Advance Sustainable Science, Engineering and Technology (ASSET)
Vol. 8, No.2, April 2026, pp. 02602029-01 ~ 02602029-016
ISSN: 2715-4211 DOI: https://doi.org/10.26877/asset.v8i2.2909

A Hybrid AI–SEMPLS Model for Digital Visualization Acceptance in Blue Tourism: Evidence from Lampung Province

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Abstract. Blue tourism destinations often lack advanced digital tools capable of providing real-time, AI-driven visualization and user-centered information services. This study addresses this gap by developing JELAMBU, an AI-enabled digital visualization platform, and by evaluating user acceptance through a hybrid SEMPLS models. The research aims to: (i) design and implement an AI-based system that combines chatbot interaction, realtime sentiment analytics, and digital visualization; and (ii) examine the determinants of tourists' intention to adopt AI-enabled e-tourism technologies. A structured questionnaire was administered to 467 visitors of destinations, and 16 hypotheses were tested. The results show that platform design, facilitating conditions, AI technology, perceived ease of use, perceived usefulness, social influence, service quality, trust, and risk perception significantly shape intention to use, whereas information quality, perceived benefits, and performance expectancy do not show significant effects. The model demonstrates substantial predictive power ($R^2 = 0.703$), strong effect sizes ($f^2 > 0.225$), and acceptable fit (SRMR = 0.084). These findings highlight the pivotal role of design and system conditions in AI-driven tourism platforms and provide practical guidance for developers and policymakers in strengthening digital visualization, personalization features, and sustainable blue tourism management. Future studies may extend this framework to multi-regional settings or longitudinal adoption scenarios.

Keywords: Artificial intelligence, digital visualization, SEM–PLS, technology acceptance, blue tourism.

(Received 2025-10-27, Revised 2026-02-24, Accepted 2026-03-15, Available Online by 2026-04-30)

1. Introduction

Tourism is a vital sector for the Indonesian economy supporting the Etourism 5.0 program, contributing foreign exchange of USD 16.7 billion and growing 19.3 percent in 2024 according to the Information Portal [1]. Lampung Province is a province rich in culture and natural resources with 47 blue tourism destinations making it one of the attractive destinations in Indonesia [2]. However, the lack of digital promotion and branding for Lampung's blue tourism makes this province less well-known to domestic and international tourists despite its location close to the capital. The digital challenge in promoting Lampung's blue tourism remains one of the main priorities for Lampung Province to achieve the target number of tourist visits by 2025[3].

The problem in tourism, particularly Lampung's Blue Tourism, which remains a popular attraction but remains largely unknown, is the lack of high-quality digital technology for promotion. No one has yet promoted blue tourism using advanced Artificial Intelligence-based technology that is easily accessible to international tourists.

Advances in artificial intelligence (AI), real-time data analytics, and digital visualization technologies have transformed the tourism sector by enabling personalized recommendations, immersive content, and intelligent decision support systems[4]. However, the adoption of AI-based e-tourism platforms remains uneven, particularly in coastal and blue tourism destinations, where digital infrastructure and visualization systems are underdeveloped[5]. Despite the growing paradigm of smart tourism, many coastal areas lack an integrated platform that combines AI-based interactions, automated information processing, and user-centered interface design to support sustainable destination management[6].

Existing studies on AI in tourism have largely focused on forecasting, recommendation engines, or sentiment analysis, but few have explored digital visualization systems that integrate chatbot interactions and real-time public opinion data[7]. Blue tourism is defined as tourism activities related to coastal and marine ecosystems that require high-quality, visually rich, and reliable digital platforms due to their reliance on environmental imagery, emotionally driven decision-making, and destination uniqueness[8].

This study introduces a hybrid analysis model that combines AI-based digital visualization with SEM-PLS to empirically test technology acceptance. The proposed model integrates variables from the T-WAM, UTAUT2, ETAM, and McLean frameworks[9], offering a comprehensive approach to evaluating how AI-based visualization influences behavioral intentions in the blue tourism sector. Although these models capture different dimensions of system quality, emotional responses, and behavioral intentions, no previous study has integrated all four frameworks to comprehensively evaluate the acceptance of AI-based visualization platforms[10]. Hybrid modeling is increasingly needed to account for the complex interactions between aesthetic emotions, AI technology, platform design, facilitating conditions, trust, information quality, and perceived usefulness, as well as factors that cannot be adequately captured by a single model.

Given these limitations, there is a clear need for a technological and analytical framework that simultaneously addresses: (i) the design and implementation of AI-based digital visualization systems for blue tourism, and (ii) the assessment of adoption behavior of such systems using robust hybrid acceptance models[11]. Current research rarely connects system architecture, AI interactions, and real-time analytics with user behavior constructs, leaving a gap in understanding how these technologies influence tourist intentions and sustainable tourism outcomes[12].

To address the above gaps, this study pursues two main objectives:

RO1: Design and implement an AI-based digital visualization platform that integrates chatbot interactions, real-time sentiment analysis, and dynamic visual content for blue tourism.

RO2: Examine the determinants of user acceptance using a hybrid SEM–PLS model combining the T-WAM, UTAUT2, ETAM, and McLean frameworks.

From these objectives, this study formulates the following research questions:

RQ1: How do AI-based visualization features and system design influence tourists' intention to use e-tourism technology?

RQ2: Which factors in the hybrid model most strongly predict the acceptance of an AI-based digital visualization platform?

