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Validation of the Smart Tourism Model

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Abstract

This study aimed to validate a structural model of smart tourism by examining the impact of multiple technological, behavioral, and managerial constructs on the development of smart tourism in Kish Island, Iran. The research employed a quantitative design using a descriptive-correlational strategy and structural equation modeling (SEM) to evaluate the proposed model. A two-stage sampling method was applied: first, cluster sampling was used to randomly select 30 hotels from 51 active establishments in Kish Island; second, simple random sampling was used to select tourists from these hotels. Out of 311 distributed questionnaires, 273 were deemed valid and analyzed. A 45-item smart tourism scale developed by the researchers was used for data collection, with its content validity confirmed by experts (CVI = 0.82). Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity tests were conducted to ensure measurement reliability and validity. Data were analyzed using SPSS-24 and SmartPLS-3. All eight independent variables—perceived value, economic development, smart technology, tourist behavior, complementary activities, destination capability, information management, and smartification—had statistically significant effects on smart tourism. Smart technology ($\beta = 0.269$, $p < 0.001$) and economic development ($\beta = 0.199$, $p < 0.001$) showed the strongest influences. Model fit indices, including AVE (>0.50), CR (>0.70), and goodness-of-fit (GOF = 0.725), confirmed the model's validity and predictive power. Discriminant validity was also established using the Fornell-Larcker criterion. The validated smart tourism model demonstrates that technological infrastructure, managerial readiness, and tourist-centered strategies are essential for developing smart tourism destinations. These findings offer both theoretical insight and practical guidance for enhancing tourism innovation, competitiveness, and sustainability in similar regional contexts.

Keywords: Smart tourism, structural equation modeling, smart technology, tourist behavior, destination management, Iran, Kish Island, digital transformation.

1. Introduction

In recent years, the global tourism industry has undergone a significant transformation, driven largely by the rapid integration of digital technologies and data-driven systems. These developments have led to the emergence of "smart tourism," a concept that encompasses the use of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and blockchain to enhance tourists' experiences, improve destination management, and foster sustainable development (Buhalis, 2020; Nam et al., 2021). Smart tourism is not only a technological innovation but also a paradigm shift in how tourism ecosystems are designed, managed, and experienced. As such, the validation of smart tourism models is essential to ensure that theoretical frameworks are grounded in empirical evidence and are adaptable to the diverse and evolving demands of modern tourism landscapes (Idrus et al., 2025).

The concept of smart tourism is rooted in broader transformations across industries, particularly in the context of smart cities and digital economies. A smart tourism destination leverages smart infrastructure, open data, participatory governance, and real-time service delivery to create an interactive and personalized experience for visitors (Gretzel, 2021; Xu et al., 2024). The application of smart tourism technologies has been shown to directly influence tourist satisfaction, revisit intentions, and destination loyalty by enabling better access to information, improving safety and convenience, and enhancing environmental sustainability (Azis et al., 2020; Lee et al., 2020). As tourism destinations compete in a technologically saturated global market, the implementation of smart systems offers a strategic advantage, particularly for emerging economies seeking to modernize their tourism sectors.

Despite its widespread appeal and potential, the operationalization of smart tourism remains a complex endeavor. A variety of interrelated dimensions—including perceived value, infrastructure readiness, stakeholder collaboration, technological adoption, and visitor behavior—must be integrated to form a comprehensive smart tourism model. Moreover, effective management of smart tourism destinations requires a deep understanding of both the technological components and the human factors that shape the user experience (Bhuiyan et al., 2022; Shen et al., 2020). Accordingly, researchers have emphasized the need for validated, context-specific models that can guide the implementation of smart tourism frameworks and evaluate their performance across various settings (Dulgaroglu, 2021; Salahi Kojour et al., 2020).

The Iranian tourism sector presents a compelling context for the application and validation of smart tourism models. With its rich cultural heritage, diverse natural attractions, and strategic geographic location, Iran possesses substantial untapped tourism potential. However, the industry also faces numerous challenges, including infrastructural limitations, bureaucratic inefficiencies, and insufficient digital integration (Haqverdi Zadeh et al., 2023; Naeim-Abadi et al., 2023). In this regard, cities like Kish Island—which serve as major tourism hubs—offer valuable case studies for examining the feasibility and effectiveness of smart tourism initiatives. By empirically validating a smart tourism model in such a context, this study aims to contribute to both the academic literature and the practical advancement of Iran's tourism industry.

