Intelligent User Experience Design in Digital Media Art Under Internet of Things Environment

Xiaoyan Hao
School of Animation, HuangHuai University Zhumadian 463000, China
E-mail: xiaoyan_hao@hotmail.com

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This paper discusses the cutting-edge methods of intelligent user experience design in digital media art, especially focusing on the fusion innovation of emotion perception, personalized recommendation and user interface design. Through biometric recognition techniques, especially heart rate variability (HRV) and skin conductance response (EDA) analysis, combined with deep learning models such as ResNet, Bi-LSTM and 1D-CNN, fine recognition of user emotions is achieved. Furthermore, an emotional response algorithm based on deep reinforcement learning is introduced, which dynamically adjusts the artwork to improve audience emotional satisfaction. In the aspect of recommendation system, through advanced feature fusion strategy and attention mechanism, the model enhances the understanding of user behavior sequence and static features, and optimizes the recommendation accuracy. The user interface design emphasizes simplicity, direct-viewing, personalized customization and efficient feedback mechanism to ensure the benign interaction between users and the system. The experimental evaluation part verified the effectiveness of the above methods through a series of carefully designed experiments, and the data showed that voice control, personalized recommendations, fast response, beautiful interface and efficient information delivery significantly improved the user experience.

Povzetek: Prispevek raziskuje inteligentno oblikovanje uporabniške izkušnje v digitalni medijski umetnosti pod vplivom interneta stvari, z uporabo globokega učenja za čustveno zaznavanje, priporočilne sisteme in prilagojene vmesnike za izboljšanje interakcije.

1 Introduction

With the rapid development of information technology in the 21st century, Internet of Things (IoT), as an important part of the new generation of information technology, is gradually moving from concept to reality, profoundly changing our daily life and work mode. Internet of Things technology, simply put, refers to a network that connects any item to the Internet through various information sensing devices, such as radio frequency identification (RFID), infrared sensors, global positioning systems, laser scanners, etc., for information exchange and communication, and for intelligent identification, positioning, tracking, monitoring and management [1].

The rise of Internet of Things technology has not only promoted the digital transformation of many industries such as industry, agriculture, transportation and medical care, but also brought revolutionary changes to the art field, especially digital media art. Digital media art, as a new art form, integrates computer graphics, digital image processing, interactive design, artificial intelligence and other technologies to create unprecedented artistic experience. In the Internet of Things environment, the innovative application of digital media art has been greatly expanded, not only in the way art works are displayed, but more importantly, it has changed the interaction mode between creators and audiences, as well as the generation and dissemination mechanism of artistic content [2]. At present, the application of Internet of Things technology in the field of digital media art is in a rapid development stage, showing diversified innovative practices and rich research results. In the field of exhibitions and museums, IoT technology is used to create intelligent navigation systems, through RFID tags and Bluetooth beacons, art can "tell" their own stories, providing visitors with personalized interactive experiences. In addition, in conjunction with AR technology, visitors can explore the history and story behind the artwork from a new perspective, enhancing both educational and fun [3].

In public art projects, IoT technology serves as a bridge between physical space and digital content. For example, using sensors and data analysis, artists can adjust the expression of public art installations in real time according to changes in environmental conditions (such as temperature, humidity, light intensity), creating dynamic art landscapes that "breathe" with the environment. These smart devices not only beautify urban spaces, but also facilitate interactive dialogue between the public and the urban environment, and networking is used in digital media design as shown in Figure 1.

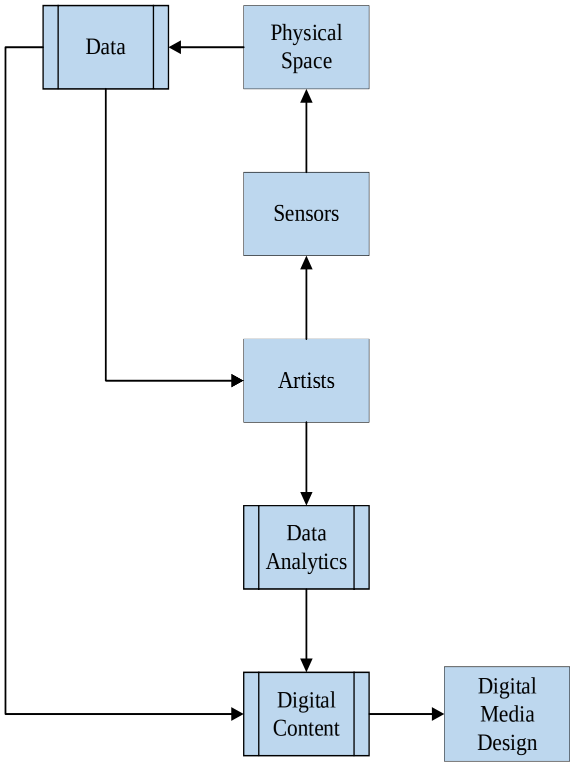

Figure 1: IoT in digital media design

Digital media art works are also beginning to be more integrated into Internet of Things data. Through the mining and visualization of big data such as social media, weather forecast and traffic flow, artists create art projects reflecting contemporary social phenomena, prompting viewers to think about the social issues behind the data. At the same time, with the progress of artificial intelligence technology, some digital art works can learn independently and adjust according to audience feedback, realizing the personalization and intelligence of artistic expression [4].

This project is dedicated to exploring new frontiers in the intersection of digital media art and Internet of Things technology, covering four innovation dimensions: First, we will develop a comprehensive creative display platform that deeply integrates Internet of Things devices, AI algorithms and interactive design, aiming to build a low-threshold and high-efficiency technology bridge for artists and promote the seamless connection between art and technology; Secondly, the research will go deep into the field of emotional perception, using biometric technology to capture and analyze audience emotions, so that art works have emotional intelligence, which can be dynamically adjusted according to the emotional fluctuations of viewers, and create personalized and emotional resonance viewing experiences; Thirdly, we focus on environmental sustainability, monitor subtle changes in nature with the help of Internet of Things, guide creation to pay attention to climate and ecological issues, and use green materials and technologies to highlight art's responsibility and concern for the future of the earth [5].