Theoretically, this study introduces a hybrid acceptance framework that combines four key behavioral models to explain the adoption of AI-based visualization systems, an approach underexplored in blue tourism research. Technically, this study develops a fully operational AI-based platform that integrates chatbot interactions, API-based sentiment scraping, real-time visualization, and user-centered design principles. Practically, these findings offer actionable insights for tourism developers and policymakers to strengthen digital tourism infrastructure, improve platform usability, and support sustainable blue tourism through data- and AI-driven solutions.

2. Methods

2.1. Study Design

This research design is analytical engineering, combining two main approaches: 1) the development of an artificial intelligence (AI)-based digital platform, and 2) the evaluation of user acceptance of AI technology, developed through quantitative surveys and SEM-PLS modeling. This approach was chosen to ensure that technological and user behavioral aspects can be analyzed in an integrated manner within a single research framework, as shown in Figure 1.

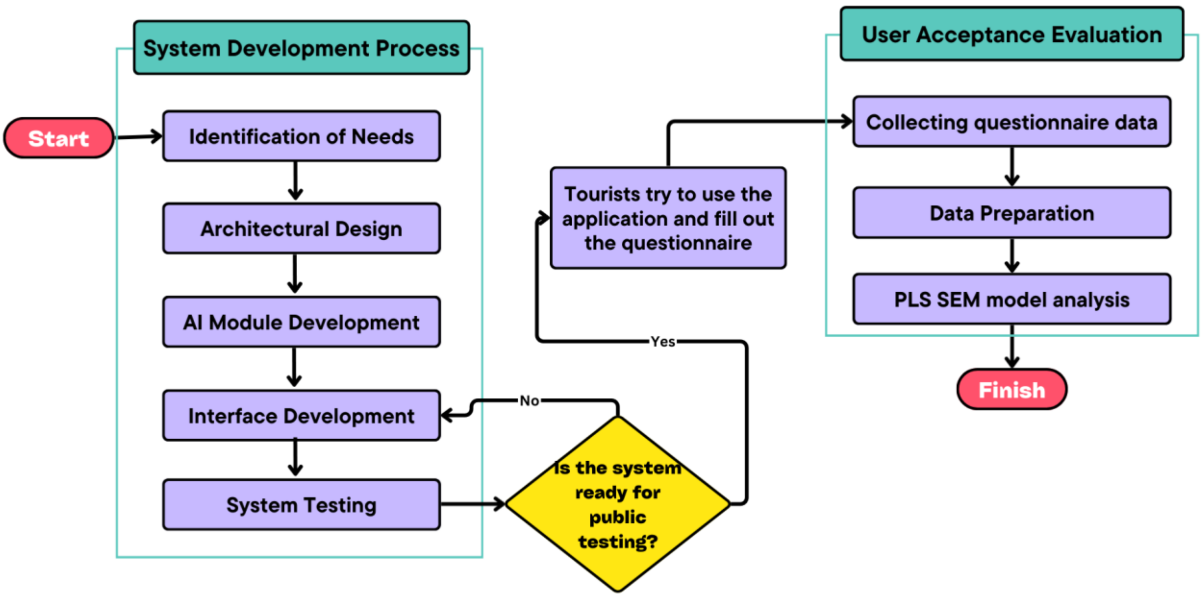

Figure 1. Research Flow

The first approach focuses on the system development process, including needs identification, architectural design, AI module development, interface development, and system testing. This phase aims to produce a platform capable of providing real-time destination visualization, AI-based chatbot interactions, and public opinion presentation.

The second component uses a cross-sectional survey to collect data on the perceptions of users who have visited marine tourism destinations. The questionnaire is based on a combination of constructs from four technology acceptance models: T-WAM, ETAM, UTAUT2, and McLean, aiming to build a more comprehensive hybrid framework. The data obtained were analyzed using Structural Equation Modeling Partial Least Squares (SEM PLS), a method suitable for complex models and predictive purposes.

By integrating system development and user behavior analysis, this research design examines not only the features of the technology being developed but also how users respond to it. This dual approach yields a more holistic understanding of AI-based digital visualization platforms and provides theoretical, methodological, and practical contributions to the development of sustainable marine tourism technology.

2.2 System Development Methodelogy

The platform was developed using an iterative software engineering approach. This process comprises several key stages: requirements analysis, architectural design, AI module and visualization development, data integration, and system testing[13]. This methodology was chosen to ensure the platform's capability to provide real-time visualization of tourist destinations, AI-based chatbot interactions, and public opinion presentation.

2.2.1. Identification of Need

This stage aims to identify the functional and non-functional requirements of the system, namely user needs for marine tourism destination information, required AI features (chatbots, recommendations, sentiment analytics), visualization needs (image galleries, interactive maps, destination highlights), and technical requirements such as data security, performance, and display responsiveness. The results of the needs analysis are used as a basis for compiling system specifications and designing modules.

2.2.2. Architecture Design

In this section, the interface design, database structure, and interaction flow between the user and the system are implemented into a runnable application. The implementation is carried out by utilizing predetermined technologies, namely Laravel, inertia.js, vue.js, Tailwind CSS, MySWL, and Python Flask with Twikit for Twitter scraping and Gemini AI. The platform, named JELAMBU (Jelajah Lampung Biru), was built as an Artificial Intelligence-based blue tourism information media for Lampung to make it easier for tourists to find information in the form of text, images, and public opinion on tourist attractions they will visit. There are two priorities for this platform: first, the touch of AI technology on the platform that has never been applied before in the Lampung province digital tourism platform and second, the utilization of public opinion data displayed in real time on the platform to attract tourists' attention. Before developing the interface, a low-fidelity mockup design was carried out using tools such as Figma. This design was used as a reference for page flow, placement of important elements, and user flow.

