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What influences user continuous intention of digital museum: integrating task-technology fit (TTF) and unified theory of acceptance and usage of technology (UTAUT) models

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Abstract

Digital museums play a crucial role in facilitating users' access to and exploration of digital cultural heritage resources. However, exploring the factors influencing user engagement with these digital museums from a user experience perspective remains essential. This study evaluates the factors driving user continuous behavioral intention towards the digital museum of Beijing's central axis, integrating the new task-technology fit (TTF) and the new unified theory of acceptance and use of technology (UTAUT) models, and introducing perceived enjoyment, design aesthetics, and perceived cultural value as additional variables. Analyzing survey data (n = 377) utilizing structural equation modeling (SEM), the study identifies the following key findings: (1) the task and technology characteristics of digital museums significantly impact the TTF; (2) performance expectancy, effort expectancy, design aesthetics, perceived enjoyment, and perceived cultural value all positively impact user continuous behavioral intention; (3) the technological characteristics of digital museums were observed to positively impact users' effort expectancy; but (4) the TTF and social influence did not have no significant impact the user continuous behavioral intention. These findings offer valuable insights into the factors driving users' continuous behavioral intention to use digital museums of cultural heritage, offering practical guidance for future development and optimization of these digital museums, and highlighting specific implications and suggestions for enhancing the user experience.

Keywords Digital museum of cultural heritage, Task-technology fit (TTF), User continuous behavioral intention, Unified theory of acceptance and usage of technology (UTAUT), Cloud-based central axis (CCA) mini program

Introduction

As cultural heritage increasingly integrates with digital technologies, various mobile technologies are being employed for its research and development [1], leading to the emergence of digital museums of cultural heritage. By transforming cultural heritage into digital information and making it accessible to the public through the Internet, digital museums effectively facilitate the presentation and dissemination of cultural heritage. In addition, digital museums empower cultural heritage to transcend the boundaries of time and space, allowing users to experience and engage with it anytime and anywhere [2]. It is important to note that the intention behind digital museums is not to replace physical experiences but rather to utilize new technologies to present cultural heritage to users in innovative ways, thereby facilitating "off-site experiences" for diverse user groups [3, 4].

Contemporarily, digital museums of cultural heritage attract a relatively niche audience, primarily composed

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of cultural heritage professionals and art aficionados [5]. However, these valuable cultural heritage assets deserve broader public engagement. Therefore, the challenge lies in improving the user experience in digital museums to promote continuous engagement in cultural heritage. While initial user adoption of digital technologies is crucial for the success of any information technology system, as Bhattacherjee argues, long-term success hinges on cultivating users' continuous behavioral intention to use it [6]. Behavioral intention refers to a user's behavioral intention to use a technology or product, either pre-adoption or post-adoption [7]. Continuance behavioral intention, specifically, focuses on a user's behavioral intention to continue engaging with a technology or product post-adoption [8]. Digital museum of cultural heritage, as digital platform built on these technologies, spread and demonstrate cultural heritage [9]. Therefore, while a positive user experience is an important first step, the ultimate success of digital museums of cultural heritage depends on the users' continuous behavioral intention to use it [10].

Effective HCI design in digital museums, through intuitive interaction and feedback mechanisms, significantly enhances user engagement with digital content [11]. This includes features such as personalized search functions [8], multi-touch screen [2], virtual reality [7], and interactive 3D [12]. By employing enjoyable and engaging HCI, digital museums of cultural heritage can better facilitate public access to cultural heritage information and enrich the overall user experience. Rather than being passive recipients of information, users become enthusiastic and active participants in the digital museum experience through touch-based interaction. Therefore, further research into optimizing HCI in digital museums of cultural heritage is crucial for improving user experiences and cultivating deeper engagement with cultural heritage.

The user interface acts as the medium between users and computer systems, enabling the exchange and communication of information [2]. This applies to digital museums of cultural heritage, where the user interface functions as a platform for HCI. It provides a complete and interactive environment for users to engage with and experience cultural heritage [12]. Hassenzahl et al. hypothesize that user experience in HCI research comprises a range of factors, including usability, aesthetics, enjoyment, emotional response, and the overall technological experience [13]. Similarly, Korzun et al. argue that key elements such as technology, enjoyment, aesthetics, and the perception of the digital museum itself are critical in engaging users and enhancing their overall experience [14]. Previous research has highlighted that the user experience of digital systems is affected not only by external factors such as technical proficiency and efficiency but also by intrinsic factors such as user interest and emotional resonance [15, 16]. Therefore, further analysis is necessary to evaluate the specific factors that influence user experience in digital museums of cultural heritage. A deeper understanding of how users interact with these digital environments will offer measurable indicators of the key elements that contribute to users' continuous behavioral intention to use digital museums of cultural heritage.

A review of existing literature indicates three primary categories to evaluating user experience in digital museums: (1) Researchers have evaluated how the integration of emerging technologies (i.e., AR, VR) affects the user experience of digital museums [1, 7, 12, 17], and users' motivations [5, 18] or barriers to using digital museums [19–21]. (2) Studies have evaluated specific user behaviors in digital museum settings, including online navigation and booking practices to enhance the user's physical experience [22–25], search features [26, 27], access behaviors and their intention to use [8, 28–32]. (3) Researchers have explored how evaluating digital technologies [4, 7, 8], the functionality and navigation of the interactive interface [26], and the visual design of the interactive interface [2]. Despite these research efforts, this study identifies two research gaps in the field of digital museums:

Gap 1: Limited research exists on the factors influencing user experiences in digital museum mini programs focused on cultural heritage. This is because existing literature primarily emphasizes technological advancements in digital museum websites and mobile applications, often overshadowing the user experience specific to mini programs.

Gap 2: Previous research primarily concentrates on attracting new users, neglecting to explore the factors that encourage users' continuous behavioral intention to use digital museums of cultural heritage.

To address the research gap, this paper explores the following research questions:

RQ1: How TTF influences users' continuous behavioral intention to use digital museums?

RQ2: How UTAUT influences users' continuous behavioral intention to use digital museums?

RQ3: How perceived enjoyment, design aesthetics, and perceived cultural value influences users' continuous behavioral intention to use digital museums?

To address these questions, this study develops a conceptual model of the user experience of a digital museum of cultural heritage, analyzing what factors influence the user experience and decision to continue utilizing the digital museum. While previous research has employed TTF and UTAUT to evaluate digital museum user experience [4], the rapid evolution of digital technology necessitates a reassessment of these models' variables. Therefore, this study takes the Cloud Central Axis (CCA) digital museum of cultural heritage as a case study, and explores the influence mechanisms between TTF, UTAUT, perceived enjoyment, design aesthetics, perceived cultural value, and users' continuous behavioral intention to use digital museum of cultural heritage through the perspective of user experience and digital museum design.

This study produces several novel contributions. Theoretically, it develops and expands upon existing models of user behavior to understand what drives users' continuous behavioral intention to use digital museums. Specifically, it evaluates various factors that affect users' continuous behavioral intention to use digital museum of cultural heritage, offering a new framework for leveraging mobile devices and interactive systems to enhance the user experience in the HCI of digital museum study. Practically, this research offers strategic suggestions for designing, developing, and optimizing digital museums of cultural heritage. These findings have implications for user experience research in this domain, assisting developers and museum professionals in creating engaging and accessible digital experiences that finally promote public engagement with cultural heritage.

