Textile & Leather Review

ISSN 2623-6281| www.tlr-journal.com | 10.31881/TLR

Design of a Multimodal Fabric Interactive Display System and Immersive Experience Modeling for Red Network Education

Mengni Zhou, Yi Zhou

How to cite: Zhou M, Zhou Y. Design of a Multimodal Fabric Interactive Display System and Immersive Experience Modeling for Red Network Education. Textile & Leather Review. 2026; 9:901-924. https://doi.org/10.31881/TLR.2026.901

How to link: https://doi.org/10.31881/TLR.2026.901

Published: 17 April 2026

Design of a Multimodal Fabric Interactive Display System and Immersive Experience Modeling for Red Network Education

Mengni Zhou[1], Yi Zhou[2,*]

[1]Jiangxi Technical College of Manufacturing, Nanchang 330100, Jiangxi, China

[2]Jiangxi Police College, Nanchang 330100, Jiangxi, China

*skyzhouyi@163.com

Article

https://doi.org/10.31881/TLR.2026.901

Received 7 August 2025; Accepted 23 September 2025; Published 17 April 2026

ABSTRACT

To address the limitations of weak physical perception and insufficient emotional resonance in historical scenes within red network education, this study proposes a multimodal fabric interactive display system and an immersive experience modeling method. By developing a tactile fabric composed of conductive polymer composite fibers and piezoelectric ceramic microunits, the physical characteristics of revolutionary historical objects are accurately restored. A cross-modal synchronization algorithm based on a Transformer-FPGA (Field-Programmable Gate Array) architecture is designed to achieve millisecond-level coordination among visual, tactile, and auditory signals, ensuring consistency in the restoration of historical contexts. A flexible electrode fabric integrated into the system collects users' brainwaves and skin electrical activity, which are then processed by an LSTM (Long Short-Term Memory) network to predict immersion levels. The system dynamically optimizes tactile intensity and audio frequency bands based on these predictions, achieving closed-loop adjustment of the user experience. Experiments demonstrate that the average user dwell time in red narrative tasks is 8.2 minutes, and the frequency of repeated operations increased to 3.5 times, indicating deeper engagement with red culture. The error rate for simulating the rough texture of a revolutionary cotton military uniform is as low as 4.7%, representing a 10.5 percentage point reduction compared to traditional piezoelectric motor fabrics. The system serves as an intelligent platform integrating physical reality and digital narrative, effectively promoting deep user participation and emotional resonance, and providing an innovative immersive solution for red cultural education.

KEYWORDS

red culture education, smart fabrics, conductive polymer composite fibers, cross-modal synchronization algorithm, physiological signal drive

INTRODUCTION

Red Network Education refers to the digital dissemination of China's revolutionary history and spirit through online platforms and new media technologies. It aims to cultivate political identity and moral values among youth by fostering emotional resonance with historical narratives. The traditional dissemination model relies on digital media, which, while enabling visualization of content through audio-visual virtual simulation, lacks the depth of physical interaction. The emergence of smart textile technology offers a novel media pathway for disseminating red culture. With its flexible, wearable characteristics and tactile feedback capabilities, smart textiles can potentially compensate for the absence of physical entities in digital interactions [1]. To overcome the limitations of traditional digital media, immersive technologies have evolved from VR/AR (visual-auditory) to haptic devices (tactile), with smart textiles now emerging as a wearable, multimodal platform that bridges digital narratives and embodied physical perception. However, existing smart fabrics still face technical bottlenecks: insufficient accuracy in dynamic tactile simulation makes it difficult to reproduce the physical characteristics of complex historical scenes; the lack of a multimodal information coordination mechanism means that differences in the transmission paths for visual, tactile, and auditory signals lead to sensory asynchrony, undermining the sense of presence [2,3]; immersive experience evaluation mostly relies on subjective questionnaires and lacks dynamic modeling methods based on physiological signals such as brainwaves and skin electrical activity, preventing real-time optimization of interactive strategies [4,5]. These issues restrict the deep integration of textile engineering and red culture communication and affect the acceptance of red education among young audiences.

In recent years, the digital dissemination of red culture has diversified, driven by technological advancements. Xiaoxia Li et al. [6] demonstrated the feasibility of virtual reality technology in recreating red cultural scenes by developing a three-dimensional interactive display system, which enhances user participation and immersion. Junbo Yi et al. [7] further refined user behavior identification mechanisms by utilizing deep learning and Back Propagation (BP) neural networks to achieve high-precision classification of red cultural audience interests. Junhua Wang [8] focused on improving the efficiency of communication pathways. Through social network analysis and diffusion model optimization, an integrated online and offline influence evaluation system was constructed, enhancing the penetration and conversion rate of red culture in the digital space. However, these studies have limitations: although VR technology enhances visual immersion, it lacks tactile feedback, making it difficult to establish a multimodal perception closed loop and to meet the needs for historical authenticity and emotional engagement; user interest classification models rely on static feature inputs and do not incorporate physiological signals for dynamic immersion prediction; communication strategy optimization does not integrate smart textile materials as new interactive carriers. These issues highlight the inability of existing technologies to address the core challenge of “lack of emotional resonance,” particularly the absence of physical entity perception capabilities and multimodal collaboration mechanisms.

Technological breakthroughs in immersive smart textile interaction have significantly advanced multimodal perception. Jeanne Tan et al. [9] developed an interactive luminous fabric based on an open-source AI model, enabling contactless gesture recognition and visual feedback. The incorporation of polymer optical fibers and a double-layer woven structure enhanced the immersive response capabilities of smart fabrics. However, this approach remains limited to single-mode visual feedback. Huanhuan Liu et al. [10] systematically reviewed the technological evolution of sensory interactive electronic textiles and proposed an immersive design framework; nevertheless, they did not address engineering challenges such as material stability and cross-modal synchronization delays. Zhen Wang et al. [11] focused on the evolution of textile display technology, from rigid devices to weavable electroluminescent fibers, analyzing the impact of active material interface design and multifunctional integration on immersive experiences, while identifying bottlenecks in system stability and scalability. Although progress has been made in material innovation and functional integration, key deficiencies remain: tactile feedback mechanisms are limited to single materials with low dynamic accuracy, making it difficult to simulate the multi-scale physical characteristics of complex historical scenes; cross-modal collaboration lacks real-time synchronization algorithm support, leaving signal asynchrony unresolved; integration and durability of; display technologies are insufficient, and there is no deep integration with physiological signal-driven modeling [12]. These challenges further highlight the technical gap in smart textiles for meeting the high-precision, multimodal, and emotional interaction requirements of red education.