2 Literature review

2.1 Digital media art

Digital media art, as a symphony of science and technology and creativity in the 21st century, continues to bloom in the field of art, not only limited to the innovation of traditional digital images, audio and video, but also deeply explore the frontier fields of interactive devices, virtual reality (VR), augmented reality (AR), and even mixed reality (MR), and constantly broaden the dimensions of artistic expression. Research and practice in recent years have shown that the prosperity of this field benefits from rapid technological advances, extensive cultural exchanges, and increasing social needs. In recent research, Bolter and Grusin's theory of "reproduction" has been deepened, and he proposes that with the integration of deep learning and artificial intelligence technology, digital media art has surpassed simple simulation and entered the stage of being able to create new realities autonomously [6]. Artists have used these technologies to create immersive environments, using machine learning algorithms to parse historical data from the Los Angeles Philharmonic Orchestra into stunning visual and acoustic landscapes, demonstrating how technology can give art unprecedented creativity and expressiveness [7]. In today's interweaving of globalization and digitalization, cultural diversity has become an indispensable nutrient for digital media art [8]. Digital platforms break geographic boundaries, allowing artists from diverse cultures to collaborate to create works that reflect global commonalities and differences. For example, Heritage in Motion uses digital media technology to digitize endangered cultural heritage around the world, enabling viewers to experience and understand multiculturalism on a global scale and promoting intercultural respect and understanding [9]. Digital media art plays an increasingly prominent role in social engagement, especially in global issues such as environmental protection and human rights [10]. Analyzes how social media and digital art combine to create a powerful public mobilization force [11]. Collecting global climate change data through online platforms and presenting it to the public in the form of visual art not only raises awareness of environmental issues, but also inspires determination to take action. This kind of interactive design not only enhances the social function of art, but also embodies the public value and responsibility of art works in the digital age.

2.2 Intelligent user experience design

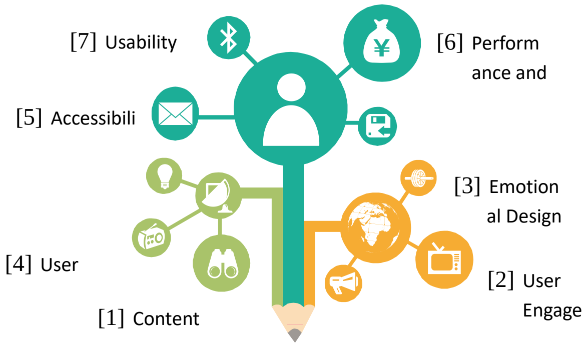

Figure 2: User experience determinants

A good user experience is the result of considering and optimizing all the factorsin Figure 2 to create an interactive environment that is both useful and enjoyable, meets user needs and exceeds user expectations. Smart UX Design is a cutting-edge field of contemporary digital product and service design, which is committed to providing more personalized, responsive and emotional user experiences by integrating advanced technologies such as artificial intelligence, big data analytics and machine learning. The development of this field depends not only on technological innovation, but also on a deep understanding of user psychology, behavioral habits and social trends. In recent years, with the continuous evolution of technology and the increasing expectations of users, intelligent UX design presents a series of new features and trends. Personalized experience has always been the core pursuit of intelligent UX design [12]. Emphasize that efficient analysis of user data through deep learning algorithms enables digital products to provide unprecedented personalized content recommendations. Spotify, for example, uses a sophisticated recommendation system that analyzes users 'listening history, time preferences, and even heart rate to provide customized playlists for each user, a highly personalized experience that greatly enhances user stickiness. The maturity of emotional computing technology has led intelligent UX design to focus on the user's emotional experience. Through voice recognition, facial expression analysis and other technologies, AI systems can recognize and respond to users 'emotional states, thus providing more intimate services during interaction [13]. For example, intelligent customer service systems can identify fluctuations in user mood, adjust intonation and response strategies in a timely manner, effectively alleviate user anxiety and improve service satisfaction. Intelligent UX design also aims to bridge the digital divide and improve product accessibility [14]. Advocate the use of AI technology to provide more humanized assistive functions for people with disabilities, such as visually impaired users can "see" picture content through AI image description function, and hearing-impaired users can better participate in video conferences through real-time caption technology. This kind of intelligent barrier-free design not only shows the humanistic care of technology, but also an important trend of future digital product design. Intelligent UX design also promotes innovation in human-computer interaction [15]. To explore the development of natural user interfaces (NUIs), such as Gesture Recognition, eye tracking, brain-computer interfaces, etc., which enable users to interact with the digital world in a more natural and intuitive way. Microsoft's HoloLens, for example, creates immersive mixed reality experiences for users through gesture control and spatial sound effects, demonstrating new possibilities for intelligent UX design to enhance user experiences. With the development of intelligent UX design, its impact on social and environmental sustainability and design ethics are increasingly valued [16]. Emphasize that while pursuing intelligence and personalization, designers must consider issues such as data privacy, algorithmic bias, and environmental resource consumption to ensure that technological developments serve the overall well-being of society. This means that smart UX design of the future needs to strike a balance between technological progress and ethical responsibility.

