Phoenix	Justyle	Hexun.com
P	5.15	4.63	4.09
A	5.83	5.36	5,28

Table 7: The score of sensibility and emotional evaluation of UI design

Website	Word pair	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	P	A
Phoenix		5.78	4.22	5.78	5.03	6.22	5.84	4.77	5.55	5.47	4.75	5.68	5.85
Justyle		3.42	3.08	2.78	3.08	4.03	2.57	3.49	3.67	4.02	4.88	4.86	5.36
Hexun.com		3.42	5.22	4.04	2.48	3.12	3.55	3.04	4.33	3.63	4.67	4.67	5.22

V. Conclusion

Using eye-tracking metrics to calculate users' PAD emotional values, the Chinese version of the PAD Emotional Scale was selected as the tool for emotional measurement. A mathematical model linking eye-tracking metrics and PAD emotional values was established through partial least squares regression analysis. An experimental design was then conducted, and the results showed that this emotional prediction model can provide more scientific and reasonable emotional inferences based on physiological signals generated during human-computer interaction. A model mapping emotions to user UI interfaces was then established. The integrated model developed in this study achieved higher recognition rates for identifying four emotional categories—happiness, sadness, anger, and fear—compared to single objective physiological signal-based emotion recognition. Finally, a mobile adaptive UI was designed and validated for practicality. The results showed that the dynamic design of the mobile UI effectively presented rich product information to users when needed while maintaining the cleanliness of the webpage.

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