To address the fundamental challenge of lacking physical realism in historical scenes and insufficient emotional resonance in the dissemination of red culture, this paper proposes a multimodal fabric interaction system that deeply integrates materials, algorithms, and modeling. At the material level, conductive polymer composite fibers are innovatively combined with piezoelectric ceramic microunits to develop high-precision tactile feedback fabrics, aiming to accurately replicate the physical characteristics of revolutionary historical objects and enhance users' embodied experience and historical perception. At the system level, a real-time synchronization algorithm based on Transformer-FPGA is introduced to ensure perfect coordination of visual, tactile, and auditory cues, minimizing cross-modal synchronization delays. Through timing alignment technology, these sensory signals are integrated to achieve millisecond-level coordinated responses, maintaining continuity and presence in users' sensory experiences during red narratives. At the modeling level, flexible electrode fabrics are incorporated to collect users' brainwaves and skin electrical activity in real time, enabling the construction of an LSTM neural network-driven dynamic immersion prediction model. Based on this model, tactile intensity and audio frequency bands are optimized in real time, allowing the system to perceive fluctuations in users' emotional states and actively sustain deep engagement. Compared with conventional solutions, this study achieves three breakthroughs: reproducing historical authenticity through materials, ensuring multisensory immersion through algorithms, and enabling emotional adaptability through modeling. It establishes an intelligent interactive platform that seamlessly integrates physical entities with digital narratives, providing an immersive solution for red cultural education that effectively promotes deep participation, stimulates emotional resonance, and strengthens value identification.

DESIGN OF MULTIMODAL FABRIC INTERACTIVE SYSTEM AND IMPLEMENTATION OF IMMERSIVE MODELING

Overall System Architecture Design for Red Education

Figure 1 illustrates a system architecture centered on multimodal interaction, establishing a closed-loop process from physical perception to immersive experience. The textile sensing layer, serving, as the entry point for physical interaction, captures users' tactile feedback and environmental data in real time through embedded sensors. The multimodal synchronization unit then aligns the timestamps, it timestamps and integrates visual, auditory, and other digital signals with the multimodal signal acquisition module, creating a cross-modal raw data stream. The signal processing unit performs noise reduction and feature extraction on this data while, simultaneously activating the panoramic perception module to engage the mixed reality system and generate a virtual scene that integrates historical context, which is then output directly to the immersive experience terminal. The physiological signal module collects users' brainwaves and skin electrical activity. After enhancing key features via signal enhancement technology, these signals are fed into the multi-layer optimization engine to adjust tactile vibration intensity and audio frequency bands. Finally, the degree of immersion is quantified through the perception model and fed back to the system core, completing the closed loop. The innovation lies in the deep integration of smart fabrics and models within a, physiology-driven closed-loop system, where real-time immersion prediction directly modulates tactile feedback, achieving a level of co-design absent in typical multimodal systems. The multimodal synchronization unit and the multi-layer optimization engine form the control center, ensuring tactile, visual, and physiological signals respond in a coordinated manner within millisecond delays, ultimately restoring the immersive narrative experience of red cultural historical scenes in a mixed reality environment.

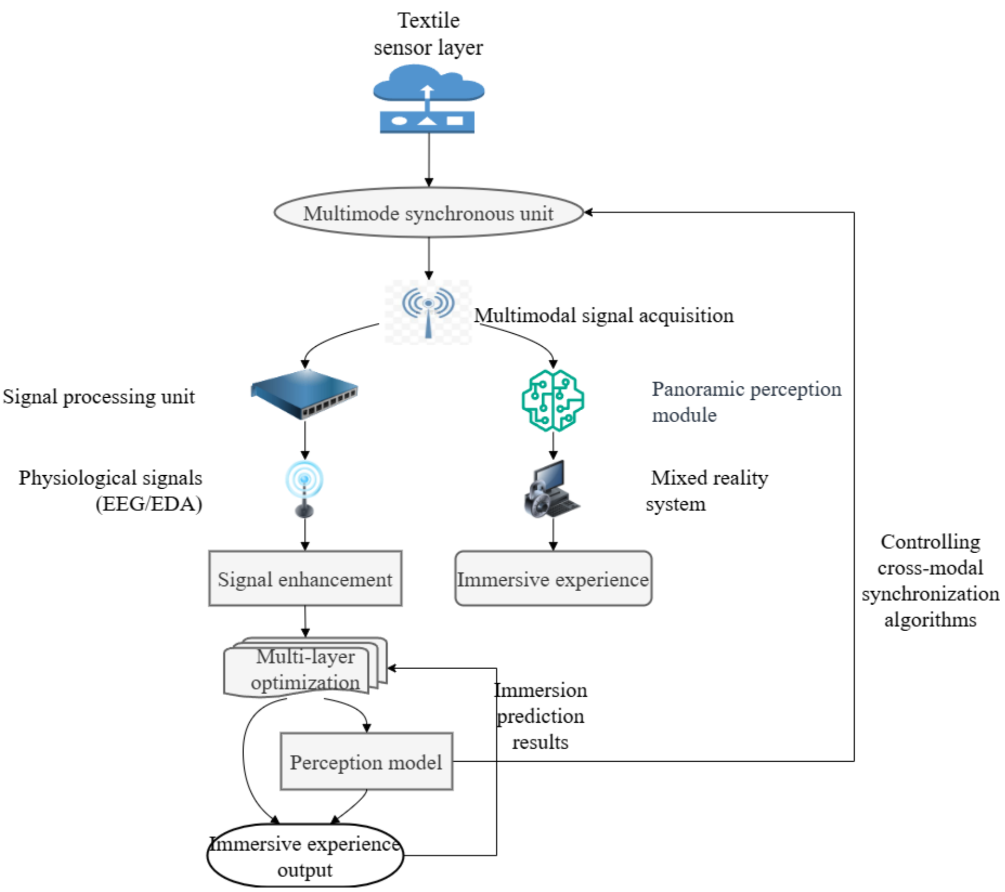

Figure 1. Overall system architecture

Preparation of Tactile Fabrics to Reproduce Historical Physical Characteristics

As the core execution unit of the multimodal interactive system, the preparation of conductive polymer composite fiber tactile feedback fabric must consider the material's conductivity, mechanical responsiveness, and compatibility with textile processing techniques. Its performance directly influences the ability to dynamically reproduce multi-scale physical features in red cultural scenes.

In this paper, an in-situ polymerization process is employed to fabricate a conductive polymer composite layer on the surface of polyester fibers. The surface conductivity σ and coating thickness d exhibit an exponential relationship.

$$\sigma=\sigma_0 \, exp(-\alpha d) \tag{1}$$

In formula (1), σ_0 is the intrinsic conductivity and α is the attenuation coefficient.

Piezoelectric ceramic microunits are integrated onto the surface of the composite fiber, and silver paste is used as the electrode layer via screen printing technology. Interface coupling between the piezoelectric phase and the conductive layer is achieved through high-temperature sintering. When an AC voltage is applied, the piezoelectric ceramic generates radial vibration, and the material parameters determine its resonant frequency f (Hz):

$$f=\frac{1}{2\pi}\sqrt{\frac{k_{31}^2\varepsilon_{33}E}{\rho d_p^2}} \tag{2}$$

In formula (2), k_{31} is the electromechanical coupling coefficient; ε_{33} is the dielectric constant; E is Young's modulus; ρ is the density; and d_p is the thickness of the piezoelectric sheet.

Composite fibers are aligned in the warp direction, and the base fabric is woven using a plain weave structure. The interfacial bonding strength between the fibers is improved through hot pressing. The rate of resistance change meets the interactive system's requirements for material durability.

The dynamic response characteristics of this module establish the physical foundation and define the parameter boundaries essential for the precise coordination of subsequent cross-modal synchronization control algorithms in red historical scenes.

