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Research on user satisfaction with AIGC assisted museum scenario design

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In the context of digital transformation, artificial intelligence generated content (AIGC) technology provides an innovative path for museum smart scene design, but existing research lacks a user-centered systematic framework. This study uses questionnaire surveys and structural equation models (SEM) to explore the mechanism of AIGC technology adaptability, user demand fit, scene design innovation, technology acceptance and user satisfaction. The results show that user demand fit has the strongest direct impact on satisfaction, highlighting the "user-centered" design core; AIGC technology adaptability improves satisfaction through direct and indirect paths, verifying the mediating effect of the technology acceptance model (TAM); scene design innovation needs to transform value through technology acceptance to affect user satisfaction. The study constructs a closed-loop model of "demand drive-technology adaptation-scene innovation-acceptance conversion", and proposes a design strategy based on cognitive load balance, which provides a theoretical basis and practical path for museums to use AIGC technology to improve user experience, and promotes the paradigm shift of museums from "object-centered" to "people-centered".

As the core carrier of cultural heritage, knowledge dissemination and public education, the scene design of museums has a profound impact on the audience's cognitive experience and emotional resonance. In the context of the digitalization wave sweeping the world, the rapid development of artificial intelligence generated content (AIGC) technology has injected unprecedented vitality into the transformation and upgrading of museums[1]. With its strong capabilities in content generation, visual presentation, and interactive narrative, AIGC is gradually reshaping the exhibition form, narrative logic and interactive experience of museums[2]. It can efficiently generate realistic virtual cultural relics restoration, construct immersive historical scenes, provide personalized guided tours, and even assist in the design of cultural and creative products[3], providing an innovative path to overcome the bottlenecks of traditional museums in terms of space limitations, narrative monotony, lack of interactivity, and resource activation and utilization[4]. Current research has made significant progress in AIGC-enabled museum scene design. Scholars have actively explored the application potential and specific strategies of AIGC in the fields of spatial narrative optimization, virtual museum construction, immersive experience creation, digital display and dissemination of cultural heritage, and cultural and creative product innovation. On the technical level, the research covers the integrated application of key technologies such as image recognition based on deep learning, VR/AR/MR interaction, emotional computing and interaction, and recommendation systems[5–11]. However, research and practice in this field still face a series of key issues and controversies that need to be resolved, highlighting the urgency of focusing on the "user-centered" perspective: First, there is a lack of insight into user needs and scene adaptation[12]. There is often a gap between the content generated by AIGC and the actual expectations of users, resulting in a disconnect between technology application and user experience. Although existing research widely uses various technologies, it does not explore the deep cognition, emotions, behavioral habits and personalized needs of different groups, such as elderly audiences, children or people with special needs in museum scenes[13–16]. Secondly, there are challenges in balancing the depth of AIGC application and cultural authenticity. Although AIGC has improved efficiency and form innovation, there are significant controversies on how to ensure the cultural accuracy, historical seriousness and emotional depth of generated content. Third, there is a lack of a user-centered evaluation system. Existing research focuses on technical implementation or macro effect description, lacking a systematic and standardized user experience evaluation model to scientifically evaluate the effectiveness of AIGC-assisted scene design. The lack of empirical, fine-grained factor correlation analysis of key indicators such as user satisfaction, immersion, cognitive load, emotional resonance, and continued use intention has led to a lack of clear direction for design optimization and difficulty in accurately improving user value[17–19]. These limitations point to a core problem: the current

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application of AIGC in museum scenarios has not yet fully established a driving mechanism and design paradigm centered on user needs, experience, and value.

In response to the above challenges, this study focuses on the user-centered AIGC-assisted museum scene design elements. The core objectives are: to deeply analyze the core needs and expectations that affect the user's museum experience; to systematically identify and refine the key design elements that have a decisive impact on the user experience in the process of AIGC technology empowering museum scene design, and to explore the correlation mechanism between these elements and core experience indicators such as user satisfaction, immersion, learning effectiveness, and cultural identity. Finally, a user-demand-driven AIGC-assisted museum scene design element is constructed to provide theoretical guidance and empirical basis for design practice. This study uses questionnaire surveys and structural equation models (SEM) to demonstrate that it has significant value in guiding AIGC technology to serve user needs more accurately and improve the cultural communication effectiveness and emotional connection depth of museum scenes. It contributes to the key path to promote the fundamental transformation of museums from "object-centered" to "people-centered" in the digital era.

Literature review

Technology acceptance

The Technology Acceptance Model (TAM) provides a core theoretical framework for analyzing the user's cognitive process of AIGC-assisted museum scenarios. Studies have shown that the dynamic interface layout generated by AIGC can improve the perceived usability of virtual museums, and users' evaluation of operational efficiency is significantly better than traditional designs[20,21]; in VR narrative scenarios, the multi-line narrative paths generated by AIGC can improve the perceived usefulness score, among which "content relevance" is the key variable driving continued willingness[22]. Empirical evidence from gamification application scenarios shows that enjoyment experience and meaningful experience significantly and positively affect technology acceptance through the dimension of perceived usefulness, and "knowledge acquisition efficiency" and "interaction fun" constitute its core evaluation indicators[23]. Research on emotional interaction design shows that facial expression interaction given by AIGC can reduce the negative perception of response delay, and users' evaluation of the system's "intelligence" and "naturalness" is significantly improved [2], when the trust variable is incorporated into the TAM model, the cultural semantic accuracy and interaction consistency of AIGC significantly enhance perceived usefulness through the mediation of trust, thereby improving technology acceptance intention[24].

The effect of AIGC technology on improving user experience satisfaction forms a two-way coupling with technology acceptance. AI-generated museum cultural products can effectively improve overall satisfaction through multimodal database strategies[25], and tactile interaction solutions significantly promote emotional engagement through improved operational accuracy and immersion[26]. The structural equation model further verifies that the cultural identity cues generated by AIGC have a significant positive impact on user recommendation intention through the dual mediation of satisfaction and stickiness intention. This process relies on technology acceptance as a cognitive transformation bridge[27]. The digital museum service evaluation model also points out that the application of AIGC in guided tours can effectively improve information acquisition satisfaction, but the technology adaptation fault will lead to a decrease in overall satisfaction, reflecting the direct impact of the continuity of technology acceptance on experience evaluation[28] Based on this, this study proposes the following hypotheses:

H1 *Technology acceptance positively affects user experience satisfaction.*

Technical adaptability of AIGC in museum scene design

The deep involvement of AIGC technology in the field of museum design is promoting multi-dimensional paradigm innovation, and the correlation mechanism between its technical adaptability and user satisfaction has become the core of research. At the cultural communication level, AIGC is based on the three-dimensional design logic of semantics, grammar, and pragmatics. Through the four-layer innovative architecture of theme generation, creative optimization, and content adaptation to carrier presentation, it can improve the service efficiency of cultural and creative products, and dynamically adjust the narrative path through user portraits to significantly enhance the personalization of interactive experience[29]. In spatial interaction innovation, the multimodal AI system integrates gesture recognition, voice interaction, and eye tracking technology to achieve personalized customization of immersive experience[30]; the crowd prediction model based on the LSTM algorithm dynamically controls the light environment and guide path, effectively improving the efficiency of space use[16]. In terms of venue experience upgrades, micro-expression modeling technology will effectively improve the credibility of virtual digital human interpretation, and the correlation coefficient of audience empathy intensity will also increase significantly[31]; fMRI experiments have confirmed that the combination of generative AI and AR technology can activate the prefrontal cortex, reduce anxiety levels, and directly affect user emotional experience[32].

