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RESEARCH ARTICLE

Determinants of Digital Museum Visit Intention: An Integrated TAM–TPB Model

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ABSTRACT

Against the backdrop of the digital transformation of cultural heritage institutions, mobile Internet and cloud computing technologies have gradually made digital museums an important alternative to physical visits. To deeply explore the underlying behavioral motivations of tourists choosing mobile digital museums, this study integrates the Technology Acceptance Model (TAM) with the Theory of Planned Behavior (TPB), taking the Palace Museum in Beijing as a specific context, and constructs a contextualized direct effect model that includes four core antecedent variables: convenience, technological familiarity, social influence, and cost. Based on the verified 552 research data, we conducted an empirical test of the conceptual path using the structural equation model. The key findings indicate: (1) Social influence is the most crucial factor driving tourists' visit intention (β= 0.327), highlighting the core role of group identification and social sharing in cultural consumption; (2) Cost (β= 0.263), technology familiarity (β= 0.260), and convenience (β= 0.259) also have a significant positive impact on the visit intention. This research helps to alleviate the limitations of a single theoretical framework when explaining complex cultural consumption decisions, and provides valuable management insights for large cultural heritage institutions to optimize their cloud computing architectures and mobile platform designs, and enhance cultural accessibility.

Contribution/Originality: This study contributes to the existing literature by integrating the Technology Acceptance Model and the Theory of Planned Behavior with four contextual antecedents: convenience, technological familiarity, social influence, and cost.

1. Introduction

The field of cultural heritage is currently undergoing a major digital transformation, with new technologies gradually being integrated into it. The Palace Museum in Beijing is a prime example of this - as one of the world's most popular cultural landmarks, it has successfully transferred its vast collection resources to the digital world through the Digital Palace Museum project, leveraging virtual reality, augmented reality and immersive panoramic imaging technologies (Li et al., 2021; Shi et al., 2023). However, the physical venues themselves are under pressure due to their excessive popularity. Nowadays, tourists not only have to deal with strict daily limit measures and the persistent problem of hard-to-get tickets, but also face the actual experience of overcrowdedness. Adding to the significant time investment required for on-site visits, it is clear that digital museums are no longer just an add-on option for many people, they have become a practical and necessary alternative (Shi et al., 2023).

Although digital tools have matured rapidly, we still lack a clear and comprehensive understanding of why people tend to prefer visiting digital museum screens rather than physical exhibition halls (Shi et al., 2023; Lee et al., 2019). Most current research tends to adopt a single stance - either by delving deeply into the technical characteristics through the technical acceptance model (Davis, 1989), or by strictly focusing on individual psychological factors through the Theory of Planned Behavior (Ajzen, 1991). At present, we lack a unified approach that can comprehensively consider how technical specifications, social pressures, and personal obstacles interact with each other, especially in the unique field of cultural heritage. Even for a world-class cultural institution like the Palace Museum, we still don't know how visitors weigh the convenience of using the website against the convenience of skipping the physical visit. Filling this empirical gap is precisely the goal of this research.

1.1. Research Objectives

i. Construct an integrated framework that combines the Technology Acceptance Model (TAM) with the Theory of Planned Behavior (TPB), and introduce cost, convenience, and technological familiarity as antecedent variables.
ii. Through an empirical investigation of 552 visitors to the Palace Museum, the influence paths of each dimension on the intention to visit the digital museum were revealed.

1.2. Research Questions

i. How do perceived usefulness, perceived ease of use, subjective norms, and perceived behavioral control significantly influence the visiting intentions of the audience towards digital museums?
ii. To what extent did convenience and technical familiarity enhance this willingness?

1.3. Research Innovation and Significance

i. Theoretical Significance: Our study combines the TAM and TPB models. This approach fixes the gaps left by using just one theory (Taylor & Todd, 1995). We need more than a single framework to explain complex cultural choices. This integration offers a fresh theoretical base for future digital heritage research (Shi et al., 2023; Lee et al., 2019).
ii. Practical Significance: These findings give direct advice to large institutions like the Palace Museum. Our research helps them improve digital platform design. It

also shows how to lower user access barriers. Ultimately, these steps will make cultural heritage more accessible to everyone.

