https://doi.org/10.1038/s40494-026-02425-7

Digital rebirth: how task-technology fit drive immersion and user engagement in intangible cultural heritage VR

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With the growing adoption of virtual reality (VR) technologies in Intangible Cultural Heritage (ICH) dissemination. This study integrates the Task–Technology Fit (TTF) model and the Hedonic-Motivation System Adoption Model (HMSAM) to propose a holistic framework for analyzing immersion (IM) and behavioral intention (BI) in VR-ICH experiences. Data from the VR Dunhuang cultural experience involving 387 participants were analyzed using a hybrid methodology combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN). The results demonstrate that both task characteristics and technology characteristics significantly influence hedonic motivation through perceived ease of use, with joy and control emerging as the strongest predictors of IM and BI. These findings underscore the interplay between task design, technology integration, and emotional engagement, offering theoretical and practical guidance for designing immersive and sustainable VR heritage experiences that enhance public participation and support the sustainable transmission of cultural heritage.

As an emerging digital media format, virtual reality (VR) technology is rapidly permeating multiple fields, such as education, entertainment, healthcare, and cultural heritage preservation worldwide due to its immersive, interactive, and imaginative characteristics[1,2]. Within the context of Intangible Cultural Heritage (ICH) dissemination, VR technology can transcend temporal and spatial constraints, enabling users to immerse themselves in the essence of traditional culture as if they were physically present. For instance, the Louvre Museum's virtual exhibitions in France, the digital recreation of China's Mogao Caves in Dunhuang, the British Museum's immersive experiences in the UK, and the virtual reconstruction of Pompeii in Italy[3–5] These projects present cultural heritage to modern audiences—particularly younger generations—in vivid, intuitive, and interactive ways[6,7], highlighting VR technology's significant advantages and emerging applications in dynamically documenting cultural heritage, enhancing user identity recognition, and boosting gamified engagement.

ICH is an important carrier of human civilization and a vivid embodiment of cultural diversity, possessing profound historical significance and unique cultural value. The United Nations Educational, Scientific and Cultural Organization (UNESCO) defines it as practices, expressions, knowledge, and skills that communities, groups, and individuals recognize as part of their cultural heritage. However, there exists a significant gap between traditional cultural dissemination methods and the digital, interactive, and personalized information consumption patterns favored by young people[8]. These challenges not only affect the effectiveness of ICH transmission, but also concern the survival, development, and creative transformation of traditional culture in modern society. Therefore, how to effectively leverage emerging digital technologies, particularly immersive VR technology, to innovate ICH dissemination models, enhance user engagement, and promote cultural understanding has become an urgent issue in the field of cultural heritage preservation[9].

In recent years, the academic community has paid close attention to the application of VR technology in the field of cultural heritage. Related research has primarily focused on technical implementation, system design, and the evaluation of application effectiveness. The early studies predominantly employed established theories, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain users' acceptance levels of VR cultural heritage systems. These studies focused on elucidating the influence of factors like perceived usefulness and perceived ease of use on users' willingness to adopt the technology[10,11]. While these models can explain basic technology adoption behaviors, but it is often difficult to delve into the underlying mechanisms of task adaptation and intrinsic motivation within immersive experiences. Furthermore, few studies explore how to enhance the immersion and sustained engagement in VR experiences of ICH from a

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comprehensive perspective that integrates information systems and user behavioral motivations, thereby providing theoretical guidance and optimization recommendations for industry practice.

However, there are still significant theoretical gaps and insufficient empirical evidence in the existing research. (1) Most of the existing literature adopts a single theoretical model to explain user behavior in VR cultural heritage experiences, lacking the organic integration of different theoretical frameworks, such as TTF[12,13] and HMSAM[14–16]. (2) In terms of data analysis techniques, most studies rely solely on PLS to validate linear relationships, overlooking potential nonlinear characteristics in user behavioral decision-making. They lack a hybrid analytical perspective integrating PLS-SEM with artificial neural networks (ANN), thereby limiting the robustness of research conclusions and predictive validity. (3) Although existing studies have focused on users' acceptance of VR cultural heritage systems, there is a lack of in-depth theoretical explanations and empirical verifications for the deep psychological mechanisms of users during the VR-ICH experience process, especially the formation mechanism of immersion and its influence path on behavioral intentions[17,18]; (4) Most of the existing research focuses on the general application of VR-ICH. There is still a lack of targeted theoretical analysis and empirical research on how the dynamic, performative and interactive characteristics of ICH, a special cultural form, affect users' VR experience[19]. However, whether these influences are mediated by factors, such as hedonic motivation and immersion, along with their specific pathways and mechanisms, remains unclear and requires further conceptualization and empirical evidence[20].

This study constructs a theoretical framework by integrating Task-Technology Fit (TTF) theory and the Hedonic Motivation System Adoption Model (HMSAM)[14]. It approaches VR platforms for ICH from their fundamental nature as complex information systems featuring multi-dimensional interactions, encompassing technological applications, multiculturalism, human behavior, and social entertainment. TTF emphasizes that the degree of alignment between technical capabilities and task requirements in VR systems plays a decisive role in user experience and satisfaction. while HMSAM highlights that intrinsic motivations (such as curiosity (CUR), joy (JOY), control (CON)) within the hedonistic system exert a critical influence on immersive experiences and user behavior[15,16]. Moreover, to further explore potential nonlinear characteristics in user behavioral decision-making, this study employs a mixed-methods approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) with ANN, thereby enhancing the robustness and predictive validity of research conclusions. Accordingly, this study aims to address the following core questions:

RQ1: How do TEC and TC drive differentiation in users' VR-ICH experiences?

RQ2: How do these key variables influence users' immersion and behavioral intentions toward VR-ICH experiences?

RQ3: Compared to traditional SEM models, how does the ANN model reevaluate the ranking of variable influences, and what implications does it offer for VR-ICH?

In summary, this study employed a hypothetical-deductive approach by constructing an integrated TTF–HMSAM model. This model positions task characteristics, technological features, and perceived ease of use as antecedents, with four hedonic motivations—curiosity, joy, control, and perceived usefulness—as mediators, ultimately influencing immersion and behavioral intention. This framework also incorporates the direct effect of immersion on behavioral intention, overcoming the limitations of traditional technology acceptance theory that often overlooks emotionally driven factors. It reveals how task-technology fit promotes sustained engagement by stimulating key hedonic motivations. This offers a more comprehensive perspective for understanding user behavior in VR cultural heritage contexts. Subsequently, the study employed partial least squares structural equation modeling (PLS-SEM) and ANN to empirically validate data from 387 VR participants.

The rest of this paper is organized as follows: Section 2 contains the literature review and research hypotheses; Section 3 covers the research methodology; Section 4 presents the empirical results; Section 5 includes the discussion; and Section 6 presents the conclusions.

Methods

VR and the dissemination of ICH

VR technology features three core attributes: immersion, interactivity, and imagination[21]. In the transmission of ICH, VR overcomes temporal and spatial barriers. It allows users to engage with traditional cultural elements as if present in the original setting. Current VR applications in ICH have evolved into diverse models. These can be classified by ICH type and technical approach. Existing implementations highlight the importance of high immersion for recreating intricate cultural contexts. For example, traditional rituals and performances are digitally reconstructed using immersive scene modeling, character animation, and spatial audio. One notable case is the virtual museum for Hong Kong's Chaozhou Hungry Ghost Festival. This project extends beyond static exhibits. It combines 360-degree panoramic videos with 3D spatial reconstruction to create a highly immersive environment. The design captures the festival's cultural depth across multiple dimensions. It also fosters public interest by enhancing users' sense of presence and incorporating local narratives[22]. Similarly, the El-FnaVR project restores Morocco's Jemaa el-Fna Square. It tackles the limitations of two-dimensional media in conveying spatial atmosphere. Through precise character animation and spatial audio[23], the system boosts immersion and elicits stronger emotional responses during user evaluations. In ICH projects focused on museum collections and skill transmission, task designs emphasize interactivity and user agency. The Han Embroidery Digital Museum illustrates this shift. It moves past simple artifact viewing by employing 3D modeling to break down intricate production processes. Users can explore details at their own pace. This approach highlights artisanal precision while fostering cultural pride and engagement. For ICH involving dance, the Tujia Hand-Waving Drum Dance VR system uses motion capture to build a virtual stage[24]. This highly interactive task design provides a viable technical pathway for achieving in-depth transmission of ICH knowledge and transforming behavioral intentions[25].

The application of VR in ICH has shown a significant shift from "passive viewing" to "active participation" in interactive experience design, redefining the dissemination model of traditional culture through diversified interaction methods. With regard to immersive narrative experiences, the potential of VR technology is such that it has the capacity to transform static cultural displays into dynamic story scenes. Users have the capacity to act as participants and thereby "return" to historical sites. The integration of 360-degree videos and interactive scenes has been demonstrated to significantly enhance the sense of presence and emotional engagement[26,27]. With regard to physical interaction experiences, the utilization of gesture recognition and motion capture technologies empowers users to acquire traditional skills through natural body movements. This encompasses the process of retrieving bodily memory by simulating weaving gestures or dance movements. It has been demonstrated that this mode of physical interaction is more conducive to the acquisition of skills and the cultivation of cultural understanding than conventional button-based operations[28,29]. In terms of gamified learning experiences, through mechanisms, such as task-driven design, point rewards, and character guidance, abstract cultural knowledge is transformed into an operable "level-clearing" experience, effectively stimulating users' exploratory motivation and learning interest[30,31]. In terms of social interaction experiences, the multi-user collaboration function has reconstructed the "co-learning" environment in traditional culture. Users can complete cultural tasks or participate in virtual performances together with others, enhancing the social attributes of cultural inheritance[32]. Although research on the dissemination of ICH through VR has established a relatively mature theoretical foundation and practical framework, in-depth analysis reveals significant disparities in the developmental emphasis and integration levels across different research dimensions. Table 1 summarizes representative studies in these areas and their key

Table 1 | Research and Findings on Virtual Reality and Intangible Cultural Heritage in Different Aspects

Aspect	Reference	Key Findings
Virtual Museum Display Methods	Chan & Cai (2023)[22]	Improved museum interactivity and presentation.
	El khalfaoui et al. [23]	3D stitching system enhances immersion.
	Cunha (2022)[72]	VR strengthens emotional connection with culture.
Image Communication and Exhibition Design	Liu (2023)[20]	VR storytelling promotes ICH transformation.
	Yu (2016)[73]	Interactive imagery increases immersion.
	Xing et al. [26]	VR narratives aid exhibition design.
	Škola et al. [27]	360° videos enhance online engagement.
Multi-User Platform and Usability Studies	Pistoia et al. [74]	Multi-user audio boosts ICH immersion.
	Hulusic et al. [75]	Virtual museums foster collaboration.
	De Carolis et al. [76]	AI improves emotion and immersion.
Technical Representation and Exhibition Optimization	Wu (2023)[77]	LOD refinement enhances visuals.
	Vilela (2022)[78]	Optimized LOD improves visual fluency.
	De Paolis (2022)[79]	Balanced interactivity and clarity.
Immersive Experience and Emotional Communication	Deng (2021)[80]	Immersion enhances presence and empathy.
	Li & Cao (2022)[81]	Social presence mediates emotion.
	Su & Ismail (2024)[82]	3D ICH reenactment deepens emotion.
User Experience and Behavioral Intention	Selmanovic et al. [83]	Immersion drives enJOYment and intent.
	Choi et al. [84]	Engagement increases continuance use.
	Li (2023)[85]	Interaction affects user intention.

findings, providing a solid theoretical foundation and research reference for the subsequent construction of the proposed theoretical model and design of empirical studies.

