

RESEARCH ARTICLE

Emotional design of digital applications for art therapy in the context of college students' mental health

Zhihui Wang*

Huanghe S&T University, Zhengzhou, Henan, China.

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Digital art therapy has emerged as a promising non-pharmacological intervention for mental health. Its application in addressing the escalating psychological distress among college students remains underexplored with most existing tools lacking personalization and theoretical grounding in emotional design. This study developed and validated an emotional design model for a digital art therapy application specifically tailored to the mental health needs of this population. The proposed model integrated the pleasure-arousal-dominance (PAD) emotional state quantification framework with multimodal intervention strategies encompassing visual, auditory, and interactive design elements. A dynamic flow regulation mechanism was incorporated to maintain user engagement and therapeutic efficacy. Empirical experiments were conducted with college student participants to evaluate the model's performance. The findings revealed that interactive design elements contributed most significantly to enhancing users' sense of psychological control with a normalized contribution weight of 0.85 on a scale from 0 to 1. The model achieved high user satisfaction and therapeutic effectiveness, scoring above 4.4 out of a maximum of 5 points across all three of Norman's emotional design levels of visceral, behavioral, and reflective. The dynamic flow regulation mechanism successfully maintained a high flow index, and the model demonstrated robust generalizability across users with different baseline emotional states. These results confirmed that a personalized, dynamically adaptive digital art therapy tool, grounded in affective computing, was both feasible and effective in providing full-link psychological support from emotional perception to self-actualization for the college student population.

Keywords: emotional design; art therapy; college student; mental health; flow experience; personalized intervention.

*Corresponding author: Zhihui Wang, Huanghe S&T University, Zhengzhou, Henan 450005, China. Email: sophiew1215@163.com.

Introduction

College students are currently confronting an escalating mental health crisis with recent national health data indicating that approximately 24.8% experience depressive symptoms and 31.6% suffer from varying degrees of anxiety, primarily stemming from academic competition, interpersonal relationships, and employment pressures [1]. Conventional on-campus psychological counseling services such as

lecture-based education and group therapy are often constrained by insufficient professional staffing, limited coverage, and significant student resistance due to privacy concerns and social stigma, rendering them inadequate for addressing the needs of a large number of subclinical students [2]. As a non-pharmacological alternative, art therapy that utilizes painting, music, and creative expression as safe emotional outlets has demonstrated efficacy in reducing psychological defensiveness,

modulating cortisol levels, and alleviating emotional dysregulation through sensory and auditory stimulation [3].

In recent years, the integration of digital technologies has advanced the field of art therapy. Research has increasingly explored immersive healing environments using virtual reality to enhance engagement through multi-layered sensory interactions [4, 5], while artificial intelligence algorithms have been employed to analyze user preferences for personalized delivery of therapeutic materials such as digital paintings and music [6]. Concurrently, emotional design theory has progressed beyond basic usability with multimodal data such as visual, auditory, and interactive cues to dynamically optimize product interactions and strengthen human-machine emotional connections [7]. Studies have further demonstrated that such artistic interventions can positively alter alpha brainwave activity and enhance neuroplasticity, thereby mitigating anxiety and depression [8, 9]. However, despite these technological and theoretical advances, a critical gap remains in the practical translation of these findings into effective, daily-use digital tools tailored for the college student population. Current digital mental health applications exhibit several fundamental shortcomings. They often neglect the specific emotional logic and aesthetic preferences of young users, offering homogeneous therapeutic content that fails to resonate emotionally or sustain long-term engagement [10, 11]. Many existing products blur the boundary between art entertainment and genuine psychotherapy, operating without robust psychological frameworks or effective emotional feedback mechanisms, thus rendering them incapable of capturing or responding to dynamic changes in users' affective states [12]. Furthermore, emotional design is often misunderstood as mere visual beautification, a one-sided pursuit of trendy, minimalist interfaces that overlook users' deeper psychological needs for attentive interaction and emotional nourishment [13]. Crucially, the majority of these digital solutions remain detached from the daily

learning and living scenarios of college students, deviating from their usage habits and failing to provide a truly immersive and personalized healing atmosphere [14, 15].

This study constructed a digital art therapy application specifically designed for college students, grounded in a systematic emotional design model to accurately identify and categorize the emotional pain points of this demographic including anxiety, depression, and stress overload and to map them into appropriate therapeutic design elements that aligned with young users' aesthetic and acceptance standards. The research integrated the pleasure-arousal-dominance (PAD) emotional state quantification framework with a multimodal intervention strategy, which coordinated visual, auditory, and interactive design elements. Additionally, a dynamic flow regulation mechanism was incorporated to maintain optimal user engagement by balancing task challenge with individual skill levels. This research bridged the existing gap between affective computing and practical mental health intervention, offered a personalized, dynamically adaptive, and full-link therapeutic pathway from initial emotional perception to long-term self-actualization that could effectively generalize across diverse user baselines [16, 17], thus provided both a theoretical foundation and an empirical validation for the application of emotional design in digital art therapy with substantial implications for scalable, non-stigmatizing mental health support in higher education settings [18, 19].