2.2.3. AI Chatbot Module

The chatbot interaction flow illustrates how a user communicates with the system[14]. The process begins when a user types a question on the chatbot page. This question is sent via the frontend (Vue.js + Inertia.js) to the Laravel backend via the POST /chatbot/chat endpoint[15]. The backend then processes the question and forwards it to the Gemini API in the form of a JSON request. After Gemini processes it, the answer is sent back to the backend and then displayed to the user in a conversational format[16]. The flow can be seen in Figure 2.

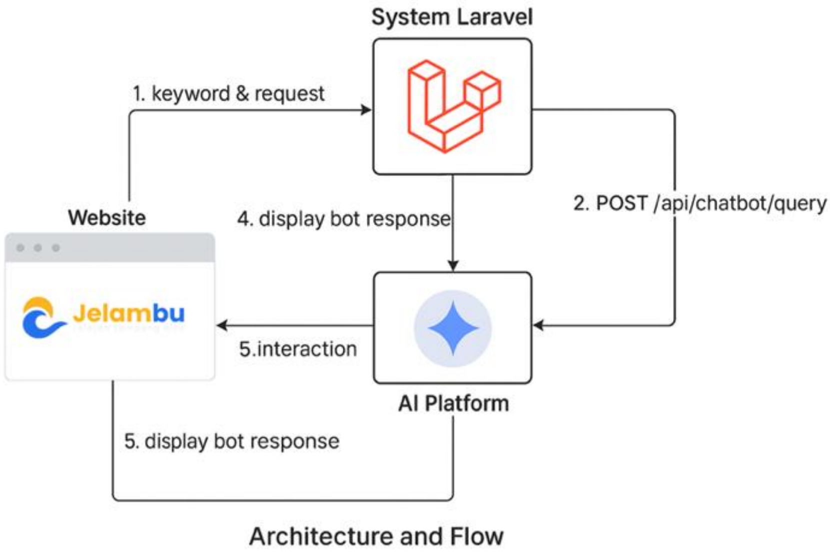

Figure 2. Module AI

To provide a more natural experience, this module also features a typing indicator (isTyping). This indicator makes users feel like they're talking to a real assistant, as there's a pause indicating the system is thinking. Furthermore, the system adds an auto-scroll mechanism to the latest chat bubbles so users don't have to manually scroll every time a new response appears[17].

This interaction is further enhanced by storing conversation history in the browser's local storage. This way, even if the user closes or reloads the page, the chat history can still be displayed. This creates a more consistent and continuous conversation experience. Overall, this interaction flow module ensures that communication between the user and the chatbot is smooth, comfortable, and easy to understand

2.2.4. Data Scraping Module

The Twitter Scraper API module is built separately from the main Jelambu application to maintain lightness, credential security, and ease of scalability[18]. The service uses Python (Flask) as a lightweight web framework and Twikit to retrieve public tweets based on keywords managed in the Admin Panel. Communication between Jelambu and Scraper is via HTTP (JSON), allowing the frontend to dynamically display reviews on the review page[19]. The scraping process flow is shown in Figure 3.

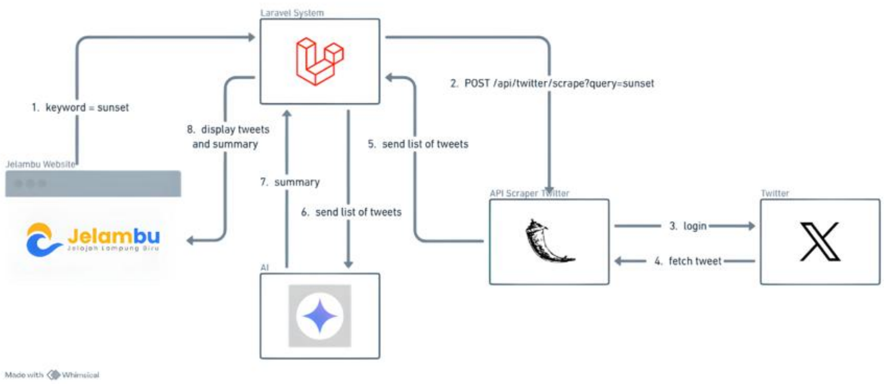

Figure 3. Scraping Process Flow

3.3. Literature Review

Recent research confirms that artificial intelligence (AI) can improve service quality and tourist experiences through information automation, data processing, and more personalized digital interactions [20]. However, most studies still discuss AI functions separately, such as chatbots, recommendations, or public opinion, without integrating them into a comprehensive digital visualization platform. Furthermore, research on technology acceptance in tourism generally uses only a single theoretical model, thus failing to comprehensively explain how platform design, visual emotions, system quality, and AI technology influence user behavior. Based on this gap, this study proposes the development of an AI-based digital visualization platform (JELAMBU) and user acceptance testing using a hybrid model of T-WAM, ETAM, UTAUT2, and McLean to provide a more comprehensive understanding of the adoption of AI-based e-tourism technology.

Abed found that Generation Z in Saudi Arabia has a high intention to use AI-based e-tourism services, with usefulness and ease of use as key determinants. However, this study only assessed general AI acceptance and did not examine how visual design, aesthetic emotion, and system quality work simultaneously in a hybrid model[21].