2. Theoretical Foundation and Research Hypotheses

2.1. Theoretical Foundation: Contextual Application of TAM and TPB

The core theoretical framework of this study is based on the integration of the Technology Acceptance Model (Davis, 1989) and the Theory of Planned Behavior (Ajzen, 1991). As shown in Figure 1, the Technology Acceptance Model explains the degree to which individuals accept new technologies through perceived usefulness and perceived ease of use, and it demonstrates strong predictive capabilities in the field of information systems.

Figure 1: Technology Acceptance Model (Davis, 1989).

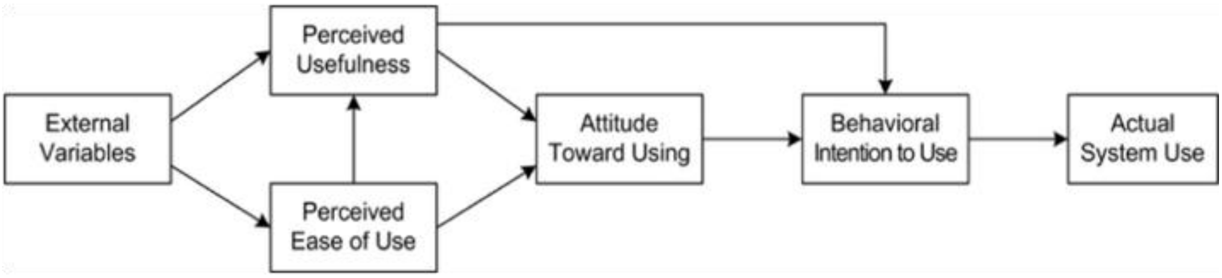
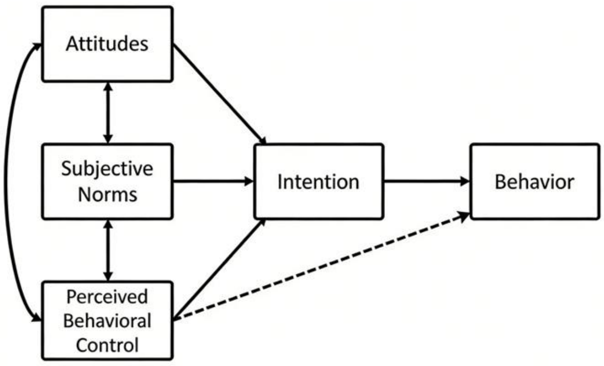


Figure 2 illustrates the advantages of our combined model. The original technology acceptance model often neglects social context and external constraints. To address this issue, we introduced the framework of the Theory of Planned Behavior, incorporating two new variables, subjective norms and perceived behavioral control, thereby providing a more explanatory approach for understanding the choices made by visitors.

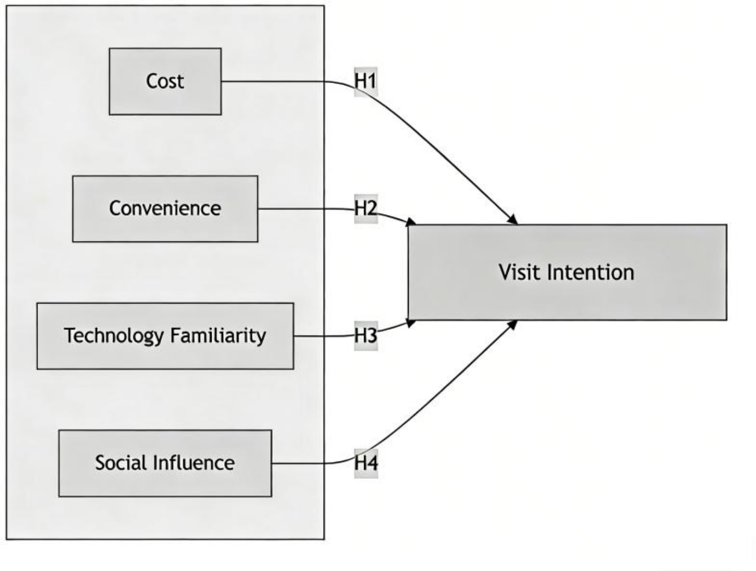
Figure 2: The Theory of Planned Behavior model adapted from (Ajzen, 1991).