Design of Cross-Modal Synchronization Control Algorithm with Red Scene Priority

The asynchronous problem among visual, tactile, and auditory signals requires a solution via a cross-modal synchronization control algorithm. A time alignment model based on the Transformer architecture is adopted. The lightweight Transformer on FPGA is chosen to overcome the precision-latency trade-off: the Transformer's self-attention mechanism excels at capturing long-range temporal dependencies in asynchronous signal streams. The FPGA ensures deterministic millisecond timing, while the pruned and quantized model maintains high accuracy with low computational load. The input is the visual frame timestamp sequence $T_v=\{t_{v1},t_{v2},\ldots,t_{vN}\}$, the tactile pulse sequence $T_t=\{t_{t1},t_{t2},\ldots,t_{tM}\}$, and the audio feature vector sequence $F_a=\{f_{a1},f_{a2},\ldots,f_{aK}\}$, and the output is the synchronized time embedding vector $E\in \mathrm{R}^{d\times L}$, where d is the feature dimension and L is the sequence length. By minimizing the multimodal time difference loss function:

$$L_{sync}=\frac{1}{N}\sum_{i=1}^{N} // \Delta t_{v\text{-}t}(i) //_2^2+\lambda\frac{1}{M}\sum_{j=1}^{M} // \Delta t_{t\text{-}a}(j) //_2^2 \tag{3}$$

In formula (3), $\Delta t_{v\text{-}t}(i)$ reflects the visual-tactile synchronization accuracy; $\Delta t_{t\text{-}a}(j)$ constrains the temporal consistency of the tactile-auditory modality; and λ is the cross-modal weight coefficient, which optimizes the model parameters to achieve millisecond alignment of multimodal signals.

A lightweight Transformer model is deployed on an FPGA platform, employing channel pruning and mixed-precision quantization techniques to compress the model parameters. Simultaneously, a pipeline parallel architecture is designed to enhance computational efficiency. During operation, multimodal data acquisition is triggered by a hardware timer, with the sampling window size set to 50 ms. This 50 ms window represents the total data block processed per cycle; however, a sliding window mechanism with a 10 ms step size enables real-time updates every 10 ms, ensuring that the end-to-end coordination delay remains below 20 ms. The synchronized time-embedding vector is updated in real time using the sliding window mechanism, ultimately achieving a low-latency coordinated response across vision, touch, and hearing modalities within the red cultural narrative, ensuring the coherence and immersion of historical context restoration.

Integration of Physiological Signal Acquisition and Immersion Prediction Module

A user status feedback closed loop is established through the collection of physiological signals and immersion prediction. The core objective is to construct a mapping relationship among EEG (electroencephalogram), EDA (electrodermal activity), and interactive behavior.

A flexible Ag/AgCl electrode fabric is used as the medium for collecting physiological signals, and the electrode layer is integrated into a polyester fiber substrate through screen printing technology. After the preamplifier processes the EEG signal and the bandpass filter, the α wave power P_α is separated, and its transfer function is:

$$H(f)=\frac{V_{out}(f)}{V_{in}(f)}=\frac{1}{\sqrt{1+(f/f_c)^{2n}}} \tag{4}$$

In formula (4), f_c is the α wave cutoff frequency, n = 4 is the filter order, V_{out} and V_{in} are the output and input voltages, respectively. The EDA signal drives the electrode pair through a constant voltage to measure the rate of change of $\Delta G/G_0$ of skin conductance G. The first-order derivative calculation formula is:

$$\frac{d(\Delta G/G_0)}{dt}=\frac{G(t+\Delta t)\text{-}G(t)}{\Delta t} \tag{5}$$

In formula (5), Δt = 100 ms is the sampling time window, and G_0 is the baseline conductance value.

The preprocessed EEG α wave power P_α and EDA derivative $\frac{d(\Delta G/G_0)}{dt}$ are input into the LSTM network as feature vectors, and the update formula for its hidden layer state h_t is:

$$\begin{gathered} h_t = o_t \odot \tanh\ (c_t) \\ c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \end{gathered} \tag{6}$$

In formula (6), o_t, f_t, and i_t are the activation values of the output gate, forget gate, and input gate, respectively; $\odot$ represents element-wise multiplication; and $\tilde{c}_t$ is the candidate cell state. The network output layer uses a Softmax classifier to calculate the immersion level $y \in [0, 1]$, with its cross-entropy loss function:

$$L_{cls} = -\sum_{k=1}^{K} w_k \left[y_k \log\left(\hat{y}_k\right) + \left(1 - y_k\right) \log\left(1 - \hat{y}_k\right) \right] \tag{7}$$

In formula (7), K= 5 is the number of discrete categories of immersion level; w_k is the category weight; y_k and $\hat{y}_k$ are the true label and predicted probability, respectively.

This module achieves high immersion prediction accuracy through the collaborative design of a flexible electrode fabric and an LSTM network [13]. The predicted immersion level serves as the primary input parameter for dynamic interaction parameter optimization, enabling real-time adjustments of multimodal stimulation to maintain or enhance users' emotional engagement within the red historical context.

Dynamic Interaction Parameter Optimization Strategy

This paper adopts an improved proportional–integral–derivative (PID) control model, which takes the error $e(t)$ between the target immersion level and the predicted value as input and outputs the control signals for the tactile vibration intensity $V(t)$ and the audio frequency band $f_a(t)$:

$$V(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \tag{8}$$

$$f_a(t) = f_{a0} + \beta \cdot sgn\left(\frac{d\left(\frac{\Delta G}{G_0}\right)}{dt} \right) \cdot \left| \frac{d\left(\frac{\Delta G}{G_0}\right)}{dt} \right|^{\gamma} \tag{9}$$

In formulas (8) and (9), K_p, K_i, and K_d are PID gain coefficients; f_{a0} is the reference frequency band; β is the modulation coefficient; and γ is the nonlinear index. The tactile vibration unit uses a piezoelectric ceramic microarray, with output force F and voltage V satisfying a quadratic relationship:

$$F=\eta\cdot V^2 \tag{10}$$

In formula (10), η is the force–voltage conversion coefficient, and the control signal is converted into a 0–10 V driving voltage via a high-voltage amplifier.

Initial values for the PID gain coefficients are set to K_p= 0.15, K_i= 0.05, and K_d= 0.08, determined via a Ziegler–Nichols tuning process on a representative user dataset to achieve a stable baseline response. A fuzzy PID controller is deployed on the FPGA platform, and the error $e(t)$ is divided into five fuzzy sets: negative large, negative small, zero, positive small, and positive large. The gain coefficients are dynamically adjusted through the rule base to suppress overshoot: if $e(t)$ is negative large, K_p increases by 30% and K_d decreases by 20%; if $e(t)$ is positive large, K_p decreases by 20% and K_d increases by 40%. During operation, the sampling period is set to 10 ms, and the tactile vibration intensity adjustment response time and audio frequency band adjustment delay are optimized.

This strategy maintains user immersion above the target threshold, and features dynamic response characteristics that establish an interactive foundation with adjustable parameters for the subsequent red cultural scene narrative framework, enabling real-time responses to users' emotional states and aiming to maximize emotional resonance and educational effectiveness.