Existing research shows that the lack of technical adaptability will significantly restrict the improvement of satisfaction: in recent years, the lack of a mechanism for inheritors to participate in intangible cultural heritage digitization projects has led to cultural translation deviations, and small sample training has effectively reduced the mean absolute error (MAE) of personalized recommendations[33,34]. The iteration of multilingual smart guide systems and innovations in barrier-free interaction technology can improve user participation by expanding the inclusive boundaries of services[35,36]. Digital twin technology and dynamic monitoring models under the metaverse framework raise the data security level to international certification standards, providing guarantees for experience continuity in virtual-real symbiosis scenarios[37,38]. In addition, technology adaptability can also affect user satisfaction through technology acceptance. Existing research has been verified by structural equation model: in the interactive research of VR Museum, the impact of device compatibility on user satisfaction is entirely mediated by perceived ease of use, and its mechanism lies in the optimization of adaptability to reduce operational friction, thus enhancing users' willingness to accept technology[39,40]; Through the immersion exhibition research, it is further found that the mediating effect of perceived usefulness is significant in the correlation between technology response speed and satisfaction. When the aigc system adapts to different network environments and stably outputs cultural content, users' perception of "technology assisted cultural acquisition" is enhanced, which indirectly improves satisfaction[41]. From this we can draw the following hypothesis:

H2 *Technology adaptability positively affects user satisfaction.*

H3 *Technology adaptability positively affects user satisfaction through the mediation of technology acceptance.*

User needs compatibility

The diversity of museum user groups determines the complexity of demand adaptation, covering different portraits such as Generation Z teenagers, adult audiences, research groups and professional researchers. The core of the user perspective is to promote the transformation of the museum experience paradigm from "object-centered" to "user-centered" based on emotional resonance, cognitive habits, interactive experience, intelligent services and cultural identity needs. At present, the application of AIGC technology in museum scene design has gradually shifted to the "demand-driven" mode, realizing four levels of innovation such as theme generation and creative optimization through semantics, language structure and pragmatics three-dimensional logic, significantly improving the personalized experience of cultural and creative products[42]. From the perspective of user experience, the core value of AIGC technology is reflected in the optimization of cultural scene interaction mode. Related studies have shown that personalized narrative paths generated based on AIGC can expand users' cultural participation from the perspective of perceptual depth and emotional experience, and improve their cognitive validity of cultural contexts[2]. Research introducing psychological empathy theory further confirms that AIGC systems with psychological empathy can significantly improve the user experience of museum products by intelligently generating interactive content that meets users' emotional demands[43]. At the technical integration level, the fusion of AIGC and immersive technology has become the key to optimizing the experience—the combination of virtual museums and intelligent virtual avatars driven by generative AI can build a unified user experience framework and coordinate the coherence of virtual scenes[44]; AIGC-assisted mixed reality technology can effectively enhance the audience's sense of immersion and cognitive depth by dynamically generating interactive content that adapts to the user's cognitive characteristics[45].

Structural equation model analysis shows that user demand fit has the most significant direct impact on user satisfaction. This conclusion is highly consistent with the theory of emotional design. When the content generated by the AIGC system accurately matches the diverse needs of users, satisfaction can be effectively improved[46]. Specifically, emotional cultural identity strengthens the emotional connection between users and cultural relics through narrative design, and together constitutes the core mechanism of demand-driven satisfaction[47]. The application cases of mixed reality devices further confirm that the demand adaptation design of physical cultural relics and virtual environments can improve the efficiency of cultural heritage learning and simultaneously promote the growth of satisfaction[48]. The current application of AIGC technology in museum scenarios still needs to overcome challenges such as insufficient accuracy of emotional generation and real-time defects of multi-user interaction. Future research can focus on the deep integration of technology and experience, multidisciplinary cross-methodology and service intelligent upgrade to build a more inclusive user demand-satisfaction driving system. Based on this, this study proposes the following hypotheses:

H4 *User demand fit has a positive impact on user satisfaction.*

H5 *User demand fit positively affects user satisfaction through the mediation of technology acceptance.*

Innovation of scene design

Research on museum scene design is developing towards the cross-integration of spatial narrative, digital experience and cultural innovation. In the field of spatial narrative and interactive experience optimization, the study proposed a spatial narrative strategy of multi-cue coupling. Through the semantic embedding of light and shadow and materials, it was confirmed that the linkage of narrative rhythm and structure can awaken the audience's "scene memory". The light and shadow material semantic system constructed by this study provides a quantitative analysis framework for spatial emotional expression[49]. The study that introduces "scene" theory into immersive interactive design points out that museums need to achieve a paradigm shift from "object-centered" to "human-dominated" interaction, and achieve time and space reset through multi-media integration. The "passive viewing-active interaction" experience transformation model proposed by it has been widely adopted in virtual museum research[50]. In the study of the integration of digital experience and education, the technical integration level effectively solves the problem of the single traditional display channel through VR/AR and multi-classifier interaction engine[51]; the virtual reconstruction technology of museum space based on Unity3D effectively improves the restoration degree of virtual model to physical space through three-dimensional coordinate calculation and point cloud information fusion, and establishes technical standards for VR/AR scene reconstruction[52]. In educational scene design, the combination of immersive scenes and biofeedback technology shows that multi-sensory interaction can improve the efficiency of knowledge transfer, and the cognitive intervention model constructed provides a medical basis for the experience design of special groups[53]. Research on cultural space innovation and digital transformation is based on scene theory. For example, through the superposition of digital projection and physical exhibition, the decoding technology of urban cultural genes is applied to spatial layout to enhance the audience's emotional resonance with regional culture[54]. In terms of virtual simulation technology, the virtual data generation method based on scene flow prediction and VR interface optimization research based on balanced cognitive load theory shows that dynamic adjustment of interface elements can reduce the incidence of cognitive overload[55], and relevant evaluation models have been included in industry design guidelines[56,57]. In addition, the introduction of multi -sensory communication design and empathy design of digital characters further strengthens the emotional connection ability of the scene[58].