Materials and methods

Quantitative representation of college students' emotional state based on PAD model

The emotional state quantification process began with the reception of user emotional signals as input. A three-dimensional emotion vector was defined as $E = [p, a, d]^T$, where p was pleasure, a was arousal, and d was dominance. An ideal emotional state was predefined as $E_{ideal} =$

$[0.5, -0.2, 0.4]$, representing a psychologically balanced condition. The deviation between the current emotional state and the ideal state was calculated using the Euclidean distance formula as below.

$$\Delta E = \sqrt{[(p_{ideal} - p_i)^2 + (a_{ideal} - a_i)^2 + (d_{ideal} - d_i)^2]} \quad (1)$$

Based on the magnitude of this deviation value, the system determined the required intensity of intervention, where a large ΔE triggered a strong intervention, while a small ΔE corresponded to a weak intervention. The healing strategy was then matched accordingly with strong interventions being associated with active art forms such as music, painting, and dance, whereas weak interventions were linked to more passive activities including reading, meditation, and handicraft. Accurately perceiving a user's emotional state was a prerequisite for precise analysis and intervention. An emotion model was set up to monitor and analyze emotions. However, these emotions were not merely happiness or sadness, rather, they were complex and nuanced emotions that conveyed multiple layers of meaning. Especially under the pressure of multiple factors such as academics, interpersonal relationships, and the future, anxiety and fatigue might coexist and exhibit anisotropy. Therefore, a definition of the emotion dimension was needed. The PAD emotion model deconstructed human emotions into three independent dimensions. The emotion was defined as a three-dimensional vector as shown in Equation 2 [20, 21].

$$E = [p, a, d]^T \quad (2)$$

where p was the positive and negative polarity of emotion, ranging from -1 to 1 with 1 representing extreme pleasure and satisfaction and -1 representing pain, which was the core indicator for measuring the user's affinity and avoidance of the current experience. a was the excitation level of the nervous system and the physiological activation state. High activation corresponded to emotions such as excitement, anxiety, and

tension, while low activation represented calmness, depression, and fatigue. For college students facing various pressures, emotions were often expressed as a high a value and a low p value [22]. d was the individual's ability to perceive and influence the environment. When d was high, the individual felt powerful and in control. When d was low, the individual felt powerless and controlled, which produced feelings of powerlessness or frustration when college students faced setbacks or a decline in their advantages. The user's state could be perceived at any time through the three-dimensional vector composed of PAD. The goal of art therapy was to perceive emotions and guide everyone to a standard emotional state E_{ideal} [23]. The core was to transform the user from their current uncomfortable state to a more comfortable and balanced state of mind. The balanced state was defined as a triple consisting of 0.5, 0, -0.2, and 0.4 representing a positive mindset of pleasure, calmness, and control. The optimization goal of this system was to transform the user from their current psychological state $E_{initial} = [p_i, a_i, d_i]^T$ to the target psychological state E_{ideal} . The bias of this psychological state was obtained by calculating the Euclidean distance between two points as follows.

$$\Delta E = \sqrt{(p_{ideal} - p_i)^2 + (a_{ideal} - a_i)^2 + (d_{ideal} - d_i)^2} \quad (3)$$

where ΔE was the degree to which emotions deviated from the standard. The larger the value, the further the current state deviated from psychological normality, and the stronger the intervention required.

Art therapy design elements and emotional intervention mapping model

A four-layer architecture for a multimodal collaborative intervention model was constructed. The input layer captured the user's current emotional state and calculated emotional deviation. The processing layer contained three parallel intervention channels of visual, auditory, and interactive. The decision logic layer implemented a dynamic weight allocation strategy. When high anxiety was

detected, it increased visual and auditory weights while decreasing interactive weight. When low control was detected, it decreased visual and auditory weights while increasing interactive weight. When low pleasure was detected, it equally distributed weights across all channels. The output layer delivered the adjusted emotional state and evaluated the healing effect. A design variable library accompanied this architecture, specifying visual variables including color, composition density, motion frequency, auditory variables including music mode, rhythm, timbre, and interactive variables including control freedom, operation complexity, feedback delay. After obtaining the initial psychological representation, the abstract design language was transformed into concrete adjustment methods. The core purpose of this part was to construct systematic mapping through information from a series of modalities such as audiovisual interaction, guiding how various elements could be used as intervention variables to optimize various dimensions of the PAD model. The performance of digital healing was quantified, and its performance was not the sum of multiple elements, but a comprehensive manifestation as below.