Construction of the Narrative Framework for Red Cultural Scenes

By constructing a narrative framework for red cultural scenes, multimodal stimulation and historical context are deeply integrated. The system is built around two core narratives: *Battlefield Rescue*—users wear a tactile military uniform that simulates coarse cotton fabric to experience the physical hardships faced by medics. As they perform virtual rescue tasks, synchronized auditory cues (such as gunfire, wind) and visual scenes are triggered, while the fabric provides dynamic resistance to simulate movement in heavy clothing. *Material Transportation*—users handle a tactile blanket that simulates a coarse wool texture to reenact the transportation of supplies. The system uses users' EEG/EDA-derived immersion levels to dynamically adjust tactile intensity, increasing resistance to reflect growing fatigue, thereby deepening emotional resonance with the historical context. The military uniform's coarse cloth simulation fabric is woven with a twill structure, and the warp and weft yarn buckling wave height h and surface roughness R_a conform to the empirical formula:

$$R_a = \frac{h}{2}(1 - \cos\theta) \tag{11}$$

By controlling the twist of the weft yarn and adjusting the tension of the warp yarn, h, the surface friction coefficient is made close to the measured value of cotton military uniforms from the 1940s, aiming to accurately restore the material conditions of the revolutionary historical period and enhance users' perception of historical authenticity. Thermochromic fibers are embedded on the fabric surface, and the relationship between their resistance R and driving current is:

$$R = \rho_0[1 + \alpha(T - T_0)] \tag{12}$$

In formula (12), ρ_0 is the reference resistivity, and T_0 is the initial temperature. When users touch the fabric, the current pulse triggers a local temperature increase, causing the fiber to change from blue (cold state) to red (hot state), dynamically displaying red cultural and historical information.

The double-layer woven structure integrates conductive polymer composite fibers and piezoelectric ceramic microunits. The upper layer is responsible for tactile feedback, and the lower layer carries AR projection markers. Finite element analysis is used to optimize fiber spacing so that the vibration energy density E_v satisfies:

$$E_v = \frac{1}{2}\rho v^2 A \omega^2 \xi^2 \tag{13}$$

In formula (13), ρ is the fiber density; v is the speed of sound; A is the cross-sectional area; ω is the angular frequency; ξ is the strain amplitude. For example, in the "battlefield rescue" scenario, when users simulate bandaging actions, the system triggers local vibration and synchronously projects the bandage-winding animation, enhancing the consistency of operational perception and deepening understanding and empathy for the hardships of wartime rescue.

Through the collaborative innovation of twill weave structure design, thermochromic fiber integration, and double-layer weaving processes, this framework transforms the physical properties of textile materials narrative elements that convey historical context narrative elements, providing a quantifiable scenario-based interaction benchmark for the subsequent comprehensive verification of the integration of technical performance and educational effects [14,15].

EXPERIMENTAL DESIGN AND VERIFICATION

The experiment focuses on performance verification and immersive experience modeling of a multimodal interactive system designed to disseminate red culture. Conductive polymer composite fiber tactile feedback fabric serves as the core interactive medium. The comparison group includes traditional Piezoelectric Motor Fabric (PMF), Shape Memory Alloy Fabric (SMAF), and pneumatic microfluidic fabric, which controls deformation through microfluidic channels. The user study involved 100 participants: 40 college students (aged 18–25), 40 high school students (aged 15–17), and 40 middle-aged adults (aged 40–55). This diverse cohort ensures broad demographic representation across different age groups and educational levels, enhancing the generalizability of the findings. The study was approved by the Ethics Committee of Jiangxi Technical College of Manufacturing, and all participants provided informed consent prior to participation.

Experimental equipment includes a laser profilometer to measure fabric surface deformation, a high-speed camera to record cross-modal signal delay, a flexible Ag/AgCl electrode fabric to collect EEG/EDA data, and an FPGA platform to run the cross-modal synchronization algorithm and dynamic optimization strategy.

The experimental process is divided into three phases: material performance testing, system stability verification, and user immersion evaluation. The mechanical durability of the fabric is assessed through cyclic stretching, while bending stiffness is measured according to the ASTM D1388-18 standard, using a 200 mm spline length and a loading rate of 100 mm/min. The voltage gradient is controlled, and fiber deformation error rates are quantified using a laser profiler. Two types of red cultural scenes-- “battlefield rescue” and “material transportation”—are established. Participants wear augmented reality (AR) headsets and physiological signal collection electrodes. The system automatically records interaction duration, gesture trajectories, and EEG/EDA data. EEG and EDA signals are sampled at 250 Hz and 100 Hz, respectively. The EEG signal is filtered using a 4th-order Butterworth bandpass filter (0.5–45 Hz), while the EDA signal is processed with a low-pass filter (<5 Hz). Features are extracted using a 3-second sliding window. After each task, participants complete a structured questionnaire based on a 5-point Likert scale. The questionnaire is designed to measure key dimensions of the user experience in red cultural education, including sense of presence, emotional resonance, value identification, learning interest, and overall satisfaction, providing subjective feedback to evaluate the system’s effectiveness.

Model training is based on a self-constructed red culture interactive task dataset containing multiple sets of synchronized tactile, visual, and auditory event labels. After data preprocessing, the input to the LSTM network is a fused feature vector comprising EEG wave power and the derivative of EDA signals. The output layer classifies five levels of immersion using a Softmax classifier. Training parameters are set as follows: batch size = 32, learning rate = 0.001, optimizer = Adam, and a loss function that balances sample distribution by combining cross-entropy and focal loss. Finally, the Pearson correlation coefficient between users’ subjective questionnaire scores and the predicted physiological values is used as the convergence criterion. Analysis reveals a strong Pearson correlation ($r = 0.83$, $p < 0.01$) between subjective reports and physiological predictions, indicating high alignment. Discrepancies observed in moderate immersion states suggest that the physiological model captures subconscious engagement that may be underreported in self-assessments. The system model parameter initialization is presented in Table 1.

Table 1. Parameter Initialization Table

Parameter Name	Initial Value
Number of LSTM Hidden Units	128 (per layer)
Learning Rate	0.001
Batch Size	32
Optimizer	Adam

Loss Function Weight (λ)	0.8
Hidden Layer Activation Function	ReLU
Output Layer Activation Function	Softmax
Dropout Rate	0.3
Number of Training Rounds	100

This study examines on the performance and immersive experience of multimodal fabric interactive systems and by designing five core evaluation indicators: physical perception accuracy, cross-modal collaboration efficiency, immersive experience modeling capability, user behavior effectiveness, and textile material stability. This indicator system establishes a multidimensional verification framework encompassing the physical properties of textile materials, system control accuracy, physiological signal modeling, and user behavior feedback, thereby ensuring that the experimental results are directly relevant to the requirements of red culture communication scenarios.

This study was approved by the Institutional Review Board (IRB). All participants provided written informed consent after being fully informed about the purpose of the research, the data collection process, and their right to withdraw at any time. All physiological data (EEG/EDA) were anonymized immediately upon collection and stored on a secure, encrypted server. The data were used solely for research purposes and will be deleted upon completion of the study, in strict adherence to ethical guidelines.