The mechanism of the effect of scene design innovation on satisfaction presents a dual-path transmission characteristic. Through the cognitive optimization path, the VR interface optimization based on the balanced cognitive load theory effectively improves the operation accuracy and directly drives the behavioral experience satisfaction[59]; In addition, through the emotional resonance path, the cultural identity clues generated by AIGC indirectly enhance the willingness to recommend through the dual mediation of satisfaction and sticky intention. Previous research still has gaps in the depth of spatial narrative theory, the excavation of the cultural connotation of digital experience, and the construction of a scene design theory system[60]. Future research can focus on the in-depth construction of the theoretical framework, the organic integration of technology and culture, and the integration of interdisciplinary methodologies, and promote the upgrading of museum scene design from the technical tool level to the value creation level, thereby forming an influencing mechanism on user satisfaction. Based on this, this study proposes the following hypothesis[61]:

H6 *Scene design innovation has a positive impact on user experience satisfaction.*

H7 *Scenario design innovation positively affects user satisfaction through the mediating effect of technology acceptance.*

Proposed theoretical model

Based on the above theory, this study proposes a comprehensive model (Fig. 1) by fully considering the characteristics of museum scenes and drawing on previous research techniques, methods and results. Technology compatibility (ATC), scene design exploration (SDE), user needs emphasis (UNE), technology acceptance (TA), customer satisfaction (CS) are considered in five dimensions, and seven related hypotheses are proposed to explore users' satisfaction with the museum scene design generated by AIGC.

Research methods

Research ideas

This study carried out data collection through questionnaire survey, and the research scope was limited to social science survey, without any human experimental operation. All participants participated on a voluntary basis, and anonymization was used throughout the data collection process to fully protect individual privacy. The research methods strictly follow academic norms and industry standards, and the relevant experimental schemes have been approved by the institutions affiliated to the research team.

In terms of ethical review, this study strictly abides by the ethical standards advocated in the declaration of Helsinki, and follows the measures for ethical review of life sciences and medical research involving human beings (Trial) issued by China in 2023: it has been submitted to the institutional review board (IRB) of Tsinghua University for review. Prior to the study, all participants were provided with written informed consent, which clearly informed them of the purpose of the study, the purpose of the data and privacy protection

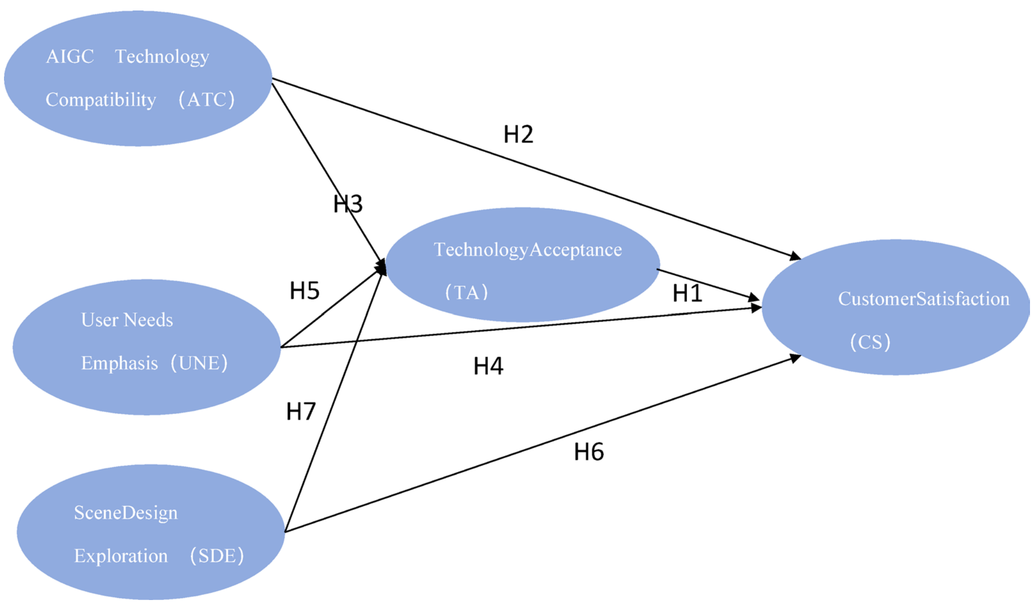

Fig. 1. Conceptual model.

measures. Participants signed the consent and were included in the study. Minors (12–17 years old) need to sign a consent form with their guardians to participate; The anonymity and confidentiality of information are ensured throughout the data collection process, which meets the requirements of ethical review. Therefore, the implementation process of this study fully meets the requirements of the current ethical norms.

The first part of the questionnaire is to investigate the basic demographic information of the respondents. The second part of the questionnaire mainly focuses on the influencing factors, which are mentioned in the relevant theoretical overview in the second part: aigc technology adaptability, user demand fit, scene design innovation, technology acceptance, user experience satisfaction, including 20 secondary indicators. Aigc technology adaptability is represented by five dimensions: technology integration efficiency, intelligent interaction level, personalized generation ability, technology response speed, and system sustainability; User needs fit: emotional cultural identity, intergenerational needs adaptation, interactive control autonomy, ethical transparency and trust, intelligent cross platform integration; Innovation of Museum scene design: space narrative efficiency, digital technology adaptation, education communication efficiency, digital expression of cultural symbols; Technology acceptance: perceived usefulness, perceived ease of use, attitude tendency; User satisfaction: cognitive experience satisfaction, emotional experience satisfaction, behavior experience satisfaction, and overall scene satisfaction. The questionnaire uses the 7-point Likert scale to assess user satisfaction. The scale has been widely used in many research fields because of its excellent performance in both accuracy and simplicity. During the survey, the researchers explained the AI design scheme and creation process in detail to the respondents, and guided them to objectively evaluate the experience according to the scoring standard of 1 (strongly disagree) to 7 (strongly agree).

Questionnaire

After the design proposal was completed, this study used a random sampling method to conduct a questionnaire survey and systematically collect consumer satisfaction data. The questionnaire design strictly refers to the 5 dimensions and 25 indicators developed in the evaluation system (Table 1), and through a literature review, the research results in related fields were systematically sorted out to ensure the validity and scientificity of the questionnaire. The survey content is divided into two parts: the first part focuses on consumers' cognition of AIGC and their attitude towards AI-generated design, while collecting demographic information of respondents; the second part focuses on AI-generated museum cultural and creative products, using a five-point Likert scale to deeply evaluate user opinions from the two dimensions of importance and satisfaction. This scale is excellent in balancing measurement accuracy and simplicity, and has therefore been widely used in many research fields. During the survey, the researchers explained the AI design plan and creation process in detail to the respondents,

