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The Role of Facilitating Conditions and Social Influence in Users' Behavioral Intention to Use Digital Tourism Information Systems

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Abstract. Digital tourism information systems have changed how travelers search for information and plan their trips. However, user acceptance still varies, especially in areas with limited internet access. This study examines the factors that influence users' intention to use digital tourism information systems, focusing on facilitating conditions, social influence, perceived usefulness, and perceived ease of use. A digital survey was conducted with 144 students enrolled in information technology-related higher education programs, aged 17–21 years, who had more than three years of experience using digital tourism information systems. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that facilitating conditions have the strongest effect on behavioral intention, followed by social influence. In contrast, perceived usefulness and perceived ease of use do not have significant effects. These findings show a context-specific pattern in technology adoption, where facilitating conditions and social influence are more important for the respondents in this study. However, the findings should be interpreted within the context of this homogeneous sample of young, digitally experienced students and should not be generalized to all digital tourism users. The results also suggest that the importance of technology adoption factors may differ depending on user characteristics and the context of system use. This study measures behavioral intention, not actual or continued system use.

Keywords: Digital Tourism Information Systems, Behavioral Intention, Social Influence, TAM, UTAUT

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1. INTRODUCTION

Digital tourism information systems are digital platforms that support tourism-related activities, including destination information websites, mobile travel applications, online booking services, and tourism recommendation systems. These systems help users search for information, plan trips, and make travel decisions more efficiently [1], [2], [3], [4]. However, their adoption depends not only on technical functionality but also on users' willingness and readiness to use them over time [5], [6]. Therefore, understanding user acceptance and behavioral intention has become an important focus in information systems research. Behavioral intention may be shaped by perceived usefulness, perceived ease of use, social influence, and facilitating conditions, such as access to suitable devices, reliable internet connectivity, and digital competencies [7], [8], [9], [10].

Despite these developments, most studies on digital tourism information systems concentrate on specific applications, such as mobile tourism applications, online reservation platforms, and location-based services, often emphasizing technical features and service quality. Although these studies provide valuable contributions, their findings are often limited to specific application contexts and may not fully explain user behavior across different types of digital tourism platforms. Therefore, this study does not evaluate a single digital tourism platform. Instead, it examines users' general experiences with different types of Digital Tourism Information Systems. Moreover, numerous empirical studies are predominantly explanatory and focus on identifying adoption factors without clearly linking their findings to the practical design and development of digital tourism information systems. As a result, a disparity persists between behavioral insights and system design methodologies, constraining the capacity of current research to inform the creation of more user-centric platforms [11], [12]. In the context of continuing digital transformation, understanding the factors associated with users' behavioral intention is important for informing the development of digital tourism information systems[13], [14]. Such insights may help digital tourism information systems respond more effectively to users' needs, expectations, and circumstances, thereby supporting more inclusive adoption. Moreover, insights derived from user perceptions and behavioral intention may inform design considerations that support system accessibility, ease of interaction, and user acceptance[15], [16], [17]. However, this study focuses on behavioral intention and does not measure actual or continued system use.

Although TAM and UTAUT have been widely applied in tourism technology research, many previous studies have focused on perceived usefulness, perceived ease of use, or the adoption of specific tourism applications. Evidence regarding the role of facilitating conditions across different types of digital tourism information systems remains comparatively limited, particularly when device access, internet connectivity, and digital skills are examined together with perceived usefulness, perceived ease of use, and social influence.

This study examines whether facilitating conditions, social influence, perceived usefulness, and perceived ease of use affect users' behavioral intention to use digital tourism information systems. Perceived ease of use refers to users' perception of the effort required to learn and operate a system. System usability is a broader concept that may include effectiveness, efficiency, accessibility, satisfaction, and error prevention. User-centered design refers to an approach that considers users' needs and contexts throughout the system development process. Therefore, this study measures perceived ease of use rather than overall system usability or the user-centered design process. The study is expected to provide theoretical insight into digital tourism adoption and practical guidance for developing systems that are usable, accessible, and responsive to users' contexts.

This study examines the relationships between perceived usefulness, perceived ease of use, social influence, facilitating conditions, and users' behavioral intention to use digital tourism information systems. The four predictors are evaluated simultaneously within an integrated technology-adoption model. Specifically, the following effects are examined:

1) To examine the relationship between perceived usefulness and users' behavioral intention to use digital tourism information systems.
2) To examine the relationship between perceived ease of use and users' behavioral intention to use digital tourism information systems.
3) To examine the relationship between social influence and users' behavioral intention to use digital tourism information systems.
4) To examine the relationship between facilitating conditions and users' behavioral intention to use digital tourism information systems.