SYSTEM PERFORMANCE EVALUATION AND IMMERSIVE EXPERIENCE VERIFICATION

Tactile Texture Simulation Error Evaluation

To evaluate the capability of conductive polymer composite fiber tactile feedback fabric in replicating physical features, this section quantitatively measures the simulation error rate of four representative red cultural texture materials using a laser profilometer. The results are compared with those obtained from traditional piezoelectric motors, shape memory alloys, and pneumatic microfluidic systems. All comparison groups were tested under identical conditions: a driving voltage of 5 V at 20 Hz for piezoelectric motors, a current of 0.5 A at 1 Hz for shape memory alloys, and an air pressure of 80 kPa at 0.5 Hz for pneumatic microfluidics, ensuring a fair and reproducible comparison. The comparison results are shown in Figure 2.

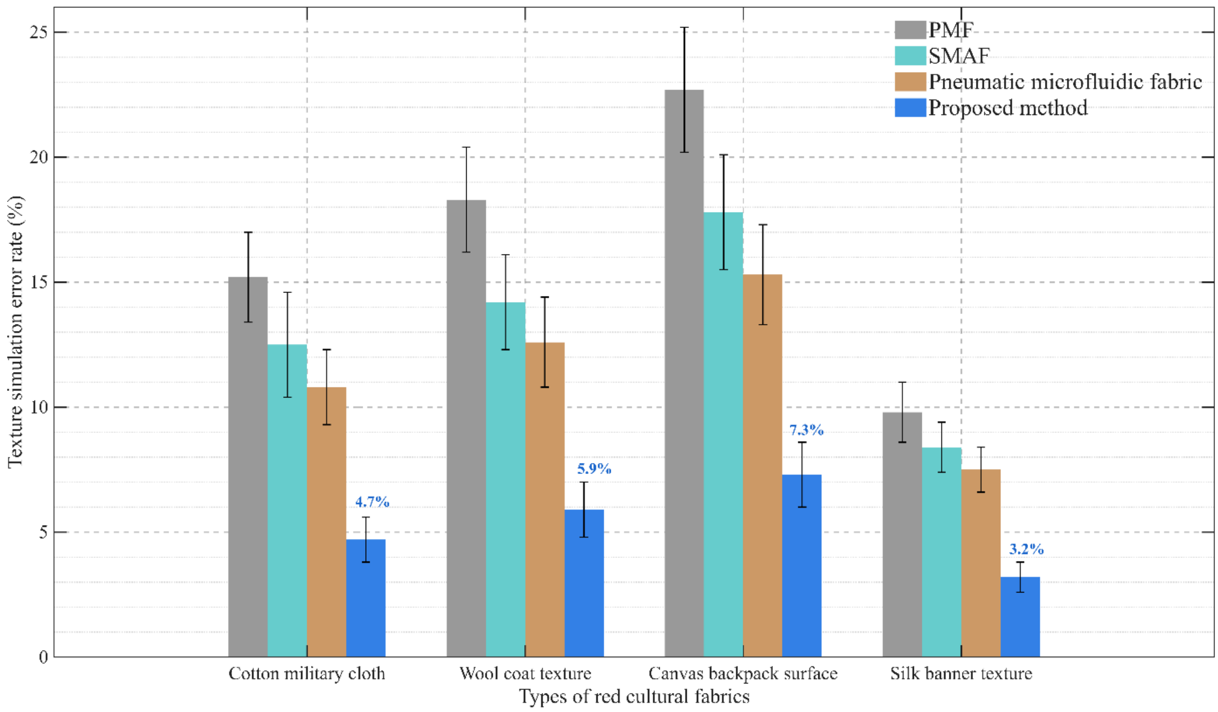

Figure 2. Comparison of tactile texture simulation errors of multiple materials

Figure 2 shows four typical red culture texture materials on the horizontal axis and quantifies tactile simulation error on the vertical axis. The error of traditional piezoelectric motor fabrics on cotton military uniforms is 15.2%, rising to 22.7% on canvas backpacks; this solution achieves a breakthrough reduction, with only 4.7% on cotton military uniforms—a reduction of 10.5 percentage points—and 7.3% on canvas backpacks, a reduction of 15.4 percentage points. This step-by-step decline reveals that this solution achieves ultra-high-precision tactile restoration—less than 5% on the iconic red cotton fabric of military uniforms—through the coordinated design of conductive polymer composite fibers and piezoelectric ceramic microunits. The standard deviation of ±0.9 verifies technical stability.

Cross-Modal Synchronization Delay Test

To address the asynchronous issues in multimodal signal coordination, this section evaluates the optimization effect of the Transformer-FPGA architecture on visual–tactile–auditory cross-modal synchronization delay using high-precision timing measurements. The experiment employs a laser profiler and a high-speed camera system to compare the delay timing data of four technical solutions in a battlefield rescue scenario. The comparison results are shown in Figure 3.

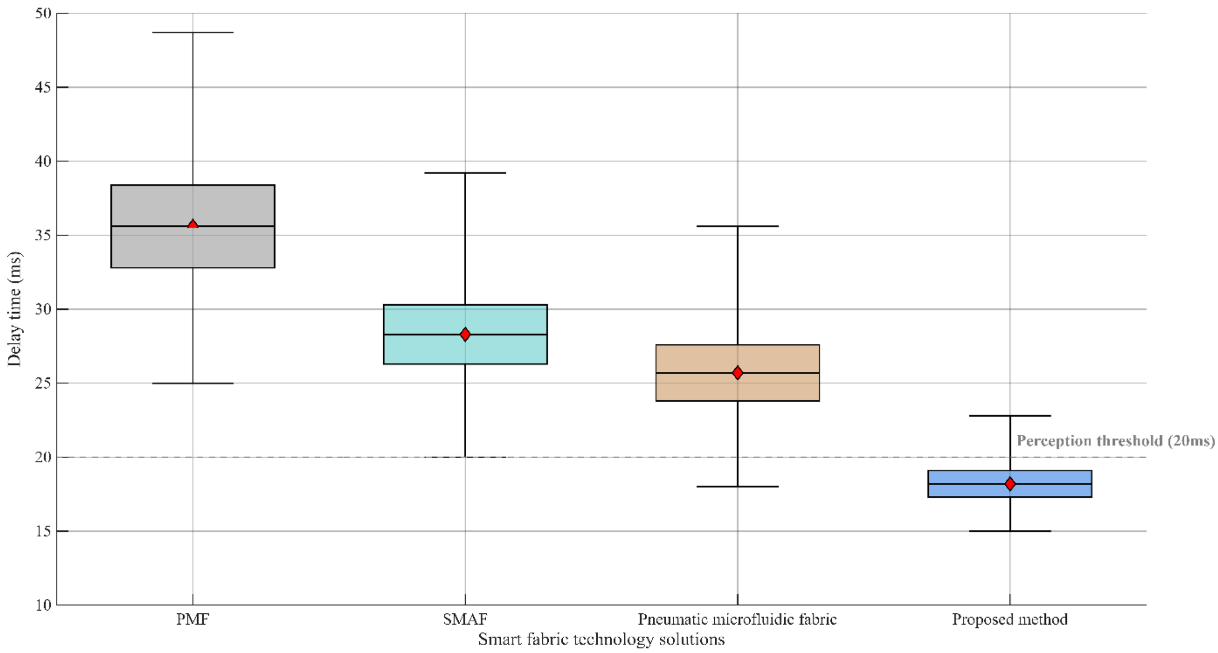

Figure 3. Comparison of cross-modal synchronization delay performance

Figure 3 presents a comparison of cross-modal synchronization delay performance across four smart fabric technology solutions. The data show that the traditional PMF solution exhibits the widest delay range, with values spanning 32.8 to 38.4 ms, a box plot range of 32.8–38.4 ms, and a median delay of 35.6 ms; the SMAF solution has a delay range of 20.0–39.2 ms, a box plot range of 26.3–30.3 ms, and a median of 28.3 ms; the microfluidic solution is further optimized, with delays ranging from 18.0 to 18.0–35.6 ms, a box plot range of 23.8–27.6 ms; and this solution compresses the delay range to 15.0–22.8 ms, with a box plot range of only 17.3–19.1 ms, and a median of 18.2 ms. The gray dotted line indicates the 20-ms perception threshold.