Although the classic technology acceptance model and the Theory of Planned Behavior are valuable, their core constructs are often too broad for this study. To accurately capture the reasons why visitors to the Palace Museum choose to view the exhibits on digital screens rather than in person, we followed the new trend in digital heritage research (Loureiro et al., 2020) and conducted contextualized operationalization of these two theories.

This model incorporates 4 main antecedent variables: convenience; technical familiarity; social influence and cost. Each of which corresponds to a core construct of the TAM or TPB theories. The relationships are illustrated in Figure 3.

Figure 3: Contextualized Direct Effects Model of Digital Museum Visit Intention.



2.1.1. Convenience acts as the core empirical proxy for perceived usefulness.

As shown in Figure 1, the technology acceptance model defines "usefulness" as the degree to which an individual believes that a certain technology can enhance their performance. In this study, this performance improvement specifically refers to the digital museum experience it enables visitors to bypass physical barriers such as geographical distance, queuing for tickets, and crowded exhibition halls during physical visits. Digital platforms meet users' needs more efficiently than physical visits by offering services that allow instant access to cultural content anytime and anywhere. Therefore, when visitors recognize these tangible time saving advantages, convenience becomes the most direct and functional manifestation of perceived usefulness (Shi et al., 2023; Davis, 1989).

2.1.2. Technical familiarity lays the practical foundation for perceived usability.

In the framework of the technology acceptance model shown in Figure 1, "usability" is defined as the degree to which an individual expects a certain technology to require no effort. In this study, this psychological judgment largely depends on the existing digital technology background of the visitors. For instance, individuals who have already mastered the operation methods of VR environments or interactive panoramic navigation will naturally experience a lower cognitive load when using the digital museum platform. This prior knowledge eliminates the learning curve and enables immediate usability perception. Therefore, in the field of digital cultural tourism, technical familiarity is not only a key prerequisite for users to perceive ease of use, but also an intuitive reflection of it (Lee et al., 2019; Davis, 1989).

2.1.3. Social influence essentially serves as the practical counterpart of the subjective norms in this model.

Looking at the framework of the Theory of Planned Behavior in Figure 2, subjective norms essentially refer to the social pressure that individuals perceive that is, "What would my peers or mentors expect me to do?" This is the inner voice. When dealing with a prestigious cultural brand like the Palace Museum, this pressure is not abstract; rather, it is driven by very specific social factors. Whether it is the recommendation from a close friend, the popular "check-in" posts on social media, or the professional guidance from educators, all these external voices carry significant weight in the final decision making of visitors. In the specific field of digital heritage, social influence is precisely the most real and observable external manifestation of these potential subjective norms (Taylor & Todd, 1995; Ajzen, 1991).

2.1.4. The cost factor in this research model essentially corresponds to the concept of perceived behavioral control.

Refer to Figure 2. The Theory of Planned Behavior defines "behavior control" as an individual's subjective perception of having sufficient resources and opportunities to actually carry out a certain behavior. When people plan to visit an actual museum, they often encounter significant obstacles high travel expenses, time consumption, and frustration caused by the reservation limit. In contrast, digital museums have significantly lowered the entry barriers in terms of both money and time, thereby eliminating these obstacles. This transformation directly empowers visitors, giving them a stronger sense of control over the exhibition viewing activity. Based on this, we consider the rationality of the perceived cost as the most practical proxy indicator for measuring the user's ability to control their behavior (Li et al., 2021; Ajzen, 1991).

2.2 Research hypothesis derivation

2.2.1. Cost and Visit Intention

The framework of the Theory of Planned Behavior regards resources and costs as important control beliefs. These factors often constitute obstacles to action - money and time can both prevent individuals from taking action. The Motivation Theory also tells us that lower costs can enhance an individual's sense of self-efficacy. Visiting physical museums usually involves high costs and long durations, including transportation, accommodation, and long queues (Li et al., 2021). In contrast, digital museums offer a more accessible option, allowing visitors to have a greater sense of control (Ajzen, 1991; Li et al., 2021). Therefore, reasonable pricing has become an important driving factor, encouraging visitors to choose the digital platform over physical exhibitions.