Theoretical background and research model

Digital museum of cultural heritage

The integration of technology in the museum setting began in the late 1960s, initially focusing on documenting collections and automating management processes [33]. As the internet emerged in the early 1970s, museums began establishing their online presence through text-based information repositories [34]. This period also witnessed the rise of the museum's communication-focused role [35]. By the 1980s, museums were leveraging the internet to create digital image databases, enabling efficient storage and retrieval of multimedia information related to digital museums [36]. A critical moment arrived in 1990 when the Library of Congress launched the "American Memory" program, a significant starting point for the digital museum concept [37]. The late 1990s saw the rise of digital museums, offering innovative ways for the public to engage with cultural heritage. The following decades brought advancements in information and digital technologies, prompting a paradigm shift from "object-centered" to "experience-centered" museum experiences [36, 38], thereby significantly enhancing user engagement. Digital museums, through the visualization of cultural heritage, create immersive virtual exhibition spaces. Users can access these spaces at their convenience anytime and anywhere, unrestricted by physical limitations [39]. Moreover, interactive interfaces in digital museums allow users to engage with cultural artifacts in great details, cultivating a richer and more realistic experience.

The dawn of digital museums in China began relatively recently, officially starting in the late 1990s [37]. In 1998, Taiwan, China launched its "Digital Museum" program that sought to create digitally accessible museums, each reflecting unique local characteristics through the integration of diverse museum materials [40]. Mainland China soon followed suit, in September 2001, the National Cultural Heritage Administration (NCHA) of China launched the "Cultural Relics Census and Database Management System" project, signifying the first foray into national museum digitization in mainland China [33]. Currently, the NCHA is actively championing a technology-driven strategy to strengthen the nation's cultural influence. This includes the "Internet Plus Chinese Civilization" action plans, designed to cultivate the development of an open and accessible platform for sharing cultural relic resources [5]. Accordingly, numerous cultural heritage and museum institutions, such as the Palace Museum and the Dunhuang Academy, have opted to collaborate with renowned international counterparts. These partnerships aim to further develop and leverage technology to demonstrate China's rich cultural heritage to a global audience [37]. Employing a captivating blend of media, including text, images, audio narration, animations, and even virtual reality, digital museums offer a significantly enriched user experience. This approach renders cultural heritage more approachable, comprehensible, and readily available to the public [40, 41].

The burgeoning digitization and informatization of museums have given rise to several overlapping concepts such as digital museums, virtual museums, and online museums. While these terms are often utilized interchangeably, subtle yet significant distinctions set them apart. Essentially, digital museum is a carrier that leverages digital and multimedia technologies to demonstrate museum information and content [2]. Existing in the digital space, it offers online exhibitions of cultural heritage through websites, mobile applications, and digital platform [42, 43]. Virtual museums, on the other hand, emphasize the immersive nature of the museum experience. Employing virtual reality technology, they may exist online or offline, and allow visitors to engage with exhibits through virtual reality devices and technologies [44], allowing users to interact with virtual reality devices or technologies [45, 46]. Online museums, meanwhile, represent gateways to museum collections, displays, and related information on the internet. These can take the form of digital museums, dedicated websites, or online exhibitions created by traditional brick-and-mortar museums [47]. In essence, the differences lie in their method of presentation, accessibility, and the overall visitor experience. The digital museum acts as a "carrier," the virtual museum as a "form," and the online museum as a "channel."

This study evaluates the concept of the 'digital museum,' a term chosen over 'virtual museum' or 'online museum' to emphasize the 'digital' aspect as a museum carrier. Digital museums consist of a range of technologies, including AR, VR, interactive media, and web-based technologies [39, 42, 43, 48]. This carrier to cultural heritage preservation and exploration in the digital age is characterized by its interactivity, gamified experiences, virtual environments, and open access [49]. While virtual museums prioritize the simulated nature of their displays and online museums focus on utilizing the internet as a dissemination channel, digital museums represent a broader category. Essentially, any engagement with exhibits and museum content through internet platforms is under the umbrella of digital museum [50]. In addition, digital museums are unique with three core characteristics: the digitization of cultural heritage resources, networked information transmission, and the facilitation of online viewing and exploration [37]. This study concentrates specifically on the digital display and interactive engagement with cultural heritage, emphasizing its potential to reach a global audience; hence, the deliberate use of the term "digital museum."

Digital central axis

Beijing's Central Axis, the magnificent north–south axis running through the heart of Beijing is not only the city's symbolic spine but also the most exceptionally preserved urban axis in all of China. For over seven centuries, from the Yuan dynasty through the Ming, Qing, and into the contemporary era, this central axis has embodied the essence of Beijing's cultural and historical legacy. Recognizing its significance, "Beijing's Central Axis (including Beihai)" was added to the "*China's Tentative List for World Cultur*al Heritage" in 2012 [51]. Securing its rightful place as a World Heritage Site, however, demands a concerted effort. It requires the support of both the nation and its government, along with the enthusiastic participation of individuals from all walks of life. By leveraging the power of digital technology, "Digital Central Axis" can vividly demonstrate the historical, cultural, aesthetic, technological, and contemporary values embodied in the Beijing Central Axis. Through this digital perspective, the captivating historical and modern narratives of this urban masterpiece can be shared with the world [52]. With respect to the Beijing Central Axis in the digital age, the "Digital Central Axis" is poised to become an indispensable platform. It will represent a space for World Heritage experts and the global community to engage with, deepen their understanding of, and contribute to the nomination and preservation efforts for the Beijing Central Axis [52].

In December 2021, the Beijing Municipal Administration of Cultural Heritage (BMACH) partnered with Tencent to launch the innovative "Digital Central Axis" project. The project comprises three components: the Beijing Central Axis digital exhibition, Beijing Central Axis IP enhancement, and the Beijing Central Axis cultural heritage sustainability index [53]. The "Beijing Central Axis Digital Exhibition" is categorized into two experiences: an online digital museum and an offline immersive exhibit [52]. The online museum offers several access points, including the CCA mini program, the official Beijing Central Axis website, and a dedicated Beijing Central Axis app [52]. This case study focuses on the digital platform supporting the Beijing Central Axis's nomination to the World Heritage List: a WeChat mini program named Cloud-based Central Axis (CCA).

WeChat, ranking fifth among the world's most popular smartphone applications [54, 55], has over a billion monthly active users [56]. This massive user base offers a powerful platform for distributing information and promoting WeChat Mini Programs. Introduced in 2017, these mini programs are lightweight applications accessible directly in WeChat, eliminating the need for downloads or installations. Users can enjoy access and use them instantly with ease, with the added convenience of not requiring uninstallation afterwards [57, 58]. This "micro, lightweight, and small" nature defines their appeal. While mini program development shares similarities with mobile app development, its integration in the WeChat ecosystem facilitates the process. Abandoning the cumbersome procedures of traditional internet products, mini programs feature a simpler architecture and more direct page code [58, 59], resulting in a superior user experience compared to websites and conventional applications. In essence, as a lightweight application operating in the WeChat platform, a CCA mini program can deliver a convenient, integrated, and feature-rich digital museum experience. Accordingly, this encourages greater user engagement and participation.

Launched on the evening of December 29, 2021, the CCA mini program (version 1.0) quickly captivated attention. In merely 5 h, half a million users engaged with the program's creative interactive experience, "Beijing's Central Axis, the heritage application has me," effectively enhancing the nomination of Beijing's Central Axis for heritage status [52]. This innovative program, featuring a colorful digital swift designed by Tencent, allows users to virtually glide over the Beijing Central Axis and experiencing its breathtaking beauty from a bird's-eye perspective [60]. In addition, the program utilizes immersive, scroll-like scenes to transport users through time, recreating the historical ambiance of the Beijing Central Axis across different eras [53].