This study provides a contextual examination of behavioral intention across different types of digital tourism information systems rather than focusing on a single application. It evaluates perceived usefulness, perceived ease of use, social influence, and facilitating conditions within one empirical model. The findings also provide preliminary practical insights for digital tourism system development. In particular, the measured facilitating conditions and social influence indicators may help identify contextual factors associated with users' intention to use these systems.

This study enhances the literature on technology adoption in tourism by offering a thorough, user-focused examination of behavioral intentions in digital tourism information systems. It consolidates essential elements from recognized adoption models, such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions into a cohesive empirical framework. This approach expands upon prior research that typically concentrates on certain applications or analyzes these elements in isolation. Moreover, the results underscore the significance of behavioral intentions as a pivotal notion in comprehending the adoption of digital platforms within tourism-related information systems. The findings provide empirical insight into how user perceptions and contextual conditions are associated with behavioral intention within the sampled group.

The findings provide practical considerations for digital tourism information systems. For the respondents in this study, access to adequate devices, sufficient internet connectivity, basic digital skills, recommendations from people around them, and social media reviews were associated with behavioral intention. These findings may inform future system-development and user-engagement strategies, although they should not be interpreted as comprehensive design principles. This approach connects theoretical insights into user behavior with practical system development and supports the creation of digital tourism solutions that are functional, user-friendly, and more likely to be accepted by users.

2. RESEARCH METHOD

This section presents the research design, data collection procedures, measurement instruments, and data analysis techniques applied in this study.

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2.1. Research Type and Design

This study employed a quantitative, cross-sectional survey design to examine behavioral intention to use digital tourism information systems. The selected methodology is suitable as it emphasizes the examination of correlations among latent variables grounded in recognized technology adoption theory. The explanatory design was used to examine the relationships between user perceptions, contextual factors, and behavioral intention to use digital tourism information systems. In this study, digital tourism information systems refer to electronic platforms that support tourism-related information search, trip planning, booking, destination selection, and recommendation activities. The analysis prioritizes system acceptance and utilization from a user-centric viewpoint, rather than a solely technical or application-specific approach.

2.2. Related Work

An increasing body of research highlights the importance of digital tourism information systems, including travel websites, mobile tourism applications, and online recommendation platforms, in supporting travelers' information search, trip planning, and decision-making processes [18], [19], [20], [21], [22]. These systems augment destination visibility, boost service accessibility, and facilitate more tailored travel experiences. Nevertheless, a significant portion of the current literature remains concentrated on particular applications, such as hotel booking platforms, mobile tourism applications, and destination information systems, rather than investigating digital tourism information systems as a cohesive and comprehensive ecosystem. Consequently, findings from application-specific studies may not fully explain adoption patterns across different types of digital tourism information systems.

Technology adoption frameworks, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), have been extensively utilized to analyze user acceptance of digital services. TAM emphasizes perceived usefulness and perceived ease of use as central determinants of technology acceptance, whereas UTAUT identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of behavioral intention and technology use [23], [24]. These frameworks have also been widely applied within the tourism sector [25], [26], [27]. Davis found that perceived usefulness exerted a stronger influence on system usage than perceived ease of use, although both constructs remained important in explaining technology acceptance [23]. Prior research has also consistently demonstrated that perceived usefulness and perceived ease of use influence consumers' behavioral intentions to use digital platforms. Moreover, UTAUT-based studies highlight the importance of social influence and facilitating conditions, particularly in contexts where social support and technological resources play significant roles. Nonetheless, despite their extensive applicability, much of the existing research remains focused on statistical relationships and explanatory models, with limited attention to how these findings can inform the design and development of digital tourism information systems.

Recent studies emphasize the importance of a user-centered approach in comprehending digital tourism adoption. In addition to system-related qualities, factors such as users' access to devices, internet connectivity, and digital proficiency significantly influence their engagement with digital platforms. Simultaneously, social factors such as peer recommendations, electronic word of mouth, online reviews, and community engagement can strengthen user trust and influence tourism-related adoption and booking decisions [26] [28]. Nevertheless, a significant portion of the current literature persists in regarding these characteristics mainly as explanatory predictors of user behavior, rather than as inputs for system design, leading to a continual disparity between behavioral insights and their practical implementation in system development [29], [30], [31], [32], [33]. Despite the extensive application of TAM and UTAUT, several gaps remain. Previous studies commonly examine specific applications, while facilitating conditions across different digital tourism platforms and their practical implications remain less frequently discussed.