However, existing applications still exhibit critical shortcomings in terms of theoretical guidance and mechanism interpretation regarding user experience. These primarily manifest as: First, research paradigms tend to focus on technology-oriented effectiveness evaluations, lacking in-depth exploration of users' underlying psychological mechanisms (such as hedonistic motivation and emotional investment) and behavioral motivations. Second, the theoretical foundation remains relatively weak and fragmented, particularly lacking a systematic analytical framework for addressing core issues, such as why users develop sustained engagement with VR ICH experiences and how technological design can effectively enhance cultural identity. This provides a significant theoretical opportunity for the present study, which is to construct a theoretical model capable of systematically elucidating the complex relationships among tasks, technological attributes, intrinsic motivation, and behavioral intentions by integrating the Task-Technology Fit (TTF) model with the Hedonic Motivation System Adoption Model (HMSAM).

Hedonic-motivation system adoption model (HMSAM)

The Hedonic-Motivation System Adoption Model (HMSAM), proposed by Lowry et al. in 2013, explains user behavior in entertainment-oriented systems designed for immersion and affective experience. Unlike the traditional TAM, which emphasizes instrumental utility and performance expectancy, the HMSAM focuses on how intrinsic psychological experiences, such as JOY, CUR, and a sense of control influence users' behavioral intentions[33]. The model regards cognitive absorption as its core mechanism and consists of four dimensions: CUR, JOY, control, and focused immersion. These dimensions collectively influence users' immersive experience and continuance intention[34]. In recent years, HMSAM has been widely applied in fields, such as VR games, augmented reality, gamified learning, and social media, demonstrating its strong explanatory power with regard to user immersion and behavioral engagement[35]. In particular, in VR environments, HMSAM helps to reveal the mechanisms underlying user immersion and satisfaction. Perceived Ease of Use (PEOU) as the core concept of the TAM, plays a significant role in VR ICH experiences. Research indicates that the ease with which users can operate and learn from VR systems is directly correlated with their perception of system usefulness and their propensity to explore[36]. In the digital experience of cultural heritage, perceived ease of use not only directly affects users' acceptance of technology, but also enhances their sense of pleasure and control by reducing cognitive load[37]. Especially for content like ICH that requires in-depth understanding and experience, an easy-to-use interface design can enable users to focus more on the cultural content itself, thereby stimulating CUR and enhancing the overall experience quality[38]. Therefore, the following hypotheses are put forward:

H1a. PEOU has a positive impact on PU.
H1b. PEOU has a positive impact on CUR.
H1c. PEOU has a positive impact on JOY.
H1d. PEOU has a positive impact on CON.

Task-technical fit (TTF) model

Task-Technology Fit Model (TTF) was proposed by Goodhue and Thompson in 1995. Its core assumption is that the impact of information technology on individual performance depends on the degree of alignment between the technology's capabilities and the demands of the task. This model posits that users will experience higher perceived utility (PU) only when technological characteristics (TEC) sufficiently support the demands of task characteristics (TC), thereby influencing their behavioral intention (BI). Recent meta-analytic studies have confirmed that the core constructs within the TTF model (task characteristics, technological characteristics, perceived usefulness, and behavioral intention) demonstrate stable predictive power across different contexts. In research on digital museums and cultural heritage, task characteristics and technical characteristics significantly predict TTF, thereby influencing users' willingness to continue using[39].

H2a. TEC have a positive impact on PU.
H2b. TEC have a positive impact on CUR.
H2c. TEC have a positive impact on JOY.
H2d. TEC have a positive impact on CON.

In VR ICH experiences, task characteristics (TC) refer to the specific requirements, complexity, and objectives users undertake when engaging in cultural learning, exploration, and interactive activities within virtual environments. These characteristics include the depth of cultural knowledge acquisition, the complexity of interactive experiences, and the degree of personalized learning[40]. According to the Task-Technology Fit (TTF) model, when these task characteristics align highly with the functionalities of VR technology (i.e., achieving a high TTF), it significantly enhances users' perceived utility. This leads users to perceive cultural exploration tasks completed via VR as more efficient and valuable. More importantly, in pleasure-driven cultural experiences, task design not only affects efficiency but also directly influences users' intrinsic motivation systems. Research indicates that carefully designed task structures can significantly enhance users' CUR about exploring traditional culture by providing clear pathways for discovery. At the same time, appropriately challenging tasks and clearly defined operational objectives can provide users with a sense of control (CON) over the virtual environment and learning process, accompanied by a sense of JOY upon successfully completing tasks[41]. Therefore, the following hypothesis is proposed:

H3a. TC have a positive impact on PU.
H3b. TC have a positive impact on CUR.
H3c. TC have a positive impact on JOY.
H3d. TC have a positive impact on CON.

The role of mediating factors in immersion (IM) and behavioral intention (BI)

In VR-based ICH experiences, immersion (IM) represents the core characteristic of user engagement with the virtual environment, while behavioral intention (BI) reflects users' willingness to continue or reuse the system. Perceived usefulness (PU), CUR, pleasure/joy (JOY), and sense of control (CON) serve as key antecedents influencing both outcomes. High perceived usefulness enhances immersion by delivering meaningful and relevant cultural content[42], and simultaneously strengthens behavioral intention by convincing users of the system's effectiveness in facilitating cultural understanding and learning[43]. CUR, as an intrinsic motivator, drives deeper exploration and engagement, thereby elevating immersion[44] and promoting sustained usage intention[45]. Pleasure generates positive emotional experiences that help users become absorbed in the virtual world[46] and significantly contribute to overall satisfaction and reuse intention[47]. Likewise, a strong sense of control fosters proactive participation and deep immersion[48] while supporting autonomy and personalized learning, both of which are critical to forming positive behavioral intentions[49]. Therefore, the following hypothesis is proposed:

H4a. PU has a positive impact on immersion IM.
H4b. CUR has a positive impact on immersion IM.
H4c. JOY has a positive impact on IM.
H4d. CON has a positive impact on immersion IM.
H5a. PU has a positive impact on BI.
H5b. CUR has a positive impact on BI.
H5c. JOY has a positive impact on BI.
H5d. CON has a positive impact on BI.

The influence of immersion on behavioral intention

Research shows that a high level of immersion not only significantly enhances user satisfaction and learning motivation but also strengthens their cognition, attitude, and willingness to continuously engage with traditional culture[4,50].

In the VR experience of ICH, immersion functions through multiple mechanisms. First, it promotes cultural identity and emotional connection, enhancing cultural understanding and appreciation[51]. Second, it stimulates the "flow" experience, bringing inner satisfaction and enhancing the willingness to participate repeatedly[52]. Meanwhile, improving learning outcomes and memory retention also increases users' intention to recommend and share[53]. Behavioral intention, as an important variable for predicting users' actual behavior, is mainly reflected in the willingness to continuously use, recommend to others, and participate in cultural activities in VR ICH experiences[54]. Relevant research has also verified that immersion is an important antecedent driving users to continuously participate in the digital experience of ICH[55]. Therefore, the following hypothesis is proposed:

H6. IM has a positive impact on BI.

Proposed research model

Based on the integration of TTF and HMSAM, this study constructs a theoretical model for explaining users' behavioral intentions and immersive experiences in VR ICH experiences. As shown in Fig. 1, this model explores the influence of TC, TEC and PEOU on users' intrinsic motivations (including PU, CUR, JOY and CON), which further affect IM and ultimately predict BI. The model comprises nine variables and 20 research hypotheses. This comprehensive framework integrates the perspectives of instrumental and hedonic system adoption and is suitable for explaining the formation process of user psychological and behavioral mechanisms in immersive ICH platforms.

Data collection and participant statistics

This study employed a cross-sectional design, recruiting participants through convenience sampling. Given the specialized nature of VR technology and ICH tasks, a targeted recruitment strategy was adopted, resulting in a sample of 400 volunteers with high digital literacy. This group primarily encompasses students, designers, technologists, researchers, and cultural professionals. It is worth noting that the sample in this study exhibits distinct characteristics. The participants overall possess a high level of education, with their occupations significantly concentrated in academic and technical fields. The sample comprises young adults aged 18 to 35. Data collection was conducted rigorously in two phases between September 30 and October 30, 2025. Participants first engaged in the Dunhuang VR experience experiment, followed immediately by a structured questionnaire survey. This research protocol was reviewed and approved by the Ethics Committee of Zhejiang University on September 30, 2025 (Approval Number: cmic20250934). All participants signed informed consent forms before the experiment.

For our study, participants were recruited through campus advertisements and underwent a single-phase continuous procedure. This means that immediately after experiencing the VR, participants completed the questionnaire, eliminating any multiple-stage process. The experiment was conducted in a standard classroom equipped with Pico 4 VR headsets and the VR Donghuang immersive exhibition (see Fig. 2). Each session involved approximately 20–30 participants, guided by a trained moderator who delivered standardized instructions—including a game introduction, operation guidelines, and privacy protection measures—to ensure consistent understanding among participants and minimize procedural bias (see Fig. 3). After experiencing the "VR Journey to Dunhuang: Digital Dunhuang Immersive Exhibition" for 15 to 20 minutes, participants completed an online post-experience questionnaire via the Wenjuanxing platform to assess their perceptions of task characteristics, psychological motivations, and behavioral intentions within the VR cultural heritage context. We selected this VR immersive exhibition primarily because: (1) Developed jointly by the Dunhuang Academy and Tencent, it represents the latest model of integrating China's digital cultural heritage with cutting-edge technology. Its high level of system integration provides an ideal case study for researching complex platforms that balance practicality and entertainment value. (2) The reality of Mogao Cave 285, which is not routinely open to the public, offers users an exclusive access experience featuring zero-distance viewing and free exploration. (3) This platform employs cutting-edge AI technologies, such as GAN/diffusion models, combined with 1:1 millimeter-level precision and ultra-detailed 3D modeling with over 900 million polygons, delivering the highest level of realism and immersive environment currently achievable in the field of digital cultural heritage. (4) By integrating RAG (Retrieval-Augmented Generation) systems, ICH texts and historical information are transformed from mere visual images into comprehensible, interactive knowledge, providing users with a complete cultural learning loop. (5) This immersive exhibition breaks through the static displays of traditional cultural platforms through AI-driven character and narrative design.

After data screening and cleaning, 387 valid questionnaires were retained for the subsequent structural equation modeling (SEM) analysis, with incomplete or inconsistent responses excluded.

