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A Study on the Relationship between Spatial Emotion Expression Models for Multidimensional Data Computational Analysis and Indoor Design Space Comfortability

Hanyang Zhou[1,*]
[1] School of Architecture and Engineering, College of Science & Technology, Ningbo University, Ningbo, Zhejiang, 315000, China
Corresponding authors: (e-mail: Hanyang_Zhou20999@163.com).

Abstract Emotional design has always been an important topic in indoor spaces, significantly impacting people's living experiences and quality of life. This paper first uses the PAD model to construct a mood space and a state space model to construct an emotional space, quantitatively describing the relationship between personality, mood, and emotion. Subsequently, based on the OCC and PAD emotional models, emotional calculations are performed on the various dimensions of "place attachment," analyzing emotional characteristics through people's satisfaction with the spatial environment of buildings. Finally, a multiple regression model is established to explore the subjective comfort scores of interior design under a spatial emotional expression model based on multi-dimensional data calculation and analysis. In simulated experiments comparing the comfort of interior design spaces, comfort scores were mostly above 4 points, indicating that, overall, people have a positive evaluation of the comfort of interior design spaces.

Index Terms PAD model, multiple regression, interior design, spatial comfort

I. Introduction

The emotional response to a space is an innate human instinct, with basic emotional reactions deeply ingrained in human genetics [1]. While nature presents humans with dangers and competition, it also provides food and shelter. The characteristics and elements of a spatial environment serve as criteria for humans to assess risks and opportunities [2], [3]. Therefore, when a person is in a space, their senses are stimulated by the various elements of the space, leading to changes in hormone levels, which help them quickly form expectations about the space and make decisions. At the same time, influenced by hormones, emotional responses also occur [4]-[6]. "Spatial emotion" is a real phenomenon of spatial experience, and human emotional responses to space have evolved through various historical stages and continue to this day [7].

Indoor spaces are one of the most important venues for modern human activities, and indoor spatial emotions have already been identified and studied to some extent [8]. Literature [9] found through research on the impact of indoor space design on emotions and work performance that unpopular indoor spaces, by increasing a sense of control, enhance short-term work efficiency, while personalized indoor spaces, by eliciting positive emotions, improve long-term work efficiency. Literature [10] interprets indoor spaces from a phenomenological perspective, exploring the emotional connection between space and experience. It argues that stimulating emotional experiences through bodily sensations, materiality, and emotional connections can enhance spatial perception and create multi-sensory spaces. Literature [11] explores the emotional responses of different age groups to various indoor elements. The study found that natural-style and vibrant indoor spaces are more likely to evoke positive emotions, while basic-style and modern-style indoor spaces tend to trigger negative emotions. "Indoor space emotion" refers to the use of interior design techniques to create a distinct emotional atmosphere within a space.

Properly creating an emotional atmosphere in a space can guide users' behavior in the right direction, thereby achieving the designer's intended purpose for the space. Literature [12] developed a customized emotional assessment model based on indoor environmental data, achieving approximately 80% assessment accuracy through the use of multiple sensors, demonstrating the effectiveness of accurately assessing emotions from indoor spatial environmental data. Literature [13] developed a graphical analysis method to explore how spatial emotional representation is influenced by environmental and personal characteristics. Literature [14] investigated the impact of different geometric shapes in a space on human emotions, finding that geometric features such as protrusions, curves, proportions, and dimensions significantly influence human emotions. This finding holds significant implications for residential, educational, and rehabilitative indoor spaces. Literature [15] combines technology with user experience to develop a new method for assessing emotions during spatial interaction, aiming to explore the user experience and emotional aspects of spatial design.

Currently, research on spatial comfort primarily focuses on office buildings. Only in the past decade has the comfort of indoor design gradually attracted the attention of scholars. Literature [16] provides a comprehensive literature review on human comfort in indoor environments, focusing on comfort assessment standards, data collection methods, and data analysis methods. This study offers theoretical references for research on indoor comfort. Literature [17] investigated the relationship between perceived indoor environmental quality and comfort in office buildings, finding that noise is the most significant influencing factor, followed by air quality, lighting, and thermal comfort, while personal characteristics and building characteristics also influence these relationships. Literature [18] found that indoor comfort is significantly associated with users' physical and mental health, work efficiency, and overall health status. Therefore, they utilized computational fluid dynamics (CFD) technology to create a visual chart of indoor comfort, which was used to simulate and analyze the comfort conditions of indoor spaces. Literature [19] explores the interrelationship between indoor space design, indoor environmental quality, and occupant behavior, aiming to ensure energy efficiency and a healthy environment. It focuses on the impact of thermal comfort, visual comfort, indoor air quality, and acoustic quality on the emotional expression of space.

This paper first constructs a transition probability matrix for emotional spaces, calculates the distance between moods and basic emotions in the mood space, and uses this as a basis to adjust the transition probability matrix of the emotional space, quantitatively calculating the relationship between moods and emotions, and establishing a personalized emotional model. Second, a synonym dictionary is used to bridge the “place attachment” emotional elements to the OCC emotional model, and combined with PAD emotional semantic quantification values, emotional calculations are performed on “place attachment” to reveal the emotional intensity values of each dimension. Subsequently, based on surveys of people's perceptions of spatial scenes, combined with “place attachment” PAD and emotional intensity values, emotional elements are evaluated and classified from the perspectives of necessity, expectation, and activation. Finally, regression analysis methods were used to explore the relationship between electrocardiogram (ECG) signal indicators and spatial comfort, and to quantitatively evaluate indoor spatial comfort based on the model designed in this paper.

II. Personalized emotion model based on PAD

II. A.PAD Model

There is no unified definition of the concept of mood in the field of psychology. The PAD model has three dimensions: pleasantness, arousal, and dominance. P represents pleasantness, indicating the positive or negative characteristics of an individual's emotional state. A represents arousal, indicating an individual's level of neurophysiological activation. D represents dominance, indicating an individual's state of control over situations and others [20]. The numerical range for each dimension is [-1, +1], where -1 indicates the lowest value on that dimension, and +1 indicates the highest value on that dimension.

II. B.State Space Model

Let us assume for the moment that basic emotions consist only of the three simplest emotions: happiness, anger, and fear. The three-dimensional emotional state space is shown in Figure 1, where the three basic emotions form a three-dimensional emotional space.