Ibrahim demonstrated that AI such as chatbots, virtual assistants, and recommendation systems can enhance the tourist experience through more personalized and efficient interactions. However, this study did not develop an integrated digital visualization platform that comprehensively incorporates these AI features for the marine tourism context[22].

Sousa reported that positive emotions while using AI services influence perceived usefulness and future usage intentions, highlighting the importance of service design and quality. However, these studies have not yet examined how the influence of emotions, platform design, and AI performance are combined into a more comprehensive model of technology acceptance[23].

3.5. Survey Design and Data Collection

3.5.1 Population and Sampling

The population in this study was tourists who had visited marine tourism destinations in Lampung Province. A convenience sampling technique was used to facilitate the reach of respondents in the field, particularly at tourist locations and online distribution channels. This technique was chosen because it aligns with the characteristics of user behavior research, which requires a rapid response from a population actively using digital services. A total of 467 valid respondents met the study criteria.

3.5.2 Inclusion and Exclusion Criteria

In this study, respondents were selected based on several inclusion criteria to ensure the data's relevance to the study's objectives. Eligible respondents were individuals aged at least 17 years, had previously visited marine tourism destinations, were familiar with the use of digital devices or online platforms, and were willing to complete the questionnaire. Several categories of respondents were excluded from the analysis, including those who had never visited marine tourism destinations, completed the questionnaire incompletely or inconsistently, and exhibited unusual response patterns such as random responses. These criteria were applied to maintain the quality and validity of the data before further analysis.

3.6 Data Collection and Instrumens Hypothesis

This study uses a quantitative method with a survey method. The survey method was carried out to collect primary data that is original and not engineered[24]. This questionnaire was distributed to the general public who had visited blue tourism in Lampung province and directly interviewed at tourist locations with tourists. The population of this study was filled with various types of generations, namely the Baby Boomer generation (1946-1964), Generation X (1965-1980), Millennials/Generation Y (1981-1996), Generation Z (1997-2012). The distribution of questionnaires used the Convenience Sampling technique, namely the sample was selected based on anyone who happened to be available, easily reached and willing to be a respondent.

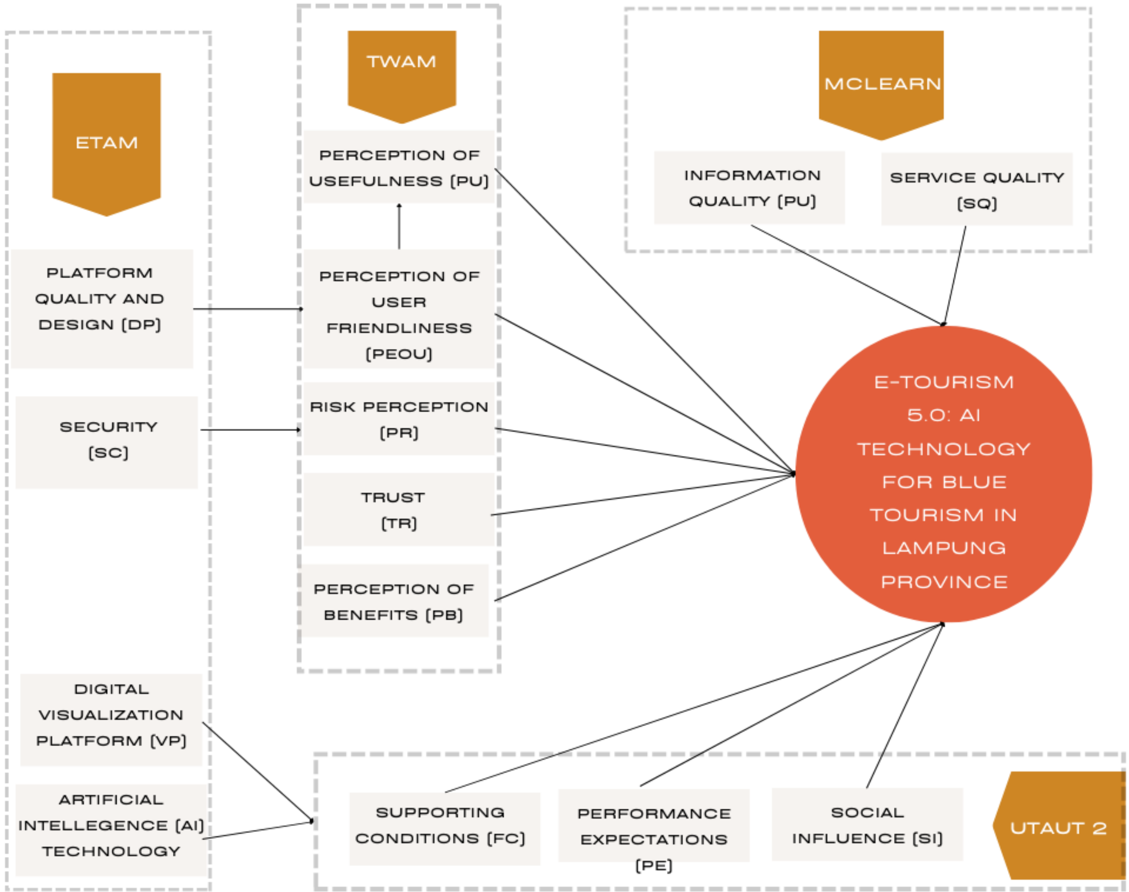

Figure 4. Research Model Hypothesis

Identify factors that influence the acceptance of technology by users by determining the formulation of a hypothesis that combines the framework of the Tourism Web Acceptance Model (T-WAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the E-Tourism Technology Acceptance Model (ETAM) and the McLean Model which consists of 15 variables with independent variables can be seen in Figure 4