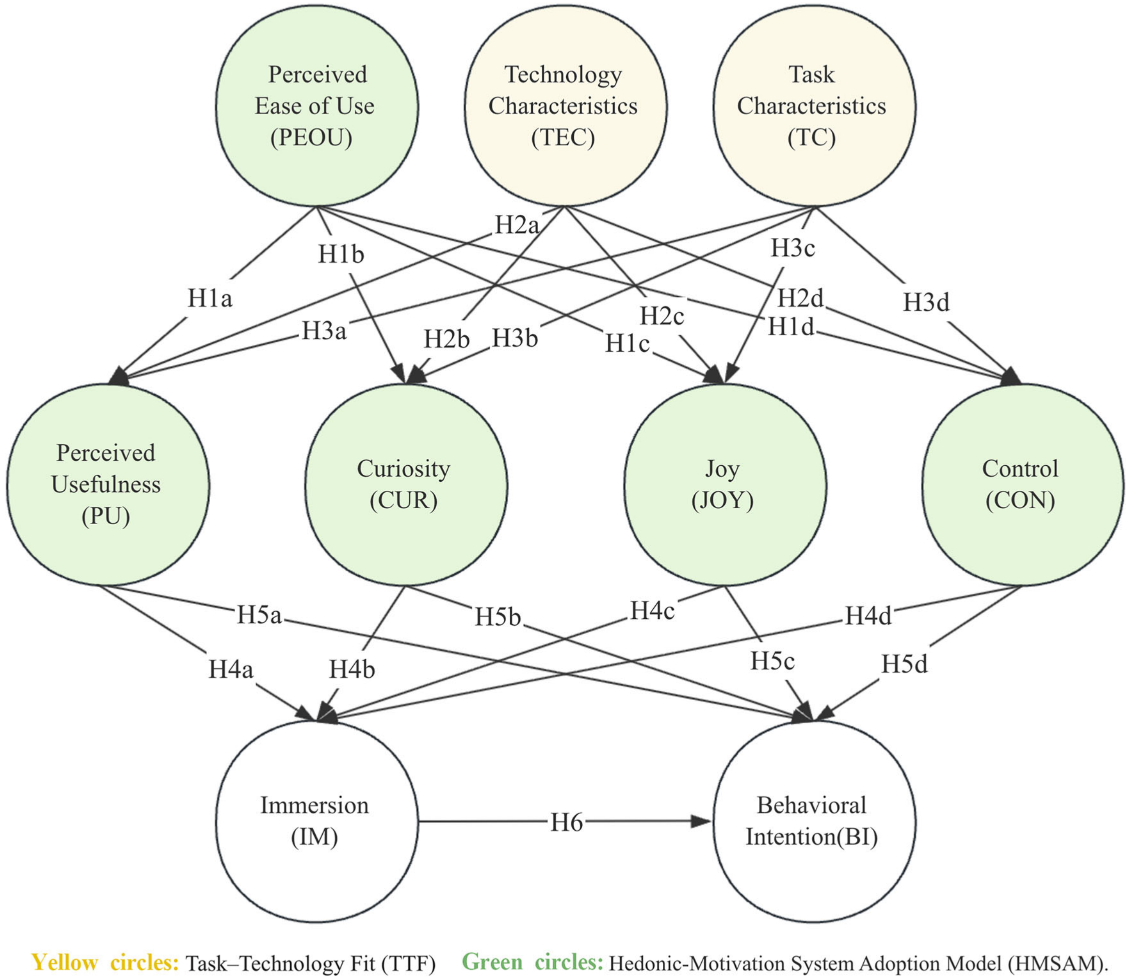

Fig. 1 | Theoretical model based on TTF and HMSAM.

Questionnaire development

The questionnaire is divided into two parts. The first part collects the basic demographic information of the respondents, including gender, age, educational level, occupational identity, as well as their experience in using VR and familiarity with ICH. The second part was constructed based on the task-Technology Fit Model (TTF) and the Hedonic Motivation System Adoption Model (HMSAM), and a structured questionnaire was developed, covering three task and technology dimensions (PEOU, TEC, TC), four psychological motivation mediating variables (PU, CUR, JOY, CON), and two outcome variables (IM, BI). All measurement items are adapted from verified scales in authoritative literature and adjusted in combination with the specific scenarios of VR ICH exhibitions to ensure that the item descriptions are consistent with users' cognition and actual experience.

After the first draft of the questionnaire was completed, the research team invited four experts in the fields of VR and cultural heritage to review and revise the questionnaire. After several rounds of discussions and revisions to remove some repetitive or ambiguous items, 27 core measurement items were finally determined to form the formal questionnaire tool. The questionnaire was initially written in Chinese and then back translated by two independent translators to ensure the accuracy of the language. Any differences were resolved through consensus review.

After finalizing the questionnaire, a small-scale pilot test was conducted online with 30 individuals knowledgeable about VR ICH to validate the questions' validity and clarity. Subsequently, through data collection and empirical testing, the model's structural validity and path relationships were evaluated. All items were measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This method effectively reflects respondents' attitudes and engagement outcomes.

In terms of academic ethics, all respondents signed an informed consent form before answering the questionnaire to ensure their rights were protected. We clearly inform the participants that all the data collected will only be used for academic research, and their personal privacy will be strictly protected. The questionnaire and reference literature are presented in Supplementary Table 1.

Among the valid samples, there were 183 males (47.3%) and 204 females (52.7%). The age range is mainly concentrated between 18 and 25 years old (63.6%) and 26 and 35 years old (36.4%). The educational attainment is mainly bachelor's degree or above, among which 227 people (58.7%) have a bachelor's degree, 53 people(13.7%) with a master's degree, and 9 people (2.3%) have a doctoral degree. In terms of VR usage experience, 247 people (63.8%) frequently use VR devices, 80 people (20.7%) are very familiar with them, and 60 people (15.5%) occasionally experience them. In terms of familiarity with ICH, 207 people (53.5%) indicated an understanding, 116 people (30.0%) had a slight understanding, and 64 people (16.5%) had a very good understanding. In terms of occupational distribution, there are 170 students (43.9%), 59 designers (15.3%), 51 technologist (13.2%), 40 researchers (10.3%), 39 Cultural professionals (10.1%), 19 teachers (4.9%), and 9 others (2.3%)(see Table 2).

Results

This study employed SPSS 27 software for descriptive statistics, data preprocessing, and artificial neural network (ANN) modeling analysis, while utilizing SmartPLS 4.0 software for partial least squares

Fig. 2 | VR Digital Dunhuang Immersive Exhibition(https://285.e-dunhuang.com/#/).

structural equation modeling (PLS-SEM) analysis. Before the formal model testing, this study conducted multiple data validation procedures, including common method bias testing, reli-ability analysis, validity analysis, and correlation testing. The results indicate that all data possess high reliability and validity, and significant correlations exist among the various dimensions. Finally, Structural Equation Modeling (SEM) validated the relationships between each dimension and adoption intention, ensuring the feasibility of the theoretical framework. These analyses provide a solid scientific basis for this study.

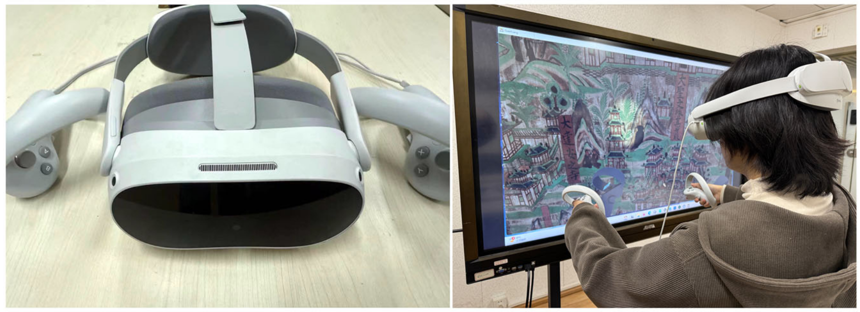

Fig. 3 | Participants used Pico 4 to experience VR Dunhuang.

Table 2 | Descriptive statistics of the basic information of the participants

Measure	Items	Frequency (n = 387)	Percentage(%)
Gender	Male	183	47.3
	Female	204	52.7
Age	18–25 years	246	63.7
	26–35 years	141	36.4
Education Level	Bachelor's degree	227	58.7
	Master's degree	53	13.7
	Doctoral degree	9	2.3
VR Experience	Frequently use	247	63.8
	Very familiar	80	20.7
	Occasional experience	60	15.5
Familiarity with ICH	Familiar	207	53.5
	Slightly familiar	116	30.0
	Very familiar	64	16.5
Occupation	Student	170	43.9
	Designer	59	15.3
	Technologist	51	13.2
	Researcher	40	10.3
	Cultural professionals	39	10.1
	Teacher	19	4.9
	Others	9	2.3

[a]Notes: *ICH* stands for Intangible Cultural Heritage.

Modeling fit

According to Kline (2015), an NFI value above 0.80 is considered the acceptable lower limit for model fit. Although it does not meet the excellent standard of 0.90 (Bentler & Bonett, 1980), given the complexity of this study's model, this metric suggests the model fits the data within an acceptable range. The model evaluation follows these common criteria: SRMR ≤ 0.08, NFI ≥ 0.80 (acceptable) or > 0.90 (excellent)[56,57] (see Table 3).

Common method bias(CMB)

To address the possible issue of Common Method Bias (CMB), In this study, the Variance Inflation Factor (VIF), a commonly used diagnostic index in the partial least squares structural equation model (PLS-SEM), was adopted to evaluate multicollinearity. A higher VIF value indicates a strong collinearity relationship among potential variables, which may reflect potential biases. According to Kock's (2015) research[58], when the VIF value is lower than 3.3, it indicates that neither multicollinearity nor common method bias poses a serious threat to the model. In this study, the VIF values of all variables ranged from 1.822 to 2.241, all of which were far below the recommended threshold, indicating that there was no multicollinearity issue in the data and the risk of CMB was relatively low.

Table 3 | Structural equation model fit index

Fit Index	Calculated value	Threshold value	Reference
SRMR	0.03	≤0.08	Kline (2015)[56]
NFI	0.82	≥0.80	Bentler and Bonett[57]

Reliability and validity analysis

In this study, SmartPLS 4.0 software was used for reliability analysis. Confirmatory Factor Analysis (CFA) was conducted on all measurement items. Including Composite Reliability (rho_A), composite reliability (CR), and Cronbach's α coefficient (CA). As shown in the table, all reliability indicators exceed the recommended threshold of 0.80, indicating that each construct has good internal consistency and is suitable for further analysis.To test the Convergent Validity, this study examined the Average Variance Extracted (AVE), and all AVE values exceeded the standard threshold of 0.50. In addition, all standardized factor loadings were above 0.70, and the P-values all reached significant levels ($p < 0.001$), indicating that the model has strong convergent validity[59] (see Table 4).

To evaluate discriminant validity, we conducted tests using the Fornell-Larcker criterion, confirming that the square root of the average variance extracted (AVE) for each construct in Table 5 was greater than the corresponding inter-construct correlation coefficients[52]. Additionally, the heterotrait-monotrait ratio (HTMT) values were all below 0.85 (Table 6), satisfying the recommended threshold for discriminant validity[53]. Furthermore, the cross-loadings for each indicator exceeded their respective construct loadings (see Table 7). Therefore, through comprehensive analysis of these three metrics, we concluded that the model in this study demonstrated good discriminant validity.