2.3. Research model

The research model was developed based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT)[23], [24]. The model includes four predictor constructs—perceived usefulness, perceived ease of use, social influence, and facilitating conditions—and behavioral intention as the dependent construct. The conceptual model specifies a direct relationship between each predictor construct and users' behavioral intention, encapsulating the framework offered in this study together with its theoretical underpinnings. The resulting conceptual framework and the proposed relationships among the constructs are presented in Figure 1.

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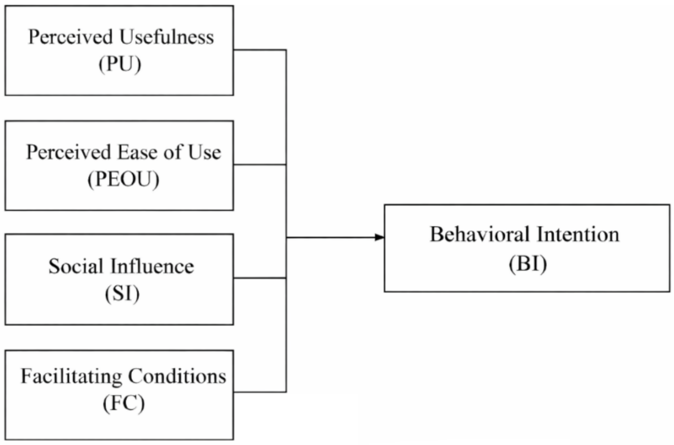

Figure 1. Conceptual model of digital tourism information systems adoption

Figure 1 illustrates the conceptual framework of the study, showcasing the direct relationship between perceived usefulness, perceived ease of use, social influence, and facilitating conditions as independent variables, and users' behavioral intention to utilize the digital tourism information system as the dependent variable.

2.4. Research hypotheses

Based on the proposed conceptual model, four hypotheses were formulated to examine the relationships between the predictor constructs and behavioral intention. The hypotheses are articulated as follows:

H1: Perceived usefulness is positively associated with users' behavioral intention to use digital tourism information systems.

H2: Perceived ease of use is positively associated with users' behavioral intention to use digital tourism information systems.

H3: Social influence is positively associated with users' behavioral intention to use digital tourism information systems.

H4: Facilitating conditions are positively associated with users' behavioral intention to use digital tourism information systems.

2.5. Respondent Characteristics and Sampling

The respondents were students enrolled in information technology-related higher education programs who had experience using digital tourism information systems, including travel websites, booking platforms, destination information services, and recommendation systems. Data were collected voluntarily through an online questionnaire in April 2026. A purposive screening procedure was applied using the inclusion criteria of respondents aged 17–21 years with more than three years of experience using digital tourism information systems. The respondents' demographic characteristics are presented in Table 1.

Table 1. Demographic characteristics of respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	90	62.5
	Female	54	37.5
Age	17–21 years	144	100.0
Experience using digital tourism Information System	> 3 years	144	100.0
Respondent status	Students in IT-related higher education programs	144	100.0

A minimum sample-size calculation was performed for a linear multiple regression model with four predictors. Assuming a medium effect size (f^2 = 0.15), a significance level of 0.05, and statistical power of 0.80, the minimum required sample size was 85 respondents. Therefore, the final sample of 144 respondents was considered adequate for the proposed PLS-SEM model. The inclusion criteria ensured that the respondents had sufficient familiarity with the digital platforms examined in this study.

2.6. Research instrument

Data were collected using a questionnaire whose measurement items were adapted from established TAM and UTAUT constructs. The items were modified to ensure their relevance to the context of digital tourism platform use. All items were assessed with a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree).

The perceived usefulness and perceived ease of use items were adapted from the Technology Acceptance Model proposed by Davis [23], while the social influence and facilitating conditions items were adapted from the Unified Theory of Acceptance and Use of Technology developed by Venkatesh et al. [24]. Each construct was operationalized using three measurement items representing perceived usefulness, perceived ease of use, social influence, facilitating conditions, and behavioral intention. Table 2 presents the measurement constructions and the corresponding number of items utilized to operationalize each construct.