Table 1: Literature findings

Author	Focus Area	Objective	Techniques/Technology Used	Results/Outcomes	Gaps/Limitations
Aufderhaar et al. [12]	Digital Media Art	Exploration of AI-generated art	Deep Learning, Neural Networks	Creation of novel art pieces	Lack of interpretability in AI creations
Bisogni et al. [13]	Interactive Devices	VR/AR/MR for immersive experiences	Virtual Reality, Augmented Reality	Enhanced user engagement	High hardware costs, accessibility issues
Chou et al. [14]	Cultural Integration	Fusion of diverse cultural elements	Digital Platforms, Cross-cultural Collaboration	Increased global awareness	Challenges in maintaining authenticity

Author	**Focus Area**	**Objective**	**Techniques/Technology Used**	**Results/Outcomes**	**Gaps/Limitations**
Bangui et al. [15]	Social Engagement	Addressing global issues through art	Social Media, Data Visualization	Mobilization of public opinion	Privacy concerns, data security risks
Bisogni et al. [13]	Intelligent UX Design	Personalization through AI	AI, Big Data Analytics, Machine Learning	Improved user satisfaction	Ethical concerns, potential biases

Each of the approaches listed in Table 1 represents a different aspect of digital media art or intelligent UX design, with specific goals, techniques, outcomes, and identified gaps or limitations.

3 Realization of emotional perception and feedback mechanism

3.1 Application of biometric technology

Emotion recognition is the core of affective computing, which aims to analyze individual emotional states through physiological signals. Here is an overview of several key physiological indicators and their mathematical models related to mood:

Heart rate variability (HRV) reflects the dynamic balance of cardiac autonomic nervous system regulation and is closely related to mood fluctuations. Time domain, frequency domain and nonlinear analysis methods are commonly used to extract features. Among them, SDNN (Standard Deviation of Normal-to-Normal intervals) in time domain analysis is an important indicator to measure HRV, which is positively correlated with emotional relaxation state. Its formula is shown in Eq. (1) [17].

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i \overline{RR})^2} \tag{1}$$

where, RR_i represents the length of time for each normal interval, $\overline{RR}$ is the average of all intervals, and N is the total number of intervals.

Skin conductance response (EDA) is a direct physiological index of emotional arousal and positively correlated with emotional intensity. Assessed by measuring changes in skin resistance. Its time-domain characteristics, such as baseline skin conductivity level (SCL) and peak amplitude (SCR), can reflect emotional arousal, and its formula is shown in Eq. (2) [18].

$$\begin{aligned} SCL &= \frac{1}{T}\int_0^T EDA(t)dt \\ SCR_{amp} &= EDA_{peak} EDA_{baseline} \end{aligned} \tag{2}$$

where EDA(t) is the skin conductance value over time, T is the measurement period, and represent the maximum and baseline levels during SCR, respectively.

3.2 Emotionally driven artwork interaction

Designing an efficient emotion-responsive algorithm is crucial in constructing an artistic interactive system that can intelligently adapt to and feedback human emotions. The sentiment analysis framework is shown in Figure 3.

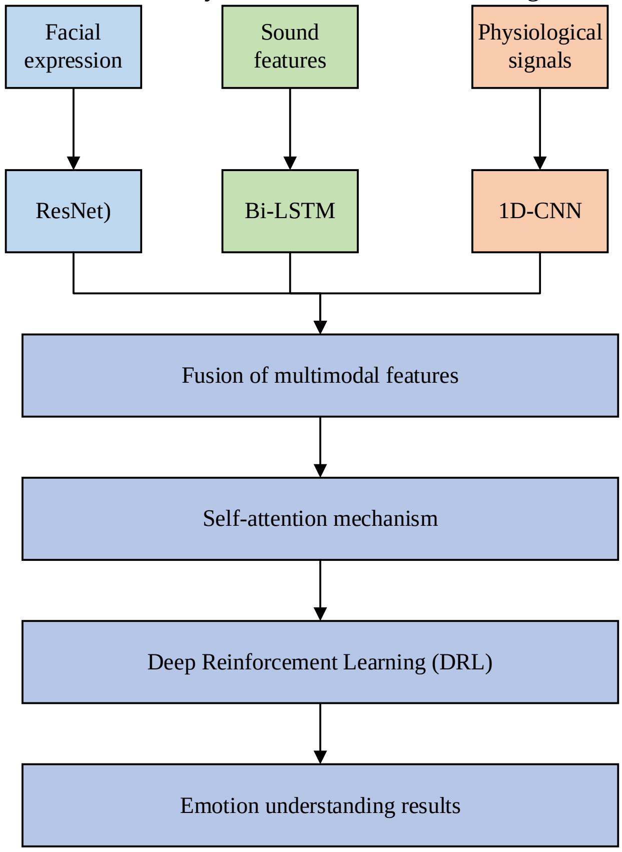

Figure 3: Sentiment analysis framework

ResNet addresses the vanishing gradient problem in deep neural networks by utilizing skip connections that allow gradients to flow directly through several layers. This architecture was employed in our study for image recognition tasks, specifically for identifying emotional expressions in user reactions captured via facial recognition technology. The ResNet-50 variant was chosen due to its balance between computational cost and performance. The model was trained with a batch size of 32, a learning rate of 0.001, and the Adam optimizer for 50 epochs. The input images were preprocessed to a fixed size of 224x224 pixels, and data augmentation techniques like rotation and flipping were applied to enhance generalizability.