A growing body of literature has sought to conceptualize the key components of smart tourism. Buhalis (2020) defines smart tourism as an extension of e-tourism that integrates interconnected digital systems to support dynamic and real-time service delivery (Buhalis, 2020). Similarly, Pencarelli (2020) highlights the role of digital platforms, data analytics, and participatory innovation in shaping the smart tourism ecosystem (Pencarelli, 2020). Meanwhile, researchers like Kontogianni and Alepis (2020) have conducted systematic reviews to classify the main dimensions of smart tourism, including mobility, governance, economy, people, and living environment (Kontogianni & Alepis, 2020). While these theoretical models offer a broad overview, their applicability in specific cultural and organizational contexts remains underexplored, particularly in developing countries where infrastructural and institutional readiness may be limited (Sussan, 2018).

Empirical research has also demonstrated the benefits and challenges associated with smart tourism. For example, Azis et al. (2020) found that the implementation of smart tourism technologies enhances destination loyalty through improved service quality and tourist engagement (Azis et al., 2020). Similarly, Wang et al. (2020) argued that the integration of 5G and IoT technologies enables real-time decision-making and personalized services, thus transforming the tourist experience (Wang et al., 2020). However, challenges such as data privacy concerns, lack of interoperability between platforms, and insufficient digital literacy among stakeholders continue to hinder the full realization of smart tourism's potential (Nam et al., 2021; Peng et al., 2021). These findings underscore the need for localized validation of smart tourism models that consider contextual barriers and enablers.

Recent research in Iran and other parts of the Middle East has started to address these gaps. For instance, Salahi Kojour et al. (2022) proposed a qualitative model of smart tourism for the sports industry, emphasizing the importance of cross-sectoral integration and stakeholder collaboration (Salahi Kojour et al., 2022). Similarly, Naeim-Abadi et al. (2023) conducted a narrative analysis of the challenges in developing smart tourism destinations in Mashhad, identifying issues such as fragmented governance and inconsistent policy implementation (Naeim-Abadi et al., 2023). These studies highlight the urgency of adapting global models to local realities through empirical research and stakeholder engagement. In this context, the present study seeks to develop and validate a comprehensive smart tourism model based on the lived experiences of tourists, tourism managers, and service providers in Kish Island.

The multidimensional nature of smart tourism necessitates a holistic analytical framework. According to Bhuiyan et al. (2022), smart tourism ecosystems involve multiple layers of interaction among physical, digital, and social infrastructures (Bhuiyan et al., 2022). A successful smart tourism model must, therefore, account for variables such as perceived value, smart infrastructure, economic development, information management, and visitor behavior. These variables are not only interdependent but also dynamically influenced by external factors such as policy environment, technological change, and global tourism trends. By examining the relationships among these components, this study aims to validate a model that captures the systemic nature of smart tourism in the Iranian context.

From a methodological perspective, the validation of a smart tourism model requires rigorous measurement and analytical techniques. The present study employs a structural equation modeling (SEM) approach to assess the reliability, validity, and explanatory power of the proposed model. This technique allows for simultaneous analysis of multiple dependent and independent variables and is particularly suited for complex, multi-layered constructs like smart tourism (Idrus et al., 2025; Xu et al., 2024). Additionally, the use of composite reliability, average variance extracted (AVE), and discriminant validity tests ensures the robustness of the measurement model, while path coefficients and t-statistics provide empirical support for the structural relationships hypothesized.

Ultimately, this study contributes to the existing literature in several key ways. First, it operationalizes the concept of smart tourism within a specific cultural and geographic context, thereby enriching the theoretical understanding of how smart tourism evolves in non-Western settings. Second, it employs a validated empirical approach to test the relationships among critical dimensions of smart tourism, offering practical insights for destination managers, policymakers, and technology developers. Finally, by focusing on a real-world case study in Iran, the study addresses the persistent gap between theoretical models and their practical applicability, aligning with global efforts to foster sustainable and inclusive tourism development (Cueria, 2022; Lee et al., 2022; Shafiee et al., 2018).

In summary, as smart tourism continues to reshape the global tourism landscape, it is essential to develop, adapt, and validate models that reflect the complexity and specificity of local conditions. This research aims to fill a crucial gap by presenting a contextually grounded and empirically tested model of smart tourism in Kish Island.