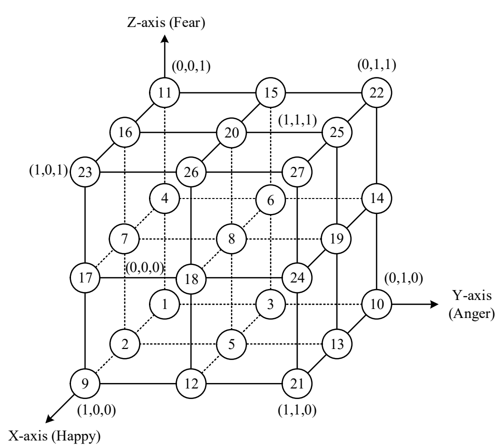


Figure 1: Three-dimensional emotional state space

Assuming that there are m basic emotions, each of which can be divided into n levels, the emotional space has n^m emotional states. Let $l = n^m$, then the l-dimensional Markov transition matrix $P_{emotion}$ is:

$$P_{emotion} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,j} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,j} \\ \vdots & \vdots & & \vdots \\ p_{j,1} & p_{j,2} & \cdots & p_{j,j} \end{pmatrix} \tag{1}$$

(1) In the formula, $p_{i,j}$ is the transition probability from the i th emotional state to the j th emotional state, and satisfies the following relationship:

$$\sum_{j=1}^{l} p_{i,j} = 1, (i = 1, 2, \cdots, l) \tag{2}$$

In order to evaluate the overall performance of the emotion model, borrowing the concept of information entropy, we define emotion entropy as:

$$Entropy = -\sum_{i=1}^{l} p_i \log p_i, (i = 1, 2, \cdots, l) \tag{3}$$

(3) In the formula: Entropy is the emotional entropy of the emotional model. p_i is the probability of the i th emotional state occurring.

II. C.Model Establishment

II. C. 1) Basic Concepts

1) Personality space

In this paper, human personality is considered to be constant. Personality space is constructed using FFM. Personality vectors are represented as 5-dimensional vectors:

$$\begin{gathered} P_{personality} = [p_O, p_C, p_E, p_A, p_N] \\ 0 \le p_O, p_C, p_E, p_A, p_N \le 1 \end{gathered} \tag{4}$$

2) Mood Space

There is no unified definition of mood in the field of psychology, so the PAD model is used to describe mood. Based on this, mood space uses the PAD model to describe [21].

The mood vector is defined as a 3-dimensional vector:

$$\begin{gathered} M_{mood} = [m_p, m_A, m_D]^T \\ -1 \le m_p, m_A, m_D \le 1 \end{gathered} \tag{5}$$

3) Emotional space

Assume that there are m basic emotions, and each basic emotion can be divided into n levels. Thus, the emotional space has n^m nodes, i.e., n^m emotional states.

4) Basic Emotion Intensity

For convenience, let $l = n^m$. Suppose the coordinates of the j th node in the emotional space are $[v_{1,j}, v_{2,j}, \cdots, v_{m,j}]$, $\left(v_{i,j} \in \left\{ 0, \frac{1}{n-1}, \frac{2}{n-1}, \cdots, 1 \right\}, i = 1, 2, \cdots, m \right)$ the probability of this node appearing is p_j. Then, the components of all node coordinates in the i th dimension can be represented as a vector $[v_{i,1}, v_{i,2}, \cdots, v_{i,l}]$, since the i th dimension corresponds to the i th basic emotion, this vector represents the change in the intensity of the i th basic emotion when emotions transfer between nodes. The intensity of basic emotions is defined as:

$$Expectation_i = \sum_{j=1}^{l} v_{i,j} \cdot p_j, (i = 1, 2, \cdots, m) \tag{6}$$

(6) In the formula, $Expectation_i$ is the intensity of the i th basic emotion in the emotion space, which represents the average intensity value of the i th basic emotion. The higher the value, the stronger the basic emotion; conversely, the lower the value, the weaker the basic emotion.

II. C. 2) Interrelationships between personality, mood, and emotions

1) Mapping of personality space and mood space

Personality is a 5-dimensional space, and mood is a 3-dimensional space. Therefore, the mapping relationship between personality and mood is established as follows:

$$\begin{cases} P = 0.21 \cdot E + 0.59 \cdot A + 0.19 \cdot N \\ A = 0.15 \cdot O + 0.30 \cdot A - 0.57 \cdot N \\ D = 0.25 \cdot O + 0.17 \cdot C + 0.60 \cdot E - 0.32 \cdot A \end{cases} \tag{7}$$

(7) In the formula: P, A, D represent Pleasure, Arousal, and Dominance, respectively. O, C, E, A, N represent Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, respectively.

That is:

$$M_{mood} = P\_M \cdot P_{personality}^{T} \tag{8}$$

(8) In the formula:

$$P\_M = \begin{bmatrix} 0 & 0 & 0.21 & 0.59 & 0.19 \\ 0.15 & 0 & 0 & 0.30 & -0.57 \\ 0.25 & 0.17 & 0.60 & -0.32 & 0 \end{bmatrix} \tag{9}$$

Defined as a personality and mood mapping matrix.

2) Mapping of mood space and emotion space

Define the Euclidean distance matrix in the emotion space as:

$$D_{emodion} = \begin{pmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,j} \\ d_{2,1} & d_{2,2} & \cdots & d_{2,j} \\ \vdots & \vdots & & \vdots \\ d_{j,1} & d_{j,2} & \cdots & d_{j,j} \end{pmatrix}, (j = 1, 2, \cdots, l) \tag{10}$$

In equation (10), $d_{i,j}, i = 1, 2, \cdots, l$ is the Euclidean distance between the i th node and the j th node in the emotional space. It represents the magnitude of the transition probability between two emotional states. If the distance between two nodes is greater, the probability of transition between the two nodes is lower. Conversely, the probability is higher.

The transition probability matrix in the emotional space is defined as:

$$P_{emotion} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,j} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,j} \\ \vdots & \vdots & & \vdots \\ p_{j,1} & p_{j,2} & \cdots & p_{j,j} \end{pmatrix}, (j = 1, 2, \cdots, l) \tag{11}$$

In the formula (11), $p_{i,j}$ is the transition probability from the i th node to the j th node in the sentiment space. It satisfies the following relationship:

$$\sum_{j=1}^{l} p_{i,j} = 1, (i = 1, 2, \cdots, l) \tag{12}$$

Suppose that the transition probability from one node to another is inversely proportional to the Euclidean distance between them, i.e.:

$$p_{i,j} = \frac{C_i}{d_{i,j}}, (j = 1, 2, \cdots, l) \tag{13}$$

In the equation (13), C_i is a constant, $i \in \{1, 2, \cdots, l\}$. By combining equations (12) and (13), we can calculate $p_{i,j}$, and thus construct $P_{emotion}$.

If the emotion space has m dimensions, i.e., there are m basic emotions, then the mood space also corresponds to m basic emotion points. To accurately construct the emotion space and conform to cognitive laws, the values of $z_k, (k = 1, 2, \cdots, m)$ and the superposition process should satisfy the following conditions.

(1) Since z_k is added as a multiplication coefficient to the Euclidean distance, $z_k \geq 0$. When $z_k = 0$, the distance between a node in the emotional space and different nodes will be 0, so $z_k \neq 0$.

Therefore, $z_k > 0$.

(2) When the distance between M_{mood} and all basic emotion points in the PAD space is equal, the additional influence of mood on emotion should be canceled out in all directions. thus, when $x_1 = x_2 = \cdots = x_m$, $z_1 = z_2 = \cdots = z_m = 1$.

(3) In this model, the probabilities of nodes not on the coordinate axes are not directly processed, so all nodes in the emotion space whose appearance probabilities need to be changed appear on the coordinate axes.

(4) In $d_{i,j}$, how the specific values are changed is the key to constructing the model and also the key to achieving the mechanism of mood influencing emotion.