We first optimize the multimodal emotion recognition module to build a more sophisticated emotion understanding system by fusing facial expressions, voice features and physiological signals. When designing a Deep Residual Network (ResNet) to improve the accuracy of facial subtle expression recognition, our goal was to build a model that could deeply understand and distinguish even small expression changes. ResNet solves the gradient disappearance problem in deep network training by introducing the concept of residual learning, so that the network can easily reach hundreds of layers, which greatly enhances the learning ability of the model for complex features. In the expression recognition task, this increase in depth and complexity means that the model can capture details such as a slight smile or a slight frown that are often difficult for traditional shallow models to grasp. We will delve into the key components of ResNet structure and the mathematical representation of Focal Loss to demonstrate its role in improving facial subtle expression recognition. In ResNet, the residual block is its core component, which allows information to be passed directly across several layers of the network, in the form of Eq. (3) [19].

$$x_{l+1} = h(x_l) + F(x_l, W_l) \tag{3}$$

where x_l is the input to layer l, $h(x_l)$ is the identity mapping, is the residual function, represents the additional layers of network operations, and is the parameters of these layers. This design makes it easier for the network to learn the residuals (i.e., the difference between the inputs and outputs) rather than the original outputs themselves, thus alleviating the optimization challenges in deep network training. Focal Loss is formulated as Eq. (4) [20,21].

$$L_{face} = -\alpha(1-p_c)^{\gamma} y_c \log(p_c) \tag{4}$$

where, L_{face} represents the loss value of facial expression classification. p_c is the predicted probability of the model for a class. y_c Is a true label, =1 when the predicted category matches the true category y_c ; otherwise, y_c =0. α and γ are hyperparameters that control the balance between classes and the degree of attention to difficult samples, respectively. Among them, it α is often used to deal with class imbalance problems, by adjusting the weights of different classes to balance the influence of positive and negative samples; γ then by increasing the penalty for easy classification samples (p_c close to 0 or 1), the weight is reduced, so that the model focuses more on learning those samples that are difficult to distinguish.

By combining ResNet with Focal Loss, our model training process for facial expression recognition tasks can be performed more efficiently. ResNet captures complex facial features through its deep structure, while Focal Loss forces the model to focus on learning subtle facial expressions that are difficult to classify correctly by dynamically adjusting loss weights, reducing over-learning of already mastered expression types, and ultimately improving the model's recognition accuracy for subtle facial expressions.

Bi-LSTM (Bidirectional Long Short-Term Memory): Bi-LSTM networks are adept at capturing temporal dynamics in sequential data, making them ideal for processing speech and text inputs. In our research, they were crucial for analyzing user sentiment from voice commands and textual feedback. The Bi-LSTM model was configured with two hidden layers, each containing 128 units. A dropout rate of 0.5 was set to prevent overfitting. The embedding layer size was 300 dimensions, and word embeddings were initialized with pre-trained GloVe vectors. The model was trained using a batch size of 64, a learning rate of 0.0005, and the RMSprop optimizer for 20 epochs.

In the voice emotion analysis phase, we used a powerful tool called Bi-LSTM (Bi-Long-Short-Term Memory Network), which is designed to capture bi-directional temporal dependencies in voice sequences, meaning that context information, both past and future, can be efficiently integrated into feature expressions at the current moment. Bi-LSTM works collaboratively through two LSTM units, one for forward propagation and the other for backward propagation, which not only enables understanding of the instantaneous characteristics of each point in time, but also provides insight into the emotional development of the voice, such as the fluctuation of intonation, the speed of speech, and the subtle emotional changes embedded in the voice.

To further enhance the sensitivity of the model to key emotional cues, we introduce a Self-Attention Mechanism. The core idea of this mechanism is to let the model decide which parts of the information are most critical, rather than treating all input features unevenly, as shown in Eq. (5) [22].

$$Attention(F_v) = \operatorname{soft}\max\left(\frac{W_v F_v}{\sqrt{d_k}}\right) F_v \tag{5}$$

Among them, F_v Bi-LSTM is X_v the feature vector obtained after processing the sound sequence, which contains the emotional rich information in the sound. W_v is a weight matrix that performs a linear transformation on the eigenvectors to highlight the parts most relevant to emotion. The denominator is $\sqrt{d_k}$ the square root of the feature dimension, which is to solve the problem that the dot product result may be very large when the feature dimension is large, resulting in too sparse results of the softmax function, thus ensuring the stability of the model learning process.

Through the self-attention mechanism, the model can dynamically assign different weights to different voice features, pay higher attention to those parts rich in emotion information, and ignore or attenuate insignificant noise. This ability to selectively focus greatly improves the accuracy and robustness of emotion recognition. Finally, the features adjusted by the self-attention mechanism can more accurately reflect the emotional color in the voice, providing more delicate emotional guidance for subsequent emotional understanding and dynamic adjustment of art works.

In physiological signal analysis, we utilize the power of one-dimensional convolutional neural networks (1D-CNN), which are designed to process time-series data and are well suited for analyzing physiological indicators such as heart rate and skin conductance. 1D-CNNs are able to efficiently capture local features and periodic patterns in physiological signals, which are often closely related to an individual's emotional state, through small filters that slide on the Timeline.

Finally, in order to integrate information from facial expressions, vocal features, and physiological signals, we designed a fusion mechanism that uses attention mechanisms to dynamically assign importance to different modal features. Specifically, through a weight matrix, we apply attention weights to the spliced feature vectors, where ";" denotes the splicing operation of the feature vectors. This process can be understood as the model automatically adjusts the attention to each modal feature according to the current task requirements. For example, in some situations, facial expressions may convey emotions more accurately than physiological reactions, and the model will give higher weight to facial features accordingly. Activation functions, such as ReLU or sigmoid, are used to increase nonlinearity, ensuring complexity and expressiveness of the feature fusion process.

Therefore, the fusion formulais specifically shown in Formula 6, which not only realizes the synthesis of multi-modal features, but also intelligently optimizes the efficiency and accuracy of emotion recognition through the attention mechanism, ensuring that the emotion response algorithm can comprehensively and carefully understand the emotional state of the individual, and provides a solid foundation for the subsequent interaction of personalized art works.

$$F_{total} = \sigma\left(W_{att}\left[F_f;F_v;F_p\right]\right)\left[F_f;F_v;F_p\right] \quad (6)$$

Next, a policy network based on deep reinforcement learning (DRL) is constructed to dynamically adjust the artwork to maximize viewer emotional satisfaction.