Table 1. Research Hypothesis

Hyphothesis		**Information**
H1	AE -> FC	The influence of aesthetic emotion on supporting conditions
H2	AI -> FC	The impact of AI technology on supporting conditions
H3	DP -> PEOU	The influence of platform quality and design on perceived user-friendliness
H4	FC -> INT	The Influence of Supporting Conditions on Intention to Use ETourism Technology
H5	IQ -> INT	The Influence of Information Quality on Intention to Use ETourism Technology
H6	PB -> INT	The Influence of Perceived Benefits on Intention to Use ETourism Technology

H7	PE -> INT	The Influence of Performance Expectancy on Intention to Use ETourism Technology
H8	PEOU -> INT	The influence of perceived ease of use on intention to use ETourism technology
H9	PEOU -> PU	The influence of perceived user convenience on perceived usefulness
H10	PR -> INT	The influence of risk perception on intention to use ETourism technology
H11	PU -> INT	The Influence of Perceived Usefulness on Intention to Use ETourism Technology
H12	SC -> PR	The influence of security on risk perception
H13	SI -> INT	Social Influence on Intention to Use ETourism Technology
H14	SQ -> INT	The Influence of Service Quality on Intention to Use ETourism Technology
H15	TR -> INT	The Influence of Perceived Trust on Intention to Use ETourism Technology
H16	VP -> FC	The influence of digital platform visualization on supporting conditions

3.7 Data Analysis Procedure

Data analysis was conducted using the Structural Equation Modeling – Partial Least Squares (SEM–PLS) method with the aid of SmartPLS 4 software. This method was chosen because it is suitable for complex research models involving multiple constructs and has a predictive orientation. Furthermore, SEM–PLS does not require the assumption of a normal data distribution, making it suitable for use with heterogeneous survey data.

The analysis process consists of two main stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model). In the outer model stage, indicator quality is tested through factor loading values, convergent validity based on AVE (≥ 0.50), construct reliability using Cronbach's Alpha and Composite Reliability (≥ 0.70), and discriminant validity using the Fornell–Larcker and HTMT criteria. Indicators that do not meet the criteria are re-evaluated and eliminated to improve model quality.

The next stage is the inner model evaluation, which assesses the relationships between constructs through path coefficients and statistical significance obtained from a bootstrapping process with 5,000 resamplings. The R^2 value is used to assess the predictive power of the model, while the f^2 value measures the magnitude of the influence of the independent construct on the dependent construct. The model is also tested using Q^2 (predictive relevance) and SRMR to assess overall model feasibility.

The evaluation results from these two stages provide a basis for drawing conclusions regarding the constructs that significantly influence intention to use, as well as providing insight into the factors that shape user acceptance of the JELAMBU platform.

3. **Results and Discussion**

3.1. Artificial Intelligence Application Development

The AI-based JELAMBU website was developed as a publicly accessible digital platform to support blue tourism information services through intelligent interaction and visual presentation. The system was designed not merely as an informational website, but as an AI-enabled digital visualization platform that integrates user-centered interface design with automated data processing and interaction features[25].

From a technical perspective, the frontend interface was implemented using Laravel, Inertia.js, Vue.js, and Tailwind CSS, enabling a responsive, modular, and device-adaptive layout suitable for both desktop and mobile environments. This technology stack was selected to support dynamic content rendering, seamless interaction with AI services, and efficient integration between the frontend and backend layers. The design emphasizes clarity, visual consistency, and intuitive navigation, which are critical for enhancing user experience in digital tourism platforms.

Beyond visual appearance, the platform incorporates AI-driven functionalities, including an interactive chatbot module and real-time data processing features, to assist users in exploring tourism destinations more effectively. These AI components were designed to reduce information search effort, improve engagement, and support personalized interaction, aligning with human–computer interaction (HCI) principles and technology acceptance requirements.

3.2 Outer Model Testing

The testing model consists of five SEM PLS models, namely ETAM, TWAM, UTAUT, MCLEAN, and Intention to Use ETOURISM Technology. Each model has latent variables and indicators, and testing is carried out as can be seen in Figure 5.