By November 2022, an upgraded version 2.0 of the CCA mini program was released. Since its launch, the program has amassed an impressive user base, exceeding 4 million cumulative users and 600,000 registered users online [60]. This updated version focuses on three key enhancements: the central axis guide, the exploration interface, and the "fingertip" landmarks. Building upon the "one step, one view" design concept of version 1.0, version 2.0 also incorporates digital displays of the 15 major landmarks comprising Beijing's central axis. This digital representation enhances the interactive and visual design, rendering the central axis "visible, sensible, experiential, and touchable" [53] (Fig. 1).

Task-technology fit

In the proposed TTF model, Goodhue explains the interconnectedness of technology, user adoption, performance, and usage [61]. Task characteristics consist of the user's need to access relevant information, pursue personal interests, and engage in hobbies, all facilitated by pervasive, real-time services [62]. Technology characteristics, on the other hand, refer to a digital product's ability to not only offer users with their required information but also to cultivate a supportive virtual community [63]. Essentially, the TTF model illustrates the relationship between the 'tasks' users seek to accomplish, the 'technology' or digital tools at their disposal, and their willingness to engage with these tools—a decision largely affected by the perceived alignment between their tasks and the technology offered [64].

The TTF model is valuable for understanding how well technology aligns with user needs. It illustrates how effectively technological tools support individuals in completing specific tasks [65]. Zhou has confirmed that task and technology characteristics affect the TTF model [66]. Gebauer and Ginsburg indicated that the suitability of mobile information systems in TTF is dictated by the specifics of the task and the effectiveness of the technology [67]. Specifically, the TTF model is crucial for evaluating the effect of digital interactions, particularly in technology-enhanced learning environments for students [68]. A strong task-technology fit, achieved through well-designed features, leads to greater user satisfaction by effectively meeting their needs [69]. Essentially, users are more likely to engage with a digital product when its "technology" directly supports the specific "tasks" they aim to accomplish [4].

The TTF model has been proven effective in understanding user behavior intention, specifically in how aligning technology with tasks yields positive effects [66]. Widely recognized as a key factor in successful information technology decisions across various types of digital transformation [70, 71], the TTF model has significantly affected user adoption. For instance, research has presented the significant effect of the relationship between technology and task characteristics on blog adoption rates [72]. Similarly, Zhou found that TTF directly affects users' continuous behavioral intention to use mobile banking [66]. This model has also been extensively utilized to investigate usage intentions in various domains, including learning management systems [73], VR-enhanced learning [74], and digital museums, where Sun and Guo confirmed its positive effect on visitor engagement [4]. Considering the extensive evidence supporting the role of effective TTF in cultivating positive user intention towards digital products, we propose the following hypotheses: H1, H2, and H3.

H1: Task characteristics of digital museums positively impact TTF.

H2: Technology characteristics of digital museums positively impact TTF.

H3: The TTF of digital museums positively impacts users' continuous behavioral intention.

Unified theory of acceptance and usage of technology

Venkatesh developed the UTAUT model to explain the initial and continuous use of technology [75], drawing upon elements from eight different models and theories of technology adoption [76]. Zhou demonstrated that UTAUT can explain up to 70% of the variance in user adoption behavior, demonstrating greater accuracy in predicting behavioral intention compared to earlier technology adoption models [66]. In 2012, Venkatesh et al. optimized the UTAUT model, incorporating hedonic motivation, price value, and habit as three new dependent variables, resulting in UTAUT2 [77]. The robustness of UTAUT has led to its widespread adoption in research across various domains over the last decade, including digital travel adoption [4], advanced technology services [78], and mobile payment systems [23].

While UTAUT2 represents an advancement over UTAUT, it does not necessarily translate to significant advantages for this particular study. Rather, it introduces additional factors that may not be essential for explaining technology acceptance behavior. This study specifically prioritizes the core variables of performance expectancy, effort expectancy, and social influence. UTAUT2, in contrast, incorporates variables such as price value, a factor irrelevant to this research since the digital museums under consideration are free of charge. Therefore, such variables lack direct applicability to this study's focus. Moreover, introducing

Fig. 1 Cloud-based Central Axis (CCA) mini program

unnecessary variables could lead to increased complexity without meaningfully improving the model's explanatory power. The choice of UTAUT, therefore, enables a more focused and clear exploration of the roles and effects of these core variables on users' continuous behavioral intention to use digital museums.

Venkatesh [76] identified four key factors of UTAUT that significantly affect user acceptance and adoption of technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy, which reflects the extent to which users believe utilizing a digital museum will be beneficial, is a critical driver of new technology adoption [79]. This positive relationship between performance expectancy and the acceptance of digital technologies has been well-documented. Effort expectancy refers to the perceived ease of use of digital museums. Studies have consistently demonstrated a positive correlation between effort expectancy and user intent [79]. A user-friendly digital platform enhances the user experience, finally leading to more frequent app usage [45]. Social influence pertains to the degree to which users perceive that important individuals in their lives believe they should engage with digital museums. Research has highlighted the positive connection between social influence and behavioral intentions, particularly in digital museums [4]. Therefore, the effect of these factors on digital museum reuse is significant.

Facilitating condition refers to external factors, such as available technology and equipment, significantly affect user experience by influencing a system's ease of use [79]. As of June 2023, China has a total of 1.079 billion mobile internet users according to the 52nd "Statistical Report on Internet Development in China," achieving a remarkable internet penetration rate of 76.4% [56]. This widespread adoption signifies the successful integration of the internet into the lives of the majority of Chinese citizens. Accessing digital platforms through mobile devices has become incredibly convenient, effectively eliminating technology and devices as barriers to digital product adoption [55]. Therefore, these factors have a reducing effect on user intention and behavior. Building upon the foundational UTAUT model, this study retains performance expectancy, effort expectancy, and social influence as key constructs while excluding facilitating conditions. Therefore, we propose the following hypotheses: H4, H5, and H6.

H4: Performance expectancy positively impacts users' continuous behavioral intention.

H5: Effort expectancy positively impacts users' continuous behavioral intention.

H6: Social influence positively impacts users' continuous behavioral intention.

The technology characteristics directly affect a user's effort expectancy. While previous research has established a relationship between TTF and UTAUT variable structures [66, 75], digital museum mini programs present a unique case. In contrast to complex websites offering a multitude of functions, these mini programs utilize streamlined interfaces with limited features [58]. This approach simplifies user interaction and enhances usability, particularly for average users [66]. In addition, analyzing the connection between TTF and UTAUT allows for a deeper understanding of how specific technological characteristics translate into effort expectancy. This connection highlights the importance of aligning user effort with the functionality offered by the digital tool [80]. Therefore, it is reasonable to hypothesize that:

H7: Technology characteristics of digital museums positively impact users' effort expectancy.

Perceived enjoyment, design aesthetics, perceived cultural value

Perceived enjoyment

Perceived enjoyment, often derived from an individual's environmental experience [81], shapes internal beliefs and motivations. Building on this, perceived enjoyment can be understood as the positive interaction between users and digital products, cultivating a desire for users' continuous behavioral intention to use it. Numerous studies emphasize the significant effect of perceived enjoyment on user behavior and intentions in digital systems. For instance, a high level of perceived fun directly correlates with increased engagement in augmented reality museums [5] and digital museums [8]. This connection extends to other digital spaces as well. Research by See-To highlights a significant correlation between perceived enjoyment and user experiences in mobile video applications [82], while Park's work indicates that perceived enjoyment significantly affects user participation in gaming activities [83]. Similarly, the enjoyment and pleasure derived from digital textbooks can effectively enhance learning motivation [84]. This pattern is reflected in online social networking services, where perceived enjoyment significantly influences users' continuous behavioral intention to use it [85]. Therefore, the following hypothesis is proposed:

H8: Perceived enjoyment positively impacts users' continuous behavioral intention.