Latent variable	Coding	Item	References
AIGC Technology Compatibility (ATC)	ATC1: Technology Integration Effectiveness	AIGC tools can achieve good technical integration	Yanzhang and Jiawei (2024)[20], Ling[21] Yuzhen (2025)[30] Kayaalp (2022)[16] Tang (2024)[31] Wang and Cai (2022)[42]
	ATC2: Intelligent interaction level	AIGC tools have a good level of intelligent interaction	
	ATC3: personalized generation capability	AIGC tool personalized generation capability	
	ATC4: technical response speed	Using AIGC tools for design has a fast technical response speed	
	ATC5: System Sustainability	AIGC tools have high technical sustainability	
Scene Design Exploration (SDE)	SDE 1: Emotional Cultural Identity	I agree with the emotional culture conveyed by the content of AIGC's generative design	Xiduo and Congcong (2025)[50] Zhang and Liu (2023)[52] Yang and Wang (2022)[53] Liu and Mi (2023)[39]
	SDE 2: design requirements adaptation	The works generated by AIGC can be adapted to different scene designs	
	SDE 3: interactive control autonomy	When designing with AIGC tools, you can interactively control	
	SDE 4: Ethics Transparency Trust	AIGC-generated works are ethically transparent	
	SDE 5 : Intelligent Cross-Platform Integration	AIGC tools can integrate resources across platforms intelligently	
User Needs Emphasis (UNE)	UNE1: Spatial Narrative Effectiveness	AIGC-generated works have excellent spatial narrative capabilities	Fang and Jiang (2023)[44] Bayat et al. (2024)[45] Long and Han (2024)[46]
	UNE2: digital technology adaptation	AIGC technology can adapt digital technology well	
	UNE3: Educational Communication Effectiveness	AIGC can effectively carry out educational dissemination	
	UNE4: Digital Expression of Cultural Symbols	Designing through AIGC can realize the digital expression of cultural elements	
Technology Acceptance (TA)	TA1: Perceived usefulness	Using AIGC tools is useful for museum scene design	Chang and Suh (2025)[22] Sangamuang et al. (2025)[23] Jolibois et al. (2025)[2]
	TA2: Perceived ease of use	I can easily use AIGC tools	
	TA3: Attitude	I will recommend museum cultural and creative products generated by AIGC to others	
Customer Satisfaction (CS)	CS1 : Cognitive experience satisfaction	AIGC tools can optimize knowledge transfer paths and cognitive load management to enhance user cognitive experience	Li et al. (2024)[25] Alvarado-Vanegas et al. (2024)[26] Gayathri and Nam (2024)[28] Zhang et al. (2022)[60]
	CS2:Emotional experience satisfaction	AIGC tools can enhance multimodal interaction and cultural narrative to enhance user emotional resonance	
	CS3:Behavioral experience satisfaction	AIGC can optimize interaction efficiency and enhance behavioral experience through participatory design	
	CS4:Overall scene satisfaction	Designing with AIGC tools can comprehensively optimize museum scenes and affect users' overall satisfaction and behavioral intentions	

Table 1. Measurement scale.

Measure	Items	Frequency	Percentage
Gender	Male Female	152 175	46.4% 53.5%
Age	12–25 26–40 40–50	125 102 100	38.2% 31.2% 30.6%
Education level	High school and below Junior college Bachelor Master or above	45 60 148 74	13.8% 18.34% 45.26% 22.6%
Frequency of use (per year)	1–3 4–6 6–10 > 10	70 90 108 59	21.4% 27.5% 33.02% 18.08%
Level of understanding museum culture	6.25		
Level of cognitive in AI art and design	5.65		
Level of interest in AI art and design	6.23		

Table 2. Participant characteristics (n = 327).

Cronbach's alpha coefficient	Standardized Cronbach's alpha coefficient	Number of items	Number of samples
0.859	0.859	20	327

Table 3. Reliability analysis (n = 327).

and guided them to objectively evaluate the experience according to the scoring criteria of 1 (strongly disagree) to 7 (strongly agree).

Data collection and analysis

According to the research results, the 12–50—year—old group is the core target group for museum visiting experience, and the data collection objects of this study mainly focus on individuals in this age group. The data collection period is from February 15 to April 30, 2025, and it is conducted in a combination of online and offline methods. To ensure data quality, this study set two screening questions in the questionnaire design, which are used to confirm the age range of respondents and museum visiting and design experience. During the data analysis stage, questionnaires that do not meet the conditions were eliminated, and only valid questionnaires were retained. All interviewee information is strictly confidential and anonymous throughout the process. Online data was collected through social platforms such as WeChat and Weibo; offline surveys were conducted from April 5 to 20, 2025 in the National Museum of China, the Palace Museum, and the China Science and Technology Museum. A total of 365 questionnaires were collected in the study, and after screening, 327 valid questionnaires were included in the final analysis. For detailed demographic analysis, see (Table 2). The gender ratio of the respondents is about 4:5, which is basically consistent with the gender characteristics of the main museum visitor groups. In the survey on the usage of AI-generated art design (using a 7-point scale), the average score was 5.65, indicating that most respondents have a certain understanding of this field; and the interest score was as high as 6.62, fully reflecting consumers' strong interest in this emerging art form, indicating that it has strong market appeal and development potential.

Results

Reliability analysis

This study used SPSS 27.0 software and the widely recognized Cronbach's alpha coefficient to test the reliability of the scale. Regarding the evaluation criteria of Cronbach's alpha coefficient (or half coefficient), most scholars advocate that if the coefficient value exceeds 0.9, it indicates that the scale reliability is excellent; if it is in the range of 0.8–0.9, it means that the reliability is good; if it is between 0.7 and 0.8, the reliability is within an acceptable range; 0.6–0.7 indicates medium reliability; 0.5–0.6 indicates poor reliability; if it is lower than 0.5, it is usually necessary to re-optimize the questionnaire design. After testing, the Cronbach's alpha coefficient of the questionnaire in this study is 0.859. It can be seen that the reliability index of the scale is ideal and fully meets the requirements of empirical research for the stability of the measurement tool. Subsequent analysis can be based on this. See (Table 3) for details.

Effectiveness analysis

The result of KMO test shows that the value of KMO is 0.864. At the same time, the result of Bartlett's sphericity test shows that the significant P value is 0.000***, which is significant at the level. The original hypothesis is rejected. There is correlation between the variables. The factor analysis is effective and the degree is appropriate. For details, see (Table 4).