Table 2. Measurement constructs and number of items

Construct	Code	Measurement Item
Perceived Usefulness	PU1	Digital tourism platforms help me choose tourism destinations that suit my needs.
Perceived Usefulness	PU2	Digital tourism platforms make travel planning more effective.
Perceived Usefulness	PU3	Digital tourism platforms help me find alternative tourism destinations.
Perceived Ease of Use	PEOU1	Digital tourism platforms are easy to learn.
Perceived Ease of Use	PEOU2	Digital tourism platforms are easy to use.
Perceived Ease of Use	PEOU3	I do not experience difficulties when using digital tourism platforms.
Social Influence	SI1	People around me suggest using digital tourism platforms.
Social Influence	SI2	The opinions of my friends or family influence my decision to use digital tourism platforms.
Social Influence	SI3	Reviews on social media encourage me to use digital tourism platforms.
Facilitating Conditions	FC1	I have adequate devices to use digital tourism platforms.
Facilitating Conditions	FC2	I have sufficient internet access to use digital tourism platforms.

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Construct	Code	Measurement Item
Facilitating Conditions	FC3	I have the basic skills required to use digital tourism platforms.
Behavioral Intention	BI1	I intend to use digital tourism platforms when planning a trip.
Behavioral Intention	BI2	I am interested in trying digital tourism platforms in the future.
Behavioral Intention	BI3	I am willing to recommend digital tourism platforms to others.

Table 2 presents the complete measurement items used in this study. The measurement model consists of five constructs: perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), facilitating conditions (FC), and behavioral intention (BI). PU and PEOU were adapted from the Technology Acceptance Model (TAM), while SI and FC were derived from the Unified Theory of Acceptance and Use of Technology (UTAUT). Behavioral intention was included as the dependent construct representing users' intention to use digital tourism information systems. Each construct was measured using three indicators, resulting in a total of 15 items. All items were assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

2.7. Data collection technique

Data were collected in April 2026 through an online questionnaire distributed using Google Forms. The respondents were students enrolled in information technology-related higher education programs. Participation was voluntary, and the questionnaire was distributed openly to students who were willing to participate. Submitted responses were screened using respondents' reported age and duration of digital tourism platform use. Responses that did not meet the age and experience criteria were excluded from the analysis. A total of 144 valid responses were included in the analysis. Before completing the questionnaire, respondents were informed about the purpose of the study and that their participation was voluntary. By proceeding with the questionnaire, respondents indicated their consent to participate. No personally identifiable information was collected, and all responses were kept confidential and used only for research purposes.

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2.8. Data analysis technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS version 4, following established guidelines for measurement and structural model assessment [34]. Inner VIF values below 5 were considered acceptable under the commonly applied threshold, while values above the more conservative threshold of 3.3 were interpreted as indicating potentially high collinearity. The measurement model was evaluated using indicator outer loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE). Indicator loadings above 0.708, reliability values above 0.70, and AVE values above 0.50 were considered satisfactory. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion. The structural model was evaluated using inner variance inflation factor (VIF), path coefficients, coefficient of determination (R^2), effect size (f^2), standardized root mean square residual (SRMR), and predictive relevance through PLSpredict and Q^2_predict. Hypothesis significance was assessed using a bootstrapping procedure with 5,000 resamples, a two-tailed test, and 95% confidence intervals. Common method bias was examined using Harman's single-factor test and full-collinearity VIF.

3. RESULTS AND DISCUSSION

The proposed research model was evaluated utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis was performed in two primary phases: evaluation of the measurement model and subsequent assessment of the structural model.

3.1. Measurement model evaluation

The measurement model assessment was conducted to evaluate the quality and reliability of the constructs and their corresponding indicators before examining the structural model. This assessment includes indicator reliability, internal consistency reliability, and convergent validity. Indicator reliability was evaluated using the outer loading values, while internal consistency reliability was assessed through Cronbach's alpha and composite reliability. Convergent validity was examined using the average variance extracted (AVE). The complete results of the measurement model assessment for all constructs are presented in Table 3.