2. Methods and Materials

This research employed a quantitative approach using a descriptive-correlational design, specifically structural equation modeling (SEM), to validate the Smart Tourism Model. Descriptive research aims to understand the current state of a phenomenon, exploring how a variable or subject exists in its natural condition without manipulating or intervening in the variables. It seeks to systematically and objectively describe existing conditions, characteristics, and relationships among variables, and it serves both applied and theoretical purposes. In this study, the sampling process followed a two-stage method. In the first stage, a cluster sampling technique was applied to enhance the feasibility of selecting participants from an extensive population. Given the context of the study on Kish Island—where 51 hotels were operational during the data collection period—30 hotels were randomly selected to increase the representativeness and validity of the sample. In the second stage, simple random sampling was used to select tourists staying in those hotels. As there were no restrictive inclusion criteria for selecting individual participants, Cochran's formula for infinite populations was utilized, resulting in an estimated required sample size of 311. After the survey phase, 273 completed questionnaires were deemed valid and included in the final analysis.

The data collection instrument used in this study was a Smart Tourism Scale designed by the authors to assess attitudes toward smart tourism. The instrument consists of 45 items structured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The development of the scale was grounded in thematic analysis from a qualitative meta-synthesis study, and items were formulated accordingly. Content validity was assessed by a panel of tourism management experts. The Content Validity Index (CVI) was calculated at 0.82, which confirmed the instrument's content validity. In terms of the Content Validity Ratio (CVR), five items were eliminated because their CVR scores fell below the 0.75 threshold. To assess the internal consistency of the scale, Cronbach's alpha was calculated, with values above 0.70 considered acceptable, thus ensuring the reliability of the constructs. The study also measured convergent and discriminant validity of the constructs. Convergent validity was assessed using the Average Variance Extracted (AVE), a measure introduced by Fornell and Larcker (1981), which reflects the extent to which items of a construct are correlated with each other. An AVE value above 0.50 indicated sufficient convergent validity, confirming that the indicators accurately measure their respective latent constructs.

The analysis of the collected data was conducted in two stages. In the first stage, descriptive statistics were employed to summarize the demographic characteristics of the respondents and provide an overview of the distribution of responses. In the second stage, the relationships among the independent and dependent variables were analyzed using structural equation modeling. The analysis was conducted using SPSS version 24 for descriptive statistics and SmartPLS version 3 for structural modeling. The Smart Tourism Model was evaluated through its measurement model, which is analogous to confirmatory factor analysis, to ensure the reliability and validity of the observed variables before testing structural relationships. The outer model was used to assess the relationship between observed indicators and their respective latent constructs. Establishing the appropriateness of this model was a prerequisite for analyzing inter-variable relationships. Thus, only after confirming the reliability and both convergent and discriminant validity of the measurement model, the structural paths between constructs were tested and interpreted.

3. Findings and Results

The demographic profile of the respondents indicates that 38% of participants were female and 62% were male. Regarding educational attainment, 15% held a high school diploma or lower, 7% had an associate degree, 34% held a bachelor's degree, 38% possessed a master's degree, and 3% had attained a doctoral degree or higher.

To assess the internal consistency of the questionnaire, Cronbach's alpha was calculated for each construct using a pretest sample of 30 completed questionnaires. As per standard guidelines, values above 0.70 indicate acceptable reliability. The table below presents the reliability coefficients for each variable. All constructs demonstrated satisfactory internal consistency, with alpha values exceeding the minimum threshold. Specifically, perceived value exhibited a perfect reliability score ($\alpha = 1.000$), while smart tourism also showed high internal consistency ($\alpha = 0.937$). Other constructs such as smart technology ($\alpha = 0.808$), economic development ($\alpha = 0.789$), and smartification ($\alpha = 0.773$) also achieved acceptable reliability levels.

Table 1. Cronbach's Alpha for Questionnaire Constructs

Variables	Cronbach's Alpha
Perceived Value	1.000
Economic Development	0.789
Smart Technology	0.808
Tourist Behavior	0.712
Complementary Activities	0.779
Destination Capability	0.758
Information Management	0.743
Smartification	0.773
Smart Tourism	0.937

Convergent validity was assessed through the Average Variance Extracted (AVE), a criterion indicating the average shared variance between each latent construct and its indicators. According to Fornell and Larcker (1981), an AVE greater than 0.50 is indicative of adequate convergent validity. The results confirmed this criterion for all constructs. Perceived value showed an AVE of 1.000, reflecting perfect convergence, while all other constructs exceeded the 0.50 threshold, thus confirming the validity of the measurement model in capturing the intended constructs.

Table 2. Convergent Validity (AVE) for Constructs

Constructs	AVE
Perceived Value	1.000
Economic Development	0.551
Smart Technology	0.507
Tourist Behavior	0.531
Complementary Activities	0.560
Destination Capability	0.509
Information Management	0.599

Smartification	0.514
Smart Tourism	0.522

Composite Reliability (CR) was also computed as a more refined measure of internal consistency compared to Cronbach's alpha, given that CR accounts for factor loadings and their contributions to the latent variable. Based on established benchmarks, CR values above 0.70 confirm the reliability of the measurement model. In this study, CR values for all constructs were above the recommended threshold, with smart tourism (CR = 0.943), perceived value (CR = 1.000), and smart technology (CR = 0.856) demonstrating especially high composite reliability.