Data trend analysis reveals significant improvements: the median delay decreases from 35.6 ms with the traditional PMF to 18.2 ms with this solution, a reduction of 49%; the box height decreases from 5.6 ms to 1.8 ms, indicating reduced delay volatility; the maximum value drops from 48.7 ms to 22.8 ms, demonstrating that extreme delay scenarios have been effectively mitigated. These changes confirm the effectiveness of the Transformer-FPGA architecture: through coordinated optimization of the timing alignment model and hardware acceleration, the median delay is controlled at 18.2 ms, achieving millisecond-level stability and providing essential technical guarantees for a multimodal immersive experience.

Verification of the Accuracy of the Immersion Prediction Model

To address the dynamic regulation requirements of immersive experiences, this section develops an accuracy verification system for the LSTM immersion prediction model based on dual-modal physiological signals, including EEG and EDA. Each participant completed the “battlefield rescue” task five times at varying difficulty levels, generating five time-series data segments per person. A total of 500 segments were labeled by experts into five immersion levels (100 segments per level). For model training, the dataset was split using five-fold cross-validation, incorporating repeated measures to account for intra-subject correlation. In the battlefield rescue scenario, physiological signal data from 100 subjects are collected and input into a two-layer LSTM network for five-level immersion state classification, with 100 samples per level. The results of the confusion matrix analysis are shown in Figure 4.

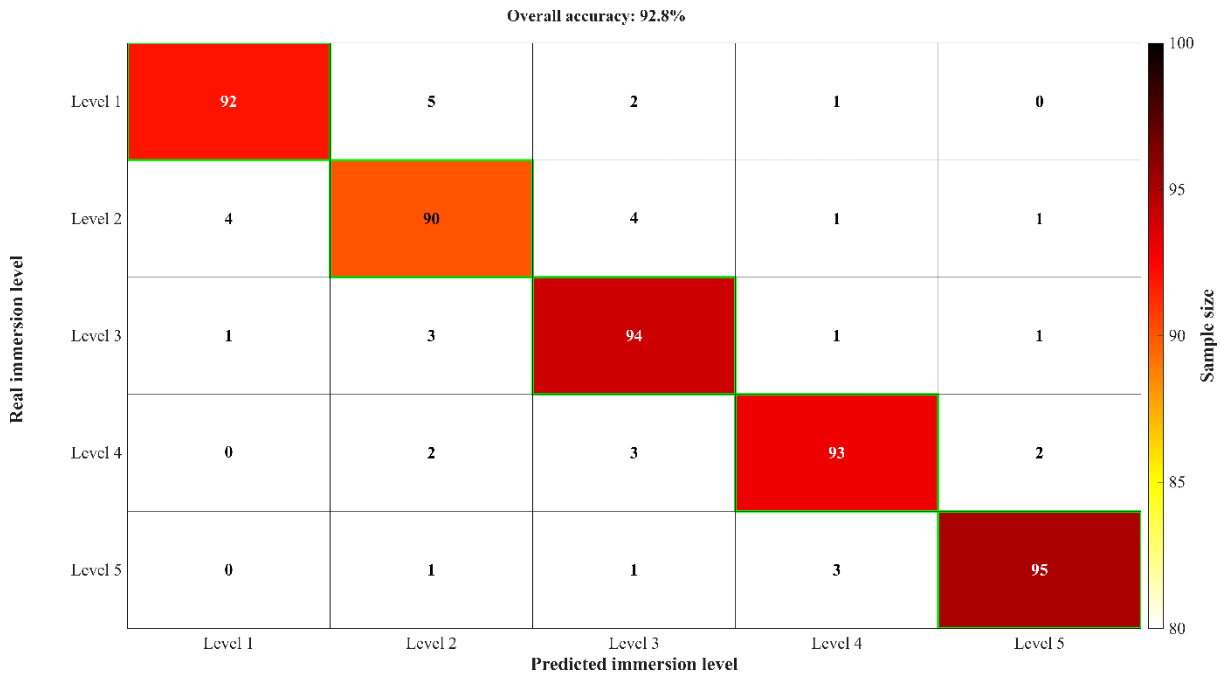

Figure 4. Confusion matrix for immersion prediction

Figure 4 illustrates the prediction performance of the LSTM model for user immersion. The horizontal axis represents the immersion levels predicted by the model, while the vertical axis corresponds to the actual immersion levels, and each cell displays the number of prediction samples. The data distribution shows a prominent concentration of correct predictions along the diagonal , with level 5 exhibiting the highest accuracy. Misclassifications primarily occur between adjacent levels. This pattern indicates that the model is more precise in identifying high immersion states, with some confusion occurring at moderate states (levels 2–3). The overall prediction accuracy reaches 92.8%, confirming that the EEG+EDA dual-signal fusion model effectively captures deep immersion states.

To evaluate the contribution of multimodal fusion, the EEG+EDA fusion model was compared with three baselines: (1) EEG-only, (2) EDA-only, and (3) the average of users' self-reported immersion scores. The comparison results are shown in Table 2.

Table 2. Comparison of Immersion Prediction Fusion Model and Baseline Models

Prediction Model	Accuracy (%)	Standard Deviation (SD)
EEG + EDA (Proposed)	92.8	0.04
EEG-only	85.3	0.08
EDA-only	82.1	0.09
User Self-Report (Average)	78.6	0.15

Table 2 shows that the EEG+EDA fusion model achieved the highest overall prediction accuracy of 92.8%. The EEG-only and EDA-only models achieved 85.3% and 82.1%, respectively, demonstrating the complementarity of the two signals. Notably, the predictions of the fusion model are significantly more stable (SD = 0.04) than self-report scores (SD = 0.15), which are susceptible to cognitive bias. This confirms that the proposed fusion method can more accurately and reliably measure user immersion.

User Interaction Behavior Data Analysis

As a key metric for evaluating the effectiveness of the multimodal fabric interactive system, the analysis of user interaction behavior data focuses on quantitatively representing operational continuity and exploration depth within red cultural scenes. By tracking users' dwell time, task completion rate, frequency of repeated operational , and EEG signal concentration during system use, the system's capacity to drive behavior in the physical–digital fusion narrative is validated. Data results for different schemes are shown in Figure 5.