Design aesthetics

Design aesthetics, including the non-verbal sensory experience of a product, can significantly enhance users' continuous behavioral intention to use it [86]. This aesthetic experience, often characterized as an "immersion in the environment," cultivates passive engagement and deep immersion in users [87]. Elements such as color palettes, imagery, font styles, typography, and layout all contribute to the overall aesthetic appeal [88]. A well-designed AR application, for instance, leverages these elements to deliver information with accuracy and accuracy [88]. Cheng emphasizes this point, noting that students' perceptions of MOOC interface aesthetics directly affect their perceived learning outcomes [89]. Similarly, Tarasewich hypothesizes that aesthetics are paramount in “designing a wholly enjoyable user experience with mobile devices” [90]. This focus on aesthetics extends to specific situations such as heritage museums, where, as Chen et al. demonstrate, visually appealing scenes significantly affect user engagement and adoption [17]. Therefore, we hypothesize that design aesthetics directly affect user behavior and intentions regarding digital museum settings:

H9: Design aesthetics positively impacts users’ continuous behavioral intention.

Perceived cultural value

Perceived value is widely recognized as a key driver of behavioral intention. This is perceived value is situational and contingent upon the context of evaluative judgments. This perspective aids in explaining the diversity of value perceptions. To truly understand perceived cultural value, one must consider a destination’s religious practices, social norms, and traditional culture. This allows individuals to connect with the heritage and its cultural significance, finally affecting their behavioral intentions. This connection, accordingly, benefits heritage conservation efforts and the development and marketing of tourism products [91]. Considering that cultural heritage can impart cultural value through the developmental process of digital products, the perceived cultural value in culture heritage digital products can affect users’ behavioral intentions [92]. Specifically, digital cultural heritage experiences offer unique engagement approaches and interactive methods of imparting heritage contents, different from on-site experiences. This difference in delivery can lead to differences in user perceptions and behaviors. Therefore, we propose the following hypothesis.

H10: Perceived cultural value positively impacts users’ continuous behavioral intention.

Building upon the prior assumptions, this study builds the research model in Fig. 2

Methods

Instruments

All variable measurement indicators were derived from verified surveys and adjusted for this study to ensure the questionnaire’s validity and accuracy. The questionnaire development process was as follows: First, an initial questionnaire was drafted by extracting well-established scales from previous studies and adapting them to digital museums. Second, to ensure content validity, three domain experts were invited to review the questionnaire. Their feedback helped optimize the measurement items and ensure alignment between the items and their intended meanings. The questionnaire was then revised based on expert suggestions, leading to a pilot version. Third, this pilot questionnaire was administered to a small sample of 15 users with experience utilizing the CCA mini program. Participants were asked to evaluate the questionnaire’s clarity and offer feedback. Based on their input, the questionnaire was further revised, addressing any ambiguities and enhancing readability, resulting in the final version. Finally, to guarantee linguistic equivalence, a bilingual researcher translated the questionnaire into Chinese, and a second researcher back-translated it into English to confirm consistency.

The survey primarily utilized a 36-item online questionnaire to collect both demographic data and responses to a series of research scales. This questionnaire first collected basic demographic information from participants, including gender, age, educational level, and whether they had previously utilized the CCA mini program. The research scales were then presented, divided into six sections: The first section, the TTF scale, comprised both task and technology characteristics, with items adapted from D’Ambra and Wilson [93], Zhou et al. [39], and Wang et al. [62]. The second section focused on the UTAUT model, incorporating measures of performance expectancy, effort expectancy, and social influence, with items adapted from D’Ambra and Wilson [93], Fong et al. [75], and Sun and Guo [4]. The third section consisted of the perceived enjoyment scale, with items originating from the work of Park [94]. The fourth section evaluated design aesthetics, utilizing a scale with items from Cheng [89]. The fifth section explored perceived cultural value, utilizing a scale with items originating from Weng et al. [91]. Finally, the sixth section analyzed users’ continuous behavioral intention, employing a scale with items originating from Shi et al. [8]. The questionnaire utilized a 5-point Likert scale throughout, ranging from 1 (strongly disagree) to 5 (strongly agree), allowing participants to select the response that best reflected their experience for each item.

Data collection

Prior to participating in the study, participants received information about its content and were asked to review an information sheet and sign a consent form. This study utilized Sojump, a platform similar to Amazon Mechanical Turk, to distribute electronic questionnaires to Chinese users who had experience with online digital museums. Recruitment was conducted through various online channels, including QQ, WeChat, Weibo, and Little Red Book. Data collection took place over ten days, resulting in 481

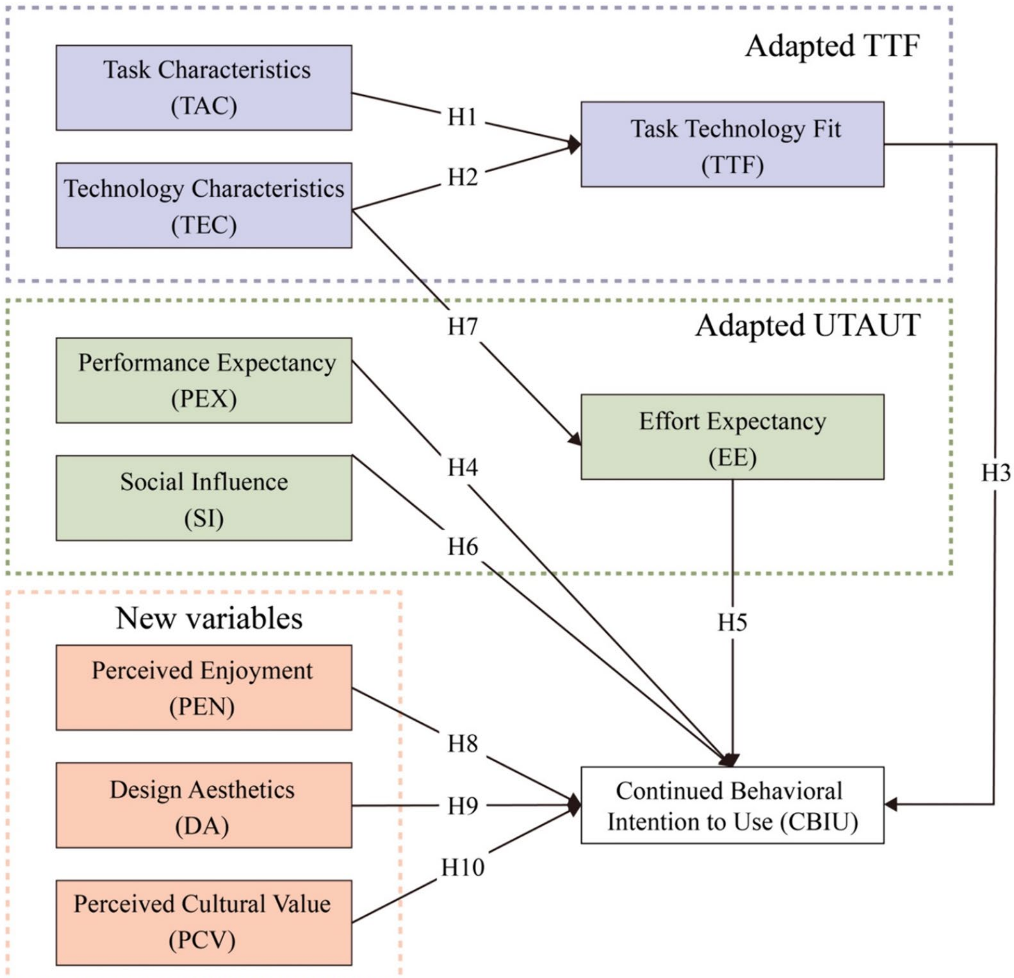

Fig. 2 The research models

attempted responses. To ensure the study focused on the intended audience, 46 questionnaires with a "No" response to the screening question, "Have you previously utilized the CCA mini program?", were excluded. Besides, 58 questionnaires completed in under 140 s were removed. This left 377 valid questionnaires, resulting in an effective response rate of 78.48%. This sample size is more than ten times the number of items analyzed (32), aligning with the requirements for structural equation modeling (SEM).