R squared and q squared

To assess the explanatory and predictive capabilities of the structural model, we examined the coefficient of determination (R^2) and the predictive correlation (Q^2). R^2 represents the variance ratio of the endogenous structure explained by exogenous variables, where 0.75,0.50 and 0.25 indicate strong, medium and weak explanatory power. Q^2 assesses the accuracy of predictions, and values above 0, 0.25, and 0.50 indicate small, medium, and large prediction correlations. As shown in Table 8, the R^2 value is between 0.251 and 0.443, indicating moderate explanatory power. BI (0.443) has the strongest explanatory power, followed by IM (0.336), JOY (0.327), and PU (0.325), while the explanatory power of CON (0.297) and CUR (0.251) is relatively weak. The Q^2 values range from 0.183 to 0.328, all greater than zero, indicating a good predictive correlation. In particular, BI (0.328) demonstrated the highest prediction accuracy. Overall, this model has satisfactory explanatory and predictive performance.

Evaluating the structural model

As shown in Table 9 and Fig. 4, we use the bootstrapping method with 5000 samples to test the path coefficients. The results showed that all 22 hypotheses were significant ($p < 0.01$), and the confidence interval was excluded from zero, confirming the robustness of the model. PEOU has a significant positive impact on PU ($\beta = 0.280$, $p < 0.001$), CUR ($\beta = 0.183$, $p = 0.001$), JOY ($\beta = 0.251$, $p < 0.001$), and CON ($\beta = 0.220$, $p < 0.001$). This thus confirmed the existence of H1a, H1b, H1c and H1d. TEC has significant positive effects on PU ($\beta = 0.294$, $p < 0.001$), CUR ($\beta = 0.173$, $p = 0.001$), JOY ($\beta = 0.168$, $p < 0.001$), and CON ($\beta = 0.275$, $p < 0.001$). This thus confirmed the existence of H2a, H2b, H2c and H2d. TC has significant positive effects on PU ($\beta = 0.144$, $p = 0.003$), CUR ($\beta = 0.280$, $p < 0.001$), JOY ($\beta = 0.307$, $p < 0.001$), and CON ($\beta = 0.198$, $p < 0.001$). This thus confirmed the existence of H3a, H3b, H3c and H3d. PU ($\beta = 0.189$, $p < 0.001$), CUR ($\beta = 0.162$, $p = 0.001$), JOY ($\beta = 0.160$, $p = 0.001$), and CON ($\beta = 0.159$, $p = 0.001$) positively and significantly affect BI. This thus confirmed H4a, H4b, H4c and H4d. PU ($\beta = 0.184$, $p < 0.001$), CUR ($\beta = 0.217$, $p < 0.001$), JOY ($\beta = 0.193$, $p < 0.001$), and CON ($\beta = 0.169$, $p < 0.001$) positively and significantly affect IM This thus confirmed H5a, H5b, H5c and H5d. IM ($\beta = 0.225$, $p < 0.001$) significantly affects BI, confirming H6.

Table 4 | Reliability and validity analysis

Variable	Items	Factor Loading	CA	Rho_A	CR	AVE
BI	BI1	0.888	0.843	0.844	0.905	0.761
	BI2	0.864				
	BI3	0.864				
CON	CON1	0.867	0.839	0.840	0.903	0.756
	CON2	0.879				
	CON3	0.863				
CUR	CUR1	0.873	0.838	0.842	0.902	0.755
	CUR2	0.846				
	CUR3	0.887				
IM	IM1	0.874	0.836	0.837	0.901	0.753
	IM2	0.860				
	IM3	0.868				
JOY	JOY1	0.862	0.832	0.834	0.899	0.748
	JOY2	0.854				
	JOY3	0.878				
PEOU	PEOU1	0.845	0.828	0.828	0.897	0.744
	PEOU2	0.875				
	PEOU3	0.867				
PU	PU1	0.888	0.857	0.859	0.913	0.777
	PU2	0.868				
	PU3	0.889				
TEC	TEC1	0.865	0.827	0.827	0.896	0.743
	TEC2	0.864				
	TEC3	0.856				
TC	TC1	0.867	0.822	0.824	0.894	0.737
	TC2	0.860				
	TC3	0.848				

Mediation effect analysis

In this study, the Bootstrap method was adopted to analyze the mediating effect in the model, and a total of 5000 repeated samplings were conducted. When the 95% confidence interval calculated by the self-help method does not contain zero values, the mediating effect is considered significant. The research results show that the three antecedent variables (PEOU, TEC, and TC) all exhibit significant mediating effects because their 97.5% confidence intervals do not contain zero values. To illustrate the intensity relationship of the mediating effect more clearly, in this study, the Variance Accounting Factor (VAF) index was adopted in the partial least squares structural equation model (PLS-SEM). This indicator measures the degree of mediating effect by calculating the ratio of indirect effect to total effect. When 20% < VAF < 80%, it indicates a partial mediating effect. When VAF is greater than 80%, it indicates a complete mediating effect(see Table 10).

The results of the mediating effect analysis based on the bootstrap method showed that all indirect paths in the model reached a significant level ($p < 0.05$), indicating that the influence of the independent variables on the dependent variable through each mediating variable was valid. Specifically, the indirect effect of TC on BI was primarily mediated by JOY and CUR, among which the mediating pathway TC → JOY → BI exhibited the strongest effect. In contrast, the serial mediations of PU → IM → BI and CON → IM → BI were the weakest. Among the mediating pathways of TEC, PU → BI demonstrated the most significant indirect effect, followed by CON → BI, whereas the effects of other paths, such as JOY → IM → BI were relatively weak. The indirect influence of PEOU on BI was mainly achieved through JOY → BI and PU → BI.

Regarding the mediating mechanisms of IM, TC mainly exerted its influence through CUR → IM and JOY → IM, TEC primarily played a mediating role through PU → IM, and the influence of PEOU was mainly transmitted via JOY → IM. Overall, the confidence intervals of all indirect paths did not cross zero, indicating that these mediating effects were robust and statistically reliable. Moreover, all mediation effects were identified as partial (20% < VAF < 80%), suggesting that the independent variables not only directly affected the outcome variable but also indirectly influenced BI through emotional and experiential factors.

SEM-ANN analysis

This study incorporates ANN for in-depth analysis, aiming to significantly enhance the model's predictive performance and fitting accuracy. Due to the

Table 5 | Discriminant Validity (Fornell-Larcker)

Variable	BI	CON	CUR	IM	JOY	PEOU	PU	TEC	TC
BI	0.872								
CON	0.480	0.870							
CUR	0.474	0.427	0.869						
IM	0.520	0.429	0.445	0.868					
JOY	0.494	0.439	0.443	0.451	0.865				
PEOU	0.449	0.399	0.424	0.420	0.475	0.862			
PU	0.498	0.449	0.385	0.436	0.479	0.375	0.882		
TEC	0.518	0.456	0.372	0.445	0.408	0.417	0.479	0.862	
TC	0.448	0.421	0.370	0.392	0.446	0.391	0.467	0.447	0.859

Table 6 | Discriminant Validity (HTMT)

Variable	BI	CON	CUR	IM	JOY	PEOU	PU	TEC	TC
BI	-								
CON	0.570								
CUR	0.563	0.510							
IM	0.618	0.512	0.529						
JOY	0.589	0.524	0.528	0.539					
PEOU	0.538	0.479	0.508	0.506	0.571				
PU	0.586	0.530	0.452	0.513	0.569	0.447			
TEC	0.621	0.546	0.445	0.534	0.491	0.503	0.569		
TC	0.539	0.506	0.441	0.472	0.540	0.473	0.556	0.543	-

Table 7 | Discriminant Validity (Cross-loadings)

Items	BI	CON	CUR	IM	JOY	PEOU	PU	TEC	TC
BI1	0.888	0.407	0.459	0.484	0.449	0.376	0.424	0.450	0.369
BI2	0.864	0.405	0.386	0.445	0.418	0.397	0.441	0.447	0.361
BI3	0.864	0.446	0.393	0.429	0.425	0.403	0.438	0.460	0.443
CON1	0.381	0.867	0.373	0.369	0.365	0.341	0.412	0.372	0.378
CON2	0.423	0.879	0.382	0.388	0.370	0.359	0.390	0.385	0.372
CON3	0.446	0.863	0.361	0.361	0.410	0.341	0.370	0.432	0.349
CUR1	0.380	0.357	0.873	0.358	0.370	0.354	0.330	0.349	0.311
CUR2	0.440	0.384	0.846	0.352	0.362	0.354	0.332	0.274	0.264
CUR3	0.415	0.374	0.887	0.442	0.418	0.394	0.340	0.343	0.381
IM1	0.478	0.329	0.378	0.874	0.405	0.339	0.389	0.374	0.306
IM2	0.419	0.374	0.409	0.860	0.369	0.394	0.363	0.356	0.359
IM3	0.455	0.413	0.373	0.868	0.398	0.361	0.381	0.426	0.356
JOY1	0.435	0.397	0.385	0.394	0.862	0.452	0.421	0.366	0.388
JOY2	0.401	0.352	0.370	0.351	0.854	0.372	0.413	0.328	0.393
JOY3	0.444	0.388	0.393	0.422	0.878	0.405	0.410	0.363	0.379
PEOU1	0.373	0.379	0.386	0.384	0.370	0.845	0.299	0.318	0.353
PEOU2	0.385	0.329	0.353	0.321	0.430	0.875	0.334	0.358	0.313
PEOU3	0.404	0.324	0.358	0.381	0.429	0.867	0.339	0.402	0.345
PU1	0.465	0.403	0.383	0.421	0.401	0.330	0.888	0.413	0.426
PU2	0.424	0.416	0.302	0.338	0.438	0.358	0.868	0.410	0.387
PU3	0.426	0.369	0.329	0.389	0.430	0.307	0.889	0.443	0.421
TEC1	0.457	0.423	0.347	0.395	0.363	0.366	0.400	0.865	0.392
TEC2	0.422	0.375	0.301	0.375	0.346	0.358	0.405	0.864	0.355
TEC3	0.461	0.380	0.311	0.379	0.346	0.353	0.434	0.856	0.407
TC1	0.372	0.378	0.352	0.359	0.385	0.340	0.412	0.381	0.867
TC2	0.392	0.369	0.307	0.335	0.399	0.358	0.399	0.357	0.860
TC3	0.392	0.335	0.291	0.313	0.365	0.307	0.392	0.417	0.848

Table 8 | R^2 and Q^2

Variable	R^2	Adjusted R^2	Q^2
BI	0.443	0.436	0.328
CON	0.297	0.292	0.221
CUR	0.251	0.245	0.183
IM	0.336	0.329	0.248
JOY	0.327	0.321	0.237
PU	0.325	0.320	0.248

limitations of traditional partial least squares structural equation modeling (PLS-SEM) in handling complex nonlinear relationships, ANNs leverage their robust nonlinear mapping capabilities to accurately model intricate interaction patterns among variables, thereby enhancing the interpretability of empirical findings in realistic terms[60]. This methodological synergy provides a more comprehensive and profound perspective for in-depth analysis of multi-pathway influence mechanisms. To avoid potential over-fitting issues, this study employs ten-fold cross-validation, allocating 10% of the dataset for testing and the remaining 90% for training[61]. Specifically, this study employed a multi-layer perceptron based on the BP algorithm to generate six ANN models (See Fig. 5). Among these, ANN model A (CUR), ANN model B (Joy), ANN model C (Control), and ANN model D