$$R = \sum_{k=1}^n w_k \cdot \phi_k(x_k, e) \quad (4)$$

where the design variables could be specifically divided into three categories of visual variables (v) such as color brightness, saturation, and composition density, auditory variables (a) including music mode, rhythm, timbre, etc., and multiple content interaction variables including gesture complexity, reaction delay, and control freedom, etc. ϕ_k was the corresponding intervention function that could be modeled and analyzed based on the design elements and the dimensions of emotional influence. w_k was K terms. The weights corresponding to the interference were determined and used through the hierarchical analysis of experts (AASI). A mapping relationship was constructed by using the three modalities of audiovisual interaction to

build the intervention function for the visual modality as color. The core idea was to intervene in trading emotions. The mapping relationship was then established as below.

$$\Delta a_{visual} = -\alpha_v \cdot \ln\left(1 + \frac{1}{B \cdot S}\right) \cdot \beta_{hue} \quad (5)$$

where B was the color brightness, ranging from 0 to 1. S was the corresponding color saturation. α_v was the visual sensitivity constant, which could be set through pre-experimentation. The hue adjustment factor β_{hue} increased this factor to greater than one through hue adjustment, while warm hues decreased it to less than one. When brightness increased and saturation decreased, it closely resembled clinical perception, causing activation of a to have a stronger inhibitory effect. This formula demonstrated a bright and soft visual style, which could stimulate the user's central nervous system, thus alleviating anxiety. For auditory mapping, the rhythm and mode of music were considered. The core optimization points were related to reading p and activating a as follows.

$$\Delta p_{audio} = \gamma_{mode} \cdot (1 - e^{-\lambda_p \cdot (BPM - BPM_0)^2}) \quad (5)$$

$$\Delta a_{audio} = \delta_{tempo} \cdot \tanh\left(\frac{BPM - BPM_{ref}}{\sigma_a}\right) \quad (6)$$

where γ_{mode} was an adjustment parameter. Adjusting to a major key $\gamma_{mode} > 0$ would increase the level of enjoyment, while adjusting to a minor key $\gamma_{mode} < 0$ might induce low enjoyment. BPM was beats per minute, representing δ_{tempo} , the current optimal comfortable accompaniment, indicated the intensity of the music's rhythm. BPM_{ref} was the intensity of the music's rhythm. $\tanh$ was an activation value, ensuring that changed within the range of -1 to 1, representing neutral adjustment. When the rhythm was above this value, activation increased, while it was below this value, activation decreased. This mapping

reflected that, when a user was in a high mood, the user could use slower-paced, major-key music and reduced tone activation. When a user was depressed, the user could use slower-paced, major-key music to increase overall enjoyment. Emotional control through interaction affected the user's sense of control. The specific intervention function was shown below.

$$\Delta d_{interaction} = \epsilon \cdot \ln\left(1 + \frac{C_{user}}{L_{complex} \cdot T_{delay}}\right) \quad (7)$$

where C_{user} was the user's control degrees of freedom including adjustable ranges such as the number of undo attempts and stroke parameters. $L_{complex}$ was a control parameter for the complexity of the interactive hierarchy. δ guided the deployment of core tasks and controlled system latency T_{delay} . As a control parameter for the interaction impact coefficient, it could influence the user's control over the application. A multimodal collaborative intervention strategy was proposed, which could weigh and fuse the intervention effects of different modalities as below.

$$\Delta E_{total} = \sum_{m \in \{V, A, I\}} W_m \cdot \Delta E_m \quad (8)$$

where $\Delta E_m = [\Delta p_m, \Delta a_m, \Delta d_m]^T$ represented the intervention vector of different modalities on the three dimensions of PAD. W_m was the weight coefficient corresponding to the model. The model weights could be dynamically adjusted based on the current user's characteristics such as the user's emotional state and usage scenario. When the user was in a high anxiety state, i.e., A was high, the weights of visual and auditory senses should be increased, prioritizing calming through sensory levels. When the user was in a low dominance state, i.e., D was low, the interaction weights should be increased to improve the user's confidence. When the user was in a low-pleasure state and had ample time, emotion regulation could be achieved through multimodal coordination. For visual healing, cool tones with high brightness and low saturation soothed emotions, while warm tones with low brightness and high saturation boosted

excitement. For auditory healing, major keys enhanced pleasure whereas minor keys reduced it, and slow tempos calmed emotions while fast tempos increased energy. For interactive healing, high freedom, low complexity, and fast feedback enhanced the user's sense of control. These principles fed into a branching decision logic. If high anxiety was detected, visual and auditory channels were prioritized. However, if low control was detected, the interactive channel was prioritized. If low pleasure was detected, a balanced adjustment was applied across all three channels.