Table 3. Composite Reliability (CR) for Constructs

Constructs	CR
Perceived Value	1.000
Economic Development	0.857
Smart Technology	0.856
Tourist Behavior	0.819
Complementary Activities	0.785
Destination Capability	0.799
Information Management	0.820
Smartification	0.793
Smart Tourism	0.943

Discriminant validity, the third metric of measurement model fitness, was evaluated using the Fornell-Larcker criterion. This criterion holds that the square root of AVE for each construct should exceed its correlation with other constructs. The matrix below shows the square root of each construct's AVE along the diagonal, while the off-diagonal elements reflect inter-construct correlations. In all cases, the diagonal values are greater than the corresponding off-diagonal values, indicating satisfactory discriminant validity. For instance, the square root of AVE for smart tourism (0.722) exceeds its correlations with smartification (0.541), information management (0.510), and economic development (0.680).

Table 4. Discriminant Validity Matrix (Fornell-Larcker Criterion)

Constructs	Perceived Value	Economic Development	Smart Technology	Tourist Behavior	Complementary Activities	Destination Capability	Information Management	Smartification	Smart Tourism
Perceived Value	1.000								
Economic Development	0.483	0.742							
Smart Technology	0.559	0.557	0.712						
Tourist Behavior	0.282	0.616	0.588	0.729					
Complementary Activities	0.644	0.589	0.570	0.630	0.748				
Destination Capability	0.139	0.554	0.541	0.460	0.386	0.714			
Information Management	0.451	0.580	0.673	0.573	0.634	0.589	0.773		
Smartification	0.350	0.629	0.638	0.423	0.539	0.687	0.534	0.717	
Smart Tourism	0.583	0.680	0.510	0.536	0.571	0.681	0.510	0.541	0.722

The findings across all reliability and validity assessments affirm the robustness of the measurement model. The constructs exhibited high internal consistency, adequate convergent validity, and acceptable discriminant validity, thus validating the Smart Tourism Model for further structural analysis.

To assess the measurement quality of the model, the outer model—or measurement model—was evaluated. This model is functionally equivalent to confirmatory factor analysis and is used to examine the relationships between latent variables and their observed indicators. Its primary aim is to determine whether the items (questionnaire statements) adequately measure the constructs they are intended to represent. Only after validating these relationships can the structural model be tested. The standardized factor loadings and t-values from the Partial Least Squares (PLS) analysis are presented in the following table.

All factor loadings exceeded the threshold of 0.30, and all t-values surpassed the critical value of 1.96, confirming that each indicator significantly contributes to its respective latent construct.

Table 5. Outer Model Results (Factor Loadings and t-values for Observed Variables)

Construct	Item	Factor Loading	t-value
Destination Capability	Q1	0.448	4.64
	Q2	0.821	25.83
	Q3	0.750	16.17
	Q4	0.750	16.56
Smartification	Q5	0.849	29.05
	Q6	0.822	22.06
	Q7	0.380	3.73
Information Management	Q8	0.579	9.72
	Q9	0.663	7.33
	Q10	0.612	8.08
	Q11	0.827	26.77
	Q12	0.515	5.17
	Q13	0.648	8.37
	Q14	0.526	5.62
Perceived Value	Q15	1.000	----
Smart Technology	Q16	0.549	8.90
	Q17	0.631	7.83
	Q18	0.713	11.95
	Q19	0.424	5.14
	Q20	0.821	39.43
	Q21	0.742	16.34
	Q22	0.623	9.27
	Q23	0.668	15.01
	Q24	0.464	4.97
Economic Development	Q25	0.797	22.15
	Q26	0.516	6.25
	Q27	0.709	13.02
	Q28	0.838	30.78
	Q29	0.805	24.33
Tourist Behavior	Q30	0.767	23.95
	Q31	0.691	9.20
	Q32	0.683	9.38
	Q33	0.770	20.01
	Q34	0.550	6.18
	Q35	0.808	19.30
	Q36	0.409	4.39
	Q37	0.397	4.47
	Q38	0.080	22.21
	Q39	0.460	4.80
	Q40	0.612	8.05

The results of the measurement model analysis reveal that all observable variables have loadings above the acceptable threshold of 0.30, and all associated t-values exceed 1.96. These outcomes indicate statistically significant and meaningful relationships between each item and its corresponding construct, thereby confirming the adequacy of the measurement model.