Based on the above conditions, the process of obtaining z_k is as follows.

a) Let $x=(x_1,x_2,\cdots,x_m)$; establish the mapping f_1 as:

$$y_k = f_1(x_k) = \begin{cases} \dfrac{(x_k - x_{mean})}{(x_{\max} - x_{\min})}, x_{\max} \neq x_{\min} \\ 0, x_{\max} = x_{\min} \end{cases} \tag{14}$$

In the formula (14): $x_{\max} = \max(x_1,x_2,\cdots,x_m)$. $x_{\min} = \min(x_1,x_2,\cdots,x_m)$. $x_{mean} = (\sum_{i=1}^{m} x_i)/m$.

b) Let $y=(y_1,y_2,\cdots,y_m)$ and establish the mapping f_2 as:

$$z_k = f_2(y_k) = \theta^{y_k}, \theta > 1 \tag{15}$$

In the formula (15): θ is the standardization factor. z_k is the distance superposition factor.

The superposition method of z_k is as follows.

Define the new distance matrix in the emotion space as:

$$D^*_{emodion} = \begin{pmatrix} d^*_{1,1} & d^*_{1,2} & \cdots & d^*_{1,j} \\ d^*_{2,1} & d^*_{2,2} & \cdots & d^*_{2,j} \\ \cdots & \cdots & & \cdots \\ d^*_{j,1} & d^*_{j,2} & \cdots & d^*_{j,j} \end{pmatrix}, (j=1,2,\cdots,l) \tag{16}$$

In equation (16), $d^*_{i,j}, i=1,2,\cdots,l$ is the new Euclidean distance between the i th node and the j th node in the sentiment space.

Let $z=(z_1,z_2,\cdots,z_m)$, then define:

$$d^*_{i,j} = d_{i,j} \cdot z_k \tag{17}$$

In the formula (17): $i \in Node; j \in Node_k; k=1,2,\cdots,m$. Node is the set of all node numbers in the emotion space, and $Node_k$ is the set of node numbers represented by the k th basic emotion.

Based on $D^*_{emotion}$, a new emotional space can be constructed.

II. C. 3) Selection of standardization factors

(15) introduces a normalization factor θ, whose selection greatly affects whether $z=(z_1,z_2,\cdots,z_m)$ adequately preserves the numerical characteristics of $x=(x_1,x_2,\cdots,x_m)$ is well preserved.

Assume that the emotional space contains only the three simplest emotions: happiness, anger, and fear, i.e., $m=3$. Thus, $x=(x_1,x_2,x_3), z=(z_1,z_2,z_3)$.

Define the following three ratios:

$$\begin{cases} R_0 = (z_2/z_1)/(x_2/x_1) \\ S_0 = (z_3/z_1)/(x_3/x_1) \\ T_0 = (z_3/z_2)/(x_3/z_2) \end{cases} \tag{18}$$

The closer R_0, S_0, T_0 are to 1, the better $z=(z_1,z_2,z_3)$ better preserves the proportional relationship of $x=(x_1,x_2,x_3)$.

Assuming that θ is a constant, and a set of personality vectors $P_{personality}$ corresponds to a set of (R_0,S_0,T_0), if all possible values of $P_{personality}$ have η, then we should get 3 η dimension vectors $R=(R_1,R_2,\cdots,R_\eta)$, $S=(S_1,S_2,\cdots,S_\eta)$ and $T=(T_1,T_2,\cdots,T_\eta)$.

Therefore, we define:

$$\begin{cases} \gamma = \sqrt{(R_{mean}-1)^2 + (S_{mean}-1)^2 + (T_{mean}-1)^2} \\ \lambda = \sqrt{(R_{var}-0)^2 + (S_{var}-0)^2 + (T_{var}-0)^2} \end{cases} \tag{19}$$

(19) where: $R_{mean}=(\sum_{i=1}^{\eta}R_i)/\eta; S_{mean}$ and T_{mean} are similar. $R_{var}=\sqrt{\sum_{i=1}^{n}(R_i-R_{mean})^2}$, S_{var} is analogous to T_{var} . γ denotes the sum of the variances from the mean to 1 for R,S,T respectively. λ denotes the sum of the variances of R,S,T relative to 0.

Considering the above, we define:

$$\Delta=\gamma\cdot\lambda/\theta^2 \tag{20}$$

In the formula (20), Δ is the selection factor. When γ and λ are smaller, and θ^2 is larger, then Δ is smaller. Conversely, it is larger.

III. Analysis of Emotional Computing and Evaluation in Architectural Spaces

III. A. Emotion computing based on PAD's "place attachment"

III. A. 1) Calculating Emotional Values for Emotional Semantics

Research on the Emotional Computing Process of "Place Attachment" in Architectural Spaces the emotional experience of "place attachment" in architectural spaces is summarized into nine specific semantic keywords, which are then calculated using the OCC emotional model. Each OCC emotional term has specific P, A, and D values. Therefore, using OCC emotional terms as a medium, place attachment emotional terms can be mapped to the emotional semantic space, yielding the position coordinates of the feature term within the emotional semantic space. The mapping relationship between "place attachment" feature terms and OCC emotional terms is shown in Table 1.

Table 1: The mapping relationship between "place attachment" and occ emotional words