Flow dynamics model of digital art creation

The difficulty of flow tasks matched with user skills, specifically quantifying this using a flow index as follows.

$$F_l = \exp\left(-\frac{(D_{task} - S_{user})^2}{2\sigma^2}\right) \quad (9)$$

where D_{task} was the specific complexity of the task such as the openness and operational complexity of the task. S_{user} was the user's performance in the current conversation over a long period such as operation speed and cancellation rate. The flow index was monitored through hesitancy analysis. Hesitancy was assessed using cancellation rate and interruption frequency to determine if the user had deviated from the flow path. Based on these monitoring results, three relevant strategies were determined and implemented including fine-tuning that provided implicit cues by adjusting brush stroke parameters, adaptive adjustment that simplified the tool panel and enabled guidance or brush stroke smoothing when the challenge was too high, and significant adjustment such as switching creative modes or changing cognitive load. Through this closed loop, the flow assessments and decisions were continuously monitored and made, which provided feedback, allowing users to dynamically adjust between challenge and skill balance, thereby achieving the therapeutic effect of art. A closed-loop feedback system for dynamic skill-based flow optimization was then constructed.

The process began with user skill assessment, which branched into two parallel evaluations including short-term skill assessment and long-term skill assessment that fed into task difficulty calculation by considering tool diversity and operation precision to determine appropriate challenge levels. Both assessment paths converged into flow index calculation, which applied a Gaussian function to model the challenge-skill match followed by multidimensional flow evaluation examining time distortion and intrinsic engagement as core indicators. The system then entered real-time monitoring, tracking hesitation rate, undo rate, and interruption frequency to detect deviations from optimal flow. These monitored metrics triggered dynamic adjustment with three tiers of intervention including fine-tuning, moderate adjustment, and major adjustment. The entire architecture operated as a closed-loop feedback cycle, continuously iterating through monitoring → evaluation → decision → adjustment with the adjusted parameters being fed back into the user skill assessment to sustain and refine the flow state over time.

Multidimensional evaluation matrix of emotional design

The matrix used Norman's three-tier theory of emotional design combined with measurable user experience metrics to create a clear framework. At the instinctive level, the core metric was sensory pleasure (P), being measured by emotional design indicators such as color harmony, font softness, and animation naturalness. These elements collectively fostered a unique aesthetic identity and privacy protection experience among college students. At the behavioral level, the core metric was immersion index (F_I), being assessed through interaction fluency, real-time feedback mechanisms, and operational error tolerance, enabling students to rapidly engage with emotional experiences during fragmented time periods. At the reflective level, the core metric was self-efficacy (D), being evaluated based on content retention rate, social media sharing propensity, and depth of self-awareness, thereby

enhancing long-term psychological resilience and self-awareness among college students.

Experimental design

A randomized controlled trial design was adopted. A total of 90 university students (48 females and 42 males), aged 18 – 28 years old (mean age of 21.3 ± 2.1), recruited from Sichuan University (Chengdu, Sichuan, China) were enrolled in this study. Among them, 32 were undergraduate students, 38 were master's students, and 20 were doctoral students. Twenty-one participants reported having a background in fine arts or design, while 69 reported no such background. Participants were randomly assigned to three groups including experimental group A (n = 30) using the full PAD-based emotion quantification model with all multimodal intervention and dynamic difficulty adjustment features being enabled, experimental group B (n = 30) using the same multimodal intervention but without the dynamic difficulty adjustment mechanism, and control group C (n = 30) using a standard drawing application without any emotion quantification or adaptive intervention features. The experiment consisted of three phases including pre-test, intervention, and post-test. During the pre-test phase, demographic information including age, gender, academic level, art background and baseline emotional states was collected using the PAD emotional state questionnaire and the generalized anxiety disorder-7 (GAD-7) scale. The intervention phase lasted two weeks. Each participant was required to complete one art creation session per day with each session lasting approximately 20 – 30 minutes. Four distinct sessions were conducted over the two-week period on days 1, 4, 8, and 11. Each session involved a digital art creation task, specifically, free-form digital painting on a tablet using a stylus with different thematic prompts such as "draw your current mood", "create a landscape that feels safe", "express a recent stressor", and "draw a place that brings you joy". During each session, the system recorded behavioral indicators including average usage time per session, total number of brushstrokes,

types of colors used, number of work saves, and number of sharing actions. Emotional states were assessed before and after each session using the PAD self-report inventory, which measured the three dimensions of pleasure, arousal, and dominance. Anxiety levels were measured using the GAD-7 scale, and depressive symptoms were assessed using the patient health questionnaire-9 (PHQ-9). User satisfaction was measured using a custom 5-point Likert scale questionnaire covering aspects of visual appeal, ease of use, comfort, and perceived therapeutic benefit. System usability was evaluated using the system usability scale (SUS). The flow index (FI) was calculated based on a formula incorporating task complexity and user performance metrics, specifically, operation speed (strokes per minute) and cancellation rate. Higher FI values indicated a more immersive and engaging experience. All the procedures of this study were approved by the Institutional Review Board (IRB) of the Huanghe S&T University (Zhenzhou, Henan, China).