To evaluate the overall model fit, the predictive relevance (Q^2) and the goodness-of-fit index (GOF) were computed. Q^2 assesses the model's predictive accuracy for endogenous reflective constructs. Values above 0.35 are considered indicative of strong predictive power. In this study, all constructs exhibited Q^2 values exceeding the weak-to-moderate threshold, thereby supporting the model's validity in predictive terms. GOF values, proposed by Tenenhaus et al. (2004), offer a holistic indicator of model fit. A GOF value of 0.725 for perceived value suggests excellent model fit, while the overall model GOF exceeded the 0.36 benchmark, indicating strong fit across the board.

Table 6. Model Fit Indices (Q^2 and GOF)

Constructs	Q^2	GOF

Perceived Value	1.000	0.725
Economic Development	0.339	
Smart Technology	0.269	
Tourist Behavior	0.422	
Complementary Activities	0.302	
Destination Capability	0.523	
Information Management	0.335	
Smartification	0.484	
Smart Tourism	0.457	

Following model fit verification, the structural model was examined by evaluating path coefficients (beta values), t-values, and significance levels for the study hypotheses. Structural relationships among variables were analyzed using the PLS algorithm, and the significance of each path was tested via bootstrapping. All hypothesized paths leading to smart tourism were found to be statistically significant, as all t-values exceeded the critical threshold of 1.96 at the 95% confidence level ($p < 0.05$). Smart technology had the highest impact ($\beta = 0.269$), followed by economic development ($\beta = 0.199$) and information management ($\beta = 0.183$). Even perceived value, with the lowest beta coefficient ($\beta = 0.052$), had a statistically significant effect.

Table 7. Structural Model Results: Hypothesis Testing

No.	Hypothesis	Beta	t-value	p-value
1	Perceived Value → Smart Tourism	0.052	7.84	0.000
2	Economic Development → Smart Tourism	0.199	16.48	0.000
3	Smart Technology → Smart Tourism	0.269	19.68	0.000
4	Tourist Behavior → Smart Tourism	0.128	10.68	0.000
5	Complementary Activities → Smart Tourism	0.180	16.41	0.000
6	Destination Capability → Smart Tourism	0.115	11.01	0.000
7	Information Management → Smart Tourism	0.183	16.30	0.000
8	Smartification → Smart Tourism	0.098	12.17	0.000

In summary, the structural model analysis supports all the proposed hypotheses. Each independent construct significantly contributes to the prediction of smart tourism development. These results confirm the model's theoretical validity and its empirical robustness in explaining the factors influencing smart tourism adoption.