The survey indicates that the respondent pool is comprised of 46.68% males and 53.32% females. Respondents' age distribution is as follows: 18–20 (11.67%), 21–30 (29.97%), 31–40 (20.42%), 41–50 (19.63%), 51–60 (13.26%), and 61–65 (5.04%). Regarding education, a significant portion of respondents (43.5%) have attained a bachelor's degree as their highest level of education, while 71.88% have at least

Table 1 Participant demographic data (n = 377)

Item	Option	Number	Percentage (%)
Gender	Male	176	46.68
	Female	201	53.32
Age	18–20	44	11.67
	21–30	113	29.97
	31–40	77	20.42
	41–50	74	19.63
	51–60	50	13.26
	61–65	19	5.04
Education	Junior high school and below	19	5.04
	High school/Secondary school	57	15.12
	Junior college	107	28.38
	Undergraduate	164	43.5
	Master's degree or above	30	7.96
Total		377	100

a junior college degree. This suggests that smartphone users who engage with digital museums tend to be tech-savvy individuals with higher educational qualifications. Structurally, the demographics of the surveyed sample align with the typical profile of a digital museum user. Specific data points are available in Table 1.

Data analysis

We utilized SPSS 26.0 and AMOS 24.0 for our data analysis. We first conducted a preliminary analysis with SPSS to appraise the skewness, kurtosis, mean, and standard deviation to ensure the data was normally distributed. Second, we performed a confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) on each study variable to assess the reliability and validity of the instrument. Finally, we utilized AMOS to perform SEM to appraise the relationship between variables. We evaluated the measurement and structural models utilizing goodness-of-fit indices.

Results

Descriptive analyses, including measures of skewness and kurtosis, were performed on the data. As presented in Table 2, the mean (M) values ranged from 3.22 to 3.41, with standard deviations (SD) between 0.99 and 1.07. Skewness values fell between − 0.28 and 0.11, while kurtosis ranged from − 0.98 to − 1.17. With skewness values below 3 and kurtosis values below 10, the data were consistent with a multivariate normal distribution [95].

Table 2 Results of descriptive statistics analysis (n = 377)

Variable	Measurement variable	Skewness	Kurtosis	Mean	Std. Dev
Task characteristics	TAC1	0.11	− 1.17	3.22	1.07
	TAC2	− 0.04	− 1.14		
	TAC3	0.00	− 1.14		
Technology characteristics	TEC1	− 0.09	− 1.15	3.33	1.02
	TEC2	− 0.10	− 1.04		
	TEC3	0.04	− 1.21		
Task-technology fit	TTF1	− 0.19	− 1.04	3.41	0.99
	TTF2	− 0.28	− 0.98		
	TTF3	− 0.13	− 1.22		
Performance expectancy	PEX1	− 0.15	− 0.92	3.31	0.98
	PEX2	− 0.03	− 1.08		
	PEX3	− 0.04	− 1.12		
Effort expectancy	EE1	0.02	− 1.06	3.28	1.00
	EE2	− 0.02	− 1.10		
	EE3	− 0.10	− 1.08		
	EE4	− 0.10	− 1.10		
Social influence	SI1	− 0.11	− 0.98	3.37	0.96
	SI2	− 0.21	− 0.87		
	SI3	− 0.12	− 1.07		
	SI4	− 0.20	− 0.93		
Continuous behavioral intention to use	CBIU1	− 0.07	− 1.19	3.30	1.06
	CBIU2	− 0.05	− 1.10		
	CBIU3	− 0.06	− 1.21		
Perceived enjoyment	PEN1	− 0.06	− 1.10	3.28	1.06
	PEN2	− 0.09	− 1.11		
	PEN3	− 0.05	− 1.10		
Design aesthetics	DA1	− 0.03	− 1.25	3.26	1.09
	DA2	0.05	− 1.17		
	DA3	− 0.10	− 1.15		
Perceived cultural value	PCV1	− 0.16	− 1.15	3.34	1.04
	PCV2	− 0.17	− 1.10		
	PCV3	− 0.03	− 1.17		

Std. Dev standard deviation

The measurement model

This study employed several indicators to evaluate the measurement model's reliability and validity: standardized factor loadings, Cronbach's alpha coefficients, convergent validity, discriminant validity, and model fit. As Whittaker and Schumacker [96] recommend, standardized factor loadings should ideally surpass 0.50. This study handily meets this criterion, as all items demonstrated loadings exceeding 0.70, ranging accurately from 0.776 to 0.816 (Table 3). Cronbach's alpha coefficient, which ranges from 0 to 1, offers a measure of reliability, with higher values signifying greater internal consistency. The results for this study indicated robust internal consistency, with all Cronbach's alpha coefficients surpassing 0.80, ranging specifically from 0.811 to 0.864 (Table 3). To evaluate convergent validity, the study analyzed both composite reliability (CR) and average variance extracted (AVE). According to Schumacker [96], CR should meet or exceed 0.70, while AVE should ideally surpass 0.50. The findings demonstrate that the CR for each variable ranged from 0.811 to 0.883, all comfortably above 0.7, indicating strong reliability for the scales employed in this study (Table 3). Further supporting this, the AVE for each measurement model fell between 0.586 and 0.671, all exceeding 0.5, and demonstrating satisfactory convergent validity (Table 3).

Discriminant validity evaluates whether items measuring a research variable are different from those measuring

Table 3 Results of validity and reliability analysis (n = 377)

Variable	Measurement variable	Factor loadings	α	CR	AVE
Task characteristics	TAC1	0.816	0.847	0.848	0.650
	TAC2	0.793			
	TAC3	0.809			
Technology characteristics	TEC1	0.787	0.829	0.829	0.617
	TEC2	0.781			
	TEC3	0.789			
Task-technology fit	TTF1	0.769	0.811	0.811	0.589
	TTF2	0.753			
	TTF3	0.781			
Performance expectancy	PEX1	0.755	0.820	0.815	0.595
	PEX2	0.782			
	PEX3	0.776			
Effort expectancy	EE1	0.784	0.814	0.850	0.586
	EE2	0.779			
	EE3	0.774			
	EE4	0.723			
Social influence	SI1	0.794	0.864	0.883	0.654
	SI2	0.813			
	SI3	0.801			
	SI4	0.825			
Continuous behavioral intention to use	CBIU1	0.783	0.845	0.840	0.637
	CBIU2	0.803			
	CBIU3	0.808			
Perceived enjoyment	PEN1	0.815	0.859	0.860	0.671
	PEN2	0.799			
	PEN3	0.844			
Design aesthetics	DA1	0.803	0.849	0.850	0.654
	DA2	0.794			
	DA3	0.829			
Perceived cultural value	PCV1	0.783	0.830	0.831	0.621
	PCV2	0.813			
	PCV3	0.767			

α Cronbach's alpha, *CR* composite reliability, *AVE* average variance extracted other variables, emphasizing their uniqueness. Essentially, it assesses if the items are measuring different constructs. Discriminant validity is strong if the square root of the variable's AVE exceeds its correlations with other constructs [95]. In this study, analysis indicates that the square root of each variable's AVE is greater than its Pearson correlation coefficients, as presented in the rows and columns (Table 4).