Table 3. Measurement model results

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
Perceived Usefulness	PU1	0.937	0.937	0.960	0.888
	PU2	0.930			
	PU3	0.959			
Perceived Ease of Use	PEOU1	0.960	0.944	0.966	0.904
	PEOU2	0.964			
	PEOU3	0.929			
Social Influence	SI1	0.918	0.907	0.942	0.844
	SI2	0.914			
	SI3	0.924			
Facilitating Conditions	FC1	0.946	0.944	0.965	0.901
	FC2	0.945			
	FC3	0.956			
Behavioral Intention	BI1	0.958	0.938	0.960	0.890
	BI2	0.924			
	BI3	0.947			

As shown in Table 3, the outer loadings of all 15 indicators ranged from 0.914 to 0.964. All values exceeded the recommended threshold of 0.708, indicating satisfactory indicator reliability. Therefore, all indicators were retained in the measurement model.
The Cronbach's alpha and composite reliability values for all constructs exceeded the recommended value of 0.70, demonstrating satisfactory internal consistency reliability. In addition, the AVE values ranged from 0.844 to 0.904, exceeding the recommended threshold of 0.50 and confirming adequate convergent validity. Nevertheless, all composite reliability values were very high, ranging from 0.942 to 0.966. Although these values demonstrate strong internal consistency, they may also indicate similarity or redundancy among some measurement items. Therefore, the results should be interpreted with consideration of possible item redundancy.

Discriminant validity was assessed to determine whether each construct was empirically distinct from the other constructs in the model. The assessment used the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion. The HTMT ratio was examined to identify potential overlap between constructs, while the Fornell–Larcker criterion

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compared the square root of the AVE of each construct with its correlations with other constructs. The complete results of the discriminant validity assessment are presented in Table 4.

Table 4. Discriminant validity assessment

Panel A. HTMT ratio

Construct	PU	PEOU	SI	FC	BI
PU	–	0.888	0.854	0.824	0.850
PEOU		–	0.853	0.816	0.837
SI			–	**0.926**	**0.942**
FC				–	**0.948**
BI					–

Panel B. Fornell–Larcker criterion

Construct	PU	PEOU	SI	FC	BI
PU	**0.942**				
PEOU	0.836	**0.951**			
SI	0.788	0.791	**0.919**		
FC	0.777	0.772	0.858	**0.949**	
BI	0.797	0.790	0.870	0.893	**0.943**

The Fornell–Larcker criterion was satisfied because the square root of the AVE for each construct was greater than its correlations with the other constructs. However, the HTMT values for SI–FC (0.926), SI–BI (0.942), and FC–BI (0.948) exceeded the recommended threshold of 0.90. These findings indicate potential conceptual overlap among social influence, facilitating conditions, and behavioral intention. Therefore, although the Fornell–Larcker criterion was satisfied, discriminant validity based on HTMT was only partially supported and should be interpreted cautiously.

3.2. Structural model evaluation

The structural model assessment was conducted to examine the explanatory power of the proposed model and the relationships among the constructs. The evaluation focused on the coefficient of determination (R^2), path coefficients, and the significance of the hypothesized relationships. Figure 2 presents the structural model, including the indicator loadings, path coefficients, and the R^2 value of behavioral intention.

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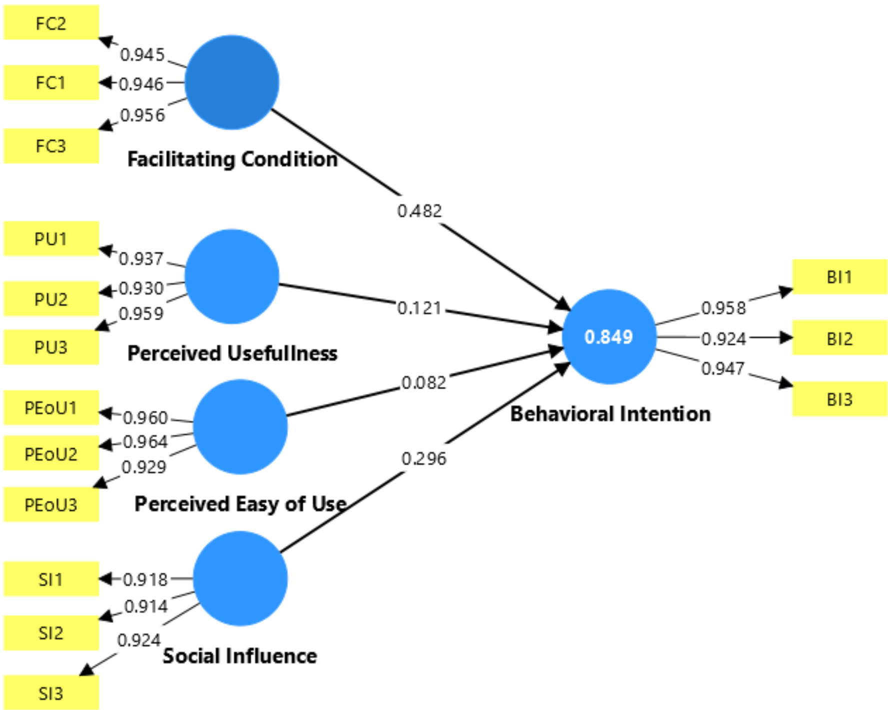

Figure 2. Structural Model Results.