H1: Cost rationality significantly enhances the visit intention for digital museums.

2.2.2. Convenience and Visit Intention:

Accessibility refers to convenience. Mobile devices enable people to access digital cultural products anytime and anywhere, which is a significant advantage of digital tourism compared to physical museums (Shi et al., 2023). The logical explanation of the Technology Acceptance Model clarifies the reasons behind this (Davis, 1989): Digital tools have broken through the limitations of time and space, significantly enhancing the value of digital museums in the eyes of visitors. For instance, people can enjoy the exhibits of the Palace Museum at any time without worrying about travel arrangements or overcrowding. When access is so convenient, visitors are more likely to choose the digital screens rather than physical travel.

H2: Convenience significantly enhances the visit intention for digital museums.

2.2.3. Technology Familiarity and Visit Intention:

Technology familiarity stems from existing experience with tools such as VR. According to Lee et al. (2019), This experience is the key to reducing the difficulty of perception. When visitors have mastered the usage of the complex interaction platform, their cognitive burden will decrease. This is highly consistent with the technical adoption logic of the technology acceptance model (Davis, 1989): higher proficiency helps users overcome psychological barriers and thus forms a stronger willingness to use the digital museum system.

H3: Technology familiarity enhances the visit intention for digital museums.

2.2.4. Social Influence and Visit Intention:

Social influence directly corresponds to the “subjective norms” dimension in the TPB model (Ajzen, 1991). As a top-tier cultural heritage IP, the dissemination of the Palace Museum’s digital experiences is strongly driven by social media “check-in culture” and peer recommendations. Relevant research indicates that recommendations from one’s social circle significantly reshape the cultural consumption habits of the younger generation (Taylor & Todd, 1995). Positive evaluations and recommendations from significant others (such as teachers and friends) create a strong sense of social identification, which in turn directly facilitates visitors’ decision-making.

H4: Social influence has a significant positive effect on intention to visit digital museums.

2.3. Research Model

Based on the above contextualized theoretical derivation, this study constructs a direct effects model (as shown in Figure 3) aimed at explaining intention to visit digital museums. This model verifies the driving role of four core antecedent variables: convenience, technology familiarity, social influence, and cost.

3. Research Design and Methodology

3.1. Research Design and Data Collection

This study adopts a quantitative approach with a cross-sectional survey design. The target population comprises visitors who have experienced or intend to experience the digital products of the Beijing Palace Museum (such as Panoramic Palace Museum and Digital Cultural Relics Database).

This study collected data through online structured questionnaires on social media platforms like Weibo and WeChat. We focused on digital museum users because of their active online presence. After the collection phase, our team performed strict data cleaning. We removed invalid responses, such as those with patterned answers or very short completion times. Ultimately, we obtained 552 valid samples (N = 552). This sample size is much larger than the usual standard required by the structural equation model (that is, 5 to 10 times the number of measurement items), ensuring the robustness of the statistical results. Table 1 summarizes the demographic characteristics of the respondents.

Table 1: Demographic Profile of Respondents, N=552

Variable	Options	Frequency	Percentage
Gender	Male	246	44.6
	Female	306	55.4
Place of Residence	Beijing	349	63.2
	Other provinces and cities	203	36.8
Age	Under 18 years old	53	9.6
	18-25 years old	242	43.8
	26-35 years old	156	28.3
	36-45 years old	51	9.2
	46-55 years old	50	9.1
Education level	High school and below	153	27.7
	Junior college	263	47.6
	Undergraduate	136	24.6

3.2. Measurement and Instrumentation

To ensure the reliability and validity of the measurement tools, the core latent variables in the research model are all derived from mature and classic scales, and have undergone semantic adjustments specifically for the specific context of digital products in the Beijing Palace Museum. Specifically, the convenience factor is adapted from the scale developed by Shi, Wang and Long (2023); the technical familiarity factor is adapted from the information system success model of DeLone and McLean (1992); the social influence factor is adapted from the subjective norm items of Taylor and Todd (1995); the cost factor is adapted from the research of Li et al. (2021); the outcome variable visit intention is adapted from the continuous intention scale of Bhattacherjee (2001). The specific item configuration is shown in Table 2. A 5-point Likert scale was used throughout the questionnaire, ranging from “1= strongly disagree” to “5 = strongly agree.”