KMO test and Bartlett's test		
KMO value		0.864
Bartlett's test of sphericity	Approximate Chi-square	5182.523
	df	210
	P	0.000***

Table 4. Validity analysis. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Discrimination analysis results					
	Group (mean ± SD)				
	0%-27%	27–73%	73–100%	T	*p*
ATC1	2.438 ± 0.673	4.107 ± 0.421	5.0 ± 0.0	− 35.887	***
ATC2	2.236 ± 0.707	3.94 ± 0.39	5.0 ± 0.0	− 36.858	***
ATC3	2.438 ± 0.706	4.013 ± 0.348	5.0 ± 0.0	− 34.214	***
ATC4	2.337 ± 0.753	4.007 ± 0.551	5.0 ± 0.0	− 33.366	***
ATC5	2.326 ± 0.735	4.04 ± 0.518	5.0 ± 0.0	− 34.32	***
UNE1	2.416 ± 0.671	4.054 ± 0.462	5.0 ± 0.0	− 36.335	***
UNE2	2.36 ± 0.644	3.94 ± 0.423	5.0 ± 0.0	− 38.681	***
UNE3	2.382 ± 0.631	4.034 ± 0.485	5.0 ± 0.0	− 39.156	***
UNE4	2.393 ± 0.668	4.107 ± 0.509	5.0 ± 0.0	− 36.829	***
SDE1	2.404 ± 0.652	3.98 ± 0.427	5.0 ± 0.0	− 37.541	***
SDE2	2.382 ± 0.731	4.047 ± 0.549	5.0 ± 0.0	− 33.791	***
SDE3	2.371 ± 0.713	3.987 ± 0.419	5.0 ± 0.0	− 34.777	***
SDE4	2.483 ± 0.624	3.973 ± 0.434	5.0 ± 0.0	− 38.074	***
TA1	2.292 ± 0.661	3.987 ± 0.465	5.0 ± 0.0	− 38.67	***
TA2	2.326 ± 0.719	3.899 ± 0.554	5.0 ± 0.0	− 35.065	***
TA3	2.348 ± 0.623	3.866 ± 0.589	5.0 ± 0.0	− 40.126	***
CS1	2.303 ± 0.664	3.953 ± 0.498	5.0 ± 0.0	− 38.308	***
CS2	2.36 ± 0.742	3.926 ± 0.466	5.0 ± 0.0	− 33.556	***
CS3	2.416 ± 0.72	4.067 ± 0.528	5.0 ± 0.0	− 33.861	***
CS4	2.348 ± 0.709	3.966 ± 0.538	5.0 ± 0.0	− 35.297	***

Table 5. Discrimination analysis. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Discrimination analysis
When conducting discrimination analysis, the discrimination ability of each analysis item is judged by considering the mean ± standard deviation, T test results and significant P value, and $P < 0.05$ is used as the significant standard. If it is significant, a difference analysis is performed based on the mean and test value. If there is a difference, it means that the scale item design is appropriate, otherwise it should be deleted. After analysis, the significant P value of all variables in the table is 0.000***, reaching the significant level, and the original hypothesis is rejected, indicating that the scale item design has a high degree of discrimination and can effectively distinguish the attitudes or characteristics of the subjects. The overall design is relatively reasonable and can be used for subsequent research. See (Table 5) for details.

Structural equation model analysis
A structural equation model of latent variables was established to explore the effects of ATC, UNE, SDE, and TA on CS. The moderating effects of CV and PP were also analyzed, and the results are as follows (Fig. 2).

Factor loading coefficient analysis
The analysis results of the factor loading coefficient table show that all measured variables have highly significant loadings on their corresponding latent variables ($P < 0.001$), indicating that the scale has ideal convergent validity. The z-values of the non-standard loading coefficients are all greater than 18.758 (corresponding to UNE2), among which CS2 has the highest z-value (22.807), further verifying the statistical significance of all path relationships. The standard error (SE) is controlled in a narrow range of 0.043–0.054, reflecting the good accuracy of parameter estimation. Overall, the measurement indicators of each latent variable meet the empirical threshold of factor loading greater than 0.7, and the statistical test results are highly significant, confirming that the measurement model has excellent reliability and validity levels, see (Table 6) for details.

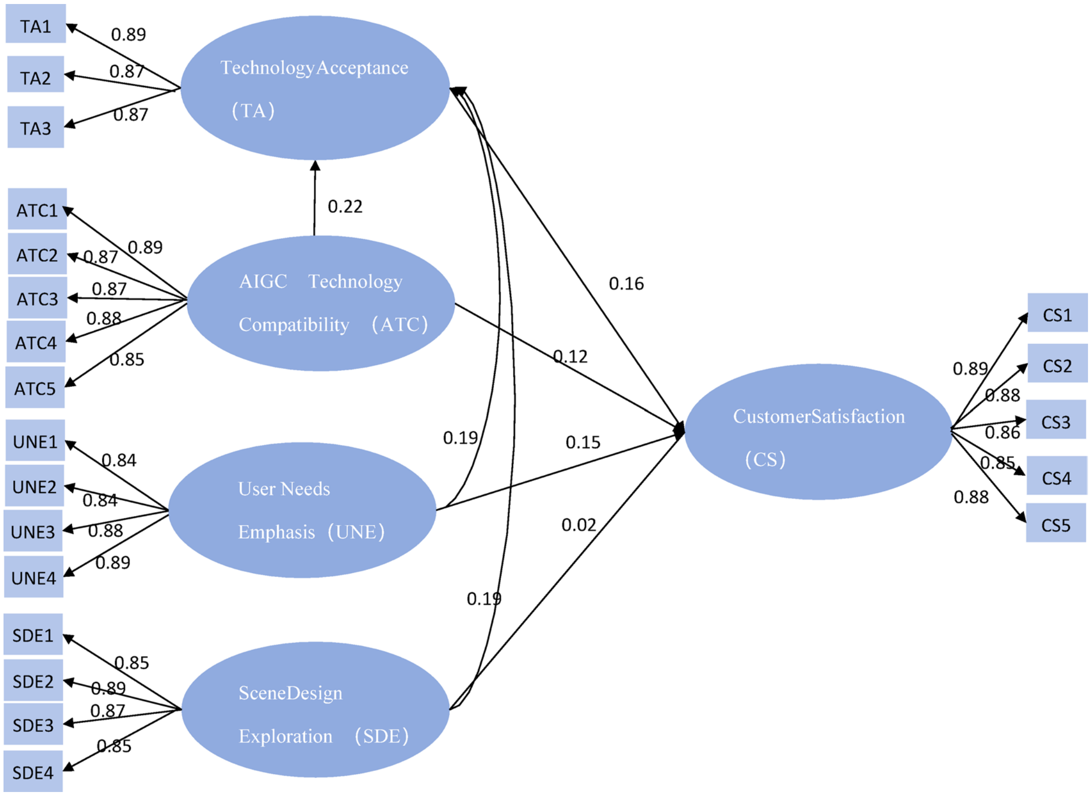

Fig. 2. Structural equation model.

Model fit analysis

The results of the model fit index showed that the χ^2 value was 168.976 (degrees of freedom df = 160), and the corresponding *P* value was 0.298 (> 0.05), indicating that there was no significant difference in the covariance matrix between the model and the data, and the null hypothesis was accepted. The chi-square degree of freedom ratio (χ^2/df) was 1.056 (< 3), which met the ideal standard and reflected the good simplicity of the model. The absolute fit index GFI value was 0.968 (> 0.9), the RMSEA value was 0.013 (< 0.10), and the RMR value was 0.065 (slightly higher than the critical value of 0.05 but acceptable), which comprehensively indicated that the absolute goodness of fit of the model met the standard. The value-added fit indexes CFI (0.998), NFI (0.968), and NNFI (0.998) all exceeded the threshold of 0.9, indicating that the theoretical model was significantly better than the baseline model. All key indicators meet or exceed the recommended standards of academia, with only the RMR value slightly deviating from the range. However, combined with the overall performance of other indicators, it can be judged that the overall fitting effect of the model is excellent and has sufficient statistical rationality, see (Table 7) for details.