Figure 2 illustrates the outcomes of the structural model assessment. The evaluation encompassed the study of the coefficient of determination (R^2), path coefficients, and hypothesis testing, executed by a bootstrapping method with 5,000 resamples. The model produced an R^2 value of 0.849 for behavioral intention, indicating that the four predictor constructs jointly explained 84.9% of its variance. However, this high value should be interpreted cautiously because construct overlap and potential common method bias may have inflated the explained variance in users' intention to utilize the digital tourism information system. Facilitating conditions showed the strongest positive and statistically significant relationship with behavioral intention ($\beta = 0.482$, $t = 4.097$, $p < 0.001$). Social influence also showed a positive and statistically significant relationship with behavioral intention ($\beta = 0.296$, $t = 3.049$, $p = 0.002$). Conversely, perceived usefulness ($\beta = 0.121$, $t = 1.136$, $p = 0.256$) and perceived ease of use ($\beta = 0.082$, $t = 1.158$, $p = 0.247$) had no statistically significant impact on behavioral intention. The results demonstrate support for hypotheses H3 and H4, whereas H1 and H2 lack support.

To provide a more detailed evaluation of the hypothesized relationships, the results were further examined based on the path coefficients, t values, p values, confidence intervals, variance inflation factor (VIF), and effect sizes (f^2). These indicators were used to

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determine the direction, strength, statistical significance, collinearity, and contribution of each predictor construct to behavioral intention. The complete results of the hypothesis testing and structural relationship assessment are presented in Table 5.

Table 5. Path coefficients and hypothesis testing results

Hypothesis	Path	β	t	p	95% CI	VIF	f²	Result
H1	PU → BI	0.121	1.136	0.256	−0.044–0.368	4.023	0.024	Not supported
H2	PEOU → BI	0.082	1.158	0.247	−0.048–0.238	4.020	0.011	Not supported
H3	SI → BI	0.296	3.049	0.002	0.089–0.453	4.653	0.125	Supported
H4	FC → BI	0.482	4.097	<0.001	0.230–0.687	4.306	0.357	Supported

Note: CI = confidence interval; VIF = variance inflation factor; f^2 = effect size.

Table 5 shows that facilitating conditions were the strongest predictor of behavioral intention, with a positive and statistically significant path coefficient ($\beta = 0.482$, $t = 4.097$, $p < 0.001$). The corresponding 95% confidence interval did not include zero (0.230–0.687), confirming the significance of this relationship. Facilitating conditions had a large effect size ($f^2 = 0.357$) within the proposed model. However, this result should be interpreted together with the high construct correlations and potential common method bias. Social influence also had a positive and statistically significant effect on behavioral intention ($\beta = 0.296$, $t = 3.049$, $p = 0.002$), with a 95% confidence interval of 0.089–0.453 and a small-to-moderate effect size ($f^2 = 0.125$). Therefore, H3 and H4 were supported.

In contrast, perceived usefulness did not have a statistically significant effect on behavioral intention ($\beta = 0.121$, $t = 1.136$, $p = 0.256$), as its confidence interval included zero (−0.044–0.368). Perceived ease of use was also not statistically significant ($\beta = 0.082$, $t = 1.158$, $p = 0.247$), with a confidence interval of −0.048–0.238. Their effect sizes were small or negligible, with f^2 values of 0.024 for perceived usefulness and 0.011 for perceived ease of use. Consequently, H1 and H2 were not supported. These non-significant relationships do not imply that usefulness or ease of use is unimportant; rather, they indicate that these constructs did not significantly predict behavioral intention within the sampled group.

The inner VIF values ranged from 4.020 to 4.653. Although all values were below the commonly applied threshold of 5, they exceeded the more conservative threshold of 3.3, indicating relatively high correlations among the predictor constructs. Therefore,

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although the VIF values remained below 5, the relatively high collinearity may have affected the stability and individual interpretation of the path coefficients.