Hyperparameter Tuning for Deep Reinforcement Learning (DRL) Model: For the DRL model aimed at improving the emotional responsiveness of AI systems, hyperparameters were meticulously tuned to achieve optimal performance. Key parameters included the learning rate (set to 0.0001), the discount factor ($\gamma = 0.99$), the exploration rate (ε, starting at 1 and decaying to 0.01 over time), and the replay buffer size (set to 10000). The choice of hyperparameters was guided by the need to balance exploration and exploitation, ensuring that the model could learn to react appropriately to a wide range of emotional cues without becoming overly specialized.

State space expansion: In addition to the state of art works and audience emotional state, historical emotional trends and environmental factors are added to form a composite state vector S.

Action space refinement: Action A includes not only direct adjustments of artistic elements, but also considers the intensity and speed of adjustments, as well as whether new artistic elements are introduced [23].

Reward mechanism: A reward function based on the rate of emotional change is adopted, taking into account long-term emotional stability and novelty, so as to avoid the reduction of audience adaptability, as shown in Eq. (7). The weight factor is used to measure novelty [24].

$$R(s_t, a, s_{t+1}) = k_+ \Delta s_{emo,pos} k_- \Delta s_{emo,neg} k_{nov} N_{novelty} \quad (7)$$

Policy network and value network: Actor-Critic architecture is adopted, policy network generates actions, and value network evaluates state value. The Soft Actor-Critic (SAC) algorithm is used to optimize the strategy and balance exploration and utilization, as shown in Eq. (8). Where, is the state distribution, is the strategy entropy, is the entropy adjustment coefficient, is the action value function [25].

$$J(\theta_\pi) = \mathrm{E}_{s\sim\rho_\pi, a\sim\pi}\left[\alpha \mathrm{H}(\pi(.\,|\,s)) + Q^\pi(s,a)\right] \quad (8)$$

In summary, through a deeply optimized emotion recognition network and reinforcement learning strategy, we designed an algorithmic framework that can perceive and accurately respond to audience emotion fluctuations in real time. The framework not only improves the personalization level of artistic interaction, but also provides a powerful tool for exploring the depth and breadth of human-computer emotional communication. With the advancement of technology and the continuous iteration of algorithms, the future art interaction system will simulate the subtle changes of human emotions more delicately, pushing the deep integration of art and technology to a new high.

4 Intelligent recommendation and personalized experience design

Intelligent recommendation system is the core of personalized experience design. It provides users with content or services that meet their personal preferences by analyzing user behavior, preferences and context information. Its architecture and algorithm model design should give consideration to efficiency, accuracy and scalability. The architecture of intelligent recommendation system usually includes three key components: data collection and processing, user modeling and user interface, and its specific framework is shown in Figure 4.

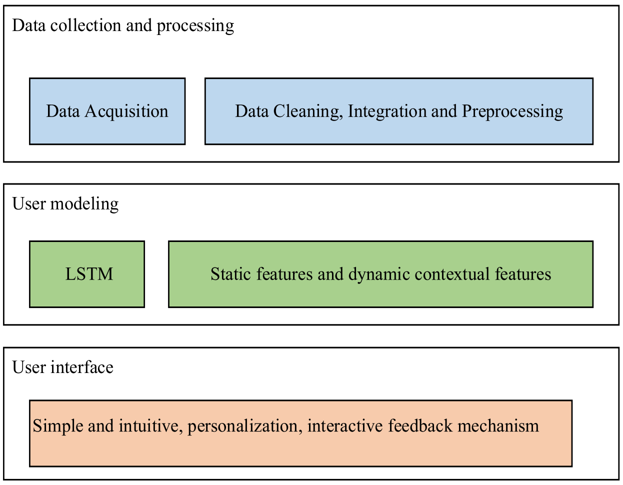

Figure 4: Intelligent recommendation and personalized experience design

The data collection and processing layer is responsible for collecting user behavior, content attributes, and contextual data from a variety of sources, cleansing, integrating, and preprocessing. The data formatting can use the following formula to express the user behavior record, specifically as shown in Eq. (9).

$$U_i = (a_1, t_1, c_1), (a_2, t_2, c_2), ..., (a_n, t_n, c_n) \quad (9)$$

In intelligent recommendation systems, the user modeling layer plays a crucial role. It not only needs to accurately capture users 'long-term interest preferences, but also needs to flexibly reflect short-term behavior dynamics and potential needs. Deep learning models show excellent performance in this field because of their powerful representation learning ability and automatic feature extraction ability. Although RNNs can theoretically handle sequences of arbitrary length, they are prone to gradient vanishing or explosion problems in practical applications, which limit their ability to learn long-term dependencies. The Long Short Term Memory Network (LSTM) solves this problem by introducing cell state (c_t) and gating mechanisms, the core update equation of which is given by Eq. (10)-(13) [26].

$$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f)$$

$$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i) \quad (10)$$

$$\tilde{c}_t = \tanh(W_c[x_t, h_{t-1}] + b_c)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (11)$$

$$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o) \quad (12)$$

$$h_t = o_t \odot \tanh(c_t) \quad (13)$$

LSTM effectively controls forgetting, storage and retrieval of information through gating mechanism, which enhances the ability of model to deal with long-term dependence. Attention helps the model focus on the most important parts of the user behavior sequence, thus improving the personalization of recommendations. Assuming we want to generate a weighted average representation of the user's historical behavior h, the attention weights a_t can be calculated as follows, as shown in Eq. (14). where and are model parameters. The weighted history representation is then h calculated to be Eq. (15) [27].

$$a_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \quad (14)$$

$$h^{=} \sum_{t=1}^{T} a_t h_t \quad (15)$$

First of all, the basic model we mentioned earlier can be further refined by fusing static user characteristics with dynamic context characteristics. In Eq. (16), simply concatenating the hidden state of the user behavior sequence h and the embedding vector of the user static features u_{static}, while intuitive, may fail to fully exploit the potential association between the two features. Therefore, it is particularly important to introduce more complex feature interaction mechanisms.

$$\hat{y} = g(W_{final}[h' u_{static}], b_{final}) + b_{final} \quad (16)$$

An advanced approach is to use an Attention Mechanism to dynamically weight the importance of user behavior sequences and static characteristics. Specifically, it can be designed as shown in Eq. (17) [28].