Statistical analysis

All statistical analyses were performed using SPSS (IBM, Armonk, NY, USA). Descriptive statistics were calculated for all demographic and outcome variables. Paired sample t-tests were used to compare pre- and post-intervention measures within each group. One-way analysis of variance (ANOVA) with Tukey's post-hoc correction was employed for between-group comparisons. Pearson correlation coefficients were computed to examine associations between behavioral indicators and therapeutic outcomes. *P* value less than 0.05 was defined as statistically significant difference.

Results and discussion

Contribution analysis of multimodal design elements

The user behavior data presented the relative contributions of different design modalities to PAD. The results showed that visual elements dominated regulating pleasure and activation

levels, contributing the most to anxiety reduction (0.45). The color brightness played a central role in calming emotions, and interaction design could enhance this advantage, reaching a weight of 0.85. Overall, visual elements were the most important of the three auditory stimuli interactions, playing an irreplaceable role in specific dimensions. Therefore, when alleviating anxiety, visual and auditory experiences must be prioritized. When enhancing confidence and control, the focus should be on interaction design.

Baseline-specific intervention effectiveness

The intervention effects at different emotional starting points demonstrated that the affective design model effectively adapted to different users and cases with varying emotional starting points. For users with high anxiety, the system alleviated anxiety by reducing difficulty and using calming sensory content such as cool colors and slow music with data point being decreased by 0.61. For users with low motivation, warm colors and medium-tempo music were used for adjustment. The results indicated that the multimodal collaborative strategy could be adapted to different populations to achieve precise intervention.

Correlation between behavioral indicators and therapeutic outcomes

The relationship between different users' in-app behavior patterns and the final results demonstrated that all indicators showed a significant positive correlation. There was a correlation of 0.521 between the number of times a work was shared or saved and the user's sense of self-efficacy, indicating that user retention and the willingness to actively save content could enhance the user's sense of achievement and value. Average usage frequency and total strokes were highly correlated with the flow index, which indicated that immersive engagement was the foundation for obtaining a high-quality flow experience (Table 1).

Influence of art background on user experience

Table 1. Correlation between user behavioral indicators and therapeutic effects.

Behavioral indicators	Correlation coefficient (r) with		
	the decrease in ΔE	flow index (FI)	increased self-efficacy
Average usage time per session	0.452**	0.501**	0.387**
Total number of brushstrokes in creation	0.398**	0.467**	0.412**
Types of color usage	0.325*	0.289*	0.301*
Number of times the work was saved/shared	0.412**	0.378**	0.521**

Notes: * indicated $P < 0.01$ and ** indicated $P < 0.001$ between experimental group A and control group C.

Table 2. Differences in experience and effect among users with different art backgrounds.

User type	Mean flow index (FI)	Task completion rate	Satisfaction with dynamic adjustment	Average decrease in ΔE
With an artistic background (n=21)	0.81 $\pm$ 0.10	95%	4.5 $\pm$ 0.6	0.56 $\pm$ 0.16
No art background (n=69)	0.77 $\pm$ 0.13	85%	4.7 $\pm$ 0.5	0.59 $\pm$ 0.17

The comparison results of participants with or without an art background across all outcome measures revealed no statistically significant differences between the two groups in terms of mean flow index ($t(88) = 1.24$, $p = 0.218$), task completion rate ($t(88) = 1.67$, $p = 0.098$), satisfaction with dynamic adjustment ($t(88) = -1.45$, $p = 0.151$), or average ΔE decrease ($t(88) = -0.72$, $p = 0.473$). These findings indicated that the model provided comparable therapeutic benefits and user experience regardless of the participants' prior artistic training. The different user experiences and effects were analyzed by examining 21 samples with an art background and 69 samples without. The results showed that regardless of art background, users achieved a high level of flow experience and demonstrated significant emotional awareness with no major significant differences in either metric. Users with an art background showed higher flow index and task completion rate, indicating greater operational confidence. However, users without an art background had slightly higher satisfaction scores, suggesting that the feature particularly protected the experience of novice users, improving user satisfaction, and reducing their frustration and learning curve (Table 2).

Emotional shift and flow index correlation

The correlation and distribution trend between emotional shift and flow index in experimental

groups A, B and control group C showed a Pearson correlation coefficient of 0.53, indicating that a smaller emotional shift corresponded to a higher flow index, and the two were negatively correlated. The difference between groups was that the points in experimental group A were concentrated in the region with lower ΔE , while the fitted curve was steeper in the region with higher FI. The kernel density curve showed that experimental group A had a higher distribution peak, concentrated in the range of 0.7 – 0.9 (Figure 1).