As presented in Table 5, the measurement model demonstrates a desirable fit, aligning with the criteria recommended by Hu and Bentler [95]. The model yielded a χ^2 value of 460.465 and a χ^2/df ratio of 1.099, under the acceptable range of 1–3. In addition, the RMSEA and RMR values of 0.016 and 0.041, respectively, signify an excellent fit as they are well below the 0.05 threshold. The model also exhibits strong performance in other fit indices: GFI (0.931), TLI (0.992), CFI (0.993), and NFI (0.930), all surpassing the 0.9 threshold for excellent performance. Therefore, the aggregated results confirm the strong suitability of the CFA model employed in this study.

The structural model

Table 5 indicates a strong fit of the structural model data, as indicated by a χ^2 value of 587.838, a χ^2/df ratio of 1.358, an RMSEA of 0.031, and an RMR of 0.097. In addition, the GFI, TLI, CFI, and NFI are all in recommended ranges, at 0.911, 0.971, 0.975, and 0.911, respectively. These indices collectively demonstrate the robustness of the model and the validity of its results.

Verification of the hypotheses was conducted by evaluating the statistical significance of the path coefficients between variables. As presented in Table 6, the test results support all hypothesized path coefficients, with the exception of H3 and H6. The standardized path coefficients indicate that task characteristics significantly impact TTF ($\beta = 0.250$, $p < 0.001$), and technology characteristics demonstrate a significant impact TTF ($\beta = 0.406$, $p < 0.001$), thus supporting H1 and H2. Similarly, performance expectancy ($\beta = 0.137$, $p < 0.05$) and effort expectancy ($\beta = 0.126$, $p < 0.05$) both exhibit a significant positive impacts users' continuous behavioral intention, lending support to H4 and H5. H7 is supported by the significant impact of technology characteristics on effort expectancy ($\beta = 0.556$, $p < 0.001$). Perceived enjoyment ($\beta = 0.135$, $p < 0.05$), design aesthetics ($\beta = 0.218$, $p < 0.01$), and perceived cultural value ($\beta = 0.131$, $p < 0.05$) all exhibit a positive correlation with users' continuous behavioral intention, confirming H8, H9, and H10. However, neither TTF ($\beta = 0.099$, $p = 0.089$) nor social influence ($\beta = 0.106$, $p = 0.114$) demonstrate a significant positive impact users' continuous behavioral intention,

Table 4 Results of discriminate validity (n = 377)

	TAC	TEC	TTF	PEX	EE	SI	BIU	PEN	DA	PCV
TAC	**0.806**									
TEC	0.370**	**0.785**								
TTF	0.356**	0.372**	**0.767**							
PEX	0.409**	0.339**	0.377**	**0.771**						
EE	0.461**	0.383**	0.445**	0.449**	**0.766**					
SI	0.338**	0.351**	0.379**	0.366**	0.424**	**0.809**				
CBIU	0.386**	0.364**	0.384**	0.425**	0.436**	0.443**	**0.798**			
PEN	0.352**	0.420**	0.308**	0.382**	0.384**	0.444**	0.434**	**0.819**		
DA	0.471**	0.422**	0.388**	0.423**	0.416**	0.496**	0.494**	0.463**	**0.809**	
PCV	0.446**	0.420**	0.350**	0.363**	0.411**	0.379**	0.415**	0.370**	0.425**	**0.788**

Bold (on diagonal) represents the square root of the variable's AVE

Asterisks represent the correlation is significant at the 0.01 level (2-tailed)

Table 5 Fit indices of the measurement and research models (n = 377)

Model	χ^2	χ^2/df	GFI	TLI	CFI	NFI	RMR	RMSEA
Measurement model	460.465	1.099	0.931	0.992	0.993	0.930	0.041	0.016
Research model	587.838	1.358	0.911	0.971	0.975	0.911	0.097	0.031
Recommended criteria	p > 0.05	< 5.0	> 0.90	> 0.90	> 0.90	> 0.90	< 0.1	< 0.08

Note that all indices meet the recommended model fit criteria

Table 6 Results of path coefficients hypotheses (n = 377)

Hypotheses	Hypothesized path	B	β	S. E	t	Result
H1	TAC → TTF	0.216	0.250	0.058	3.693***	Supported
H2	TEC → TTF	0.391	0.406	0.069	5.696***	Supported
H3	TTF → CBIU	0.113	0.099	0.066	1.703	No supported
H4	PEX → CBIU	0.161	0.137	0.078	2.079*	Supported
H5	EE → CBIU	0.137	0.126	0.059	2.315*	Supported
H6	SI → CBIU	0.128	0.106	0.081	1.581	No supported
H7	TEC → EE	0.557	0.556	0.063	8.789***	Supported
H8	PEN → CBIU	0.138	0.135	0.068	2.022*	Supported
H9	DA → CBIU	0.215	0.218	0.075	2.863**	Supported
H10	PCV → CBIU	0.137	0.131	0.068	2.005*	Supported

B Unstandardized coefficient, *β* Standardized coefficient, *S. E* Standardized estimates

*** p < 0.001, **p < 0.01, *p < 0.05

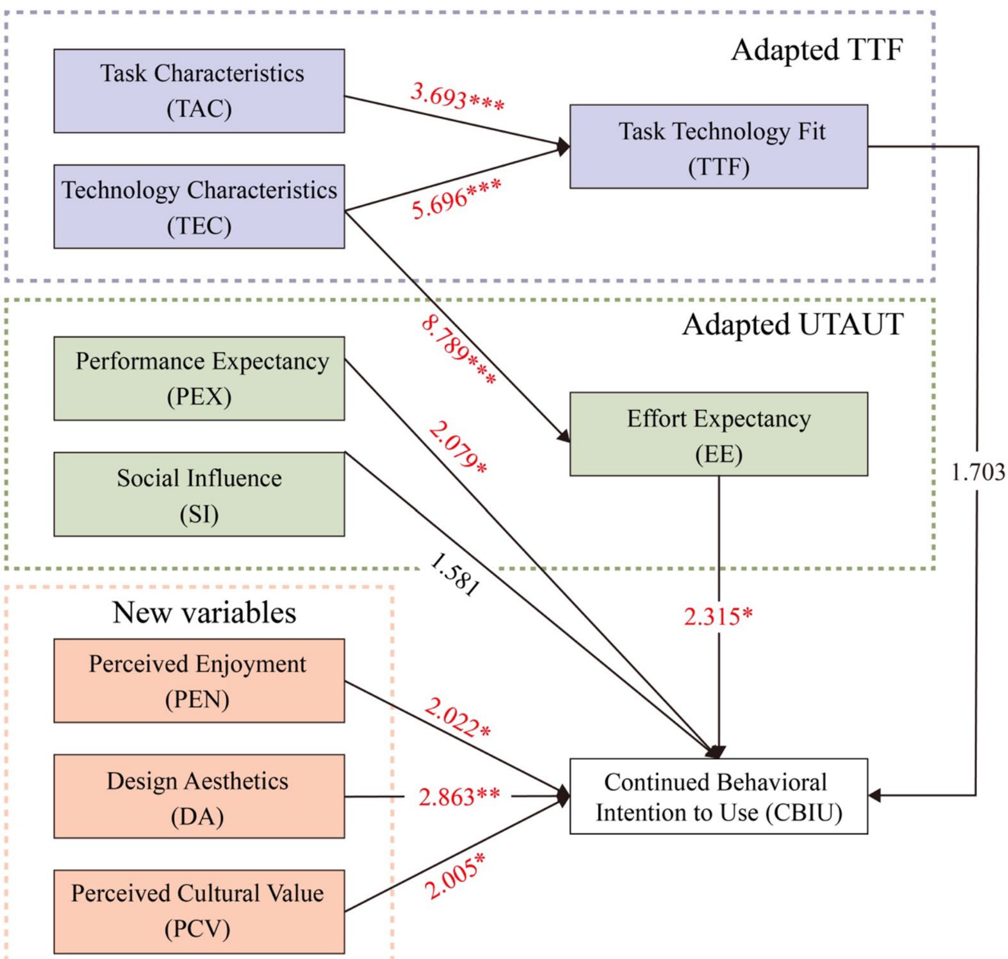

Fig. 3 Results of path analysis (Note. all hypotheses are supported, except H3 and H6.). ***p < 0.001, **p < 0.01, *p < 0.05

leading to the rejection of H3 and H6. Figure 3 offers a visual representation of the structural model of users' continuous behavioral intention to use digital museums.