Model fit and predictive relevance were also assessed. The model produced an R^2 value of 0.849 for behavioral intention, indicating that perceived usefulness, perceived ease of use, social influence, and facilitating conditions jointly explained 84.9% of the variance in behavioral intention. In addition, the standardized root mean square residual (SRMR) was 0.036, which was below the recommended threshold of 0.08 and indicated an acceptable model fit. Predictive relevance was subsequently evaluated using PLSpredict and Q^2_predict. The results are presented in Table 6.

Table 6. Model fit and predictive relevance

Assessment	Indicator	Value	Benchmark/Comparison
Coefficient of determination	Behavioral Intention	0.849	High explained variance; interpreted cautiously because of construct overlap and potential common method bias.
SRMR	Model	0.036	Below 0.08
Q^2_predict	BI1	0.764	Greater than 0
Q^2_predict	BI2	0.700	Greater than 0
Q^2_predict	BI3	0.731	Greater than 0
RMSE PLS	BI1	0.478	Lower than LM: 0.490
RMSE PLS	BI2	0.538	Approximately equal to LM: 0.538
RMSE PLS	BI3	0.524	Lower than LM: 0.554

All Q^2_predict values were positive, ranging from 0.700 to 0.764, indicating predictive relevance for the behavioral intention indicators. The PLS-SEM model generated lower RMSE values than the linear-model benchmark for BI1 and BI3, while the RMSE value for BI2 was approximately equal to that of the linear model. These results indicate preliminary out-of-sample predictive relevance. However, the predictive findings should be interpreted cautiously because of the homogeneous sample, construct overlap, and potential common method bias.

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3.3. Common Method Bias Assessment

Because all constructs were measured using data collected from the same questionnaire and respondents, common method bias was assessed to determine whether the observed relationships might have been influenced by the use of a single data source. The assessment employed Harman's single-factor test and full-collinearity VIF. Harman's single-factor test showed that the first unrotated factor explained 75.56% of the total variance, exceeding the commonly used threshold of 50% and indicating a potential common method bias concern. The full-collinearity VIF values were then examined to assess whether collinearity across the constructs provided additional evidence of this issue. The results are presented in Table 7.

Table 7. Common method bias assessment

Construct	Full-Collinearity VIF
Perceived Usefulness	4.120
Perceived Ease of Use	4.064
Social Influence	5.232
Facilitating Conditions	5.841
Behavioral Intention	6.622

The full-collinearity VIF values ranged from 4.064 to 6.622. All values exceeded the conservative threshold of 3.3, while the values for social influence, facilitating conditions, and behavioral intention also exceeded 5. The Harman's single-factor result of 75.56% and full-collinearity VIF values above 3.3 indicate a substantial potential common method bias concern. This condition may be associated with the use of a single-source questionnaire, the homogeneous characteristics of the respondents, and the high similarity among several measurement items. Potential common method bias may have increased the correlations among the constructs, inflated the R^2 value, and affected the estimated significance of the SI and FC paths. Therefore, these relationships should not be interpreted as definitive causal effects.

3.4. Discussion

This study offers significant insights into users' intentions to use digital tourism information systems. The analysis indicates that facilitating conditions and social influence significantly affect users' behavioral intention, while perceived usefulness and

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perceived ease of use do not demonstrate statistically significant effects. Facilitating conditions showed the strongest path coefficient and a large effect size ($f^2 = 0.357$), indicating their substantial contribution to behavioral intention within the proposed model. Within the sampled group, behavioral intention was stronger among respondents who reported having adequate devices, sufficient internet access, and the basic digital skills required to use digital tourism platforms. Facilitating conditions should not be interpreted solely as infrastructure readiness. In this study, the construct specifically represents access to adequate devices, sufficient internet connectivity, and basic digital skills.

Social influence in this study reflects suggestions from people around the respondents, the opinions of friends or family, and encouragement derived from social media reviews. This result is consistent with tourism studies showing that recommendations, online reviews, and electronic word of mouth can shape users' intention to adopt tourism-related digital services [21], [22], [26], [28]. This pattern aligns with previous research based on the UTAUT framework, which highlights social influence as a determinant of behavioral intention. However, the interpretation of social influence in this study should remain consistent with the specific indicators used to measure the construct.