The word being tested			OCC Feature words		Semantic similarity	The PAD value of OCC feature words			The PAD value of the word being tested		
Site attachment		Synonyms coding	OCC	Synonyms coding		P value	A value	D value	P' value	A' value	D' value
Quality identity	Comfort	Ef07A01	Disappointment	Ee08B01	0.71	-0.2	0.1	0.6	-0.6	-0.12	0.24
			Schadenfreude	Ee02B02	0.71	0.3	-0.2	-0.2	0.43	-0.34	0.32
			Pride	Ee34A02	0.71	0.6	0.3	0.3	0.28	0.54	0.29
				Ee34D02	0.71	0.6	0.3	0.3	0.26	0.49	0.27
		Ga06C01	Satisfy	Ga06B01	0.89	0.8	0.6	0.6	0.51	0.64	0.41
	Pleasure	Ga01A01	Joyfulness	Ga01A01	1.00	0.6	0.2	0.2	-0.24	0.78	0.52
	Slacken	Ga13B01	Be afraid of	Ga16B01	0.66	-0.8	0.8	-0.6	0.46	-0.44	0.21
			Panic	Ga16B04	0.66	-0.6	-0.2	-0.7	0.07	0.59	-0.24
		Ef10A01	Disappointment	Ee08B01	0.6	-0.2	0.1	0.6	-0.58	-0.16	0.22
			Schadenfreude	Ee02B02	0.6	0.3	-0.2	-0.2	0.44	-0.35	0.29
			Pride	Ee34A02	0.6	0.6	0.3	0.3	0.28	0.49	0.33
				Ee34D02	0.6	0.6	0.3	0.3	0.29	0.48	0.29
		Eb09B01	Hate	Ed41B01	0.54	-0.8	0.8	0.3	0.37	-0.34	0.21
			Love	Ed40A01	0.54	0.6	0.2	0.1	-0.11	0.4	0.27
Behavior support	Safety	Ef08A01	Disappointment	Ee08B01	0.6	-0.2	0.1	0.6	-0.56	-0.2	0.23
			Schadenfreude	Ee02B02	0.6	0.3	-0.2	-0.2	0.46	-0.35	0.3
			Pride	Ee34A02	0.6	0.6	0.3	0.3	0.31	0.52	0.3
				Ee34D02	0.6	0.6	0.3	0.3	0.29	0.5	0.3
		Ga07A01	Satisfy	Ga06B01	0.77	0.8	0.6	0.6	0.43	0.55	0.29
			Satisfaction	Ga06A01	0.77	0.3	-0.2	0.6	0.25	-0.67	0.32
	Privacy	Df02A03	Love	Df05C01	0.71	0.6	0.2	0.1	-0.15	0.55	0.35
		Ed44B01	Disappointment	Ee08B01	0.6	-0.2	0.1	0.6	-0.61	-0.15	0.22
			Schadenfreude	Ee02B02	0.6	0.3	-0.2	-0.2	0.46	-0.29	0.33
			Pride	Ee34A02	0.6	0.6	0.3	0.3	0.28	0.49	0.28
				Ee34D02	0.6	0.6	0.3	0.3	0.29	0.5	0.26
	Autonomy	Hj05A01	Blame	Hi21A01	0.63	-0.2	-0.2	0.6	-0.58	0.17	0.2
				Hi21A03	0.63	-0.2	-0.2	0.6	-0.55	0.16	0.21
		Dd01A25	Hope	Df08A01	0.52	0.2	0.2	-0.2	0.38	0.28	0.29
				Df08B01	0.52	0.2	0.2	-0.2	0.4	0.28	0.33
			Joy	Df12A04	0.52	0.6	0.2	0.1	-0.14	0.48	0.31
			Love	Df05C01	0.52	0.6	0.2	0.1	-0.1	0.49	0.33
				Df12B01	0.52	0.6	0.2	0.1	-0.14	0.47	0.31

			Resentment	Df06D01	0.52	-0.2	-0.2	-0.2	0.49	0.07	0.3
		Ee10D01	Hate	Ed41B01	0.6	-0.8	0.8	0.3	0.45	-0.37	0.3
			Love	Ed40A01	0.6	0.6	0.2	0.1	-0.15	0.51	0.34
		Ga06C02	Satisfy	Ga06B01	0.89	0.8	0.6	0.6	0.49	0.63	0.4
Emotional dependence	Familiar with	Ed31A01	Disappointment	Ee08B01	0.6	-0.2	0.1	0.6	-0.63	-0.14	0.23
			Schadenfreude	Ee02B02	0.6	0.3	-0.2	-0.2	0.45	-0.33	0.33
			Pride	Ee34A02	0.6	0.6	0.3	0.3	0.3	0.51	0.28
				Ee34D02	0.6	0.6	0.3	0.3	0.3	0.51	0.31
		Gb08A08	Like	Gb09A01	0.74	0.6	0.2	-0.2	-0.47	0.45	0.36
			Love	Gb09B01	0.74	0.6	0.2	0.1	-0.19	0.66	0.4
	Affinity	Ee07A01	Hate	Ed41B01	0.6	-0.8	0.8	0.3	0.49	-0.36	0.32
			Love	Ed40A01	0.6	0.6	0.2	0.1	-0.13	0.58	0.35
		Ed32A01	Disappointment	Ee08B01	0.6	-0.2	0.1	0.6	-0.57	-0.16	0.24
			Schadenfreude	Ee02B02	0.6	0.3	-0.2	-0.2	0.45	-0.33	0.34
			Pride	Ee34A02	0.6	0.6	0.3	0.3	0.29	0.51	0.28
	Domain	Dd05B03	Hope	Ee34D02	0.6	0.6	0.3	0.3	0.27	0.49	0.28
			Joy	Df08A01	0.52	0.2	0.2	-0.2	0.42	0.27	0.28
			Love	Df05C01	0.52	0.2	0.2	-0.2	0.41	0.29	0.31
				Df12B01	0.52	0.6	0.2	0.1	-0.12	0.5	0.32
			Resentment	Df06D01	0.52	0.6	0.2	0.1	-0.13	0.5	0.3

Based on the synonym dictionary, we constructed a mapping relationship between "place attachment" and OCC feature words. We calculated the PAD values of the "place attachment" feature words using semantic similarity values and OCC feature word PAD values. The PAD values of the "place attachment" feature words are shown in Table 2.

Table 2: The pad value of the "place attachment"

Place attachment		P' value	A' value	D' value	Emotional intensity E	Emotional Quadrant	
Quality recognition	comfort	0.25	0.48	0.29	0.64	Exuberant	+P+A+D
	pleasure	0.38	0.19	0.22	1	Exuberant	+P+A+D
	slacken	0.43	-0.43	0.25	0.67	Relaxed	+P-A+D
Behavioral support	safety	0.22	-0.65	0.33	0.8	Relaxed	+P-A+D
	privacy	-0.12	0.54	0.34	0.66	Hostile	-P+A+D
	autonomy	0.46	0.64	0.38	0.88	Exuberant	+P+A+D
Emotional dependence	Familiar with	-0.17	0.63	0.4	0.77	Hostile	-P+A+D
	affinity	-0.13	0.53	0.35	0.63	Hostile	-P+A+D
	domain	-0.11	0.48	0.35	0.63	Hostile	-P+A+D

III. A. 2) Emotional semantic calculation results for "place attachment"

Overall, pleasant, autonomous, safe, and familiar have high emotional intensity values. Among these, comfort, pleasantness, and autonomy are located in the "joy" quadrant, indicating that they generally exhibit a joyful emotional tendency. Safety and relaxation are located in the "relaxed" quadrant, exhibiting a relaxed emotional tendency. Familiarity, intimacy, affinity, and domain are located in the "hostility" quadrant, indicating an exclusive emotional orientation. The pleasure (P') mapping results show slightly more positive coordinate values than negative ones, with all positive coordinate values greater than 0.2 and all negative coordinate values less than 0.2, indicating that the pleasure of "place attachment" is more influenced by positive emotional states.

III. B. Survey on the perception of "place attachment" in architectural spaces

III. B. 1) Purpose and Significance of the Survey

This paper calculates the emotional intensity and P, A, and D values of cognitive feelings in different dimensions through "place attachment" emotional computing. The primary task in creating buildings with "place attachment" is to conduct an emotional assessment of the existing spatial environment. Therefore, this paper conducts an in-depth and detailed survey of the architectural spatial environment.

III. B. 2) Survey Content and Methods

This survey explores people's perceptions of "place attachment" in three types of spaces (bedrooms, public activity spaces, and corridors). Based on the emotional elements of "place attachment," the survey conducts in-depth interviews with people about their perceptions of the spatial environment of buildings.

III. B. 3) Overview of the survey implementation

In the preliminary stage of the study, more than 400 real-life photos of the spatial environment were collected. The case photos were divided into 10 groups (A1-A10, B1-B10, C1-C10), with each group containing 8 to 11 photos. Each participant randomly selected a group of photos for a questionnaire interview, and each group had to have more than 10 participants respond. A total of 400 valid questionnaires were collected.