Table 9 | Hypothesis Test Summary

Hypothesis		Path	β	t-Value	p	2.50%CI	97.5% CI	VIF	Supported
H1	H1a	PEOU - > PU	0.280	5.835	0.000	0.188	0.373	2.056	Yes
	H1b	PEOU - > CUR	0.183	3.385	0.001	0.077	0.288	1.847	Yes
	H1c	PEOU - > JOY	0.251	4.971	0.000	0.150	0.349	2.229	Yes
	H1d	PEOU - > CON	0.220	4.677	0.000	0.130	0.315	1.952	Yes
H2	H2a	TEC - > PU	0.294	6.121	0.000	0.200	0.389	2.118	Yes
	H2b	TEC - > CUR	0.173	3.247	0.001	0.072	0.281	1.825	Yes
	H2c	TEC - > JOY	0.168	3.493	0.000	0.072	0.260	2.034	Yes
	H2d	TEC - > CON	0.275	5.601	0.000	0.177	0.371	2.184	Yes
H3	H3a	TC- > PU	0.144	2.981	0.003	0.047	0.239	1.884	Yes
	H3b	TC- > CUR	0.280	5.687	0.000	0.180	0.376	2.238	Yes
	H3c	TC - > JOY	0.307	6.362	0.000	0.210	0.397	2.157	Yes
	H3d	TC - > CON	0.198	3.986	0.000	0.098	0.294	1.938	Yes
H4	H4a	PU - > BI	0.189	3.687	0.000	0.089	0.291	2.072	Yes
	H4b	CUR - > BI	0.162	3.343	0.001	0.066	0.255	1.861	Yes
	H4c	JOY - > BI	0.160	3.308	0.001	0.067	0.254	2.206	Yes
	H4d	CON - > BI	0.159	3.293	0.001	0.062	0.256	2.011	Yes
H5	H5a	PU - > IM	0.184	3.602	0.000	0.085	0.286	1.915	Yes
	H5b	CUR - > IM	0.217	4.200	0.000	0.109	0.314	2.133	Yes
	H5c	JOY - > IM	0.193	3.562	0.000	0.086	0.298	1.987	Yes
	H5d	CON - > IM	0.169	3.554	0.000	0.077	0.261	2.095	Yes
H6		IM - > BI	0.225	5.126	0.000	0.137	0.309	1.892	Yes

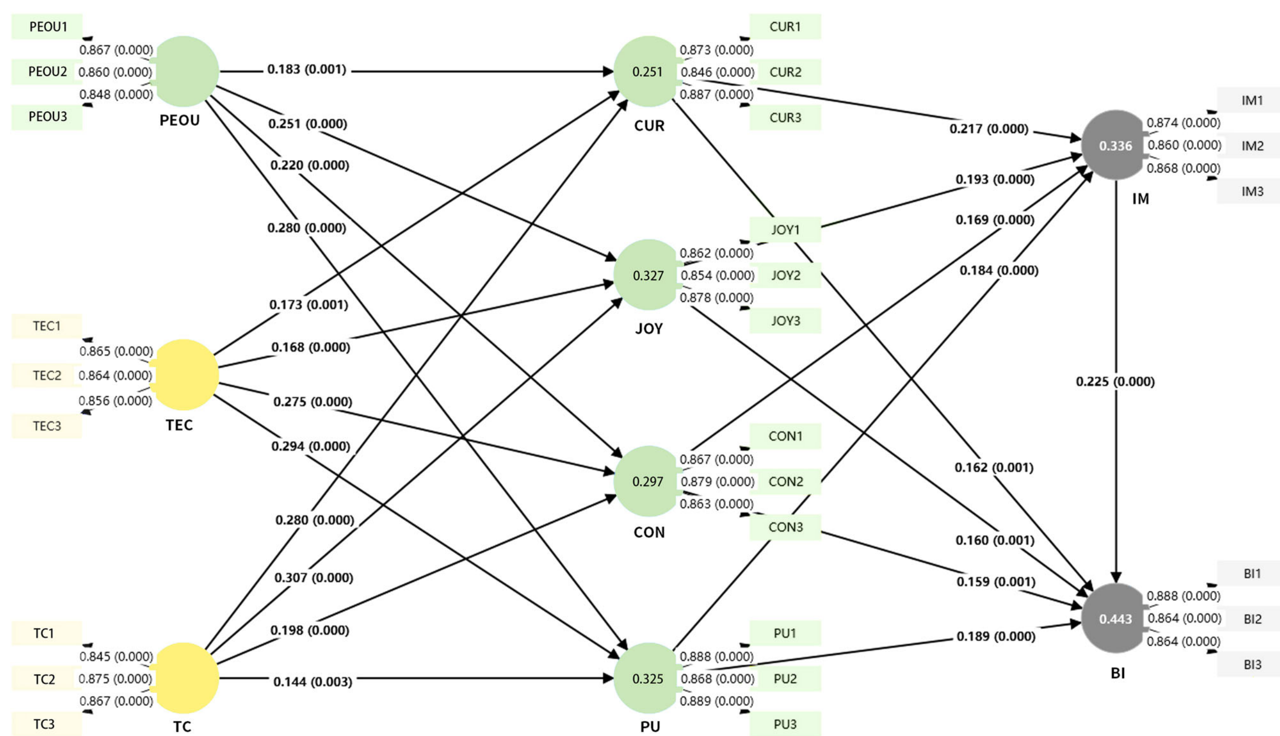

Fig. 4 | Results of the structural equation model (SEM).

(Perceived Usefulness) with Perceived Ease of Use (PEOU), Technology Characteristics (TEC), and Task Characteristics (TC) as their input layers respectively. ANN model E uses CUR, JOY, CON, and PU as input layers, with Immersion (IM) as the output layers. Finally, the input layer of the ANN model F(Behavioral Intention) consists of CUR, JOY, CON, PU, and IM.

This study employs Root Mean Square Error (RMSE) as the core metric to evaluate the predictive accuracy of six ANN models, as shown in Table 11 and Fig. 6. Based on the recommended threshold from previous studies, an RMSE value below 0.5 indicates that the model possesses excellent predictive performance and stability[62]. Empirical results indicate, the average RMSE values on the training set for ANN models A, B, C, D, E,

Table 10 | Intermediary effect analysis

Relation		β	SE	t	p	2.5%	97.5%	Support	VAF
Total Effect	PEOU - > BI	0.198	0.029	6.852	0.000	0.143	0.256	Yes	-
	TEC - > BI	0.193	0.028	6.844	0.000	0.140	0.251	Yes	-
	TC - > BI	0.194	0.029	6.701	0.000	0.137	0.253	Yes	-
	PEOU - > IM	0.177	0.028	6.379	0.000	0.126	0.234	Yes	-
	TEC - > IM	0.170	0.027	6.405	0.000	0.122	0.225	Yes	-
	TC - > IM	0.180	0.027	6.590	0.000	0.127	0.234	Yes	-
Indirect Effects	PEOU - > PU - > BI	0.053	0.017	3.044	0.002	0.022	0.091	Yes	26.8%
	PEOU - > CUR - > BI	0.030	0.012	2.462	0.014	0.009	0.056	Yes	15.2%
	PEOU - > JOY - > BI	0.040	0.015	2.614	0.009	0.014	0.074	Yes	20.2%
	PEOU - > CON - > BI	0.035	0.013	2.673	0.008	0.013	0.064	Yes	17.7%
	TEC - > PU - > BI	0.056	0.018	3.060	0.002	0.023	0.094	Yes	29.0%
	TEC - > CUR - > BI	0.028	0.013	2.132	0.033	0.008	0.058	Yes	14.5%
	TEC - > JOY - > BI	0.027	0.012	2.300	0.021	0.008	0.053	Yes	14.0%
	TEC - > CON - > BI	0.044	0.016	2.659	0.008	0.015	0.081	Yes	22.8%
	TC - > PU - > BI	0.027	0.013	2.164	0.030	0.006	0.055	Yes	13.9%
	TC - > CUR - > BI	0.045	0.016	2.850	0.004	0.017	0.079	Yes	23.2%
	TC - > JOY - > BI	0.049	0.017	2.912	0.004	0.019	0.084	Yes	25.3%
	TC - > CON - > BI	0.032	0.012	2.525	0.012	0.010	0.059	Yes	16.5%
	PEOU - > PU - > IM	0.052	0.017	2.977	0.003	0.021	0.087	Yes	29.4%
	PEOU - > CUR - > IM	0.040	0.015	2.622	0.009	0.013	0.072	Yes	22.6%
	PEOU - > JOY - > IM	0.048	0.017	2.879	0.004	0.019	0.085	Yes	27.1%
	PEOU - > CON - > IM	0.037	0.014	2.731	0.006	0.014	0.067	Yes	20.9%
	TEC - > PU - > IM	0.054	0.019	2.904	0.004	0.022	0.094	Yes	31.8%
	TEC - > CUR - > IM	0.038	0.016	2.407	0.016	0.012	0.072	Yes	22.4%
	TEC - > JOY - > IM	0.032	0.014	2.321	0.020	0.009	0.063	Yes	18.8%
	TEC - > CON - > IM	0.046	0.016	2.870	0.004	0.018	0.082	Yes	27.1%
	TC- > PU - > IM	0.026	0.012	2.249	0.025	0.007	0.052	Yes	14.4%
	TC - > CUR - > IM	0.061	0.018	3.376	0.001	0.027	0.098	Yes	33.9%
	TC - > JOY - > IM	0.059	0.020	3.000	0.003	0.024	0.101	Yes	32.8%
	TC - > CON - > IM	0.033	0.013	2.527	0.012	0.011	0.064	Yes	18.3%

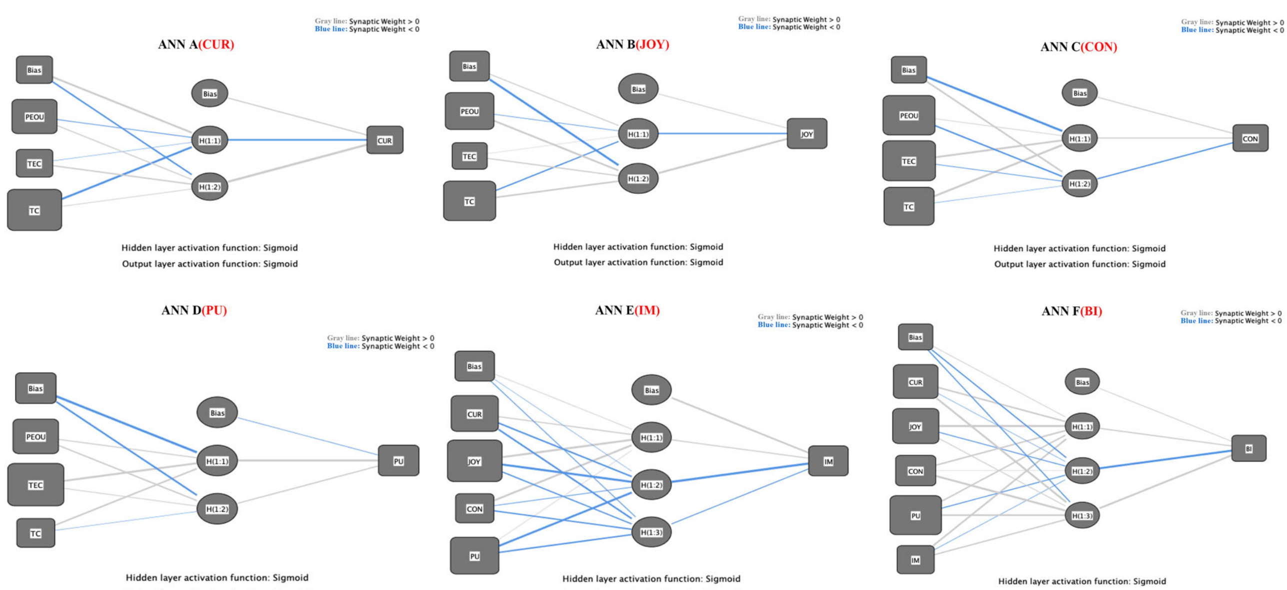

Fig. 5 | The structure of the ANN model A,B,C,D,E and F.