Long-term intervention effects

The four subplots illustrated the effects of the intervention on self-efficacy and life satisfaction. Experimental group A represented the complete model, while experimental group B involved multimodal intervention without dynamic difficulty, and the control group used a standard drawing application. The subplots showed the long-term effectiveness of the intervention. The slope of the pre- and post-test changes in experimental group A, representing the overall improvement, was significantly better than that in experimental group B and was more stable within the 95% confidence interval. Life satisfaction showed a similar improvement. The violin plot showed that multiple indicators in experimental group A were higher than those in experimental group B and the control group. This

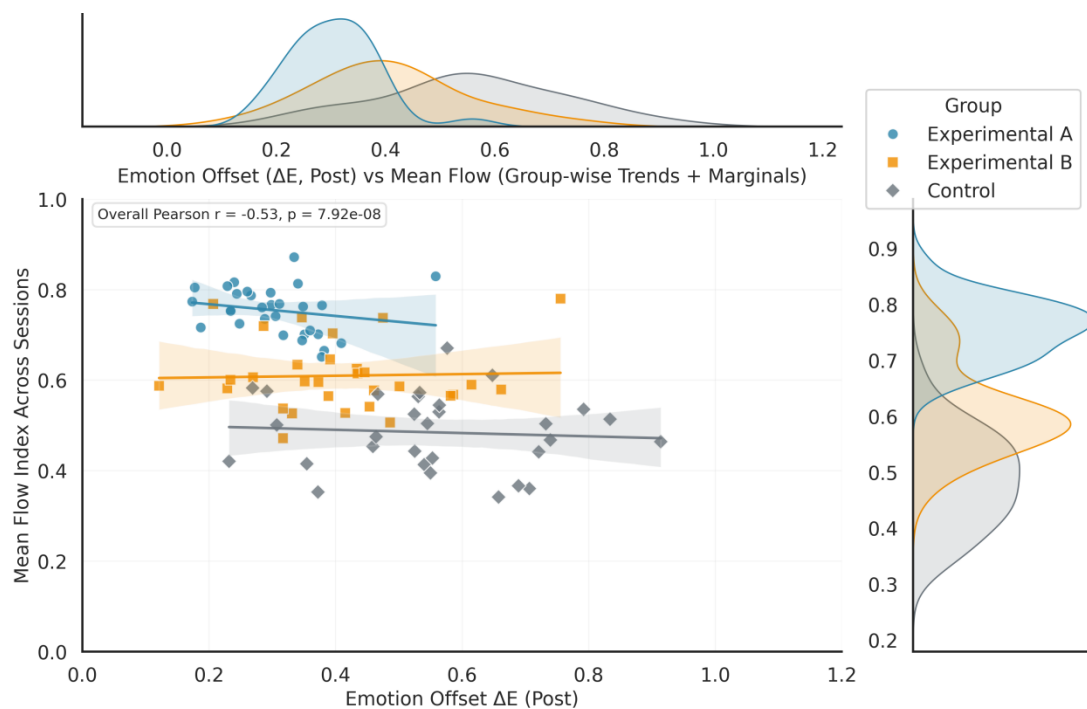


Figure 1. Correlation analysis between emotional shift and flow index.