Model regression coefficient table

From the regression coefficient table analysis of the structural equation model, we can see that there are 8 effective paths, namely ATC—>CS, with a significant *P* value of 0.041**; UNE—>CS, with a significant *P* value of 0.013**; TA—>CS, with a significant *P* value of 0.010**; ATC—>TA, with a significant *P* value of 0.001***; UNE—>TA, with a significant *P* value of 0.015**; SDE—>TA, with a significant *P* value of 0.038. There is one invalid path: SDE—>CS, with a significant *P* value of 0.700, which is not significant at the level, so this path is invalid, see (Table 8). It can be seen that technical adaptability (ATC) has a significant positive impact on user satisfaction (CS) ($\beta = 0.121$, $P = 0.041$), and its unstandardized coefficient is 0.132, indicating that for every 1 unit increase in ATC, CS will increase by 0.132 units. User demand fit (UNE) has a more significant impact on CS ($\beta = 0.148$, $P = 0.013$), and the unstandardized coefficient is 0.162. The standardized coefficient of technology acceptance (TA) on CS is 0.157 ($P = 0.010$), and its explanatory power is comparable to that of UNE, but the impact of museum scene design innovation (SDE) on user satisfaction (CS) did not pass the significance test ($P = 0.700$). In the relationship between latent variables, ATC has a significant impact on both UNE ($\beta = 0.104$, $P = 0.079$) and SDE ($\beta = 0.149$, $P = 0.011$), and its effect on SDE is stronger. UNE has the highest standardized coefficient on SDE ($\beta = 0.185$, $P = 0.002$), indicating that demand fit has a prominent driving effect on design innovation. Technology acceptance (TA) is jointly affected by three latent variables: ATC contributes the most ($\beta = 0.188$, $P = 0.001$), followed by UNE ($\beta = 0.146$, $P = 0.015$) and SDE ($\beta = 0.125$, $p = 0.038$). The Z values of all significant paths are greater than the critical value of 1.96, and the standard error range is 0.058–0.066, indicating that the parameter estimation accuracy is good. The results show that technology adaptability jointly affects

Factor	Variable	Non-standard load factors	Normalized load factor	z	SE	*P*
Technical adaptability (ATC)	ATC1	1	0.852	–	–	–
	ATC2	1.093	0.88	21.128	0.052	***
	ATC3	1.004	0.867	20.546	0.049	***
	ATC4	1.085	0.869	20.621	0.053	***
	ATC5	1.11	0.892	21.632	0.051	***
User Needs Fit (UNE)	UNE1	1	0.842	–	–	***
	UNE2	1.002	0.843	18.758	0.053	***
	UNE3	1.053	0.88	20.066	0.052	***
	UNE4	1.073	0.886	20.277	0.053	***
Museum Scene Design Innovation (SDE)	SDE1	1	0.847	–	–	***
	SDE2	1.096	0.886	20.419	0.054	***
	SDE3	1.049	0.871	19.894	0.053	***
	SDE4	0.97	0.847	19.035	0.051	***
Technology Acceptance (TA)	TA1	1	0.891	–	–	***
	TA2	0.982	0.867	20.608	0.048	***
	TA3	0.974	0.873	20.81	0.047	***
Customer Satisfaction (CS)	CS1	1	0.889	–	–	***
	CS2	0.982	0.884	22.807	0.043	***
	CS3	0.957	0.863	21.722	0.044	***
	CS4	0.991	0.881	22.631	0.044	***

Table 6. Factor loading coefficient table. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

χ^2	df	*P*	Chi-square degrees of freedom ratio	GFI	RMSEA	RMR	CFI	NFI	NNFI
–	–	> 0.05	< 3	> 0.9	< 0.10	< 0.05	> 0.9	> 0.9	> 0.9
168.976	160	0.298	1.056	0.968	0.013	0.065	0.998	0.968	0.998

Table 7. Model fit indices. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Factor (latent variable)	→	Analysis items (manifest variables)	Unstandardized coefficients	Standardized coefficient	Standard error	Z	*P*
Technical adaptability (ATC)	→	Customer Satisfaction (CS)	0.132	0.121	0.065	2.042	0.041**
User Needs Fit (UNE)	→	Customer Satisfaction (CS)	0.162	0.148	0.066	2.476	0.013**
Museum Scene Design Innovation (SDE)	→	Customer Satisfaction (CS)	0.025	0.023	0.066	0.385	0.700
Technology Acceptance (TA)	→	Customer Satisfaction (CS)	0.157	0.157	0.061	2.566	0.010**
Technical adaptability (ATC)	→	Technology Acceptance (TA)	0.206	0.188	0.064	3.196	0.001***
User Needs Fit (UNE)	→	Technology Acceptance (TA)	0.16	0.146	0.065	2.44	0.015**
Museum Scene Design Innovation (SDE)	→	Technology Acceptance (TA)	0.138	0.125	0.066	2.073	0.038**

Table 8. Model regression coefficient table. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

user satisfaction through direct and indirect paths (mediated by UNE, SDE, and TA), while scenario design innovation needs to have an indirect effect through technology acceptance.

Results of the mediation effect test

This study used bootstrapping for mediation analysis, a method for testing mediation effects. At the same time, 5000 bootstrap samples were generated, and a 95% confidence interval was applied to assess the significance of the mediation effect. According to the bootstrap standard, the statistical significance assessment of the indirect effect is based on the calculation of the confidence interval. The academic consensus is that when the confidence interval (usually at the 95% level) does not contain zero, the indirect effect is considered significant, indicating that the indirect effect of the path is significant.

According to the results of Tables 9 and 10, for the mediating path of 'ATC1 ⇒ TA2 ⇒ CS2', the 95% interval does not include the number 0 (95% CI 0.004–0.059), indicating the existence of this mediating effect path. Regarding the mediating path 'UNE2 ⇒ TA2 ⇒ CS2', the 95% interval does not include the number 0 (95% CI 0.001–0.043), indicating the existence of this mediating effect path. Regarding the mediating path 'SDE1 ⇒ TA2

	TA	CS	CS
Constant	2.415** (6.922)	2.289** (6.733)	1.938** (5.371)
ATC	0.190** (3.282)	0.142* (2.517)	0.114* (2.014)
UNE	0.123* (2.153)	0.165** (2.950)	0.147** (2.636)
SDE	0.039 (0.671)	0.085 (1.512)	0.079 (1.425)
TA			0.145** (2.708)
Sample size	327	327	327
R^2	0.055	0.062	0.083
Adjust R^2	0.046	0.053	0.071
F value	F (3,323) = 6.240, P = 0.000	F (3,323) = 7.104, P = 0.000	F (4,322) = 7.266, P = 0.000

Table 9. Mediation effect model test. $*p<0.05$, $**p<0.01$. The t in brackets is value.