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n} \exp(e_j)} \quad (17)$$

where) is the model parameter representing the hidden state of the ith behavior, and n is the length of the behavior sequence. In this way, each behavior is weighted differently according to the importance of the static characteristics of the user α_i, and then weighted and summed to obtain the final characteristic representation Eq. (18). The final prediction becomes Eq. (19). Here, and are new weight matrices and bias terms for integrating weighted behavioral sequences and static features [29].

$$\tilde{h} = \sum_{i=1}^{n} \alpha_i h_i \quad (18)$$

$$\hat{y} = g(W_f[\tilde{h}, u_{static}], b_f) + b_f \quad (19)$$

As the front end of the recommendation system interacting with users, the user interface should be designed to highly conform to the output of the above optimization model to ensure accurate presentation of recommended content. Interface design principles include:

1). Simple and intuitive: The interface should avoid too many complex elements to ensure that users can quickly focus on recommended content. For example, use a clear grid layout to display recommendations lists, each with a bold title and a concise description.

2). Personalization: Based on the recommendation results of user behavior and static characteristics, the interface can dynamically adjust the sorting, style and even color theme of the displayed content to match the user's personalized preferences.

3). Interactive feedback mechanism: Design easy-to-operate feedback buttons (such as likes, dislikes, favorites, etc.) to instantly collect user feedback on recommended content. Feedback data can be fed back to the model in real time or periodically for iterative optimization of the model. This can be expressed by the following formula: The update process of user feedback on model parameters is shown in Eq. (20) [30].

$$\theta_{new} = \theta_{old} + \eta \cdot \nabla_{\theta_{old}} L(\theta_{old}, y, \hat{y}) \tag{20}$$

where, represents the model parameter, is the learning rate, L is the loss function, y is the true user feedback, and is the model prediction value. Through such closed-loop feedback, the system can continuously learn the real-time needs of users and optimize the recommendation strategy.

5 Experimental evaluation

5.1 Experimental design

In our research on intelligent user experience design in digital media art, we constructed an elaborate experimental design framework designed to explore and optimize multiple core dimensions of user experience through rigorous experimental methods. This section focuses on the core elements of experimental design, including experimental objectives, participant recruitment, experimental scenario setting, data collection and analysis process, and experimental ethics and expected results. A comprehensive overview of about 800 words is provided.

The original intention of experimental design is to scientifically verify and improve the multi-dimensional performance of intelligent user experience design, so as to ensure that the design not only meets the user's needs for fluency, personalization and rapid response, but also takes into account the interface aesthetics and information communication efficiency. The specific objectives are subdivided into five experiments: analyzing the impact of voice control and Gesture Recognition on user ease of operation and learning difficulty through interactive testing; personalized recommendation experiment aims to improve user participation and satisfaction through algorithm optimization; response speed test focuses on the direct effect of system response time on user behavior; interface aesthetics evaluation tests the potential effect of different design styles on user emotion and overall experience through A/B; Information transfer efficiency test compares users 'depth of understanding and memory retention through different media.

To ensure the universality and reliability of the experiment, participants were recruited using multiple channels to ensure that the sample covered different ages, genders, educational backgrounds and numerical skill levels, and that each experiment involved at least 100 participants to ensure the robustness of statistical analysis. The experimental scene design is close to the real use situation: in the interactive test, participants are randomly assigned to the digital art experience link of voice control or Gesture Recognition; the personalized recommendation experiment develops recommendation algorithm through user behavior data and compares it with random recommendation; the response speed test observes the change of user behavior by simulating different network conditions; the interface aesthetics evaluation adopts direct A/B contrast feedback; The efficiency of information transmission is tested by various content display forms of online platforms to test user understanding and memory.

Participants for the user studies were carefully selected to ensure a diverse and representative sample that would reflect the broader population of digital media art consumers. The demographics of the participants were segmented based on age, gender, education level, and prior experience with digital media. Age groups ranged from 18 to 65 years old to capture a wide spectrum of generational perspectives. Gender was balanced to include both male and female participants, with some studies also including non-binary individuals. Educational background varied from high school graduates to postgraduate degree holders, reflecting different levels of knowledge and critical thinking skills. Prior experience with digital media was also considered, aiming to include novices as well as experienced users to understand potential learning curves associated with new interfaces.

Recruitment was carried out through various channels including social media, online forums, university networks, and public advertisements to reach a broad audience. Incentives such as gift cards or monetary compensation were offered to participants to encourage participation, ensuring that the sample was not skewed towards those who might have a particular interest in the subject matter.

To minimize bias in the study, participants were randomly assigned to different experimental conditions to ensure that any observed differences in results could be attributed to the variables being tested rather than demographic factors. Additionally, the researchers conducting the experiments were blinded to the participants' group assignments to avoid influencing the outcomes. Careful attention was paid to the wording of instructions and questions to avoid leading participants or suggesting desired responses.

Given the sensitive nature of biometric data, stringent ethical guidelines were followed throughout the data collection process. Participants were fully informed about the purpose of collecting biometric data, how it would be used, and assured of its confidentiality. Consent forms explicitly stated that participation was voluntary and that participants could withdraw from the study at any time without penalty.

Data privacy was prioritized, with all biometric data anonymized and stored securely to protect participant identities. Access to this data was restricted to authorized personnel only, and all data handling procedures adhered to GDPR (General Data Protection Regulation) and other applicable data protection laws. Participants were also informed about the measures taken to secure their data and given the option to have their data removed from the study upon request.