The non-significant effects of perceived usefulness and perceived ease of use differ from the classical TAM findings and many subsequent TAM-based studies. Davis demonstrated that both constructs played important roles in technology acceptance, with perceived usefulness showing a stronger influence on system usage than perceived ease of use [23]. However, the present findings do not mean that usefulness and ease of use are unimportant. Instead, these constructs did not make statistically significant contributions to behavioral intention within the sampled respondents after social influence and facilitating conditions were considered in the model.

One possible explanation relates to the characteristics of the respondents. All respondents were aged 17–21 years and had more than three years of experience using digital tourism information systems. Their familiarity with digital platforms may have contributed to usefulness and ease of use being perceived as expected baseline characteristics rather than distinguishing factors in their intention to use the systems.

Therefore, this finding represents a context-specific pattern and should not be generalized to older, less experienced, or less digitally literate users.

The finding concerning perceived ease of use should also be interpreted carefully. Perceived ease of use refers to the effort required to learn and operate a system, whereas system usability is a broader concept that may include effectiveness, efficiency, accessibility, satisfaction, interface quality, and error prevention. Therefore, the non-significant effect of perceived ease of use does not demonstrate that usability is no longer important. It only indicates that perceived ease of use was not a significant predictor of behavioral intention among the respondents examined in this study.

These findings also provide practical implications for the development of digital tourism information systems. Developers and tourism stakeholders should continue to maintain system usefulness and ease of use while also strengthening the conditions that support system utilization. Digital tourism stakeholders should ensure that platforms can be accessed through commonly available devices, function under realistic internet conditions, and provide information that can be understood by users with basic digital skills. User-engagement strategies may also incorporate credible reviews, recommendations, and socially shared tourism information, consistent with the social influence indicators measured in this study. However, these practical recommendations should remain directly connected to the facilitating conditions and social influence indicators measured in this study.

From a theoretical perspective, the findings indicate a context-specific technology-adoption pattern in which facilitating conditions and social influence contributed more strongly to behavioral intention than perceived usefulness and perceived ease of use. This pattern should not be interpreted as a rejection of TAM or as evidence that usability-related factors are no longer relevant. Instead, it suggests that the relative importance of adoption determinants may vary according to respondents' age, digital experience, and familiarity with digital platforms.

Nevertheless, the findings should be interpreted cautiously. Several HTMT values exceeded the recommended threshold of 0.90, indicating potential conceptual overlap among social influence, facilitating conditions, and behavioral intention. In addition, the common method bias assessment indicated a potential single-source measurement effect. The HTMT results and common method bias indicators suggest that the correlations among SI, FC, and BI, as well as the R^2 value of 0.849, may be partly inflated. Therefore, the significant SI and FC paths should be interpreted as context-specific associations rather than definitive causal relationships. In addition, respondents' region, frequency of platform use, and specific platform type were not collected, preventing comparisons across these characteristics. The cross-sectional survey design also limits causal and longitudinal interpretation. The purposive and homogeneous sample also limits the generalizability of the findings.

Future research should involve more heterogeneous respondents across different age groups, regions, levels of digital literacy, and frequencies of platform use. Comparative studies involving younger and older users, urban and rural respondents, and frequent and occasional tourists may provide a clearer understanding of differences in technology-adoption determinants. Future studies should also refine the measurement items to reduce conceptual overlap and examine actual or continued system usage, because the present study measured behavioral intention rather than actual usage.

4. CONCLUSION

This study found that facilitating conditions and social influence significantly influence users' behavioral intention to use digital tourism information systems, supporting H3 and H4, while perceived usefulness and perceived ease of use did not show significant effects, resulting in the rejection of H1 and H2. These findings indicate that, among young and digitally experienced students, access to adequate devices, sufficient internet connectivity, basic digital skills, recommendations from others, and social media reviews are more strongly associated with behavioral intention than perceived usefulness and ease of use. The results provide practical insight for developers and tourism stakeholders to strengthen supporting conditions and credible social information while maintaining system usefulness and ease of use. However, the findings should be interpreted cautiously because the homogeneous sample, partial discriminant validity, potential common method bias, and cross-sectional design limit generalizability and causal interpretation. Future studies should involve more diverse respondents, refine the SI, FC, and BI indicators, apply stronger controls for common method bias, and examine actual or continued system use through longitudinal research. The impact of this study lies in highlighting the importance of contextual and social support in encouraging the adoption of digital tourism information systems.

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