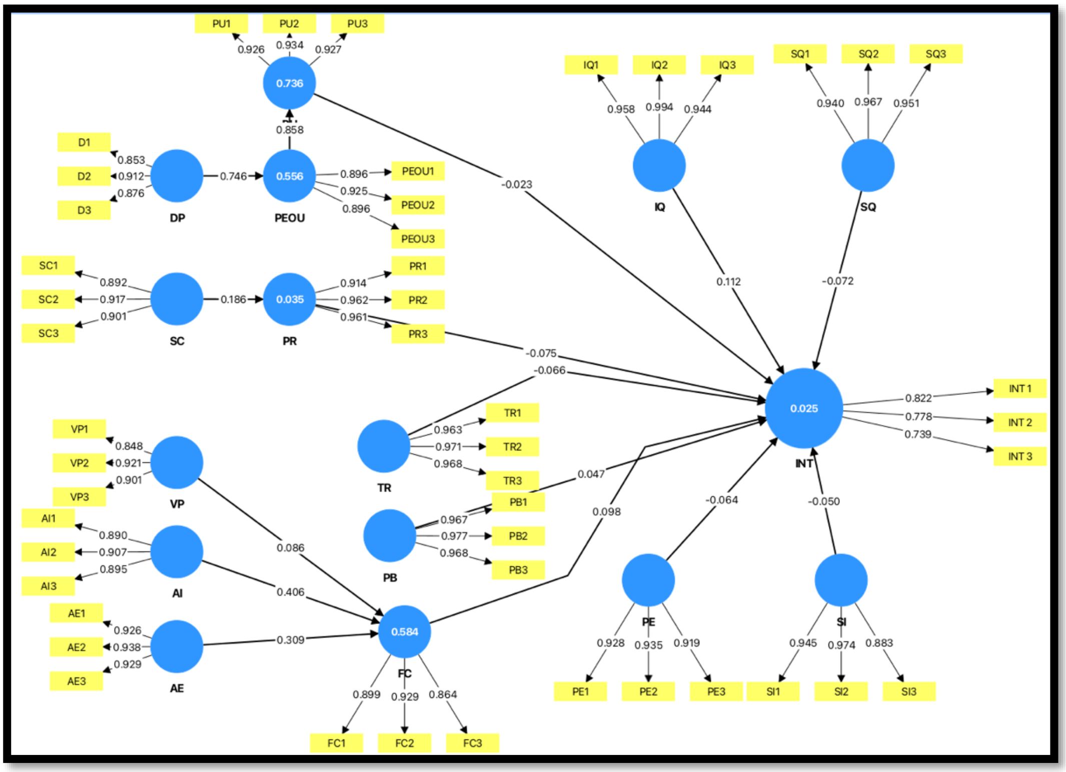

Figure 5. Research Model

The outer model includes a correlation test between constructs and latent variables through a convergent validity examination (Outer loading factor, Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE))[26]. The results obtained are as follows:

Table 2. Outer Model Testing

Indicator	Loadings	CA	CR (Rho_a)	CR (Rho_c)	AVE
AE1 <- AE	0.926	0.923	0.923	0.951	0.866
AE2 <- AE	0.893				
AE3 <- AE	0.929				
AI1 <- AI	0.890	0.879	0.882	0.925	0.805
AI2 <- AI	0.907				
AI3 <- AI	0.895				
D1 <- DP	0.853	0.855	0.860	0.912	0.776
D2 <- DP	0.912				
D3 <- DP	0.876				
FC1 <- FC	0.899	0.879	0.880	0.926	0.806
FC2 <- FC	0.929				
FC3 <- FC	0.864				
INT 1 <- INT	0.822	0.702	0.731	0.824	0.609
INT 2 <- INT	0.778				
INT 3 <- INT	0.739				
IQ1 <- IQ	0.958	0.971	0.876	0.976	0.933
IQ2 <- IQ	0.994				
IQ3 <- IQ	0.944				
PB1 <- PB	0.967	0.969	0.988	0.980	0.942
PB2 <- PB	0.977				
PB3 <- PB	0.968				
PE1 <- PE	0.928	0.919	0.935	0.949	0.860
PE2 <- PE	0.935				
PE3 <- PE	0.919				
PEOU1 <- PEOU	0.896	0.890	0.891	0.932	0.820
PEOU2 <- PEOU	0.925				
PEOU3 <- PEOU	0.896				
PR1 <- PR	0.914	0.943	0.884	0.962	0.895
PR2 <- PR	0.962				
PR3 <- PR	0.961				
PU1 <- PU	0.926	0.921	0.921	0.950	0.863
PU2 <- PU	0.934				
PU3 <- PU	0.927				
SC1 <- SC	0.892	0.887	0.889	0.930	0.816
SC2 <- SC	0.917				
SC3 <- SC	0.901				
SI1 <- SI	0.945	0.941	0.788	0.954	0.874

SI2 <- SI	0.974				
SI3 <- SI	0.883				
SQ1 <- SQ	0.940	0.949	0.954	0.967	0.908
SQ2 <- SQ	0.967				
SQ3 <- SQ	0.951				
TR1 <- TR	0.963	0.966	0.969	0.978	0.936
TR2 <- TR	0.971				
TR3 <- TR	0.968				
VP1 <- VP	0.848	0.869	0.878	0.920	0.793
VP2 <- VP	0.921				
VP3 <- VP	0.901				

Based on table 2, each indicator has a loading factor value between 0.977 and 0.702, which means the correlation value between each indicator and the latent variable/construct is considered good and valid because the standard loading factor value is considered valid if it is ≥ 0.7, then the indicator and construct have a good correlation and indicate that the indicator's reliability must be maintained[27]. Meanwhile, for CA, it produces a value of 0.98 to 0.73, which means the internal reliability value of a construct has a good reliability value. Then, for the CR rho_c value, it measures internal reliability by considering the outer loading of each indicator with a value between 0.980 and 0.824, meaning good reliability. The Cr rho_a value, also called Dijkstra-Henseler's, is used to measure the consistency of reliability between conbarch alpha rho_c by taking into account the contribution of each indicator so that it is more accurate than CA with a value ≥ 0.7, reliability is considered good[28].

Based on Table 3, the AVE value is used to describe how much of the indicator variance is explained by the construct compared to the error. AVE is calculated from the average outer loading of the indicators on the construct[29]. The resulting value is between 0.6 and 0.9, indicating the construct is considered valid.