Item	Total indirect effect	Boot SE	*z* value	*p* value	BootLLCI	BootULCI
ATC = > CS	0.028	0.014	1.960	0.050	0.004	0.059
UNE = > CS	0.018	0.011	1.662	0.096	0.001	0.043
SDE = > CS	0.006	0.009	0.660	0.509	− 0.010	0.024
The sum of indirect effects	0.051	0.023	2.184	0.029	0.012	0.102

Table 10. Total indirect effect table. BootLLCI refers to the lower limit of the 95% interval of Bootstrap sampling, BootULCI refers to the upper limit of the 95% interval of Bootstrap sampling, bootstrap type = percentile bootstrap method.

⇒ CS2', the 95% interval includes the number 0 (95% CI − 0.010 ~ 0.024), indicating that this mediating effect path does not exist.

Discussion

This study systematically reveals the impact mechanism of museum scene design enabled by artificial intelligence generated content (AIGC) on user satisfaction through a structural equation model. The core findings deepen the interactive logic of technology-user-scene. The empirical results show that user demand fit has the most significant direct impact on satisfaction. This conclusion verifies the paradigm shift from "object-centered" to "people-centered" in the museum field from a quantitative level. When the personalized narrative path generated by the AIGC system is adapted to the user's cognitive differences, user satisfaction can be effectively improved[2]. This finding is theoretically verified with the mechanism proposed by Chang Xinyuan et al. (2024) that "emotional design enhances cultural resonance through multimodal interaction", and at the same time echoes the empirical conclusion of Nikolakopoulou et al. (2022) that mixed reality devices effectively improve the efficiency of cultural heritage learning[48].

The impact of technology adaptability on satisfaction shows a dual path feature: it has both direct effect and indirect effect through the mediating effect of technology acceptance. This dual mechanism effectively explains the "technology experience paradox" in the field of digital cultural heritage.From the perspective of cultural authenticity, it can be further proved: as shown in the research of generative AI virtual clothing Museum by Zhang Qiaoling et al. (2024), even though aigc has realized the precise control of clothing physical simulation error, some users still feedback "experience fragmentation" and their final satisfaction does not meet expectations due to the cultural translation deviation caused by the failure to include the participation mechanism of intangible cultural heritage inheritors[33]; In Tang et al. (2024)'s research on the museum's spatial layout, aigc combined with regional cultural symbols such as the Forbidden City's Dougong and Suzhou embroidery to generate scenes, which effectively improved the cultural authenticity score, significantly increased the intensity of users' emotional resonance, indirectly promoted satisfaction through technology acceptance, and confirmed that cultural authenticity was the key premise for the transformation of technology adaptability into experience value[31]. Bootstrap test further shows that technology acceptance mediates technology adaptability, According to the research of Wang Zhen (2023) based on the theory of balanced cognitive load, when the interface elements exceed the user's working memory capacity, it will lead to "cognitive overload", breaking the transformation path from technology acceptance to satisfaction59. In addition, cultural authenticity is the core value appeal of the museum scene, while the SDE items of this study focus on the form innovation of spatial narrative rhythm and digital technology application, and are not included in the accuracy index of cultural symbols. Tang et al. (2024)'s research on the museum's spatial layout provides direct evidence: if there is cultural symbol distortion in the scene generated by aigc, even if the design innovation score is high, the satisfaction is still lower than the cultural real scene[29].

The "paradox of design innovation" revealed by the research has important theoretical value. Although SDE has a significant impact on technology acceptance, its direct effect on satisfaction is not significant. From the perspective of pedagogy and cognitive psychology, the root cause can be analyzed: from the perspective of pedagogy constructivism, the core of museum learning is the process of users' active construction of cultural knowledge. The SDE measurement items in this study focus on formal innovation and do not cover the design of "knowledge guidance", which leads to the innovative design only improving "sensory experience" and not transforming into "cognitive value". As shown in the research of biological specimen exhibition by Kreuzer et al. (2017), the lack of knowledge construction guidance in immersive scenes leads to the reduction of users' score of "learning effectiveness" and directly weakens satisfaction[32]; From the perspective of cognitive load theory of cognitive psychology, the multimodal innovative design of SDE in this study may increase the cognitive load of outdoor use. According to the research of Wang Zhen (2023) based on the theory of balanced cognitive load, when the interface elements exceed the user's working memory capacity, it will lead to "cognitive overload", breaking the transformation path from technical acceptance to satisfaction[57]. In addition, cultural authenticity is the core value appeal of the museum scene, while the SDE items of this study focus on the form innovation of spatial narrative rhythm and digital technology application, and are not included in the accuracy index of cultural symbols. Tang et al. (2024)'s research on the museum's spatial layout provides direct evidence: if there is cultural symbol distortion in the scene generated by aigc, even if the design innovation score is high, the satisfaction is still lower than the cultural real scene[31]. This conclusion provides a new annotation for the research on semantic embedding in architecture by Yi Xiduo et al. (2023): the effectiveness of museum spatial narrative not only depends on physical design, but also needs to be coordinated with AIGC's cognitive adaptability[50]. The principle of multisensory integration proposed by Gayadhri et al. (2024) has been validated here, and their vibration tactile feedback scheme significantly enhances the immersion of virtual museums, providing physiological mechanism support for the "cognitive emotional dual track design" in this study[28].

On a practical level, research proposes a three-dimensional optimization path: in the design aspect, it is recommended to adopt a dual track model of "emotional narrative generation + cognitive load management", such as Xu Wenguang's (2023) use of micro expression modeling to effectively enhance the credibility of virtual commentators[35]; The technical side needs to strengthen cross platform integration to bridge experience fragmentation, and establish cultural algorithm templates to ensure semantic bias[39]; The evaluation end should adopt the four-dimensional indicator system of "technology requirement design acceptance" validated in this study, instead of traditional vague evaluation.

Although this study constructed a user satisfaction model for AIGC assisted museum scenes, there are still three key limitations that need to be improved in future research: (1) insufficient sample representativeness: lack of coverage of vulnerable groups. Among the 327 respondents, the 18–45 age group accounted for 83%, lacking samples of elderly people over 60 years old, children under 12 years old, and special needs groups such as visually impaired and hearing-impaired. The sample structure of this study leads to the unknown applicability of the model to vulnerable groups. In the future, stratified sampling will be used, referring to the user centered design framework proposed by Yi et al. (2024), to include special group samples. (2) Cultural and temporal limitations: Insufficient cross-cultural adaptability and dynamism. The samples are all from China and are influenced by the demand for "cultural identity" and "collective narrative". Users have a high level of attention to the "cultural symbol expression" of SDE; However, Pisoni et al.'s (2021) cross-cultural study showed that European and American users are more concerned about "personalized interaction"[41], which may lead to cultural differences in the impact mechanism of SDE on satisfaction. In addition, cross-sectional data cannot capture the dynamic evolution of technology acceptance. In the future, cross regional comparative research based on Hofstede's cultural dimension theory is needed, and the dynamic evaluation model proposed by Tie Zheng et al. (2022) should be used for longitudinal tracking for 6–12 months[27]. (3) Incomplete outcome variable: missing behavioral intention dimension. The study only focused on satisfaction and did not include downstream variables such as "willingness to continue using", "word-of-mouth recommendation", and "cultural participation behavior". Future research should integrate the Expectation Confirmation Model (ECM), supplement behavioral intention variables, and construct a complete logical chain of "experience attitude behavior".