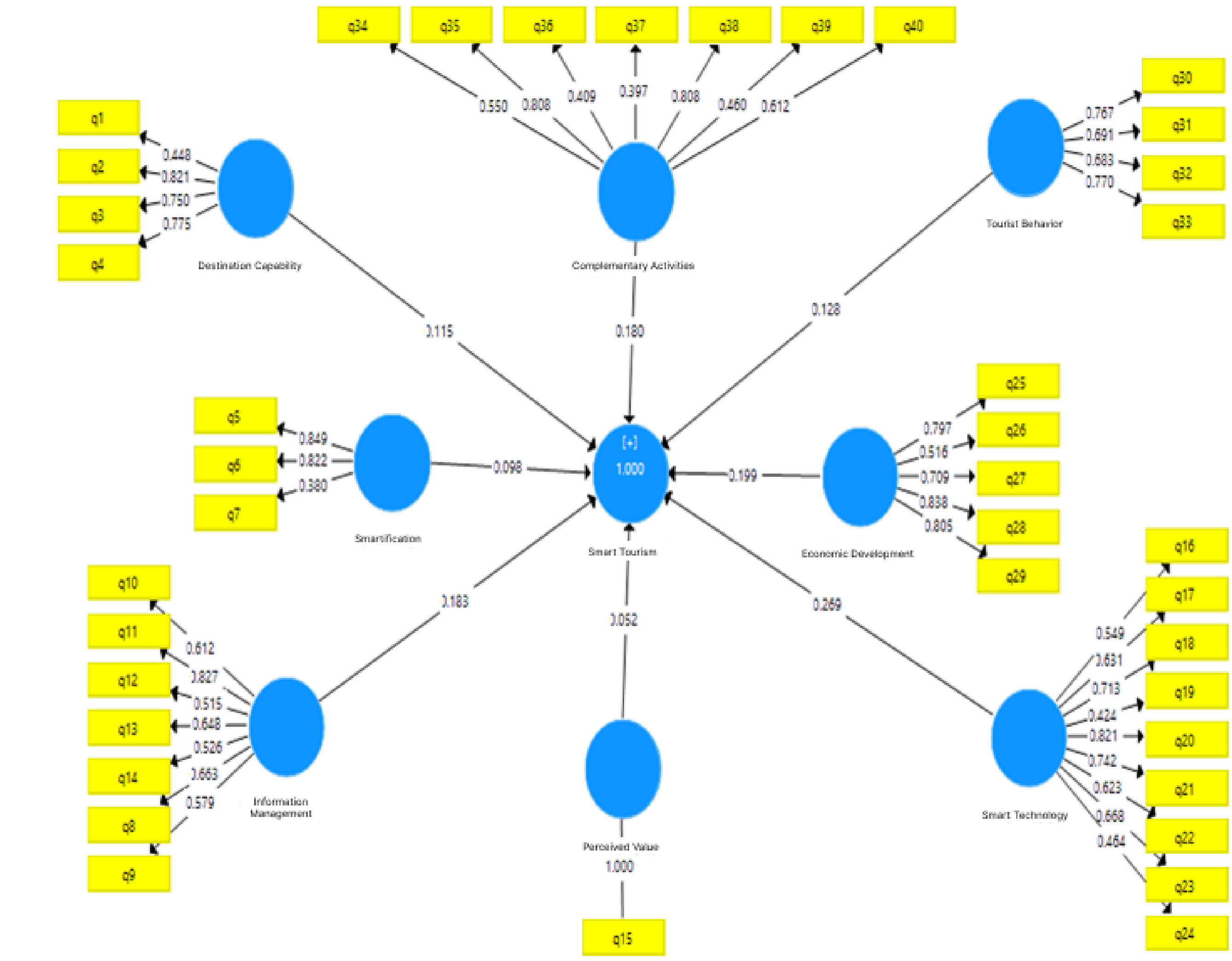

Figure 1. Model with Standard Coefficients

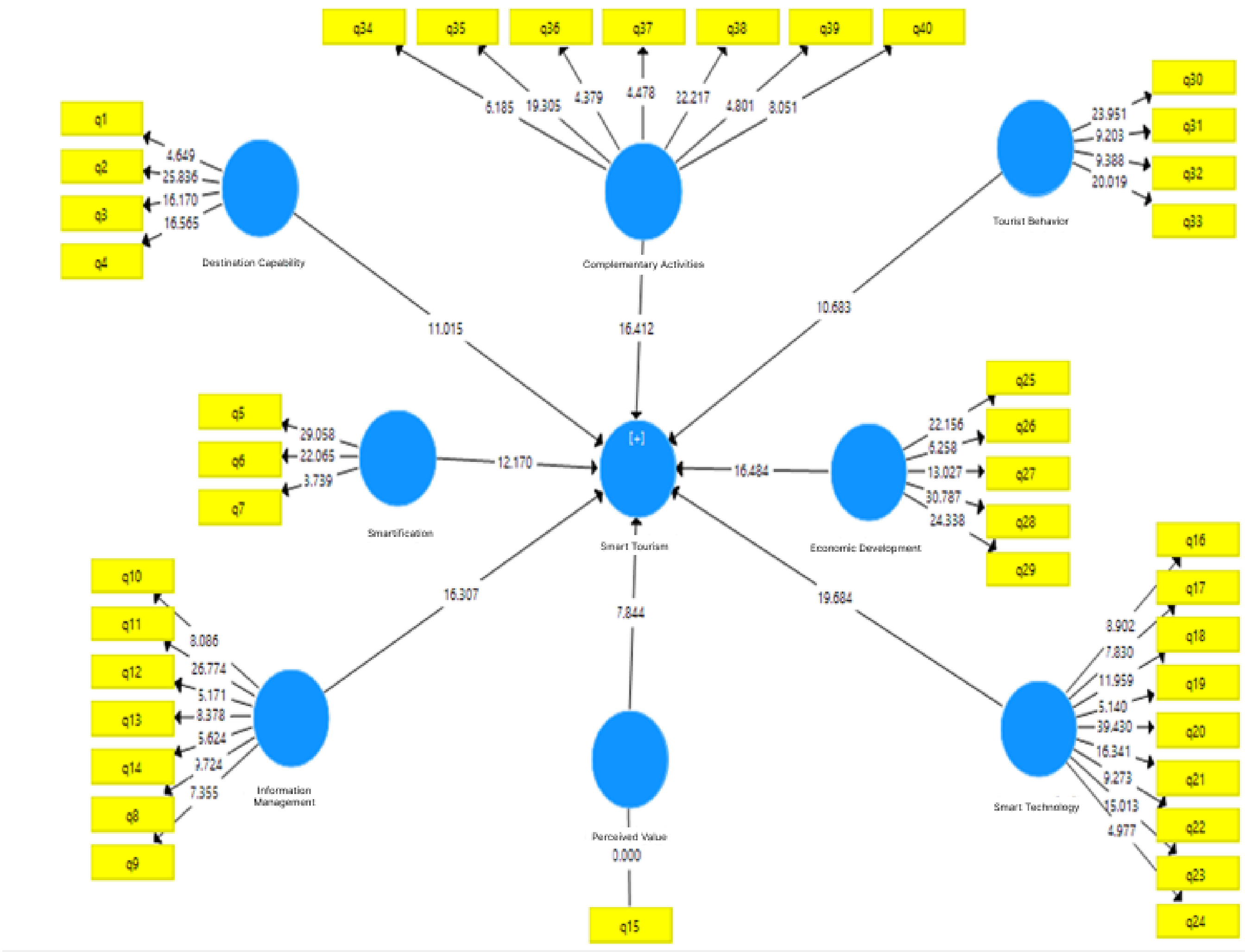

Figure 2. Model with T-Values

4. Discussion and Conclusion

The aim of this study was to validate a structural model of smart tourism by examining the relationship between multiple constructs—perceived value, economic development, smart technology, tourist behavior, complementary activities, destination capability, information management, and smartification—on the development of smart tourism in Kish Island. The findings obtained through Partial Least Squares Structural Equation Modeling (PLS-SEM) provided strong empirical support for the hypothesized relationships in the model. All eight independent variables were found to have a statistically significant effect on the dependent construct of smart tourism, with factor loadings, t-values, and model fit indices indicating high reliability, convergent validity, and discriminant validity across the model.

The most significant predictor of smart tourism was smart technology ($\beta = 0.269$, $t = 19.68$), underscoring the critical role of technological infrastructure in enabling smart tourism development. This result is consistent with the broader literature that identifies smart technology as the backbone of modern tourism ecosystems. For instance, Buhalis (2020) emphasized that the convergence of AI, IoT, and cloud computing allows destinations to deliver seamless, real-time, and context-aware services to tourists, thus transforming the visitor experience (Buhalis, 2020). Similarly, Wang et al. (2020) argued that advanced connectivity through 5G networks enhances both the efficiency and personalization of tourism services, making smart technology a cornerstone of smart destination management (Wang et al., 2020). The present findings reinforce the idea that without robust technological frameworks, other efforts toward smart tourism may falter due to the lack of digital enablement.

Economic development emerged as the second strongest predictor ($\beta = 0.199$, $t = 16.48$), indicating that smart tourism is significantly influenced by the broader economic context of a destination. This aligns with the conceptualization by Pencarelli