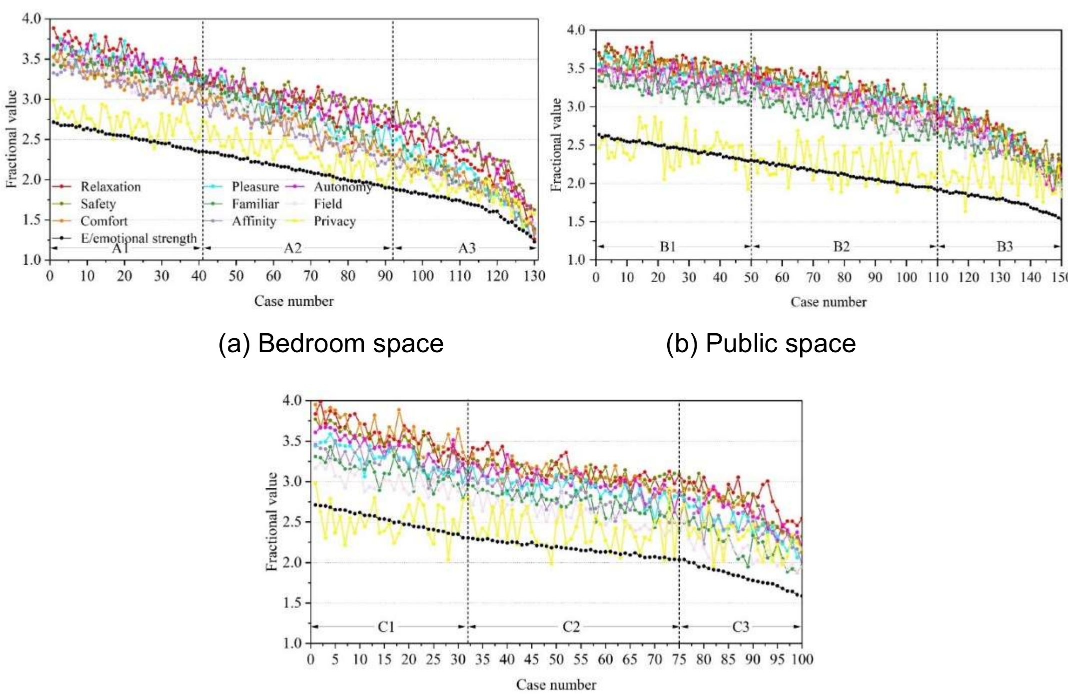
III. C. Emotional calculation and evaluation of core spaces in buildings

III. C. 1) Correlation analysis between emotional computing intensity values and perceptions of various dimensions

A total of 380 cases were selected for emotional assessment in this study. In the three functional spaces, the emotions of "comfort," "pleasure," and "identification" showed a strong correlation with "place attachment," with "pleasure" being the most prominent. "Freedom" and 'safety' showed a strong correlation with "place attachment," while "privacy" showed a weak correlation. The emotions of "familiarity," "affinity," and "territory" are strongly correlated with "place attachment," with "territory" being the most significant. This indicates that the nine constituent elements of "place attachment" constructed in this study have high rationality and validity, and are strongly correlated with the intensity of "place attachment" emotions.

III. C. 2) Emotional evaluation of space

The emotional assessment results for each space are shown in Figure 2 (Figures a to c represent residential spaces, public activity spaces, and corridor spaces, respectively). As can be seen from the figure, in residential spaces, the E value of cluster A1 is approximately 2.5, indicating a high degree of "place attachment." Relaxation is the strongest emotion, with a central value of approximately 3.53, followed by pleasure and autonomy. Privacy fluctuates greatly and is significantly lower than other emotions.



(a) Bedroom space (b) Public space

(c) Corridor space

Figure 2: The emotional assessment results of each spatial case

III. C. 3) Classification of the emotional impact of space

1) Emotional Essentials: This is an indispensable perception in "place attachment." Spaces with this perception may not necessarily increase people's 'attachment' to such spaces, but their absence can make people feel alienated and lonely. In all three types of spaces, "safety" is an essential emotional element.

2) Emotional Expectations: These are the emotional experiences people anticipate. Possessing such experiences enhances the intensity of "attachment," while their absence may negatively impact living quality to some extent.

3) Emotional Activation: This refers to the surprising and charming emotional experiences brought by "place attachment." While their absence does not affect the emotional attachment to a space, experiencing them significantly enhances place attachment.

IV. Indoor design space comfort test

IV. A. Comfort Regression Analysis

IV. A. 1) Multivariate regression analysis

Regression analysis is a statistical and analytical method used to determine the quantitative relationship between two or more variables. Multivariate regression analysis is employed to describe this phenomenon, explain its causes, and ensure greater precision and reliability in the control process, while minimizing variance and mean squared error [22]. The primary method of regression analysis involves establishing a regression model based on existing data. In this process, selecting appropriate and primary variables from among multiple explanatory variables is particularly important. In other words, the goal is to preserve variables closely related to the dependent variable while minimizing the number of independent variables, thereby ignoring factors with minimal influence.

IV. A. 2) Multivariate regression calculation method

(1) Single-dependent variable multiple linear regression model

Assume that there are m independent variables $x_1, x_2, ...x_m$ representing factors, y is the dependent variable representing the indicator, and n experiments are conducted, yielding n sets of data $y_i, x_{i1}, x_{i2}, \cdots, x_{im} (i = 1, 2, ...n)$. Assume that the dependent variable y has a linear relationship with the m independent variables $x_1, x_2, \cdots, x_m$ and can be represented by the following model:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m + \varepsilon_1 \tag{21}$$

Substituting n sets of data, we obtain:

$$\begin{cases} y_1 = \beta_0 + \beta_1 x_{11} + ... + \beta_m x_{1m} + \varepsilon_1 \\ y_2 = \beta_0 + \beta_1 x_{21} + ... + \beta_m x_{2m} + \varepsilon_2 \\ \cdots \\ y_n = \beta_0 + \beta_1 x_{n1} + ... + \beta_m x_{nm} + \varepsilon_n \end{cases} \tag{22}$$

Among these, $\beta_0, \beta_1, \cdots, \beta_n$ are the parameters to be estimated, which we refer to as regression coefficients, and $\varepsilon_1, \varepsilon_2, ..., \varepsilon_n$ are n independent random variables that follow the same normal distribution $N(0, \sigma^2)$ [23].

$$\begin{gathered} Y = \begin{pmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{pmatrix}, C = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{pmatrix} = (1_n X) \\ \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \cdots \\ \beta_m \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_0 \\ \varepsilon_1 \\ \cdots \\ \varepsilon_n \end{pmatrix} \end{gathered} \tag{23}$$

The matrix form of the regression model is:

$$\begin{cases} Y = C\beta + \varepsilon \\ E(\varepsilon) = 0_n, D(\varepsilon) = \sigma_2 I_2 \end{cases} \text{or} \begin{cases} Y = C\beta + \varepsilon \\ \varepsilon \sim N_n(0, \sigma^2 I_n) \end{cases} \tag{24}$$

The above model is referred to as the classical multiple regression model, where Y is an observable random variable, ε is an unobservable random variable, C is a known matrix, β, σ^2 are unknown parameters, and $n > m$ and $rank(C) = m + 1$.