3.3 Inner Model Testing

Inner model testing is used to assess the relationship between exogenous and endogenous latent variables[30], as seen in the path coefficient for the relationship between constructs. R2 is evaluated to calculate the extent of variability in endogenous variables that can explain the exogenous variables. F2 is used to explain the influence of certain independent latent variable values on the dependent latent variable to assess the strength of the model developed to generalize and represent the influence of the factors studied. Q2 predictive relevance serves to validate the model's predictive ability.

This testing is conducted using a bootstrapping test with a resampling method (re-sampling with replacement) to test the hypothesis/statistical significance. The test displays the path confidence value, t-statistic, p-value, original sample (O), sample mean (M), and standard deviation. The results will determine whether the relationship between variables, outer loadings, and indicators is significant. The results will then yield a p-value, indicating whether the hypothesis from exogenous to endogenous indicators can be accepted or rejected. The results of the bootstrapping test are shown in Table 3.

Table 3. Hypothesis Testing with Boothstraping

	Hypothesis	**Original Sample (O)**	**Sample Mean (M)**	**Standar Deviation (STDEV)**	**T-Statistic**	**P-Value**	**Inforamtion**
H1	AE -> FC	0,27916667	0,27777778	0.073	5.481	0.000	Hypothesis Accepted
H2	AI -> FC	0,14513889	0,14652778	0.063	3.319	0.001	Hypothesis Accepted

H3	DP -> PEOU	0,518055 56	0,519444 44	0.038	19.544	0.000	Hypothesis Accepted
H4	FC -> INT	0,142361 11	0,140277 78	0.068	3.011	0.003	Hypothesis Accepted
H5	IQ -> INT	-0.003	-0.002	0.056	0.055	0,6638 8889	Hypothesis Rejected
H6	PB -> INT	0.049	0.051	0.038	1.282	0,1388 8889	Hypothesis Rejected
H7	PE -> INT	0.072	0.074	0.052	1.395	0,1131 9444	Hypothesis Rejected
H8	PEOU -> INT	0.157	0.157	0.057	2.761	0.006	Hypothesis Accepted
H9	PEOU -> PU	0,595833 33	0,596527 78	0.019	44.367	0.000	Hypothesis Accepted
H10	PR -> INT	0.064	0.065	0.028	2.283	0.022	Hypothesis Accepted
H11	PU -> INT	0.104	0.103	0.052	2.025	0.043	Hypothesis Accepted
H12	SC -> PR	0,127777 78	0,129861 11	0.043	4.298	0.000	Hypothesis Accepted
H13	SI -> INT	0,084722 22	0,0875	0.049	2.512	0.012	Hypothesis Accepted
H14	SQ -> INT	0,188888 89	0,184027 78	0.071	3.813	0.000	Hypothesis Accepted
H15	TR -> INT	0,200694 44	0,200694 44	0.058	4.977	0.000	Hypothesis Accepted
H16	VP -> FC	0,190277 78	0,190277 78	0.060	4.565	0.000	Hypothesis Accepted

The study uses a 95% confidence level or p value <0.05, so all relationships between variables have an effect (t statistic ≥ 1.968) and are significant for the significance level of p <0.05 so that based on table 4 it is known that there are 13 accepted hypotheses and 3 rejected hypotheses. The rejected hypothesis is H5 The Effect of Information Quality on Intention to Use ETourism Technology, this indicates that even though the information presented is accurate, complete, and relevant, tourists have not made it a major factor in determining the use of e-tourism technology. Possibly, users are more influenced by other factors such as ease of use or social recommendations. then H6 The Effect of Perceived Benefits on Intention to Use ETourism Technology, Hypothesis testing shows that perceived benefits do not have a significant effect on the intention to use e-tourism technology in the sense that users are aware of potential benefits such as time efficiency or improved travel experience, this factor is not strong enough to encourage them to use technology-based services. Finally, H7 The Effect of Performance Expectations on Intention to Use ETourism Technology, this is possible because respondents emphasize aspects of direct experience or emotional factors more than rational expectations of performance. The following is an analysis of the Inner Model

Table 4. Inner Model Evaluation

No	**Construct**	**Value**	**Information**
1	R^2 Value	0.703	Substansial
2	f^2 Value	All variable >0.225	Strong
3	SRMR	0.084	Good Model

The results of the structural model evaluation showed that the coefficient of determination (R^2) was 0.703, which is categorized as substantial (Hair et al., 2019). This indicates that the independent dvariables in the model are able to explain 70.3% of the variation in the dependent variable, thus the model has strong predictive power. Furthermore, the results of the effect size (f^2) analysis showed that all variables had an f^2 value > 0.225, which is categorized as a strong effect (Cohen, 1988). This finding confirms that each independent variable makes a strong contribution to the dependent variable. In addition, the SRMR value = 0.084 is below the 0.10 limit, so it can be concluded that the model has an adequate level of fit (good model fit). Thus, the structural model estimated in this study can be said to be feasible and has good validity in explaining the relationship between the variables tested.

3.4 RQ1: Platform Design and AI Technology as Key Determinants of Intention to Use

The results of the SEM–PLS analysis indicate that the Platform Design (DP) construct has the strongest influence on the intention to use the JELAMBU platform compared to other constructs. This finding confirms that in the context of an AI-based digital visualization platform for marine tourism, the quality of interface design, visual layout, and ease of navigation are the main factors determining user acceptance. A high path coefficient value in the DP indicates that users are more motivated to adopt the technology when the platform is able to provide an attractive and easy-to-use visual experience.