Discussion and conclusion

This study evaluated a constructed technology acceptance expansion model for digital museums utilizing SEM to explore the factors influencing users' continuous behavioral intention to use digital museums, aiming to address the research questions.

TTF has no significant influence on the continuous behavioral intention

The following findings discuss possible answers to RQ1. Our findings discovered that both task characteristics and technology characteristics strongly impact the TTF (supporting H1 and H2), the results provide support for the findings of previous research [65, 88, 97]. Task characteristics of digital museum users include activities such as browsing exhibits, searching for information, and engaging in interactive experiences, and the alignment of these characteristics with user needs on the digital platform enhances task-technology matching. Technology characteristics consist of aspects such as interface design, navigation functionality, content display, multimedia support, and interactivity features, directly affecting the user experience and functional support in the digital museum. A higher degree of task-technology matching is achieved when users' task requirements are effectively met by the platform's technical features, leading to a more satisfying and engaging user experience in the digital museum.

In contrast to earlier findings [4], this study indicates that TTF does not significantly impact users' continuous behavioral intention to use digital museums (not supporting H3). This discrepancy could be attributed to users' insufficient understanding of digital museums, as they may not have yet formed stable patterns of use and experience, nor are they fully cognizant of the latest updates and enhancements. This lack of awareness may weaken the effect of the task-technology fitness model on users' continuous behavioral intention to use digital museums. In addition, individual reliance on digital museums varies, leading to subjective perceptions of task matching that are difficult to quantify. Therefore, when promoting cultural heritage through digital museums, institutions should not only prioritize the timely adjustment of functionalities to align with users' actual needs but also emphasize the suitability between user task requirements and the functionalities offered by the digital museum. A strong alignment between these elements contributes to a positive user experience, which can motivate users' continuous behavioral intention to use digital museum.

In summary, while the technical capabilities of digital museums align with the need to support experiential tasks, ensuring that users fully understanding and experience this consistency between the technical characteristics of digital museums and their engagement tasks is essential for cultivating continuous behavioral intention to use these platforms.

UTAUT has significant influence on the continuous behavioral intention, except social influence

This study's findings, which directly address RQ2, suggest that both performance expectancy and effort expectancy have a positively impact users' continuous behavioral intention to use digital museums (supporting both H4 and H5). This finding is consistent with established evidence from existing UTAUT studies [66, 79, 98]. Essentially, when users anticipate that they will be able to understand and experience the cultural heritage of the cultural heritage more effectively through the digital museum platform, they are more inclined to use the platform consistently. This is because users perceive that utilizing the digital museum offers them with useful information and offers an efficient experience that effectively meets their performance expectations, which motivates them to continue utilizing the digital museum. More specifically, the more the digital museum enables users to realize efficient information access and convenient function operation, complete with a simple and clear interaction process and effortless use of relevant functions, the more motivated those users will be to continue utilizing the platform.

However, this study found that social influence does not significantly impact the continuous behavioral intention to use digital museums (not supporting H6). This finding differs from some previous studies but aligns with more recent research [4]. This trend suggests that digital museums, especially those accessed through smartphone applications, are increasingly characterized by privacy and user experience personalization. Accordingly, users are becoming more autonomous in their engagement. While the experiences of others might factor into a user's initial decision to engage, it is more likely that the continuous behavioral intention to use digital museums is driven by factors such as the prioritization of the user's personal experience, autonomous choices, and personal ideology.

Therefore, users' continuous behavioral intention to use digital museums is primarily determined by their expectations regarding the platform's performance and the effort required to utilize it. By presenting cultural heritage information through intuitive interfaces and thoughtfully designed layouts, digital museums empower users to navigate effortlessly and locate desired content with ease. Accordingly, this leads to higher user satisfaction in terms of both perceived performance and reduced effort. In addition, when users find that digital museums offer a superior alternative to other options—demonstrating a user-friendly experience and influential cultural heritage content—users' continuous behavioral intention to use these platforms is likely strengthened.

Moreover, our findings also indicate intriguing connections between TTF and UTAUT constructs (supporting H7). Specifically, technological characteristics significantly impact effort expectancy, aligning with previous research [39]. Digital museums, characterized by user-friendly interfaces, intuitive functionality, and operation, minimize user effort and reduce potential hurdles. These advanced technological characteristics, coupled with high-quality technical support [63], elevate the overall user experience, further reducing the behavioral efforts of using them. In addition, our results suggest that the technological characteristics of digital museums indirectly affect users' continuous behavioral intention to use the platform by affecting their effort expectancy. Positive technological characteristics, by minimizing perceived effort and enhancing user experience, cultivate a greater willingness to continue utilizing digital museums. This finding further validates the critical role of both technological characteristics and user effort expectancy in influencing continuous engagement in digital museums.

Perceived enjoyment, design aesthetics, and perceived cultural value has significant influence on the continuous behavioral intention

This section explores potential answers to RQ3. Our findings indicate a strong positive correlation between users' continuous behavioral intention to utilizing digital museums and their perceived enjoyment, design aesthetics, and perceived cultural value. These results align with previous research [51, 53, 54], strengthening the significance of perceived enjoyment in cultivating users' continuous behavioral intention to use technology. Essentially, the more engaging and enjoyable a digital museum experience is, the more likely users are to return. This suggests that the interesting interactive nature of digital technologies in museums can significantly enhance user engagement and increase their desire to continue utilizing these platforms through intuitive and interesting interface design.

Design aesthetics are positively correlated to users' continuous behavioral intention to utilizing digital museums, as highlighted in previous research [88, 89]. Schenkman and Ronson emphasize the significant effect of aesthetics on the popularity of public interfaces, stressing its role in affecting users' initial perception [99]. Essentially, an aesthetically appealing interface not only draws users to engage with cultural content but also enhances their overall experience. By incorporating innovative visual design, thoughtful color palettes, and intuitive layouts, digital museums can create an engaging user experience, finally influencing users' continuous behavioral intention to utilizing the platform. This underlines the importance of prioritizing design aesthetics for digital museum interfaces.

Moreover, the perceived cultural value has a positively impacts users' continuous behavioral intention, a finding that aligns with well-established evidence from previous studies [91]. When users engage with a digital museum, they can experience the richness and diversity of cultural heritage firsthand, an experience that can fulfill their innate desire to connect with the past. Users often express that they can more deeply engage with and perceive the deeper meanings and value in cultural heritage through their digital museum experiences. This acquisition of perceived cultural value then strengthens users' continuous behavioral intention to use the digital museum. Therefore, we can conclude that enhancing the accessibility of cultural heritage information, along with enhancing a higher level of user perception in the digital space, finally helps users more quickly and thoroughly complete the task of understanding and appreciating cultural heritage.