Table 2: Constructs and Measurement Sources

Dimension	Question
Cost	CB1 I believe that the fees charged by Digital Palace are reasonable. CB2 Compared to the physical Palace Museum, the overall cost of Digital Palace is lower. CB3 I am willing to pay a reasonable fee for the high-quality content offered by Digital Palace.

	CB4 The price of Digital Palace is within my budget.
Convenience	BL1: Compared to physical museums, using digital museums makes it much easier for me to understand the museum's artifacts. BL2: Compared to physical museums, using digital museums saves me a lot of time understanding the museum's artifacts. BL3: Compared to physical museums, using digital museums is very efficient for understanding the museum's artifacts. BL4: Compared to physical museums, digital museums make it easier for me to obtain the information I need.
Technology Familiarity	JS1: I think the digital museum is very responsive and can be used smoothly. JS2: I think the digital museum's interface is well-organized, making it easy to find the information and functions I need. JS3: I think the digital museum's navigation is convenient. JS4: I think the digital museum's functions are stable and reliable.
Social Influence	SH1: I prefer to choose a digital museum recommended by teachers, classmates, or friends. SH2 Extensive publicity for digital museums increases my willingness to use them. SH3 Enhanced public outreach to digital museums can increase my willingness to use them. SH4 A positive development atmosphere for digital museums can increase my willingness to use them.
Visit Intention	CG1: After my initial experience with the digital museum, I would use it again. CG2: I would continue to use the digital museum more frequently or even increase it. CG3: I would recommend the digital museum I used to others, in addition to using it personally.

3.3. Data Analysis Strategy

The statistical analysis of the data was conducted in two stages. First, SPSS software was used to perform descriptive statistical analysis of the sample and to conduct data normality tests. A fundamental prerequisite for structural equation modeling is normally distributed data (Kline, 2016; Byrne, 2016). Consequently, we evaluated the sample's distributional properties utilizing both the Kolmogorov-Smirnov and Shapiro-Wilk procedures.

To empirically evaluate the proposed theoretical paths, we utilized structural equation modeling (SEM) guided by Anderson and Gerbing's (1988) traditional two-stage methodology:

Phase 1: Evaluating the Measurement Model. We first executed a confirmatory factor analysis (CFA) to verify the psychometric properties of our instrument. This stage confirmed the overall robustness of all latent variables by assessing their internal consistency Cronbach's$\alpha$and composite reliability (CR), as well as convergent and discriminant validities.

Phase 2: Structural Model Evaluation. After confirming the sufficiency of the measurement model, we shifted our analysis focus to the structural relationships. Specifically, we calculated the standardized path coefficients and their corresponding p-values to conduct an empirical test of the proposed hypotheses.

4. Data Analysis and Empirical Results

To analyze the 552 valid responses, we applied structural equation modeling (SEM). In accordance with the established two-stage methodology from Anderson and Gerbing (1988), our investigation began by validating the measurement model's psychometric properties. Once confirmed, we proceeded to evaluate the structural model to test the hypothesized paths.

4.1. Measurement Model Evaluation

4.1.1. Reliability and Convergent Validity Testing

Initially, we evaluated the reliability of the measurement tools. For each potential construct - namely cost, convenience, technical familiarity, social impact, and visit intention the calculated Cronbach'sα coefficients ranged from 0.843 to 0.916. Because of these figures comfortably exceed the conventional 0.70 cut off, the measurement scale possesses excellent internal consistency.