From the perspective of the Technology–Website Acceptance Model (T-WAM) and the Extended Technology Acceptance Model (ETAM), the dominant influence of platform design reinforces the role of aesthetic emotion as a crucial mediator between technology and usage intention. Marine tourism relies heavily on visual appeal and perceived experience, so aesthetic elements serve not only as complements but also as core components in shaping user attitudes toward the system. This explains why Aesthetic Emotion (AE) and Visualization Performance (VP) also demonstrated a significant influence on usage intention.

In addition to visual design, the constructs of AI Technology (AI) and Facilitating Conditions (FC) also contributed significantly to usage intention. These findings indicate that users not only pay attention to system appearance but also assess the extent to which AI technology provides responsive, relevant interactions, and supports their travel information needs. In the context of JELAMBU, the presence of AI-based chatbots, real-time sentiment analysis, and public data integration are perceived as features that enhance the destination exploration experience.

From a systems engineering perspective, the results of RQ1 provide clear design implications. The development of AI-based digital visualization platforms should prioritize user-centered interface design, dynamic and contextual visualizations, and adaptive AI integration, rather than simply informative. AI features should be designed to enhance the user's visual and emotional experience, for example through preference-based visual recommendations, natural chatbot interactions, and easy-to-understand graphical presentations.

Overall, the findings of RQ1 confirm that the successful adoption of AI-based tourism platforms is not determined by technological sophistication alone, but rather by how that technology translates into visual design and user experience. This suggests that, in the context of marine tourism, platform design and AI technology should be viewed as a mutually reinforcing entity in shaping user intentions.

3.5 RQ2: Technology Acceptance in Hybrid Model

SEM–PLS test results indicate that several constructs in the hybrid model—namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Social Influence (SI), Service Quality (SQ), Trust (TR), and Perceived Risk (PR)—have a significant influence on intention to use the JELAMBU platform. This finding confirms the relevance of UTAUT2 and the DeLone–McLean IS Success Model in explaining the acceptance of AI-based technology in the digital tourism context.

From a UTAUT2 perspective, the significant influence of PEOU and PU indicates that ease of use and functional usefulness remain fundamental factors in technology adoption. However, in the context of AI-based digital visualization platforms, these two factors act as enablers, not primary determinants. This means that users expect an easy and useful system as a minimum prerequisite, while usage decisions are more influenced by the visual experience and platform design, as demonstrated in RQ1.

The Social Influence (SI) construct also demonstrated a significant influence on usage intention, indicating that recommendations from social circles, online reviews, and technology usage trends play a significant role in driving the adoption of digital tourism platforms. This aligns with the characteristics of travelers who are heavily influenced by public opinion and the experiences of other users, particularly on social media and digital platforms.

Within the McLean Model framework, the significance of Service Quality (SQ) and Trust (TR) underscores the importance of digital service quality and user trust in AI systems. Trust is crucial because the JELAMBU platform relies on data processing, automated interactions, and the integration of external sources. These findings suggest that the success of an AI platform depends not only on feature sophistication but also on perceived security, reliability, and service consistency.

Conversely, Perceived Risk (PR) showed a significant negative effect on usage intention, indicating that the higher the perceived risk—related to data security, information accuracy, or AI reliability—the lower the user's likelihood of adopting the system. This strengthens the argument that risk management and system transparency should be an integral part of AI platform design.

Interestingly, several constructs in the model did not show a significant effect, namely Information Quality (IQ), Perceived Benefits (PB), and Performance Expectancy (PE). This insignificant path can be explained by the context in which AI-based digital visualization platforms are used, where users no longer evaluate technology solely based on the completeness of information or expectations of technical performance. The available information is considered to meet minimum standards (baseline requirements), and therefore is no longer a differentiating factor in shaping usage intention. Instead, the visual experience, AI interaction, and platform design quality become more dominant elements in user decision-making.

Theoretically, the findings of RQ2 indicate that a hybrid model combining T-WAM, ETAM, UTAUT2, and McLean provides a more comprehensive understanding than using TAM or UTAUT2 separately. This model is able to capture the shift in user behavior from a utilitarian orientation to an experience-driven acceptance orientation, particularly on AI-based tourism platforms and digital visualizations.

4. **Conclusion**

This study developed an Artificial Intelligence-based Blue Tourism E-Tourism application which then analyzed the acceptance of technology by tourists by distributing questionnaires to tourists and obtaining questionnaire data of 467 respondents. Then the data was analyzed using SEM-PLS, based on the results of the structural model analysis with the PLS-SEM approach, several important findings were obtained. First, the R^2 value of 0.703 indicates that the model has substantial predictive ability, where the independent variables are able to explain 70.3% of the variation in the dependent variable. Second, all independent variables have an f^2 value above 0.225, which means they have a strong influence (strong effect) on the dependent variable. Third, the SRMR value of 0.084 indicates that the model has a good level of suitability so that it can be stated as a good model fit. Thus, this research model as a whole can be concluded as suitable for use and is able to explain the relationship between variables well.

Declaration of AI and AI assisted technologies in the writing process

During the preparation of this work the author(s) used [SCISPACE/ SERVICE] ex.ChatGPT in order to [Studi Literature Review]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication

Declaration of Competing Interest

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

Acknowledgements
Thank you to the Directorate of Research and Community Service (DPPM) of the Ministry of Education, Science and Technology and the University of Teknokrat Indonesia for the support provided to the fundamental research scheme.

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