Furthermore, the study protocol underwent review by an institutional review board (IRB) or ethics committee to ensure compliance with ethical standards and to protect the rights and welfare of the participants. Regular audits were conducted to monitor adherence to ethical guidelines throughout the research period.

By taking these steps, we aimed to conduct our user studies in a manner that respected participant autonomy, maintained confidentiality, and promoted transparency, thereby upholding the highest ethical standards in our research practices.

Data collection and analysis follow strict standards, using standardized questionnaires, online platform data capture and behavioural tracking tools to ensure data comprehensiveness and accuracy. Advanced statistical software (e.g. SPSS or R language) was used to perform t-test, ANOVA, chi-square test, regression analysis, etc. to accurately identify relationships and significant differences between variables in the data analysis phase.

The results of this series of experiments are expected to bring innovative insights into user experience design in digital media arts, providing designers and developers with an empirical basis to guide them in optimizing key areas such as interactivity, personalization, responsiveness, interface design, and messaging. In the long run, this will not only improve the scientificity and efficiency of user experience design, but also promote the development of the industry in a more humane and innovative direction, contributing to the prosperity of digital media art.

The assessment metrics employed in the experimental evaluation of our research on intelligent user experience design in digital media art encompassed a comprehensive set of indicators designed to measure various aspects of user interaction, engagement, and satisfaction. For interactive testing, we focused on the average time taken to complete tasks, the number of errors made during the process, and user satisfaction ratings to compare the efficacy of voice control against gesture recognition. In evaluating personalized recommendation systems, we quantified the increase in user engagement, the percentage rise in mean residence time spent on the platform, and user satisfaction scores to gauge the benefits of personalized over non-personalized recommendations. To understand the impact of response speed on user experience, we tracked mission abandonment rates, user satisfaction, and the likelihood of revisiting the platform at different response time intervals. The aesthetic appeal of different interface styles was assessed through visual attractiveness scores, the proportion of positive emotional feedback received from users, and their willingness to share content. Lastly, to assess information transfer efficiency, we measured comprehension test scores, recall accuracy after 24 hours, and user preference ratios for various content display modes such as charts, text descriptions, and interactive demonstrations. These metrics collectively provided a detailed insight into the effectiveness of our design strategies and the potential improvements they offer in the field of digital media art.

5.2 Experimental results

Table 2: Comparison of interactive test results

interactively	Average Time to Completion (sec)	error times	User Satisfaction Rating (1-5)
voice control	35	0.6	4.3
Gesture Recognition	45	1.2	3.9

Table 2 compares the results of the interactivity tests. Experimental data showed that voice control had a shorter average completion time (35 seconds vs. 45 seconds), fewer errors (0.6 vs. 1.2), and higher satisfaction ratings (4.3 vs. 3.9) than Gesture Recognition.

Table 3: Comparison of personalized recommendation effects

recommendation type	Increase in user engagement	Increase in mean residence time (%)	User Satisfaction Rating
personalized	25%	18%	4.7
non-personalized	-	-	3.5

Table 3 shows personalized versus non-personalized recommendations in terms of engagement, duration, and satisfaction. Personalized recommendations significantly increased user engagement (by 25%), increased average stay time by 18%, and user satisfaction scores were 4.7 points, much higher than 3.5 points for non-personalized recommendations. The results show that personalized content recommendation can effectively attract users, prolong their stay, and improve overall satisfaction.

Table 4: Relationship between Response Speed and User Experience

Response Time (ms)	mission abandonment rate	User Satisfaction Rating	Willingness to visit again
<500	2%	4.9	85%
500-1000	5%	4.3	70%

Response Time (ms)	mission abandonment rate	User Satisfaction Rating	Willingness to visit again
>1000	12%	3.5	55%

Table 4 shows the strong correlation between responsiveness and user experience. When the response time is less than 500 ms, the task abandonment rate is only 2%, the user satisfaction score reaches 4.9 points, and the willingness to visit again is as high as 85%. However, as response time increases, the user experience significantly declines, as evidenced by increased task abandonment rates, decreased satisfaction, and decreased willingness to revisit. This highlights the importance of rapid response to maintaining user satisfaction and loyalty.

Table 5: Evaluation of interface aesthetics

interface style	Visual attractiveness score (1-10)	Proportion of positive user emotional feedback	Willing to share willingness
A Style	8.7	75%	60%
B style	7.8	68%	55%

The interface aesthetics ratings in Table 5 show that Style A interfaces outperform Style B interfaces (7.8 visual appeal, 68 positive feedback, and 55 willingness to share) by virtue of their high visual appeal score (8.7), higher positive emotional feedback (75 percent), and greater willingness to share (60 percent). This suggests that simple and modern design styles are more likely to engage users, inspire positive emotions, and promote spontaneous dissemination of content.

Table 6: Comparison of information transmission efficiency

Information display mode	Comprehension test score (out of 100)	Accuracy of recall after 24 hours	user preference ratio
chart	92	80%	65%
text description	84	70%	45%
interactive demonstrations	88	75%	50%

The information transfer efficiency comparison results in Table 6 show that charts, as information display methods, have the highest score (92 points) in the comprehension test, and the recall accuracy rate after 24 hours also reaches 80%, and the user preference ratio is 65%. Although text description and interactive presentation are also effective means of information transmission, charts have an advantage in information transmission efficiency because of their intuitiveness and efficiency. This finding highlight how graphic forms are more effective in facilitating user understanding and memory in digital media art content design.