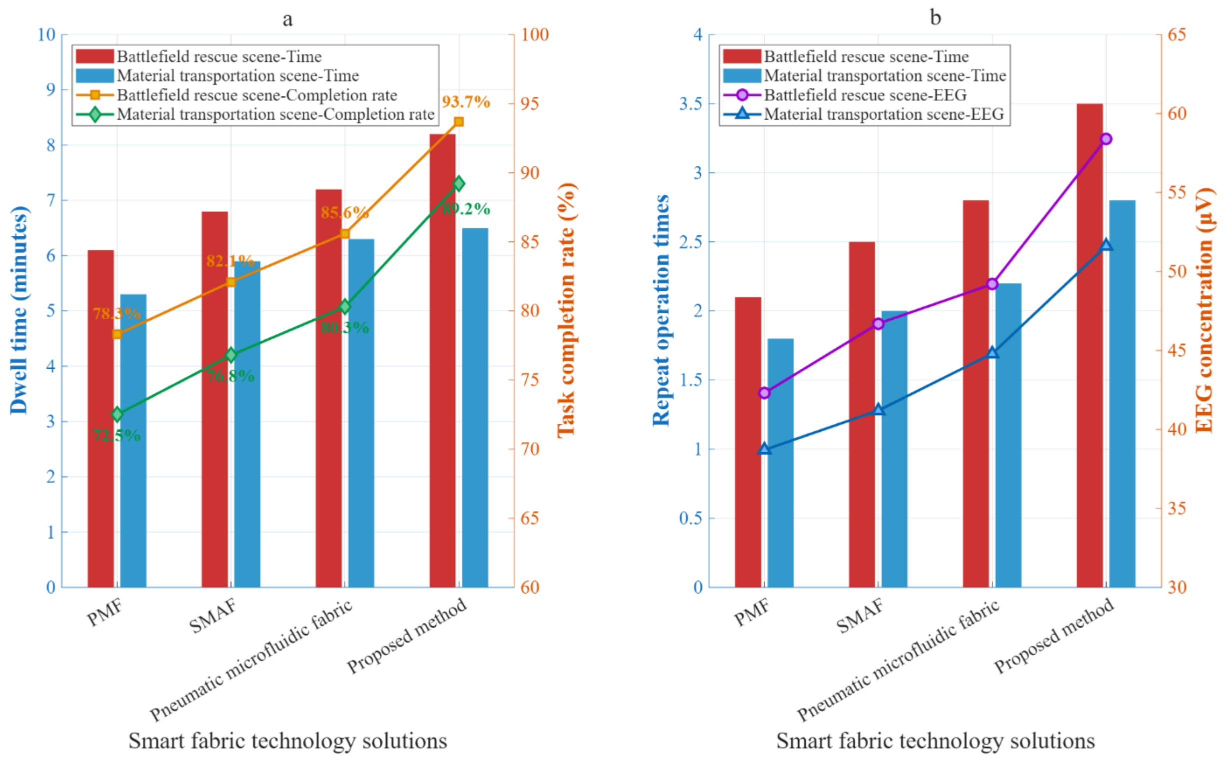

Figure 5. Analysis of user interaction behavior under different schemes. a Dwell time and task completion rate, b Operational frequency and neurophysiological response

Figure 5 systematically illustrates the intrinsic correlation between user interaction behavior and physiological responses across different solutions. The horizontal axis of sub-figure a compares four technical solutions; the left vertical axis quantifies dwell time, while the right vertical axis indicates task completion rate. In the battlefield rescue scenario, this solution achieves the longest dwell time and the highest task completion rate, which are 34% and 15.4 percentage points higher than those of the traditional PMF, respectively. The left vertical axis of sub-figure b records operational frequency, and the right vertical axis measures EEG concentration. The data highlight that this solution triggers the most frequent operations and the strongest neural responses in battlefield rescue scenarios. This cross-indicator consistency demonstrates that the multimodal interaction system enhances task completion efficiency and neural engagement by increasing user participation and operational depth. In the material transportation scenario, this solution also provides significant advantages: user dwell time reaches 6.5 minutes, task completion rate is 89.2% (a 16.7 percentage-point increase over PMF), and repeated operations average 2.8 times. EEG concentration increases to 51.6 μV, a 33.3% increase over PMF. These results show that the multimodal interaction system is effective in both narrative and task-oriented scenarios, enhancing users' operational concentration and execution efficiency through tactile–visual collaborative feedback.

Fabric Durability Test

Fabric durability directly influences its long-term suitability for in red culture education. This study evaluates the mechanical stability and conductive durability of the conductive polymer composite fiber tactile feedback fabric through 5,000 cycles of tensile testing, focusing on the rate of resistance change and the attenuation rate of bending stiffness. The results are shown in Figure 6.

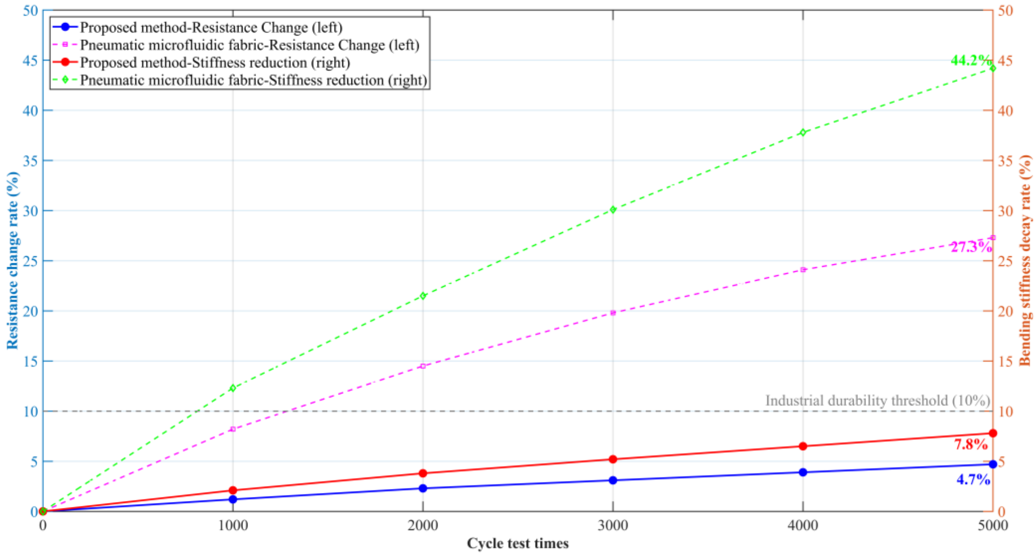

Figure 6. Durability comparison of fabrics in different schemes

Figure 6 compares the durability of this solution with that of microfluidic fabric after 5,000 cycles of tensile testing. The horizontal axis represents the number of cycles, the left vertical axis shows the resistance change rate, and the right vertical axis indicates the bending stiffness attenuation rate. The resistance change rate of this solution remains below 5%, reaching only 4.7% after 5,000 cycles, compared to 27.3% for microfluidic fabric; the bending stiffness attenuation rate is 7.8% after 5,000 cycles, significantly lower than the 44.2% observed for microfluidic fabric. The gray dotted line represents the industrial durability threshold, and both indicators for this solution remain consistently below this threshold. These data demonstrate that the coordinated design of conductive polymer composite fibers and piezoelectric ceramic microunits effectively enhances mechanical stability and conductive durability in high-frequency interaction scenarios, maintaining performance attenuation below 10% after 5,000 cycles and meeting the engineering requirements for long-term use in red cultural education.