(2) Least squares estimation of parameter vectors

In the model, the least squares estimator of the parameter β is $\hat{\beta}=(\hat{\beta}_0,\hat{\beta}_1,...\hat{\beta}_m)$ minimizes the sum of squared errors $Q(\hat{\beta})$, i.e., for all $\beta, Q(\hat{\beta})=\min Q(\beta)$.

where,

$$Q(\beta)=\sum_{i=1}^{n}\varepsilon_i^2=\sum_{i=1}^{n}(y_i-(\beta_0+\beta_1x_{xi}+...+\beta_m x_{xm}))^2=(Y-C\beta)'(Y-C\beta) \tag{25}$$

If $\hat{\beta}$ is the least squares estimate of β, then $\hat{\beta}$ is the linear unbiased estimator of β with minimum variance. If $\varepsilon \sim N_n(0,\sigma^2 I_n)$, β is also the estimator with the smallest variance among all unbiased estimators.

(3) Sum of squares decomposition

For the observed data array:

$$\begin{pmatrix} y_1 & x_{11} & \dots & x_{1m} \\ y_2 & x_{21} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ y_n & x_{n1} & \dots & x_{nm} \end{pmatrix} \tag{26}$$

There is a formula:

$$\sum_{i=1}^{n}(y_i-\overline{y})^2=\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\sum_{i=1}^{n}(\hat{y}_i-\hat{y})^2 \tag{27}$$

Among them:

$$\overline{y}=\frac{1}{n}\sum_{i=1}^{n}y_i \tag{28}$$

$$\hat{y}_i=\hat{\beta}_0+\hat{\beta}_1x_{x1}+...+\hat{\beta}_m x_{xm} \tag{29}$$

$$\hat{\beta}=\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \dots \\ \hat{\beta}_m \end{pmatrix}=(C'C)^{-1}C'Y \tag{30}$$

It is the least squares estimate of β. The above formula is called the sum of squares decomposition formula.

In the sum of squares decomposition formula, the left-hand side of the equation, $\sum_{i=1}^{n}(y_i-y)^2$, represents the total variation of the observed values of Y, $y_1,y_2,...y_n$ of the variable Y, known as the total sum of squares of deviations, denoted as L_{yy} or SST. The second term on the right-hand side of the equality, $\sum_{i=1}^{n}(y_i-y)^2$, represents the total variation of the n estimated values $\hat{y}_1,\hat{y}_2\dots\hat{y}_n$ due to the fact that there is indeed a linear relationship between the dependent variable Y and the independent variables $x_1,x_2,...,x_n$ and is caused by changes in $x_1,x_2,...,x_m$. We refer to this as the regression sum of squares, denoted as U or SMM. The first term on the right-hand side of the equation, $\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\sum_{i=1}^{n}\varepsilon_i^2$, is called the residual sum of squares, denoted as Q or SSE. Under the model assumptions, we have:

$$E(Y)=\beta_0+\beta_1x_1+\cdots+\beta_m x_m \tag{31}$$

Q is caused by random errors, so Q is also called the residual sum of squares. The sum of squares decomposition can also be abbreviated as:

$$L_{yy}=Q+U \text{ or } SST==SSE+SSM \tag{32}$$

$$R^2=1-\sum_{i=1}^{n}(\hat{y}_i-\overline{y})^2/\sum_{i=1}^{n}(y_i-\overline{y})^2 \tag{33}$$

The coefficient of determination R-squared is used to indicate the accuracy of the linear regression equation, i.e., the extent to which the linear regression equation can explain the total variation in the Y values.

(4) F-test for regression effectiveness

The validity of the regression model should be determined through a significance test of the regression effectiveness. There are three methods for testing the significance of regression analysis effectiveness: the r test, the F test, and the t test. These three methods are essentially the same. This study uses the F test method to test the regression effectiveness. That is:

$$F = \frac{r^2(n-2)}{1-r^2} F(1, n-2) \tag{34}$$

For a given significance level α , if:

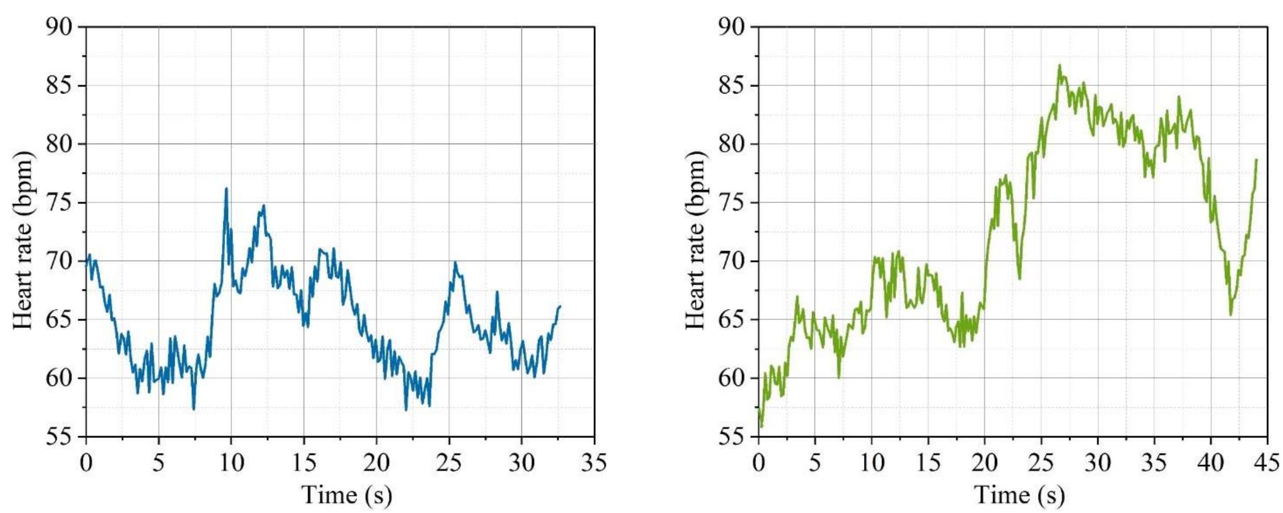
$$F \geq F_{1-\alpha}(1, n-2) \tag{35}$$

If there is a significant linear relationship between x and y , then the linear regression is considered significant. Otherwise, the linear regression is not significant. The value of $F_{l-\alpha}(1, n-2)$ can be obtained from the F distribution table.