Table 3: Reliability Analysis

Dimension	item	Cronbach's α reliability coefficient
Cost	4	0.843
Convenience	4	0.861
Technology familiarity	4	0.851
Social Influence	4	0.873
Visit Intention	3	0.916

In terms of validity testing, the results are shown in Table 4. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for the overall scale was 0.855, and Bartlett's test of sphericity reached a highly significant level ($p < 0.001$), indicating that the data are highly suitable for factor analysis. Further factor analysis results show that the standardized factor loadings of each measurement item on its respective latent variable are all at a high level (for example, the loadings for the cost dimension all exceed 0.80), demonstrating that the model possesses good convergent validity (Fornell & Larcker, 1981; Hair et al., 2010).

Table 4: Validity Analysis for Overall Scale

KMO sampling suitability measures		0.855
Bartlett's sphericity test	Approximate Chi-square	5690.595
	Degrees of freedom	171
	Significance	0.000

4.1.2. Confirmatory Factor Analysis and Model Fit

To further examine the degree of fit between the measurement model and the observed data, this study conducted a confirmatory factor analysis (CFA). The goodness-of-fit test results are presented in Table 5. As shown in Table 5, all key indices meet the ideal standards recognized in the academic community (Hu & Bentler, 1999; Browne &

Cudeck, 1993): the chi-square to degrees of freedom ratio (χ^2/df) was 2.286 (meeting the criterion of < 5.0); the goodness-of-fit index (GFI) was 0.951, and the adjusted goodness-of-fit index (AGFI) was 0.933 (both exceeding the threshold of 0.9); the root mean square error of approximation (RMSEA) was 0.048, well below the strict cutoff of 0.08. Based on the comprehensive assessment of these indicators, the measurement model of this study exhibits excellent fit.

Table 5: confirmatory factor analysis model fit indices

Fit index	**Judgment criteria**	**actual value**
Chi-square degrees of freedom ratio X^2/ df	< 5	2.286
Goodness-of-fit index (GFI)	>0.8 is acceptable; >0.9 is ideal.	0.951
Adjusted goodness-of-fit index AGFI	>0.8 is acceptable; >0.9 is ideal.	0.933
Root Square Index of Approximation Error (RMSEA)	<0.08	0.048

We relied on the Fornell-Larcker approach to verify the discriminant validity of our constructs. The data in Table 6 support this. Specifically, each construct's AVE square root (the bold diagonal values) is consistently higher than its correlations with competing factors, thereby confirming the distinctiveness of the measurement model.

Table 6: Measurement Model Validity Testing

	Cost	**Convenience**	**Technology Familiarity**	**Social Influence**	**Visit Intention**
Cost	0.760				
Convenience	0.267	0.769			
Technology Familiarity	0.172	0.327	0.767		
Social Influence	0.206	0.294	0.316	0.793	
Visit Intention	0.396	0.436	0.426	0.478	0.891

Note: The diagonal is the square root of AVE.

4.2. Structural Model and Hypotheses Testing

With the measurement model demonstrating adequate reliability, validity, and fit indices, we advanced to the structural analysis. Using AMOS software, we calculated the direct effect paths to empirically evaluate Hypotheses 1 through 4 outlined in the second chapter. The resulting structural path diagram is illustrated below:

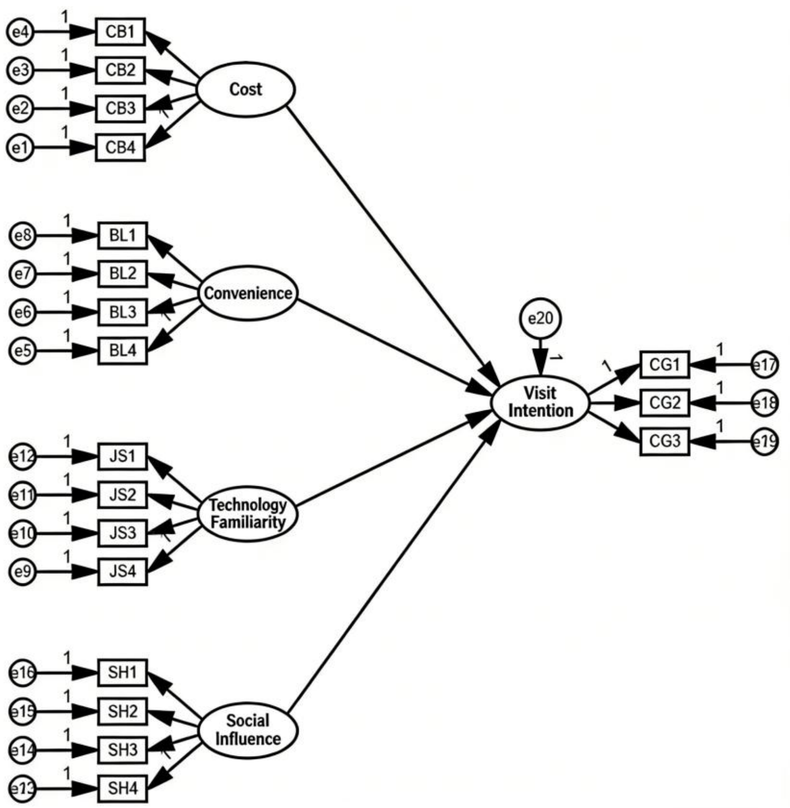
The path analysis results show that all four core antecedent paths in our model are highly significant ($p < 0.001$). The detailed test results are as follows:

Perceived Cost Reasonableness and Visit Intention: The research results confirm that cost has a significant positive impact on the visit intention ($\beta = 0.263$, $t = 6.066$, $p < 0.001$), thereby supporting Hypothesis H1. This finding indicates that reducing the monetary and time barriers can effectively stimulate the intrinsic motivation of visitors.

When these access barriers are lowered, users are more likely to choose digital cultural experiences.

The convenience demonstrated a significant positive impact on the visit intention ($\beta = 0.259$, $t = 6.190$, $p < 0.001$), thereby supporting Hypothesis H2. These results confirm that digital products have a high practical value in breaking the physical limitations of time and space, and this flexibility is a key factor that attracts visitors to shift towards digital participation.

Figure 4: Structural Model Path Diagram.



Technological Familiarity and Visit Intention: Technological familiarity has a significant positive impact on visit intention ($\beta = 0.260$, $t = 6.090$, $p < 0.001$), thereby supporting Hypothesis H3. Visitors who are more confident in operating new media such as VR and panoramic tours are more likely to develop the intention to continuously use digital platforms.

The social influence has the strongest and most significant positive impact on the visit intention ($\beta = 0.327$, $t = 7.651$, $p < 0.001$), which supports Hypothesis H4. This finding highlights the crucial role of social norms. For top cultural venues like the Palace Museum, peer recommendations, educators' guidance, and social media reviews are all of great importance. This influence is the main driving factor for digital consumption of cultural heritage.

Table 7: Path Analysis Results for Each Variable

Dependent Variable	Independent Variable	Standardized Coefficient	Standard Error	t	P
Visit intention	←Cost	0.263	0.044	6.066	***
Visit intention	←Convenience	0.259	0.032	6.190	***
Visit intention	←Technology Familiarity	0.260	0.039	6.090	***
Visit intention	←Social Influence	0.327	0.035	7.651	***

Note: *** indicates P < 0.001

Empirical data fully support the contextual direct effect model. The research results show that all four core hypotheses have been verified.

5. Conclusion

This study constructed a contextual direct effect model to explore why visitors choose digital museums over physical visits. Through an empirical survey of 552 respondents, we identified the core driving factors for this choice in the context of mobile internet. The analysis yielded the following key conclusions: Firstly, the data strongly supports all four core hypotheses ($p < 0.001$). Among these factors, social influence is the most critical factor driving the visit intention ($\beta = 0.327$). This indicates that as a top cultural IP, the digital products of the Palace Museum have significant social attributes - choosing digital experiences is closely related to group identity and social recommendations. Second, cost perception ($\beta = 0.263$), technological familiarity ($\beta = 0.260$), and convenience ($\beta = 0.259$) also exhibited significant positive driving effects. This confirms that reasonable costs, a low technical threshold, and the ability to break through time and space limitations through mobile applications all work together to provide a solid foundation for visitors. By addressing common pain points, these digital tools effectively convert user needs into actual online experiences.