Therefore, it is crucial to take into account the perceived enjoyment, aesthetic design, and perceived cultural value when planning the future growth of digital museums of cultural heritage. Through the effective integration of visual and auditory technologies, digital museums offer a captivating, aesthetically pleasing, and immersive form to present cultural heritage. Besides, during the interaction and user experience, individuals are more likely to receive feedback that is closely aligned with their cultural heritage needs, enhancing their positive perception of the digital museum and cultivating a continuous behavioral intention to use the digital museum.

Contribution and implication

Contribution

Previous studies exploring visitor digital museum use intentions and behaviors during the COVID-19 pandemic have employed the TTF model and UTAUT2, and the PATS model. These studies, framed during social distancing, have indicated how pandemic anxiety can affect the intention to use digital museums and translate into actual use behaviors [4]. However, this study is based on the growing trend of digital museums in the post-pandemic [47, 100], from the user experience and digital museum design dimensions to evaluates the two basic models of TTF and UTAUT and introduces three variables for perceived enjoyment, design aesthetics, and perceived cultural value. By integrating these variables, we have constructed an expanded technology acceptance model that clarifies users' continuous behavioral intention to use digital museums of cultural heritage. Through analyzing the relationships between these latent variables, the study aims to: (1) confirm the validity of the indicators in the structural model of digital museum user experience, and (2) offer valuable theoretical guidance for museum managers, researchers, and designers seeking to enhance the user experience of digital museums. This analysis offers the following innovative contributions:

First, this study leverages advancements in digital museum technology to propose a new adapted TTF and UTAUT model. These extensions incorporate factors such as perceived enjoyment, design aesthetics, and perceived cultural value. By re-evaluating the effectiveness of the adapted TTF and UTAUT models in modern cultural heritage, the study evaluates the significant relationship between new technologies and user experience. Finally, this exploration seeks to identify the factors that affect users' continuous behavioral intention to use digital museums of cultural heritage. By understanding these potential influencing factors and designing digital museums that cater to the needs of continuous user experience, museum professionals stimulate users' continuous behavioral intention to use digital museums.

Second, drawing on recent research in the TTF and UTAUT, this study highlights the crucial role of perceived enjoyment, aesthetic design, and perceived cultural value in cultivating users' continuous behavioral intention to use digital museum of cultural heritage. In addition, technological characteristics significantly impact effort expectancy, which indirectly affects users' continuous behavioral intention. These findings offer valuable insights into the relationship between users and digital museum interfaces, highlighting how these factors contribute to continued user engagement. Therefore, digital museum of cultural heritage should prioritize the development of robust technological features, captivating experiences, aesthetically pleasing designs, and culturally rich content to satisfy users' continuous behavioral intention to use the digital museum of cultural heritage. This study suggests four practices for optimizing the user experience and user interface of digital museums of cultural heritage.

Suggestion

This study proposes four practices to enhance the user experience and interface design of digital museums of cultural heritage.

First, in lieu of merely presenting artifacts in a virtual environment, digital museums should leverage technology to convey cultural narratives and deeper meaning. Since widespread public engagement is paramount for cultural heritage, digital museums must prioritize effective information dissemination. This necessitates optimizing how exhibits are presented and communicated [101]. For instance, specialized researchers require in-depth, accurate information as high quality research resources; whereas, cultural enthusiasts typically seek engaging, accessible content to fuel their passions and curiosity [4]. Therefore, digital museums must adjust their offerings accordingly, offering authentic, reliable, information-rich, and easily digestible exhibits and services, thereby ensures that digital museum resources meet the varied expectations of their audiences.

Second, considering the positive effect of perceived enjoyment, aesthetic design, and perceived cultural value on users' continuous behavioral intention to use digital museums, these platforms must prioritize the creation of an immersive and culturally rich experience. To achieve this, the visual design of the interactive interface should integrate with the style of the cultural heritage it presents. This ensures that the platform remains engaging and informative, enhancing the user's appreciation for the cultural heritage it demonstrates [5]. In addition, by prioritizing the authentic representation of cultural heritage scenes, focusing on vibrant image design, and incorporating immersive sound and audio elements, digital museums can enhance enjoyment, aesthetic appeal, and cultural value. This immersive approach allows users to engage with and experience cultural heritage in a captivating and engaging digital environment.

Third, in the contemporary complex and diverse Internet environment, it is essential for digital museums to constantly evolve and enhance their functionality and user experience. Users expect digital museums to meet their basic needs and deliver these experiences more quickly and efficiently [4]. Digital museums should prioritize the user perspective, minimizing interaction fatigue by implementing intuitive interfaces and streamlined processes. They should cater to users with diverse needs and offer them with quick, accurate, and convenient access to information. This will finally improve the efficiency of utilizing digital museums. Accordingly, users' experience with digital museum of cultural heritage shifts from passive consumption to active engagement. This enhanced interaction leads to a more enjoyable experience, finally increasing their willingness to continue utilizing the digital platform.

Fourth, digital museums should offer a unique experience from their physical counterparts. Cutting-edge technologies such as AR and VR should be integrated into future digital museums of cultural heritage development. This integration will boost user engagement by facilitating information delivery, enabling real-time content updates, and cultivating a more interactive experience. As an "alternative," the digital platform has the potential to offer an incredibly authentic encounter, transforming into a cultural vessel that transcends the limits of time and space [2]. Imagine, for instance, being able to "access" cultural heritage sites virtually, experience artifacts in high-definition detail, and even "touch" them through the power of technology. By leveraging multimedia elements such as text, imagery, audio, 3D interaction, etc., digital museums can provide a multi-channel response to user experience. Moreover, they can offer users with more opportunities and experiences to interact with cultural heritages, enriching their perception of the richness of the information and finally cultivating a users' continuous behavioral intention to use it.

Limitations and future research

While this study makes valuable contributions to both theory and practice, certain limitations should be acknowledged. The focus on the CCA Mini Program, a digital museum specifically dedicated to "Cultural Heritage," raises questions of generalizability. It is unclear whether the findings would hold true for digital museums exploring other themes, such as natural history, anthropology, or science. Future research should investigate these models in a wider range of digital museums to ensure broader applicability. In addition, the study's sample size (377 participants), while informative, represents a relatively small portion of the total user base. This limited sample coverage may affect the generalizability of the findings. Future studies should aim to increase the number of participants and diversify user groups to enhance the universal applicability of the results in public communication. Finally, the reliance on questionnaires as the primary research methodology introduces an element of subjectivity. To more accurately capture user interactions, future research could employ more objective and diverse methods, such as eye-tracking technology and real-time behavioral analysis.

This study suggests several avenues for future research. First, exploring the factors influencing users' continuous behavioral intention to use digital museums could be enhanced by incorporating a wider range of behavioral models and measurement variables. Second, future studies could address the needs of diverse user groups, particularly those who may face challenges accessing and navigating digital content. For instance, design considerations for elderly users or those with mobility limitations could simplify the process of finding features and engaging with cultural heritage materials. The digitalization of museums presents unique challenges for specific demographics, emphasizing the need for continued research from multiple perspectives.

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Author contributions
F. Zheng: Conceptualization, Investigation, Data statistics, Writing—original draft. S. Wu: Funding acquisition, Writing—review & editing. R. Liu: Supervision, Validation, Writing—review & editing. Y. Bai: Grammar checking, Data analysis. All authors reviewed the manuscript.

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Availability of data and materials
The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
All human participants provided written informed consent for the What Influences User Continuous Intention of Digital Museum: Integrating Task-technology Fit (TTF) and Unified Theory of Acceptance and Usage of Technology (UTAUT) Models. This study was approved by Institute of Visual Communication Design, Lu Xun Academy of Fine Arts, Dalian, China. All experiments were in accordance with the ethical standards formulated in the Helsinki Declaration.

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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