IV. B. Analysis of Results

IV. B. 1) Correlation Analysis

To investigate the relationship between the spatial emotional expression model based on multidimensional data analysis and the comfort of indoor design spaces, this section of the experiment explores the relationship between the proposed model and spatial comfort through changes in electrocardiogram (ECG) signal indicators. We conducted a correlation analysis on the ECG data collected during the experiment to determine the degree of correlation between various ECG indicators and users' subjective comfort levels, providing a reference basis for establishing a user-oriented comfort evaluation model in subsequent stages. The heart rate data in this paper was obtained through processing and calculating the raw ECG signals from wireless ECG sensors. The comparison of participants' heart rates before and after the experiment is shown in Figure 3 (Figure a shows the test results in a conventional indoor space, and Figure b shows the test results in an indoor space designed based on the method proposed in this paper). It can be observed that when entering a conventional indoor design space, users' heart rates show a slight increase. However, when participants enter the indoor space designed based on the method proposed in this paper, their heart rates begin to rise significantly and reach a peak after 5 seconds. Overall, it was found that changes in heart rate were relatively slow, with the maximum heart rate (25 seconds) not appearing until the latter half of the indoor space designed using the method described in this paper or even after the experiment had ended. This is because, during the experiment, when participants were stimulated by changes in the environment, there was a certain delay in the effects on the ECG signals, and there were also differences in the results among different participants.



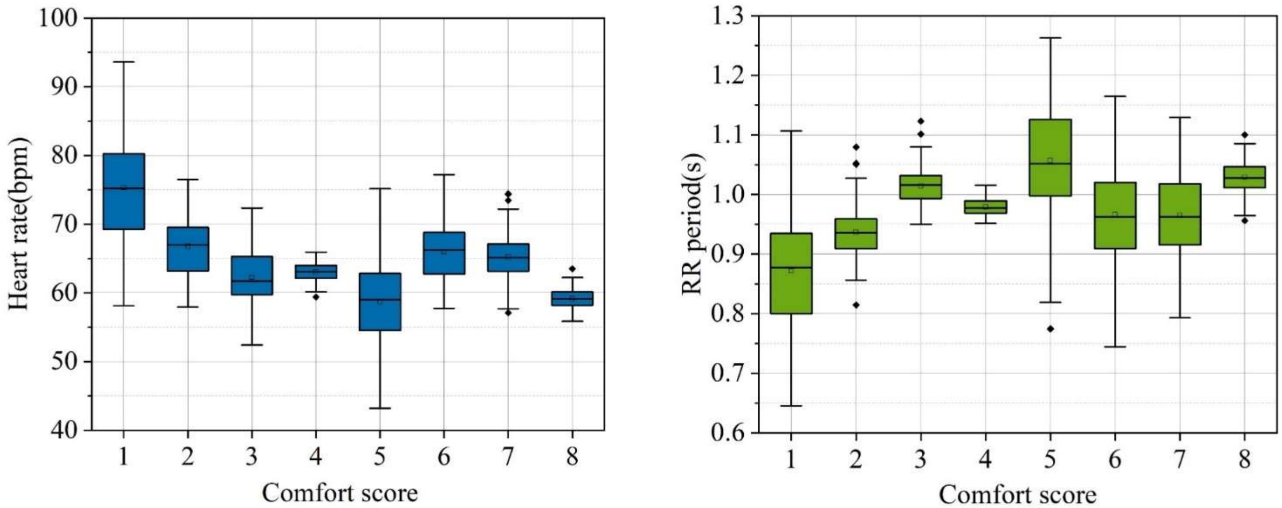
(a) Test results of ordinary indoor Spaces

(b) The test results of the indoor space designed based on the method in this paper

Figure 3: The experiment was compared with the participants' heart rate

The comfort ratings of the participants in the experiment, along with their heart rates and R-R interval distributions, are shown in Figure 4 (Figure a shows the heart rate distribution, and Figure b shows the R-R interval distribution).

From the heart rate distribution box plot, it can be seen that when the comfort ratings are high, the heart rates are distributed between 50 and 70. At this point, the participants' spatial comfort is in a good state.



(a) Heart rate distribution

(b) The distribution of R-R intervals

Figure 4: The comfort score of the subjects and the distribution of heart rate and R-R intervals

The electrocardiogram (ECG) parameter data are shown in Table 3. It was found that during the experiment, the values of all ECG parameters were generally higher than those in a typical indoor space. The lower the user comfort score, the higher the average heart rate and the greater the heart rate variability during the experiment. Additionally, since the pNN80 data was 0 during the experiment, indicating that the difference between adjacent R-R intervals generally did not exceed 80 ms, it is concluded that pNN50 is more suitable for describing changes in user comfort.

Table 3: Electrocardiogram data

Comfort rating	SDNN	RMSSD	pNN50	pNN80	HRmax	HRmin	HRc	HRmean
Base line	41.5	28.2	0.08	0	63.45	52.6	12.31	56.05
9	48.09	31.7	0.15	0.03	69.14	52.8	11.57	58
9	56.03	34.18	0.14	0.07	65.27	49.13	15.34	57.72
8	57.58	25.55	0.12	0	68.53	55.48	14.19	60.55
6	67.35	26.45	0.06	0	75.11	58.37	18.84	61.01
5	77.29	25.39	0.09	0	69.65	50.12	19.63	56.9
4	48.14	39.74	0.23	0.06	71.75	56.01	15.35	61.39
3	78.72	31.42	0.1	0.03	70.28	52.09	19.02	60.98
2	85.26	106.71	0.33	0.09	98.25	51.98	46.97	66.09
2	67.96	33.81	0.11	0.05	71.54	53.72	17.41	62.47
1	119.64	42.71	0.19	0.06	80.77	52.58	25.36	68.09
1	98.62	38.65	0.19	0.05	85.49	57.8	28.39	71.95

A correlation analysis was conducted between the user comfort scores in the table and eight ECG signal indicators. The correlation analysis between ECG indicators and comfort scores is shown in Table 4 (* indicates significant correlation at the 0.05 level (two-tailed); ** indicates significant correlation at the 0.01 level (two-tailed)). It can be seen that the absolute values of the correlation coefficients for SDNN, pNN50, RMSSD, and HRmax-min are all above 0.5, indicating that these ECG indicators have a moderate or higher correlation with comfort. The correlation coefficient for pNN80 is relatively low at -0.43, and the significance test shows 0.136 > 0.05, indicating no significant effect, and it is not suitable for describing changes in comfort.

Table 4: Correlation analysis of ECG index comfort score

Comfort rating	SDNN	RMSSD	pNN50	pNN80	HRmax	HRmin	HRc	HRmean
Correlation coefficient	-0.886**	-0.623*	-0.789*	-0.43	-0.616	-0.128	-0.856*	-0.443
Double tail test	0.001	0.067	0.035	0.136	0.069	0.721	0.002	0.055
Case number	110	110	110	110	110	110	110	110

IV. B. 2) User comfort evaluation

A regression model was established based on users' subjective ratings of the comfort of simulated indoor space designs, followed by a goodness-of-fit test for the regression equation. The significance of the regression model was tested, and the results of the variance analysis for comfort evaluation are shown in Table 5. In the table, F is the F statistic in the F-test, and Sig is the P-value. As can be seen from the data in the table, all Sig values are less than 0.05, indicating that the null hypothesis is rejected, and the regression equation is considered significant. The results of the goodness-of-fit test and significance test for the regression equation indicate that the regression equation in this study fits well, and the independent variables and dependent variables exhibit a high degree of significance in their linear relationship.