The theoretical contribution of this study lies in the contextual integration of the Technology Acceptance Model and the Theory of Planned Behavior. Previous studies on digital cultural tourism often examined technology acceptance from a single perspective. In contrast, this study transformed the abstract concepts into specific variables that are in line with the context of cultural heritage converting “perceived usefulness” and “subjective norms” into four specific factors: convenience, technical familiarity, social influence, and cost.

This contextualized model not only overcomes the limitations of a single theoretical framework in explaining complex cultural choice behaviors, but also provides a solid empirical basis for the study of the replacement effect of digital heritage. This research is the first to operationalize “perceived usefulness” in the technology acceptance model and “subjective norm” in the theory of planned behavior into the above four specific dimensions, providing an operational theoretical framework for future research on digital museums.

Based on the empirical research results, this study provides the following engineering suggestions for the development of digital platforms (applications, mini-programs, and portal websites). These suggestions focus on the information system management and human-computer interaction design of large cultural heritage institutions:

The data indicate that social influence demonstrates the strongest predictive power (β = 0.327). According to the theory of planned behavior, subjective norms play a critical role in shaping behavioral intentions (Ajzen, 1991; Taylor & Todd, 1995). For system planning, digital museums should consider integrating social sharing features. For example, within digital panoramic tours, designers can introduce interactive nodes or virtual achievement systems that allow users to generate and export digital credentials of their interaction history. Such system-level features can facilitate social dissemination, thereby leveraging the effect of social influence.

Given the significant driving effect of convenience (β = 0.259) and based on the technology acceptance model's proposition that perceived ease of use influences technology adoption (Davis, 1989), digital museums should prioritize reducing access friction. Technical teams should continuously optimize the access experience on mobile internet platforms by streamlining cumbersome account registration and authentication processes. Furthermore, by utilizing cloud computing and cloud rendering technologies, museums can ensure that users, without requiring high-end hardware configurations on their mobile devices, can quickly load and smoothly access high-precision 3D artifact displays via the cloud (Shi et al., 2023).

In response to differences among groups with varying levels of technological familiarity (β = 0.260), the interaction design of the system must adhere to inclusive and age-friendly UI/UX principles. When introducing high-tech features such as VR, AR, or spatial computing, adaptive tutorial modules should be developed. For non-digital natives, the system should provide a minimalist interface that removes redundant visual elements, effectively reducing the cognitive load associated with operating new media technologies (Lee et al., 2019; Davis, 1989).

As a low-cost alternative to physical visits, digital systems must not only maintain the accessible and inclusive nature of basic free access but also reduce users' "time cost" through underlying algorithms (β = 0.263). The backend should focus on optimizing the information retrieval algorithm and recommendation mechanism in the knowledge graph. Meanwhile, the frontend should adopt a clear and error-proof tree-like navigation logic. These improvements will help users quickly locate specific targets within the vast digital collection, thereby enhancing perceived ease of use (Davis, 1989) and reducing time costs (Li et al., 2021). By enhancing the navigability of the system, these functions directly strengthen the users' perceptual behavior control during the interaction process (Ajzen, 1991; Li et al., 2021).

5.1. Limitations and Future Research

Although this study has yielded certain findings, limitations still exist. First, the sample was primarily collected through social media. This approach may result in a respondent pool of naturally more active internet users. Consequently, the results might not fully represent the views of older populations or those with lower digital literacy. Future research could consider incorporating offline random sampling to enhance representativeness. Second, this study employed cross-sectional data to validate substitution intention; future research could introduce a longitudinal design to observe whether visitors' subsequent intention to visit physical museums undergoes dynamic transformation after their initial experience with digital museums. Furthermore, this study conceptualizes digital museums as a substitute for physical visits; however, in reality, visitors may also engage with them as a complementary experience (e.g., previewing before a visit or reviewing afterward). Future research could distinguish between these two motivations and explore differences in driving factors across different contexts.

Ethics Approval and Consent to Participate

Ethics approval was obtained from the UiTM Research Ethics Committee. All procedures involving human participants were performed in accordance with the Declaration of Helsinki, and informed consent was obtained from all participants.

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Conflict of Interest

The authors reported no conflicts of interest for this work and declare that there is no potential conflict of interest with respect to the research, authorship, or publication of this article.

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