(2020), who argued that digital transformation in tourism is tightly interwoven with economic modernization and investment in smart infrastructure (Pencarelli, 2020). In a similar vein, Idrus et al. (2025) found that public administration systems play a vital role in supporting smart tourism by allocating financial and regulatory resources to facilitate innovation and collaboration across sectors (Idrus et al., 2025). In the case of Kish Island, the support of economic institutions and tourism investment policies likely contributes to the viability of smart tourism initiatives, enhancing the capacity for infrastructure development and service innovation.

Information management also showed a considerable effect (β = 0.183, t = 16.30), supporting previous findings that emphasize the value of data-driven decision-making in tourism environments. Shen et al. (2020) illustrated how the integration of smart technologies in tourist attractions influences the entire customer journey, from trip planning to post-visit engagement, through effective data collection and analysis (Shen et al., 2020). Bhuiyan et al. (2022) further stressed that smart tourism ecosystems are predicated on the ability to process large volumes of visitor data to co-create value and provide adaptive services in real time (Bhuiyan et al., 2022). The present study's findings suggest that information systems capable of capturing, analyzing, and disseminating relevant data are indispensable for supporting operational efficiency and personalized experiences in smart tourism destinations.

Complementary activities (β = 0.180, t = 16.41) and tourist behavior (β = 0.128, t = 10.68) were also significant, illustrating the socio-cultural dimensions of smart tourism. Dulgaroglu (2021) noted that smart tourism is not solely a technological process but involves the design of immersive, culturally sensitive, and interactive activities that engage visitors on multiple levels (Dulgaroglu, 2021). Moreover, tourist behavior plays a dual role—it both influences and is influenced by smart tourism technologies. As Cueria (2022) described, digital marketing and mobile applications alter how tourists interact with destinations, prompting more informed and spontaneous decisions (Cueria, 2022). The integration of tourist behavior into the smart tourism model thus captures this dynamic feedback loop, validating the inclusion of socio-behavioral variables in tourism innovation frameworks.