Evaluation of the Effectiveness of Red Education

To quantify the system's effectiveness in red culture education, this section analyzes its impact on presence, emotional resonance, value identification, learning interest, and satisfaction based on users' subjective questionnaire feedback after "battlefield rescue" and "material transportation" tasks. Results are compared with the traditional PMF solution, using a Likert 5-point scale (full score: 5). The comparison results are shown in Table 3.

Table 3. Comparison of Subjective Evaluation of Red Education Effectiveness

Evaluation Dimension	This Solution	Traditional PMF Solution	Improvement
Presence	4.32 ± 0.51	3.21 ± 0.67	+34.6%
Emotional Resonance	4.48 ± 0.42	3.05 ± 0.73	+46.9%
Value Recognition	4.25 ± 0.49	3.17 ± 0.70	+34.1%
Study Interest	4.18 ± 0.54	3.33 ± 0.62	+25.5%
System Satisfaction	4.36 ± 0.47	3.28 ± 0.65	+32.9%

The data in Table 3 clearly demonstrate that this solution excels at stimulating users' emotional resonance and value identification, while also enhancing presence, learning interest, and overall satisfaction. This confirms the advantages of the system design in achieving the core objectives of red cultural education—promoting users' deep understanding, emotional engagement, and value recognition. Additionally, the longer dwell time and higher operation frequency observed in user behavior data further indicate its stronger appeal and deeper user participation from an objective behavioral perspective.

CONCLUSION

Focusing on the needs of red network education, this paper presents an intelligent fabric interaction system that integrates high-precision tactile feedback, multimodal signal coordination, and physiologically driven immersive modeling. Through the collaborative innovation of conductive polymer composite fibers and piezoelectric ceramic microunits, the system achieves ultra-high-precision tactile restoration of key physical features from revolutionary historical scenes, enhancing users' embodied perception of historical authenticity. The cross-modal synchronization algorithm, based on a Transformer-FPGA architecture, effectively addresses sensory signal asynchrony, maintaining a median delay of 18.2 ms. The immersion prediction model and dynamic optimization strategy, which integrate flexible electrodes and LSTM networks, enable the system to perceive users' emotional states in real time and adaptively adjust interaction parameters, thereby sustaining deep engagement and emotional investment. Experimental results demonstrate that users exhibit longer dwell times and a greater willingness to repeat tasks in typical red narrative scenarios. innovations at three levels—materials, algorithms, and modeling—this study not only overcomes technical bottlenecks in red education but also establishes an immersive interaction paradigm that effectively fosters users' emotional resonance and identification with the revolutionary spirit. A limitation of this study is the lack of diversity in the experimental user group. Future work focusing on optimizing electrode biocompatibility and incorporating federated learning will help expand the application of intelligent textiles in disseminating red culture.

Author Contributions

Conceptualization – Mengni Zhou; methodology – Mengni Zhou and Yi Zhou; investigation – Yi Zhou; writing-original draft preparation – Mengni Zhou and Yi Zhou. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Human Research Subjects

This study was approved by the Ethics Committee of Jiangxi Technical College of Manufacturing. All participants provided informed consent before the study.

Acknowledgements

Not applicable.

REFERENCES

[1] Xiang S, Chen G, Wen Q, Li H, Luo, X, Zhong J, et al. Fully addressable textile sensor array for self-powered haptic interfacing. Matter. 2024; 7(1):82-94. doi: 10.1016/j.matt.2023.10.024

[2] Xu Y, Huang L, Zhao T, Fang Y, Lin L. A timestamp-independent haptic–visual synchronization method for haptic-based interaction system. Sensors. 2022; 22(15):5502. doi: 10.3390/s22155502

[3] Jeong J, Kang M, Song Y, Pyo S. Interactive Haptic System with Multimodal Tactile Sensing and Hydraulic Feedback for Realistic Human–Machine Interaction. Advanced Intelligent Systems. 2025; 7(5):2400578. doi: 10.1002/aisy.202400578

[4] Castiblanco Jimenez IA, Olivetti EC, Vezzetti E, Moos S, Celeghin A, Marcolin F. Effective affective EEG-based indicators in emotion-evoking VR environments: An evidence from machine learning. Neural Computing and Applications. 2024; 36(35):22245-22263. doi: 10.1007/s00521-024-10240-z

[5] Ronca V, Ricci A, Capotorto R, Di Donato L, Freda D, Pirozzi M, et al. How Immersed Are You? State of the Art of the Neurophysiological Characterization of Embodiment in Mixed Reality for Out-of-the-Lab Applications. Applied Sciences. 2024; 14(18): 8192. doi: 10.3390/app14188192

[6] Li X, Deng X, Xu H. Interactive cultural communication effect in VR space of intelligent mobile communication network. Wireless Communications and Mobile Computing. 2022; 2022(1):9689272. doi: 10.1155/2022/9689272

[7] Yi J, Tian Y, Zhao Y. Design of red culture retrieval system based on multimodal data fusion and innovation

of communication strategy path. IEEE Access. 2023; 11:134118-134125. doi: 10.1109/ACCESS.2023.3336419

[8] Wang J. Evaluation and promotion of social influence of red culture based on big data of the internet of things. Journal of Computational Methods in Sciences and Engineering. 2025; 25(2):1880-1893. doi: 10.1177/14727978241306452

[9] Tan J, Shao L, Lam NYK, Toomey A, Ge L. Intelligent textiles: designing a gesture-controlled illuminated textile based on computer vision. Textile Research Journal. 2022; 92(17-18):3034-3048. doi: 10.1177/00405175211034245

[10] Liu H, Shi Y, Pan Y, Wang Z, Wang B. Sensory interactive fibers and textiles. NPJ Flexible Electronics. 2025; 9(1):23. doi: 10.1038/s41528-025-00398-4

[11] Wang Z, Liu Y, Zhou Z, Chen P, Peng H. Towards integrated textile display systems. Nature Reviews Electrical Engineering. 2024; 1(7):466-477. doi: 10.1038/s44287-024-00063-4

[12] Hwang YH, Kwon S, Shin JB, Kim H, Son YH, Lee HS, et al. Bright-multicolor, highly efficient, and addressable phosphorescent organic light-emitting fibers: toward wearable textile information displays. Advanced Functional Materials. 2021; 31(18):2009336. doi: 10.1002/adfm.202009336

[13] Song Y, Li M, Wang F, Lv S. Contact pattern recognition of a flexible tactile sensor based on the CNN-LSTM fusion algorithm. Micromachines. 2022; 13(7):1053. doi: 10.3390/mi13071053

[14] Li P, Sun Z, Wang R, Gong Y, Zhou Y, Wang Y, et al. Flexible thermochromic fabrics enabling dynamic colored display. Frontiers of Optoelectronics. 2022; 15(1):40. doi: 10.1007/s12200-022-00042-3

[15] Guennes M, Cunha J, Cabral I. Smart Textile Design: A Systematic Review of Materials and Technologies for Textile Interaction and User Experience Evaluation Methods. Technologies. 2025; 13(6):251. doi: 10.3390/technologies13060251