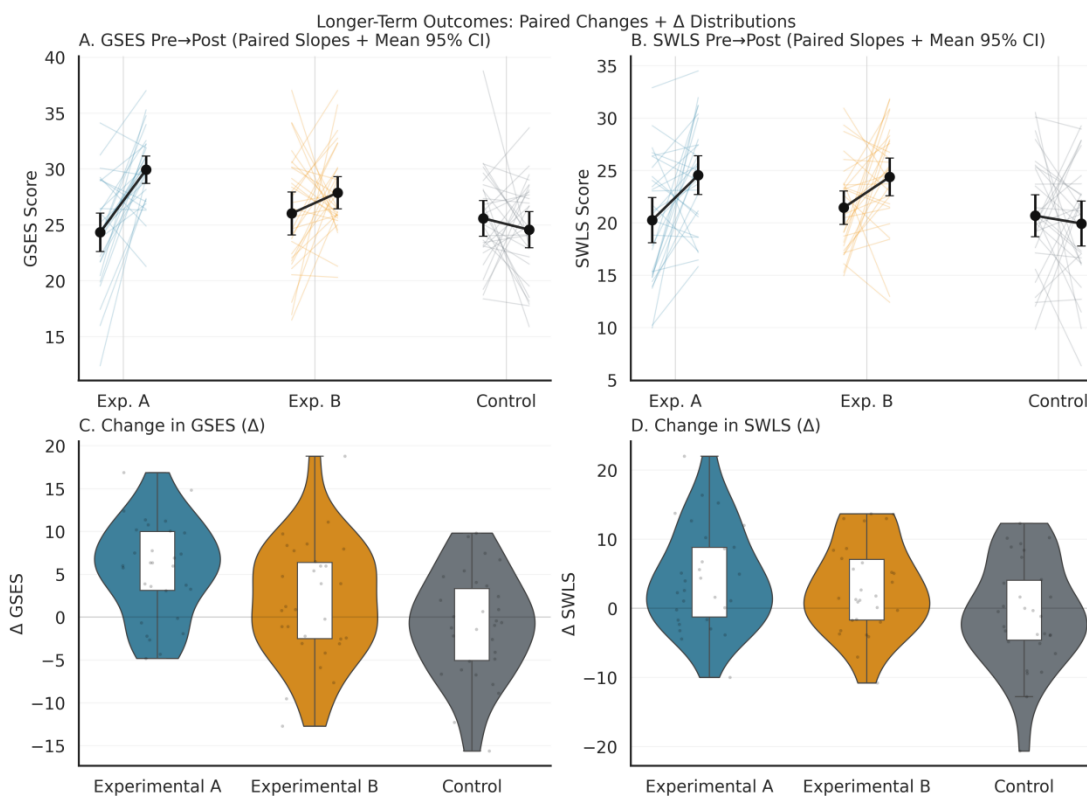


Figure 2. Long-term intervention effect.

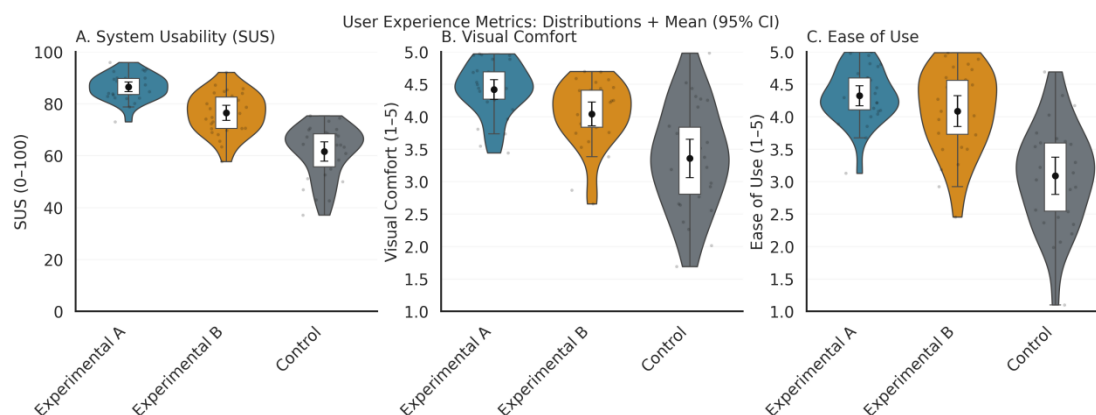


Figure 3. Distribution of core user experience metrics.

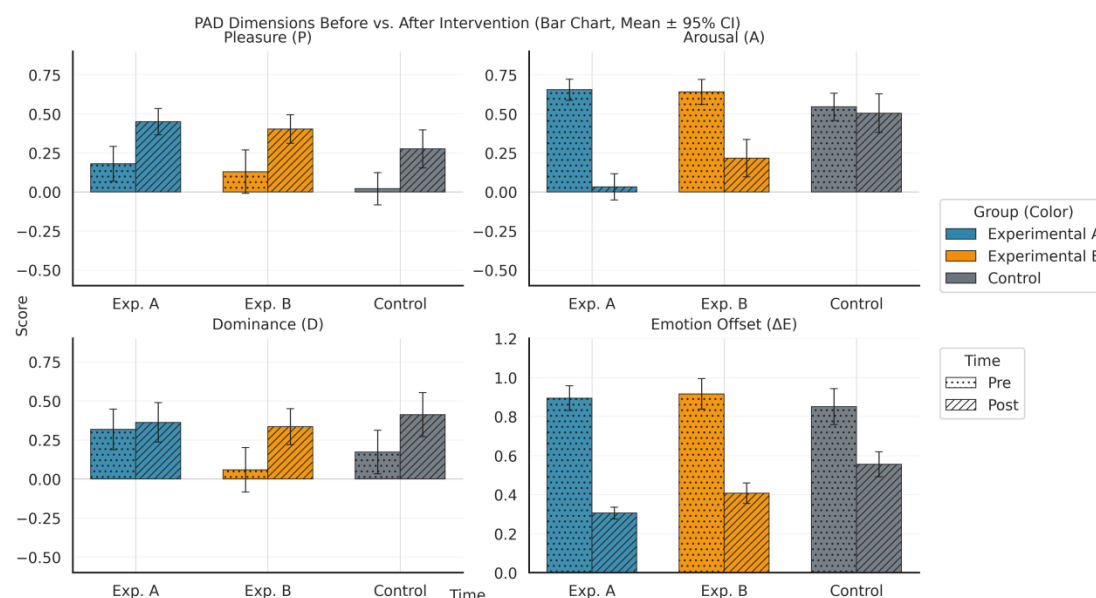


Figure 4. Comparison of PAD emotional dimension shifts before and after intervention.

plot also showed that the median and distribution were better than those in experimental group B and the control group, reflecting the limited effectiveness of standard applications in improving long-term psychological problems (Figure 2). The results indicated that the complete affective model had long-term physiological efficacy.