The influence of destination capability (β = 0.115, t = 11.01) and smartification (β = 0.098, t = 12.17) on smart tourism also affirms the foundational role of infrastructural readiness and strategic transformation. According to Nam et al. (2021), smart tourism is intricately linked to broader smart city paradigms, where the physical and organizational capabilities of a location determine its capacity to implement and sustain digital solutions (Nam et al., 2021). Haqverdi Zadeh et al. (2023) similarly observed that urban readiness, including connectivity, governance, and environmental quality, significantly affects the implementation of smart tourism initiatives (Haqverdi Zadeh et al., 2023). The current findings suggest that while these dimensions may have slightly lower beta weights compared to others, they remain statistically significant, indicating their indispensable role in shaping the overall smart tourism landscape.

Interestingly, perceived value (β = 0.052, t = 7.84) had the lowest effect size but still showed a significant relationship with smart tourism. This confirms the insights from studies like those of Azis et al. (2020), who argued that tourists' perceptions of value, derived from convenience, personalization, and quality of service, contribute to satisfaction and loyalty (Azis et al., 2020). Although value perception is more of an outcome variable in many models, its inclusion here as a predictor emphasizes the bidirectional nature of value exchange in smart tourism systems. Smart destinations not only deliver value but are also shaped by how that value is interpreted and internalized by the tourist.

The goodness-of-fit index (GOF = 0.725) and predictive relevance (Q^2 values > 0.30 for most constructs) indicated a strong overall fit of the model, corroborating its theoretical soundness and empirical robustness. These results are aligned with those of Salahi Kojour et al. (2022), who validated a model of smart tourism within the sports industry using similar fit indices and found comparable levels of statistical significance across their constructs (Salahi Kojour et al., 2022). The comprehensive alignment of the current study's results with prior theoretical and empirical works suggests that the validated model not only holds academic relevance but also carries practical implications for real-world application in developing smart tourism destinations.

Moreover, the use of advanced data analysis techniques and robust validity assessments strengthens the methodological credibility of this study. Xu et al. (2024) emphasized the importance of digital innovation and data-driven models in enhancing destination competitiveness, noting that empirical validation is crucial to translating abstract concepts into actionable frameworks (Xu et al., 2024). In the same direction, Lee et al. (2020) advocated for city-level transformations driven by integrated technology and policy ecosystems, aligning closely with the components of the present model (Lee et al., 2020).

Overall, the results of this study contribute to the expanding body of knowledge on smart tourism by demonstrating that it is a multidimensional construct requiring the alignment of technological, behavioral, economic, managerial, and perceptual factors. This complex interplay affirms the necessity of systemic thinking in both the design and management of smart tourism destinations.

Despite its contributions, the study is not without limitations. First, the research was geographically limited to Kish Island, a unique tourism hub in Iran, which may limit the generalizability of the findings to other contexts with different cultural, infrastructural, or economic conditions. Second, while the sample size (273 respondents) meets statistical standards for structural equation modeling, broader samples across multiple destinations could provide more comprehensive validation. Third, the study relied exclusively on self-reported survey data, which may introduce bias due to social desirability or misinterpretation of items by respondents. Lastly, the cross-sectional nature of the data does not allow for causal inferences or an understanding of how smart tourism evolves over time.

Future studies should aim to expand the geographic scope by including multiple tourism destinations with varying levels of smart readiness. Comparative studies between urban and rural destinations or between countries at different stages of digital transformation would offer deeper insights. Longitudinal designs could also help track the development of smart tourism over time, revealing patterns of growth, stagnation, or regression. Additionally, future research may integrate qualitative methods such as interviews or ethnographic observations to capture the nuanced experiences of tourists, service providers, and policymakers. Exploring the role of environmental sustainability, ethical data usage, and cultural sensitivity within smart tourism models would further enrich the theoretical framework and practical implications.

Destination managers and tourism policymakers should prioritize investment in technological infrastructure as a core driver of smart tourism development. Integrating digital platforms for real-time information, mobile access, and personalized services can significantly enhance tourist satisfaction and operational efficiency. Stakeholder collaboration—including public-private partnerships—should be emphasized to align technological innovation with economic development goals. Furthermore, designing complementary activities that cater to diverse tourist preferences and incorporating behavioral insights into marketing strategies can strengthen engagement. Finally, training programs to improve digital literacy among both tourists and local service providers will be critical to maximizing the benefits of smart tourism systems.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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