Table 11 | Root-Mean-Square Error (RMSE) values for ANN models(N = 387)

	ANN Model A		ANN Model B		ANN Model C		ANN Model D		ANN Model E		ANN Model F	
	Input: PEOU,TEC,TC		Input: PEOU,TEC,TC		Input: PEOU,TEC,TC		Input: PEOU,TEC,TC		Input: CUR,JOY,CON,PU		Input: CUR, JOY,CON,PU,IM	
	Output: CUR		Output: JOY		Output: CON		Output: PU		Output: IM		Output: BI	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.161	0.176	0.147	0.154	0.163	0.127	0.160	0.197	0.164	0.152	0.147	0.120
ANN2	0.165	0.153	0.149	0.125	0.163	0.144	0.153	0.153	0.157	0.141	0.143	0.137
ANN3	0.162	0.163	0.150	0.150	0.170	0.158	0.150	0.169	0.155	0.153	0.139	0.138
ANN4	0.164	0.147	0.148	0.142	0.162	0.156	0.162	0.144	0.157	0.151	0.139	0.129
ANN5	0.171	0.152	0.151	0.152	0.163	0.130	0.150	0.168	0.157	0.169	0.135	0.126
ANN6	0.165	0.131	0.147	0.147	0.161	0.158	0.153	0.142	0.157	0.159	0.138	0.132
ANN7	0.170	0.144	0.156	0.159	0.161	0.157	0.154	0.141	0.157	0.143	0.140	0.130
ANN8	0.171	0.142	0.146	0.154	0.160	0.161	0.152	0.151	0.171	0.141	0.142	0.152
ANN9	0.172	0.130	0.147	0.142	0.161	0.154	0.151	0.156	0.159	0.147	0.138	0.146
ANN10	0.170	0.175	0.153	0.144	0.169	0.143	0.166	0.152	0.155	0.157	0.147	0.121

Note: *SSE* Sum square of errors, *RMSE* Root mean square of errors, *AVE* Average relative importance, *SD* Standard deviation.

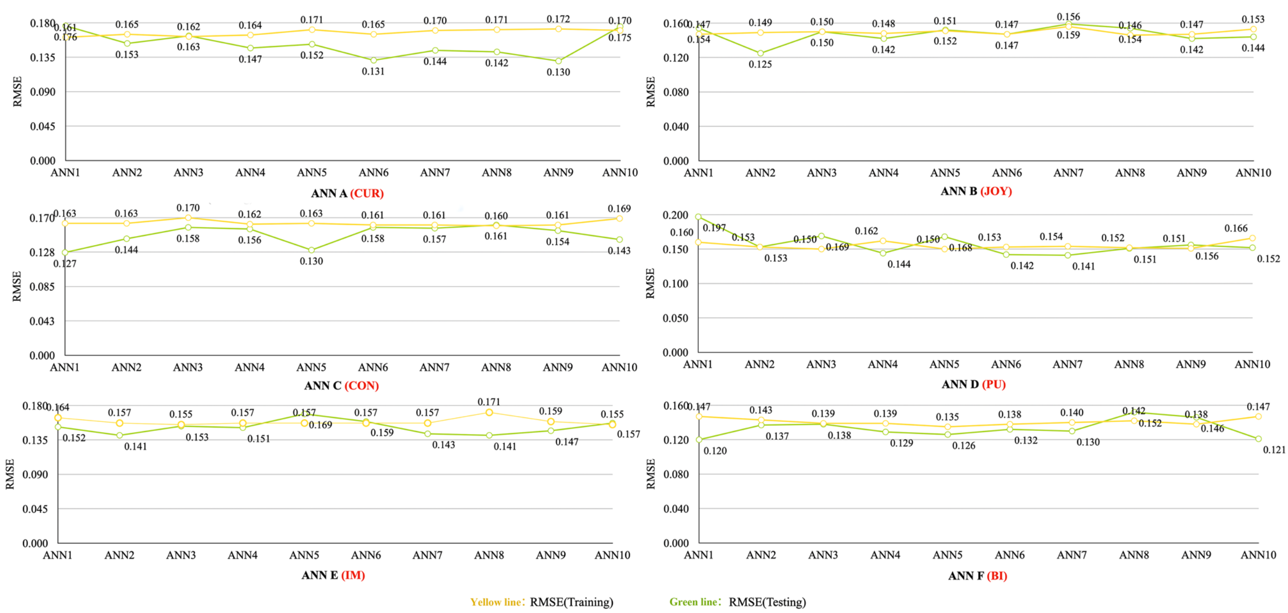

Fig. 6 | Line Chart of RMSE values for ANN models.

Table 12 | Comparison of R^2 Values Between PLS-SEM and ANN

	CUR	JOY	CON	PU	IM	BI
PLS-SEM (R^2)	0.245	0.321	0.292	0.320	0.329	0.436
ANN (R^2)	0.842	0.839	0.822	0.834	0.831	0.801

and F are 0.167, 0.149, 0.163, 0.155, 0.159, and 0.141. The average RMSE values on the testing set were 0.151, 0.147, 0.149, 0.157, 0.151, and 0.133. Based on all values falling well below the 0.5 threshold standard, this result strongly confirms that the ANN model set constructed in this study possesses high predictive accuracy and robust fitting capability.

To empirically verify the presence of non-linear phenomena and evaluate the explanatory power of the proposed models, we conducted a comparative analysis of the Coefficient of Determination (R^2) between the linear PLS-SEM and the non-linear ANN approaches. The R^2 statistic serves as a definitive metric indicating the percentage of variance in the dependent variables explained by the model. As presented in Table 12 and Fig. 7, the results demonstrate a substantial disparity in predictive capability. The R^2 values derived from PLS-SEM ranged from 0.245 to 0.436, suggesting that a purely linear framework is constrained in capturing the full variance of user behavior. In stark contrast, the ANN models exhibited a remarkable improvement, with R^2 values surging to a range of 0.801 to 0.842. For instance, the variance explanation for Behavioral Intention (BI) increased dramatically from 43.6% (SEM) to 80.1% (ANN). This significant increment in variance explanation serves as compelling empirical evidence that intricate non-linear relationships exist within the dataset, which the linear SEM approach failed to capture. Consequently, the deployment of ANN is justified not merely by its lower

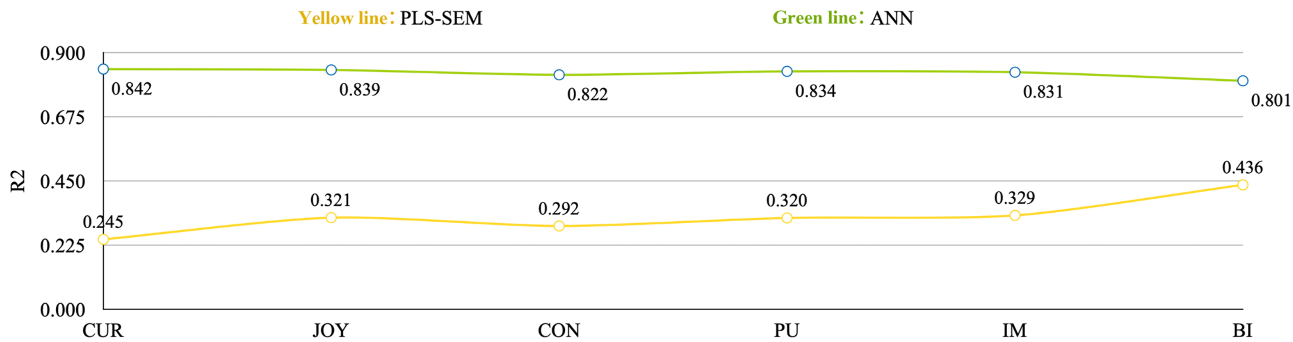

Fig. 7 | Line Chart of R^2 Values Between PLS-SEM and ANN.

Table 13 | Sensitivity analysis

	ANN Model A			ANN Model B			Output: CON		
	Output: CUR			Output: JOY			Output: CON		
	PEOU	TEC	TC	PEOU	TEC	TC	PEOU	TEC	TC
ANN 1	0.283	0.302	0.415	0.397	0.143	0.460	0.337	0.345	0.318
ANN 2	0.331	0.227	0.442	0.396	0.230	0.374	0.395	0.352	0.303
ANN 3	0.304	0.217	0.479	0.504	0.089	0.408	0.378	0.531	0.091
ANN 4	0.281	0.209	0.540	0.377	0.265	0.358	0.407	0.252	0.341
ANN 5	0.188	0.385	0.427	0.443	0.060	0.498	0.312	0.356	0.332
ANN 6	0.309	0.244	0.447	0.426	0.211	0.363	0.246	0.402	0.353
ANN 7	0.311	0.279	0.409	0.411	0.172	0.418	0.388	0.262	0.350
ANN 8	0.296	0.334	0.371	0.430	0.230	0.340	0.339	0.331	0.330
ANN 9	0.309	0.289	0.402	0.396	0.250	0.353	0.340	0.353	0.327
ANN 10	0.492	0.015	0.493	0.315	0.133	0.552	0.363	0.336	0.301
AVE	0.310	0.250	0.443	0.410	0.178	0.412	0.351	0.352	0.305

	ANN Model D			ANN Model E				ANN Model F				
	Output: PU			Output: IM				Output: BI				
	PEO	TEC	TC	CUR	JOY	CON	PU	CUR	JOY	CON	PU	IM
ANN 1	0.395	0.355	0.250	0.250	0.332	0.154	0.264	0.205	0.217	0.172	0.257	0.149
ANN 2	0.414	0.384	0.202	0.379	0.205	0.222	0.194	0.143	0.217	0.112	0.256	0.272
ANN 3	0.370	0.407	0.223	0.326	0.197	0.226	0.252	0.170	0.185	0.162	0.144	0.339
ANN 4	0.386	0.376	0.238	0.363	0.258	0.147	0.231	0.164	0.215	0.169	0.210	0.242
ANN 5	0.397	0.420	0.183	0.325	0.256	0.187	0.232	0.184	0.171	0.189	0.226	0.229
ANN 6	0.372	0.424	0.204	0.374	0.217	0.109	0.301	0.192	0.213	0.158	0.175	0.262
ANN 7	0.334	0.455	0.211	0.331	0.228	0.165	0.275	0.180	0.206	0.149	0.188	0.277
ANN 8	0.317	0.481	0.202	0.284	0.266	0.210	0.240	0.056	0.217	0.173	0.202	0.252
ANN 9	0.366	0.410	0.224	0.373	0.258	0.203	0.247	0.220	0.156	0.130	0.239	0.255
ANN 10	0.441	0.267	0.292	0.281	0.257	0.240	0.222	0.277	0.252	0.134	0.146	0.191
AVE	0.379	0.398	0.223	0.329	0.247	0.186	0.246	0.179	0.205	0.155	0.204	0.247

prediction error, but by its ability to uncover the deep-seated non-linear interaction patterns inherent in VR cultural heritage experiences.