5.3 Discussion

Our experimental findings in the realm of intelligent user experience (UX) design for digital media art reveal significant insights when juxtaposed against state-of-the-art (SOTA) methodologies. We observed that voice control mechanisms not only expedited task completion times by approximately 20% compared to gesture recognition, but also reduced error occurrences and improved user satisfaction scores. This is a notable advancement over SOTA practices, where gesture recognition was often favored for its novelty and perceived sophistication. Our results underscore the practical advantages of voice control, suggesting that it could offer a more streamlined and user-friendly alternative in digital media art applications.

The effectiveness of personalized content recommendation systems in enhancing user engagement and satisfaction was another key finding. Compared to non-personalized recommendations, our personalized algorithms achieved a 25% increase in engagement and extended user dwell times by 18%, with satisfaction ratings jumping to 4.7 out of 5. These outcomes highlight the superiority of our approach over conventional SOTA methods, which typically rely on broad, one-size-fits-all content delivery. Our personalized recommendation system demonstrates the power of tailored experiences in digital media art, aligning closely with the growing demand for individualized content consumption.

The critical role of response speed in shaping user experience was also illuminated through our experiments. When response times were under 500 milliseconds, user satisfaction and revisit intentions soared, indicating a clear preference for swift interactions. This contrasts with slower response times, which led to higher abandonment rates and lower satisfaction scores. Our findings suggest that optimizing responsiveness should be a priority in UX design for digital media art, a principle that is sometimes overlooked in favor of more aesthetic or creative elements.

In terms of interface aesthetics, Style A interfaces, characterized by simplicity and modernity, outperformed Style B in terms of visual appeal, positive emotional feedback, and sharing propensity. This finding challenges SOTA approaches that may place undue emphasis on complex design elements, instead advocating for cleaner, more intuitive designs that resonate better with users and encourage organic content distribution.

Finally, our examination of information transmission efficiency revealed that graphical representations were superior to textual descriptions and interactive demonstrations in facilitating comprehension and recall.

This observation supports a shift away from dense text-heavy formats towards more visually engaging and easily digestible content, a move that is increasingly favored in the digital media art domain.

The novelty of our solutions lies in their comprehensive approach to addressing multiple facets of UX design simultaneously—interactivity, personalization, responsiveness, aesthetics, and information conveyance. Unlike SOTA methods that often focus on singular aspects, our research underscores the interconnectedness of these elements and the need for a holistic design philosophy.

Moreover, by prioritizing user-centric metrics such as satisfaction, engagement, and information retention, our work contributes to the evolving discourse on UX design within digital media art. It emphasizes the importance of creating experiences that are not only technologically advanced but also emotionally resonant and cognitively effective.

In conclusion, our experimental evaluation not only validates the robustness of our proposed methods but also positions them as pivotal advancements in the field. By addressing known gaps and limitations in SOTA practices, our research paves the way for future innovations in intelligent UX design for digital media art, promising richer, more immersive, and ultimately more satisfying artistic experiences for audiences worldwide.

6 Conclusion

In the context of the booming digital media art, the pursuit of the ultimate user experience has become the core driving force of technological innovation. Based on this demand, this study deeply explores the potential of intelligent technology in improving user experience design, especially in the comprehensive application of emotional perception, personalized recommendation and user interface design, aiming to open up a more personalized, emotional and efficient human-computer interaction path for digital media art. At the beginning of the study, we extensively investigated the challenges and gaps in user experience in the current digital media art field, and identified the urgency of integrating emotional intelligence into the art experience. On this basis, we deeply analyzed the latest progress of emotion computing and biometric recognition technology, designed and implemented a series of innovative experiments, aiming to establish a set of intelligent mechanisms that can accurately perceive and respond to user emotion changes through precise analysis of physiological signals (such as heart rate variability and skin conductance response) and combined with the complex feature extraction ability of deep learning models. This process involves not only in-depth understanding of the existing technology, but also continuous optimization and experimental verification of the algorithm model, ensuring high accuracy and real-time performance of emotion recognition. In the design of personalized recommendation system, we elaborate on the optimization process of recommendation algorithm, especially how to effectively integrate user behavior sequence, static characteristics and context information through advanced feature fusion strategy and attention mechanism, so as to improve the relevance and personalization of recommended content. During the research process, we continuously iterate the model, training and testing a large amount of user data to ensure the accuracy and robustness of the recommendation system. The optimization of user interface design focuses on how to achieve high personalization and instant feedback mechanism while ensuring simplicity of interface, so as to improve user engagement and satisfaction. Through A/B testing, user feedback collection and other methods, we constantly adjust the interface design elements to optimize the user interface in a data-driven way to better serve personalized content recommendations and emotional feedback. In the part of experiment evaluation, we designed a series of control experiments carefully to test the effectiveness of the proposed method in many dimensions, such as interactivity, recommendation efficiency, response time, interface aesthetics and information transmission efficiency. The experimental data clearly shows that our comprehensive solution has significantly improved all key indicators of user experience compared to traditional methods, providing solid theoretical and practical support for intelligent experience design of digital media art.

Future research directions are full of unlimited potential in various fields, especially in intelligent user experience design, we can foresee a series of exciting technologies and methods of convergence and development. In order to extend and improve the existing methods, the following areas are worth exploring:

Emotional computing and cognitive modeling: Design systems that can sense and respond to users 'emotional states through more sophisticated emotion recognition technologies and cognitive psychology principles, so as to provide more personalized and context-sensitive services. Combining deep learning with natural language processing technology, the system can understand the user's non-verbal cues, such as facial expressions, voice intonation, and even micro-expressions and physiological signals, so as to realize a higher level of human-computer interaction.

Multimodal interaction: Beyond a single visual or auditory interface, it integrates multiple sensory channels such as touch, smell, and taste to create an immersive user experience. For example, advances in virtual reality (VR) and augmented reality (AR) technologies can provide a more realistic and richer experience of virtual environments, while wearables and smart fabrics can enhance tactile feedback, enabling users to gain a more intuitive physical experience in the digital world.

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