User experience metrics and PAD dimension shifts

The results of system usability (SUS), comfort, visual appeal, and ease of use showed that the

SUS scores ranged from 70 to 90 points, while comfort scores from 4 to 4.5 points, and ease of use from 4 to 4.5 points. The advantages of emotional design from both instinctive and behavioral dimensions were evaluated and showed that the complete model outperformed experimental group B and control group C on all metrics (Figure 3). Through overall analysis of pleasure (P), dominance (D), emotional shift (E), and activation (A), experimental group A showed the most significant improvement across all four dimensions in both pre- and post-tests, while experimental group B was weaker than

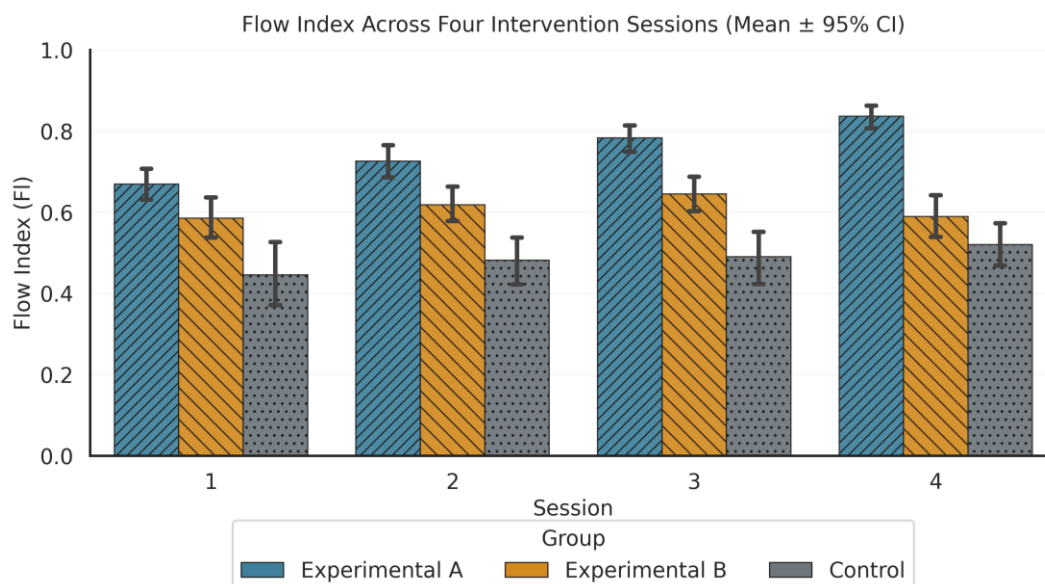


Figure 5. Dynamic changes in the flow index among the groups during the 4 interventions.

experimental group A and control group C. The changes were almost negligible, demonstrating that activation and monthly dominance were significantly improved after intervention, and the intervention's effectiveness in reducing its tendency to decline was significantly better than that of the control group (Figure 4). The mean flow index of experimental group A was 0.68, while that of experimental group B was 0.6, and that of the control group was 0.45. At the second intervention, the flow index of experimental group A increased to 0.73, while experimental group B increased to 0.62, and control group C increased to 0.49. Through four complete interventions, the complete model through dynamic difficulty adjustment could maintain the user's flow experience. In contrast, experimental group B and control group C, lacking dynamic adjustment, could not maintain the increase in immersion for an extended period. The results demonstrated that dynamically adjusting the flow mechanism could ensure the experiential and smooth flow of the therapeutic process (Figure 5).

Discussion

This research addressed the mental health issues of university students by constructing a set of digital art therapy products that encompassed psychological problem identification, quantification, intervention, and assessment. The study confirmed and validated the effectiveness of proposed methods. The PAD three-dimensional emotion quantification provided a reliable method for emotion intervention, electrolyzing users' complex emotions into three independent dimensions of pleasure, activation, and dominance, which enabled accurate representation of user emotions as a reliable input signal. The quantification framework formed the foundation of the intervention process. By combining audiovisual interaction and other elements, it guided emotional variables to form a correct mapping relationship. Compared to the control group C, the multimodal intervention system showed significant improvement, indicating that it could actively guide emotional transformation. Further, audiovisual elements had the highest weight in regulating emotional pleasure and activation, while interaction design increased user dominance by 0.85. The activation of a dynamic task difficulty automatic adjustment mechanism had a significant effect. Furthermore,

the results also showed that users with no prior knowledge of the function had relatively high satisfaction scores, proving that the model's dynamic difficulty adjustment could reduce the frustration of beginners and improve the application's inclusivity and universality. The results showed that users' self-efficacy improved after long-term use, which indicated that the model proposed in this research had a good long-term effect and provided a usable solution to address the psychological healing problems of college students. In future study, more detailed psychological quantification should be combined with physiological signals for emotion recognition to obtain more precise and effective intervention measures.

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