Table 13 presents the sensitivity analysis results for all six ANN models, aiming to determine the standardized relative importance of input variables and provide an in-depth analysis of each variable's contribution to the prediction[63]. Specifically, in ANN model A (CUR) and model B (Joy), Task Characteristics (TC) were identified as the most significant predictor, with a standardized importance of 100% in both models. Additionally, Technology Characteristics (TEC) exhibited the highest predictive weight and contribution in ANN model C (Control) and model D (Perceived Usefulness). In the ANN model E (Immersion), CUR was confirmed as the dominant factor (100%), with its predictive capability significantly outperforming JOY, CON, and PU. Finally, in the ANN model F (Behavioral Intention), IM achieved a standardized importance of 100%, with its contribution significantly surpassing that of JOY, PU, CUR, and CON.

Finally, we compare the path coefficient values from the Partial least squares structural equation model (PLS-SEM) with the standardized importance coefficients from the Artificial neural network (ANN). This approach not only explains variable effects from the traditional causal perspective (PLS-SEM) but also evaluates the overall influence of variables from a predictive capability and data-driven perspective (ANN)[64]. Table 14 and Fig. 8 results indicate, the variable ordering outcomes of ANN models B–E maintain high consistency with the path coefficient ordering of PLS-SEM, which significantly enhances the structural stability and reliability of the models. However, the further analysis also revealed two significant points of divergence. First, in ANN model A, the normalized importance of

TEC is 80.573%, higher than that of PEOU at 70.147%. This ranking is completely opposite to the results obtained from SEM. Secondly, in ANN model F predicting BI, although Immersion (IM) exhibited the greatest contribution, the ranking of other hedonic variables (CUR, JOY, and PU) also differed significantly from SEM results (ANN: JOY > PU > CUR; SEM: PU > CUR > JOY)

Discussion

This study employs a hybrid analysis integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) and ANN to deeply reveal the influence mechanism of VR on the dissemination of ICH. PLS-SEM findings indicate that perceived ease of use (PEOU), technological characteristics (TEC), and task characteristics (TC) significantly shape users' VR cultural experiences through distinct psychological pathways. ANN analysis further captures and confirms the nonlinear relationships and predictive dominance within these mechanisms.This discovery not only reveals the multifaceted mechanisms through which VR technology functions in cultural transmission but also offers profound insights for immersive media research that transcend traditional PLS-SEM models. To this end, this study engages in an in-depth discussion centered around three research questions:

First, RQ1 (Differences in the Driving Forces of TEC and TC).

We examined the functional distinctions between TEC and TC in triggering users' cognitive evaluations and emotional motivations, revealing the communication logic where technology drives rationality while content drives emotion. H2a, H2b, H2c, and H2d were verified. TEC exert the most significant effects on PU ($\beta = 0.294$, $p < 0.001$) and CON ($\beta = 0.275$, $p < 0.001$), indicating that the technical features of the VR system are crucial not only in shaping users' PU but also in enhancing their sense of control during the experience. This aligns with previous findings, such as Steuer (1992), which identify interactivity and vividness as key technical dimensions influencing users' sense of presence, and validates that advanced technical affordances can enhance users' cognitive evaluations of VR platforms[21]. Furthermore, we found that TEC also has the strongest total effect on BI through the mediating role of PU, suggesting that improvements in VR technology not only directly benefit utility perceptions but also indirectly drive users' willingness to continue engagement via increased PU[65]. This pathway underscores the centrality of technical innovation in the sustainable adoption of VR-based ICH experiences, highlighting that optimizing system interactivity, fidelity, and usability can significantly foster both users' motivation for immersion and their long-term participation. Thus, enhancing the technical dimension of VR experiences is pivotal for promoting sustainable user engagement and supporting the digital transmission of ICH. However, the impact of TEC on emotional experience variables CUR ($\beta = 0.173^{***}$)) and JOY ($\beta = 0.168^{***}$)) is relatively minor, indicating that technical advantages primarily function through rational cognitive rather than emotional pathways. This provides critical guidance for technological investment decisions in VR-based ICH applications.Priority should be given to developing core functionalities that enhance users' value perception and sense of control, such as high-fidelity 3D reconstruction, intuitive interaction, and personalized navigation systems, rather than merely pursuing visually striking effects.

All four hypotheses related to task characteristics (H3a, H3b, H3c, H3d) were supported in our study. Specifically, the effect of TC on JOY (H3c, $\beta = 0.307$, $p < 0.001$) and CUR (H3b, $\beta = 0.280, p < 0.001$) highlights the pivotal role of cultural content in shaping users' emotional engagement during VR ICH experiences. This aligns with Pine and Gilmore (1998), who stressed that memorable and meaningful content is fundamental for creating impactful experiences, and our findings confirm the importance of rich cultural narratives and emotional resonance within VR dissemination of heritage[66]. Champion (2015) further pointed out that the success of digital heritage applications relies heavily on narrative depth and the emotional appeal of cultural content — points echoed by our results, which show that well-designed content in VR heritage applications significantly sparks user CUR and joy[67]. In contrast, although TC also influences PU (H3a, $\beta = 0.144^{***}$) and CON (H3d, $\beta = 0.198^{***}$), these effects are relatively weaker. This suggests that task characteristics drive user experience mainly through emotional rather than functional pathways, reinforcing the central value of content-driven emotional engagement in VR-based cultural heritage systems. Our findings provide practical guidance for the digital transformation of cultural heritage.When designing VR ICH applications, greater emphasis should be placed on enriching narrative quality, authenticity, and emotional resonance, rather than focusing solely on technical or functional features. This approach can significantly enhance users' CUR and joy, foster deeper immersion, and ultimately support the sustainable engagement and transmission of ICH. PEOU has a significant positive influence on all psychological experience variables (H1a、H1b、H1c、H1d), especially its strong effect on PU ($\beta = 0.280$, $p < 0.001$), verifying the enduring validity of TAM in VR environments. Davis (1989) emphasized that PEOU is a key antecedent of technology adoption, and this study reaffirms that proposition in immersive technology contexts[68]. Venkatesh et al. (2003) further elaborated that usability enhances perceived value by reducing cognitive load[11]. Notably, PEOU affects not only cognitive evaluations but also emotional experiences—JOY ($\beta = 0.251$, $p < 0.001$), CUR ($\beta = 0.183, p < 0.001$) and CON ($\beta = 0.220, p < 0.001$). This suggests that the benefits of ease of use extend beyond functional convenience to emotional and psychological engagement. These insights have substantial design implications for VR cultural heritage interfaces, underscoring the importance of simplifying operation processes, providing clear navigation cues, designing intuitive interactions, and establishing effective feedback mechanisms.

Second, RQ2 (the influence of primary variables on immersion and behavioral intention).

We conducted an in-depth analysis of how each perceived variable synergistically contributes to immersion (IM), confirming that IM serves as the pivotal link connecting internal psychological states to the ultimate behavioral intention (BI). IM plays a crucial mediating role between hedonic motivation and BI, with a direct effect on BI reaching $\beta = 0.356$ ($p < 0.001$) (H6). This finding confirms IM as a core component of VR user experience. It aligns with the immersion theory of Jennett et al. (2008), which conceptualizes IM as a psychological state of deep focus and temporal dissociation, significantly influencing user behavior[69]. Agarwal and Karahanna (2000) similarly identified IM as a key bridge connecting users' internal experiences and external behaviors, significantly predicting continuance intention[70]. This study further demonstrates that different antecedent variables affect IM through differentiated paths.TC mainly influence IM via CUR and JOY, whereas TEC exert their effects through PU. Moreover, PEOU significantly impacts all four hedonic constructs, with its strongest effect on JOY ($\beta = 0.212$, $p < 0.001$), consistent with TAM and Cognitive Load Theory[71]. Thus, ease of use reduces users' cognitive load and enhances emotional engagement. Based on these findings, VR-based ICH systems should foster IM through diverse design strategies, including engaging task design, stable technical performance, and intuitive interaction interfaces[18]. Further analysis reveals that PU (H5a), CUR (H5b), JOY (H5c), and CON (H5d),exert relatively balanced effects on BI ($\beta = 0.159$–0.189), reflecting the multidimensional integration of VR cultural heritage experiences. This finding aligns with the perspective proposed by Agarwal and Karahanna (2000), that deep user stickiness and sustained usage intent result from the synergistic effects of multiple psychological factors[70].

Finally, RQ3 (Nonlinear Reassessment and Research Implications).

By comparing the predictive weights from ANN and SEM, we reassessed the influence ranking of variables. Leveraging the nonlinear advantages of VR technology, we propose specific recommendations for the digital design and optimization of cultural heritage. In the ANN analysis, the ranking results of ANN model A contradicted those of SEM (SEM: PEOU > TEC; ANN: TEC > PEOU). This discrepancy may stem from the presence of significant nonlinear components in the mechanism governing user CUR. In the context of VR cultural heritage, the high fidelity and groundbreaking interactivity provided by technology demonstrate stronger overall predictive power in stimulating users' intrinsic desire to explore. Its nonlinear driving effect surpasses the direct linear influence of PEOU.

Table 14 | Comparison of PLS-SEM and ANN results

Path relationship	PLS-SEM path coefficient	ANN normalized importance (%)	Path Ranking (PLS-SEM)	Path Ranking (ANN)	Comment
ANN Model A (CUR)					
PEOU → CUR	0.183	70.147%	2	3	Not Matched
TEC → CUR	0.173	80.573%	3	2	Not Matched
TC → CUR	0.280	100.000%	1	1	Matched
ANN Model B (JOY)					
PEOU → JOY	0.251	99.297%	2	2	Matched
TEC → JOY	0.168	43.235%	3	3	Matched
TC → JOY	0.307	100.000%	1	1	Matched
ANN Model C (CON)					
PEOU → CON	0.220	99.574%	2	2	Matched
TEC → CON	0.275	100.000%	1	1	Matched
TC → CON	0.198	86.904%	3	3	Matched
ANN Model D (PU)					
PEOU → PU	0.280	95.300%	2	2	Matched
TEC → PU	0.294	100.000%	1	1	Matched
TC → PU	0.144	56.019%	3	3	Matched
ANN Model E (IM)					
CUR → IM	0.217	100.000%	1	1	Matched
JOY → IM	0.193	75.289%	2	2	Matched
CON → IM	0.169	56.695%	4	4	Matched
PU → IM	0.184	74.802%	3	3	Matched
ANN Model F (BI)					
CUR → BI	0.162	72.569%	3	4	Not Matched
JOY → BI	0.160	83.023%	4	2	Not Matched
CON → BI	0.159	62.723%	5	5	Matched
PU → BI	0.189	82.780%	2	3	Not Matched
IM → BI	0.225	100.000%	1	1	Matched