Table 5: The results of regression analysis of variance for comfort evaluation

Subjective scoring		Degree of freedom	Sum of squares	Mean square sum	F	Sig.
Y1	Regression residue	110	391.826	3.643	1.063	0.00047
		20	53.625	3.372		
Y2	Regression residue	100	421.057	4.487	1.052	0.02395
		30	117.344	4.269		

The results of the comparison of simulated indoor design space comfort scenarios are shown in Figure 5. The figure shows a comparison between the actual scores of user comfort evaluations and the scores calculated by the regression equation. The horizontal axis represents the sample number, and the vertical axis represents the score. The accuracy of the user comfort evaluation model is within an acceptable range, with most comfort scores above 4 points, indicating that people have a positive evaluation of the comfort of indoor design spaces.

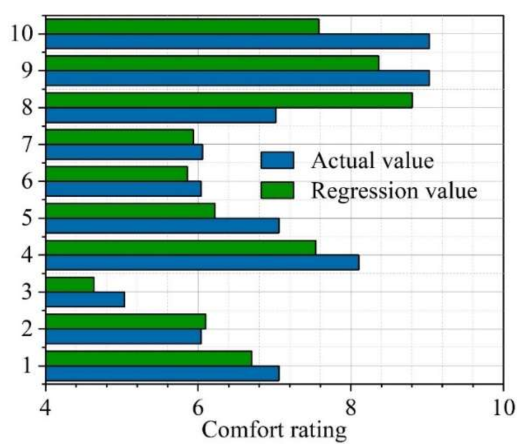


Figure 5: Experimental comparison results

V. Conclusion

In architectural design, incorporating emotional elements into spatial design can create a sense of comfort, thereby enhancing people's happiness and sense of belonging. Therefore, this paper proposes a personalized emotional model based on PAD to address the issue of spatial emotional expression. The research conclusions of this paper are as follows:

Through emotional assessments of various spatial cases, it was found that in the A-type cluster of residential spaces, the E-value of the A1-type cluster was approximately 2.5, indicating a high intensity of “place attachment.” The sense of relaxation was the strongest, with a central value of approximately 3.53, followed by feelings of joy and autonomy.

Through heart rate monitoring experiments on participants, it was found that when participants were in spaces designed using the method proposed in this paper, their heart rates were distributed between 50 and 70, indicating that their spatial comfort was in a good state.

In simulated indoor design spatial comfort scenario comparison experiments, user comfort scores were mostly above 4 points, indicating that people have a positive evaluation of indoor design spatial comfort.

References

[1] Pernau, M. (2014). Space and emotion: building to feel. History Compass, 12(7), 541-549.

[2] Pallasmaa, J. (2014). Space, place and atmosphere. Emotion and peripherical perception in architectural experience. Lebenswelt. Aesthetics and philosophy of experience., (4).

[3] Cristoforetti, A., Gennai, F., & Rodeschini, G. (2011). Home sweet home: The emotional construction of places. Journal of Aging studies, 25(3), 225-232.

[4] Schreuder, E., Van Erp, J., Toet, A., & Kallen, V. L. (2016). Emotional responses to multisensory environmental stimuli: A conceptual framework and literature review. Sage Open, 6(1), 2158244016630591.

[5] Zhao, R. (2016, July). Architectural space and psychological feelings. In 2016 5th International Conference on Social Science, Education and Humanities Research (SSEHR 2016) (pp. 1071-1073). Atlantis Press.

[6] Reddy, S. M., Chakrabarti, D., & Karmakar, S. (2012). Emotion and interior space design: an ergonomic perspective. Work, 41(S1), 1072-1078.

[7] Lewis, P. (2008). Emotion work and emotion space: Using a spatial perspective to explore the challenging of masculine emotion management practices. British Journal of Management, 19, S130-S140.

[8] Xu, Y., & Wu, S. (2022). Indoor Color and Space Humanized Design Based on Emotional Needs. Frontiers in Psychology, 13, 926301.

[9] Lee, K. T., Park, C. H., & Kim, J. H. (2023). Examination of user emotions and task performance in indoor space design using mixed-reality. Buildings, 13(6), 1483.

[10] Lee, K. (2022). The interior experience of architecture: An emotional connection between space and the body. Buildings, 12(3), 326.

[11] Rapuano, M., Sarno, M., Ruotolo, F., Ruggiero, G., Iuliano, S., Masullo, M., ... & Iachini, T. (2023). Emotional reactions to different indoor solutions: The role of age. Buildings, 13(7), 1737.

[12] Komuro, N., Hashiguchi, T., Hirai, K., & Ichikawa, M. (2021). Predicting individual emotion from perception-based non-contact sensor big data. Scientific reports, 11(1), 2317.

[13] Galvez-Pol, A., Nadal, M., & Kilner, J. M. (2021). Emotional representations of space vary as a function of peoples' affect and interoceptive sensibility. Scientific reports, 11(1), 16150.

[14] Shemesh, A., Leisman, G., Bar, M., & Grobman, Y. J. (2022). The emotional influence of different geometries in virtual spaces: A neurocognitive examination. Journal of Environmental Psychology, 81, 101802.

[15] Cho, M. E., & Kim, M. J. (2017). Measurement of user emotion and experience in interaction with space. Journal of Asian Architecture and Building Engineering, 16(1), 99-106.

[16] Song, Y., Mao, F., & Liu, Q. (2019). Human comfort in indoor environment: a review on assessment criteria, data collection and data analysis methods. Ieee Access, 7, 119774-119786.

[17] Sakellaris, Ioannis A., et al. "Perceived indoor environment and occupants' comfort in European "modern" office buildings: The OFFICAIR study." International journal of environmental research and public health 13.5 (2016): 444.

[18] Duan, Q., & Wang, J. (2017). Thermal conditions controlled by thermostats: An occupational comfort and well-being perspective. Civil Engineering and Architecture, 5(5), 173-179.

[19] Šujanová, P., Rychtáriková, M., Sotto Mayor, T., & Hyder, A. (2019). A healthy, energy-efficient and comfortable indoor environment, a review. Energies, 12(8), 1414.

[20] Xu Wuhuan,Yao Zhong,He Dandan & Cao Ling. (2025). Understanding online review helpfulness: a pleasure-arousal-dominance (PAD) model perspective. Aslib Journal of Information Management,77(2),391-412.

[21] Pugliese Erica,Saliani Angelo Maria,Mosca Oriana,Maricchiolo Fridanna & Mancini Francesco. (2023). When the War Is in Your Room: A Cognitive Model of Pathological Affective Dependence (PAD) and Intimate Partner Violence (IPV).Sustainability,15(2),1624-1624.

[22] Xing Yang,Haijie Xu,Yiming Shi & Chen Zhang. (2025). SPEVS-CC: Separated parameter estimation with variable selection based on canonical correlation analysis for multivariate functional regression. Advanced Engineering Informatics,66,103416-103416.

[23] Zhang Kewen. (2020). Analysis and application of stock price index based on multiple linear regression macroeconomic variables. BASIC & CLINICAL PHARMACOLOGY & TOXICOLOGY,127,267-267.