Conclusion

This study systematically reveals the user experience influence mechanism of AIGC-assisted smart scene design in museums through structural equation modeling, constructing a complete logical chain of "technology adaptation—demand alignment—design innovation—acceptance transformation—experience enhancement". Empirical results show that user demand alignment has the most significant direct impact on satisfaction, confirming the paradigm shift of museum design from "object-centered" to "user-centered"[33,34]; AIGC technology adaptability affects user experience through the dual paths of direct effect and the mediating effect of technology acceptance, verifying the applicability of the TAM model in cultural scenarios[30]; the innovation of scene design needs to indirectly affect satisfaction through technology acceptance, indicating that spatial narrative innovation must be optimally coordinated with cognitive load management[46].

At the practical application level, a complete operational system for the implementation of AIGC technology in museums can be constructed based on the research model, forming collaborative support from three dimensions: design, technology, and operation. Firstly, the design end needs to establish a logical system of "demand—culture—cognition", with the core being the implementation of a "hierarchical demand mapping" strategy for different user groups. For adolescents, it is necessary to rely on AIGC to generate gamified cultural narrative content, strengthen the effectiveness of educational communication and user interaction autonomy through forms such as character development and interactive exploration, which meets adolescents' demand for interesting and participatory experiences[25]; for middle-aged and elderly groups, the operation process should be simplified, and the design focus should be placed on the construction of "emotional cultural identity". At the same time, the design link must introduce a cultural authenticity verification mechanism, and professional forces such as intangible cultural heritage inheritors and historians can be invited to participate in the review and optimization of AIGC content, ensuring that the digital expression of cultural symbols conforms to historical context and cultural connotations, effectively reducing the "experience fragmentation" caused by cultural semantic deviations, and enhancing users' cultural identity with the scene. Secondly, the technology end needs to build a supporting base of "adaptability—stability—accessibility". For offline exhibition hall scenarios, the focus is on developing a cross-device compatible AIGC guided tour system, covering mainstream terminals such as mobile phones, tablets, and AR glasses, to ensure that users of different devices can obtain a smooth interactive experience. At the same time, the technical response speed should be controlled within a range that users perceive as smooth, avoiding reduced operational usability due to device delays[29]; for online virtual exhibition halls, it is necessary to strengthen technical stability design, especially focusing on the technical adaptation of special needs groups such as the visually impaired and hearing impaired. Drawing on the mature technical experience of mobile AI guided tours, multi-modal auxiliary content can be generated through AIGC to truly realize the inclusiveness of museum services, allowing different groups to obtain cultural experiences through AIGC technology. Thirdly, the operation end needs to establish a dynamic optimization mechanism of "feedback—iteration", regularly collecting user experience data, including questionnaire feedback and interactive behavior logs, and focusing on monitoring two core indicators: "perceived usefulness" and "attitudinal tendency". If users' evaluation of "perceived usefulness" is low, it is necessary to focus on optimizing the knowledge transfer value of AIGC content, improving the practical value of the content by adding in-depth interpretations of the historical background of cultural relics and multi-dimensional presentation of cultural connotations; if the "attitudinal tendency" indicator is poor, user incentive mechanisms can be used to strengthen word-of-mouth communication and guide users to actively share their experiences.

From the perspective of future research expansion, it is necessary to carry out research around three directions: cross-cultural verification, deepening the needs of segmented audiences, and methodological innovation, to further improve the generalization and practical guiding value of the research model. Cross-cultural verification is a key direction to enhance the theoretical universality of the model. Comparative studies should be carried out in countries or regions with typical cultural differences, focusing on the cultural difference analysis of core paths, especially the path of "scene design innovation→satisfaction" which was not significant in this study. It is necessary to explore how the focus of design innovation affects path effects in different cultural contexts[60]. At the same time, a "cross-cultural experiment in the same scene" can be designed, selecting typical cultural relics and generating narrative versions adapted to different cultural contexts through AIGC, so as to clarify the cross-cultural adaptation rules of AIGC scene design. Deepening the needs of segmented audiences is the core direction to solve the current limitation of sample representativeness, and special studies should be carried out for different groups. For middle-aged and elderly groups, the focus is on exploring the "operation simplification" logic of AIGC technology, analyzing the impact of factors such as interface layout, interaction methods, and information presentation forms on perceived ease of use, and ultimately forming AIGC operation adaptation standards for elderly users to reduce the threshold of technology use; for children's groups, it is necessary to study the "cognitive load adaptation" of AIGC scenes, clarify the attention bearing range and cognitive characteristics of children of different age groups, and avoid poor experience caused by information overload or complex interaction[61]. At the level of methodological innovation, it is necessary to break through the limitation of current single questionnaire data, construct a "subjective + objective" multi-modal data collection system, and record objective data such as users' interaction frequency, stay time, and operation paths through behavior logs, forming cross-validation with subjective questionnaire results to more accurately identify the real driving factors of user satisfaction. In addition, long-term longitudinal tracking research should be carried out to pay attention to the "freshness fading" effect of users' AIGC experience, that is, the dynamic change rules of users' technology acceptance and satisfaction over time, analyze the experience pain points and optimization directions in different stages, and provide a basis for museums to formulate long-term AIGC operation strategies, avoiding phenomena such as long-term experience fatigue caused by "short-term innovation".

The closed-loop model of "demand-driven—technology adaptation—scene innovation—acceptance transformation" constructed in this study not only enriches the theoretical system in the field of digital cultural heritage, but also provides a implementable plan for the digital and intelligent transformation of museums through refined practical paths. In the future, through in-depth promotion of cross-cultural verification and segmented group research, the generalization of the model should be further expanded, so that AIGC technology can not only exert technical efficiency in museum scenarios, but also carry the humanistic value of cultural communication, and ultimately realize the in-depth integration of "technology empowerment" and "cultural inheritance", promoting the transformation of museums into more inclusive, experiential and innovative smart cultural spaces.

Data availability
Data can be obtained from the corresponding author.

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Author contributions
Zhang Dongjiao is mainly responsible for the concept proposal, data management, data analysis, initial draft writing and editing of the article, while Zhang Yunlong is responsible for data investigation and partial writing of the initial draft; Jiang Xu is responsible for the accuracy of data investigation, project management, guidance of articles, and confirmation of final drafts. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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