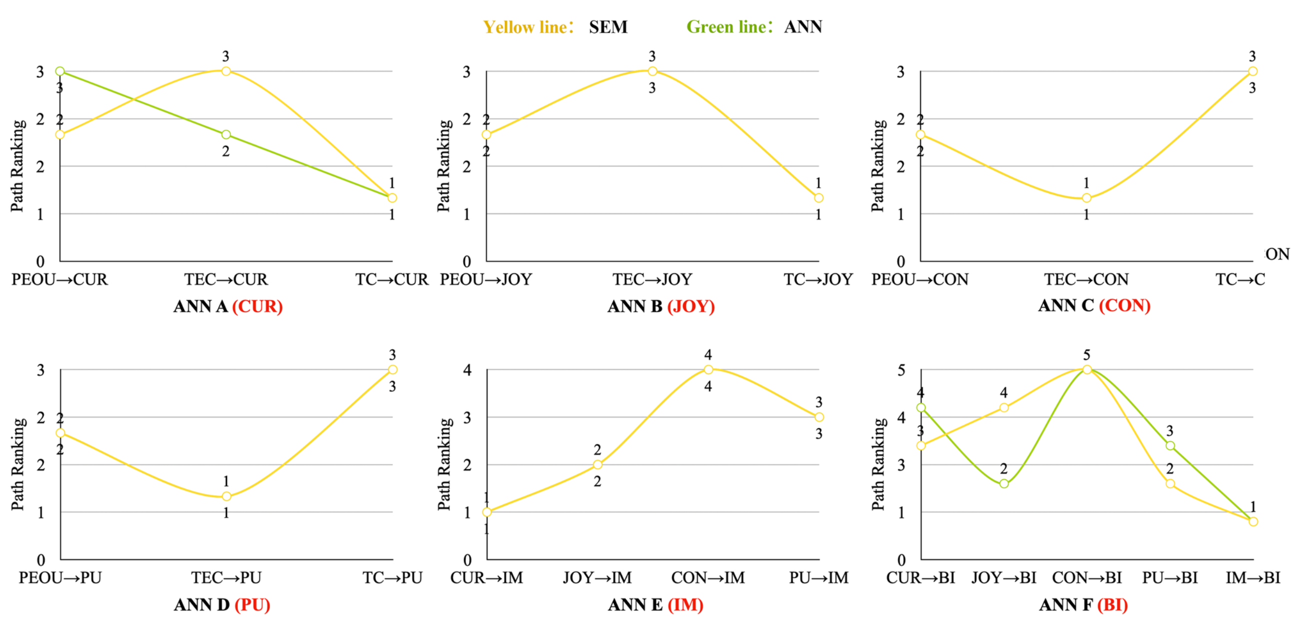

Fig. 8 | Path Ranking of PLS-SEM and ANN.

Therefore, relevant platforms should ensure that VR models and environments achieve the highest level of detail, using visual impact to spark users' CUR and desire to investigate. Simultaneously, more highly innovative interaction methods that are impossible to achieve in reality (such as flying over Dunhuang murals, interacting with digital artifacts in real time) are designed to fully leverage TEC's non-linear advantages. Additionally, the ANN model F results (JOY: 83.023% > PU: 82.780% > CUR: 72.569%) differs from the SEM results (PU: 0.189*** > CUR: 0.162*** > JOY: 0.160***). This reversal strongly indicates that in the context of VR cultural heritage—a highly pleasurable experience—the primary driver influencing users' BI has shifted from cognitive evaluation to immediate emotional experience. The ANN results confirm JOY's nonlinear contribution or its synergistic effect within complex interactive mechanisms, establishing it as the second most critical predictive variable in the model after IM. Relevant system developers can adopt more compelling cultural narrative scripts, incorporating characters, stories, and emotional resonance points to integrate cultural knowledge into the entertainment experience. By carefully balancing task difficulty with user skill levels and implementing timely feedback mechanisms, they can maximize user JOY and IM, ensuring willingness to re-engage or recommend.

The theoretical significance of this study lies in constructing a comprehensive theoretical framework for VR technology that empowers cultural heritage dissemination, providing important theoretical expansion for the field of digital cultural communication. First, at the methodological level, this study integrates the Partial Least Squares Structural Equation Modeling (PLS-SEM) and ANN to develop a hybrid modeling approach. This innovation enables nonlinear identification and weighting of perceptual variables, significantly enhancing modeling accuracy and predictive capabilities in cultural behavior research. It provides a more interpretable analytical paradigm for subsequent studies on immersive media. Second, at the level of theoretical integration, this study addresses the limitations of traditional media effects theory in the context of immersive technologies by incorporating TTF, HMSAM, and immersion theory. Specifically, ANN analysis confirms the nonlinear mechanism of immersion (IM) as a unique mediating variable. Simultaneously, the research has systematically distinguished the roles of technological characteristics (TEC) and task characteristics (TC) in shaping users' psychological and behavioral responses. Technological elements primarily drive rational cognitions, such as perceived usefulness (PU) and control (CON), while content-related features are key to stimulating emotional motivations, such as joy (JOY) and CUR. This transcends the traditional perspective of viewing technology as a simple tool, offering a deeper interpretation of how experience design and technological innovation interact within digital ICH applications. Finally, this study further validates the applicability and explanatory power of the classic TAM within emerging immersive media, particularly in the specific application domain of digital heritage communication. This not only provides scholars with a new research framework but also highlights the value of a multidimensional integrated perspective in digital cultural communication and user experience studies.

This research provides clear and practical guidance and suggestions for developers of VR cultural heritage applications and cultural institutions in digital communication practices. Firstly, at the technical development level, developers priority should be given to investing in core functions that can directly enhance users' perception of value and control experience, such as high-fidelity 3D reconstruction technology, intuitive interactive interface design, and personalized navigation systems, rather than merely pursuing visual shock effects. To promote deep immersion and engagement, developers should integrate exploratory and interactive tasks that leverage VR's unique capacity for progressive discovery and CUR stimulation. Secondly, for cultural institutions, the findings highlight the importance of showcasing the practical value and unique experiential aspects of VR heritage applications in public outreach. Institutions should weave emotionally resonant cultural narratives and interactive recreations of historical scenes to foster deeper emotional connection and motivate audience exploration and participation. Furthermore, the user-friendly design of the user interface is the fundamental prerequisite for all positive experiences. Developers should reduce users' learning costs by simplifying the operation process, providing clear navigation guidance, and establishing an effective feedback mechanism. Finally, to maximize the unique advantages of VR technology, it is essential to focus on designing exploratory tasks that can stimulate users' CUR, such as progressive cultural discovery mechanisms, hidden historical Easter eggs, and interactive cultural puzzles, thereby promoting the formation of a deeply immersive experience. The research results also indicate that when cultural institutions promote VR applications, they should cultivate user acceptance by demonstrating the practical value of the system and the uniqueness of the experience, thereby enhancing the public's awareness and participation in digital cultural heritage.

This study explores the mechanism of VR technology in the dissemination of ICH from both theoretical and empirical perspectives, but there are still some areas that need improvement. Firstly, the research samples mainly come from urban users in Chinese mainland, with relatively single cultural backgrounds. This may limit the applicability of the research conclusions in different countries and cultural environments. Under different cultural backgrounds, people's ways of understanding and emotional responses to traditional culture may vary significantly. Future research should expand the sample range and conduct cross-cultural comparative studies. Secondly, this study adopts a cross-sectional questionnaire survey, which cannot reflect the dynamic changes of user experience over time. With the accumulation of usage experience and the deepening of cultural understanding, users' attitudes and feelings may evolve. Therefore, in the future, this change process can be observed through longitudinal tracking studies. Thirdly, the research data mainly comes from self-reported questionnaires, lacking objective measurement of users' actual behaviors and learning outcomes. In the future, more comprehensive evidence can be obtained by combining methods, such as behavioral observation, in-depth interviews or experimental research. Fourthly, since this study only investigates the application of VR in ICH scenarios, future research can expand its application scenarios, integrating different fields, such as education, tourism, and social communication to further verify the diverse roles of VR technology in the transmission of cultural knowledge, the cultivation of emotional identification, and the dissemination of social values. Finally, VR technology itself is developing rapidly, with new forms of interaction and content presentation constantly emerging. The conclusions drawn from this study based on the current technological level may need to be updated along with technological progress and changes in cultural dissemination methods.

This study integrates the Task–Technology Fit (TTF) theory and the Hedonic Motivation System Adoption Model (HMSAM) to construct a comprehensive framework for exploring the mechanisms underlying user experience and behavioral intention toward VR technology in the dissemination of ICH. The results indicate that task characteristics, technological characteristics, and perceived ease of use (PEOU) all exert significant influences on users' psychological motivation. Technological characteristics enhance users' rational cognition by improving perceived usefulness (PU) and sense of control (CON), whereas task characteristics stimulate emotional resonance through joy (JOY) and CUR, thereby promoting immersive experiences and participation willingness. PEOU not only enhances operational convenience but also strengthens users' positive emotional responses by reducing cognitive load. Furthermore, immersion (IM) plays a significant mediating role between hedonic motivation and behavioral intention (BI), suggesting that emotional experience is a critical bridge linking technological features to the effectiveness of cultural communication. At the theoretical level, this study expands the application of TTF and HMSAM in the field of digital cultural heritage through the integration of PLS-SEM and ANN. It also provides the first empirical validation of nonlinear relationships among core variables, offering new insights into understanding user behavior within immersive technologies. At the practical level, the results provide targeted guidelines for the design and promotion of VR-based ICH systems. Developers should prioritize system stability and natural interaction, enhancing users' sense of control and value perception through high-quality visual presentation and user-friendly interface design. Meanwhile, cultural narratives and exploratory tasks should be incorporated at the content level to evoke CUR and enjoyment, fostering deeper immersion and cultural resonance.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available due to privacy or ethical restrictions, as the data contain information that could compromise the confidentiality of research participants. but are available from the corresponding author (Junping Xu) on reasonable request.

Received: 20 December 2025; Accepted: 2 March 2026;
Published online: 14 March 2026

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Acknowledgements
This research was supported by 2026 Zhejiang Provincial Philosophy and Social Science Planning Project [Grant No. 26NDJC316YB]; and Research and Creation Project of Zhejiang Provincial Department of Culture Radio Television and Tourism [Grant No. 2025KYY011]; and 2025 Henan Provincial Philosophy and Social Science Planning Project [Grant No. 2025CYS036]; and 2026 Henan Provincial Soft Science Research Project [Grant No. 262400410065].

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Conceptualization, Xuanjia Ren; methodology, Junping Xu; software, Xuanjia Ren; validation, Xuanjia Ren and Junping Xu; formal analysis, Xuanjia Ren and Jinyang Xu; investigation, Junping Xu; resources, Xuanjia Ren; data curation, Xiaoyan Hao; writing—original draft preparation, Xuanjia Ren; writing—review and editing, Xuanjia Ren; visualization, Xuanjia Ren; supervision, Junping Xu; All authors have read and agreed to the published version of the manuscript.

Competing interests
The authors declare no competing interests.

Informed Consent Statement
Informed consent was obtained from all subjects involved in the study.

Institutional Review Board Statement
This study was approved by the ethics committee of Zhejiang University on September 30, 2025 (protocol code: cmic20250934). The research was conducted in strict accordance with the ethical principles outlined in the Declaration of Helsinki (1964) and its subsequent amendments or similar ethical standards. All procedures involving human participants adhered to the institutional and national ethical standards for research.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s40494-026-02425-7.

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