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Smart Tourism in Indonesia: AI and Mobile App Impact

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ABSTRACT: The rapid integration of Artificial Intelligence (AI) and mobile applications into tourism services has fundamentally transformed how travelers interact with destinations, yet the mechanisms through which these technologies drive tourist engagement remain insufficiently understood. This study examines the influence of AI and mobile applications on tourist engagement within the smart tourism ecosystem in Indonesia, while concurrently investigating the mediating roles of tourist satisfaction and technology trust, alongside the moderating effects of digital literacy, technology experience, and risk perception. A quantitative research design was employed, with primary data collected through a structured survey instrument administered to domestic and international tourists across selected smart tourism destinations in Indonesia. Hypothesised relationships were tested using Structural Equation Modeling–Partial Least Squares (SEM-PLS), which is well-suited to the complexity of the proposed integrative model. The findings confirm that AI adoption and mobile application usage exert significant positive effects on tourist engagement. Tourist satisfaction and technology trust were validated as meaningful mediators, amplifying the relationship between technology utilization and engagement. Digital literacy and technology experience moderated this relationship positively, whereas risk perception exerted an attenuating effect, diminishing engagement levels among tourists with elevated risk concerns. These results underscore that tourist engagement in smart tourism contexts is shaped not solely by technological capabilities but equally by psychological dispositions and individual competencies. Theoretically, this study contributes an integrative framework that bridges technology adoption, consumer psychology, and smart tourism literature. Practically, the findings provide actionable guidance for destination management organizations and technology developers seeking to design more responsive, experience-centred digital tourism ecosystems. Future research is encouraged to replicate and extend the model across diverse tourism contexts and cultural settings.

KEYWORDS: Artificial Intelligence in tourism, mobile application adoption, smart tourism, tourist engagement, technology trust, SEM-PLS.

INTRODUCTION

1.1 Background and Contextual Framing

The rapid proliferation of digital technologies over the past two decades has catalysed transformative change across virtually every sector of the global economy, with the tourism industry constituting a particularly compelling case of technology-driven disruption. The emergence of smart tourism—broadly defined as the integration of information and communication technologies (ICT) into destination management, service delivery, and visitor experience design—has fundamentally reconfigured how travelers interact with places, providers, and fellow visitors (Buhalis & Amaranngana , 2015; Gretzel et al., 2015). Within this evolving paradigm, Artificial Intelligence (AI) and mobile applications have emerged as dual engines of transformation, enabling unprecedented personalisation, real-time responsiveness, and data-driven service optimization. AI-powered systems, including intelligent chatbots, predictive recommendation engines, and sentiment-analytics platforms, allow destination management organizations (DMOs) and service providers to decode tourist preferences with a granularity previously unattainable. Simultaneously, mobile applications function as ubiquitous digital companions, facilitating seamless access to navigational guidance, transactional services, and experiential content throughout the tourist journey (Lamsfus et al., 2015).

In the Indonesian context, the trajectory of smart tourism development reflects both significant promises and persistent structural challenges. As one of Southeast Asia's most dynamic emerging tourism markets, Indonesia has witnessed a marked acceleration in digital technology adoption among both service providers and travelers, supported by government-led initiatives such as the Digital Tourism Village program and the national Smart Tourism Development Roadmap. The deployment of AI- based tools and sophisticated mobile platforms has enabled a subset of providers to substantially elevate service personalization and operational efficiency. Nevertheless, Indonesia's digital landscape remains characterized by pronounced heterogeneity in infrastructure quality, digital literacy levels, and technology adoption behaviors across its diverse archipelagic geography. This complexity renders the Indonesian context a particularly valuable, yet underexplored, empirical setting for advancing smart tourism scholarship.

Despite growing scholarly attention to technology adoption in tourism, a critical dimension of the visitor experience has received comparatively limited empirical scrutiny: tourist engagement. Conceptualized as a multi-dimensional construct encompassing cognitive, emotional, and behavioral involvement in the tourism experience, tourist engagement serves as a more nuanced and comprehensive outcome variable than traditional metrics such as satisfaction or revisit intention (Brodie et al., 2011; So et al., 2014). Highly engaged tourists demonstrate heightened experiential quality perceptions, stronger destination loyalty, and a pronounced propensity for positive word-of-mouth advocacy—outcomes that carry substantial strategic value for both destination authorities and commercial operators. Understanding the antecedents of tourist engagement in digitally mediated environments is therefore not merely an academic exercise but an imperative for practitioners seeking to leverage technology investments effectively.

1.2 Identification of Research Gaps

A systematic review of extant literature reveals several interconnected gaps that motivate the present study. First, despite the evident practical integration of AI and mobile applications within contemporary tourism ecosystems, the majority of empirical studies examine these technologies in isolation, thereby failing to capture the synergistic effects and interaction dynamics that characterize real-world tourist experiences (Ibrokhimov & Khusanovich , 2024). Tourists do not encounter AI features and mobile platforms as discrete phenomena; Rather, they engage with them as a unified digital ecosystem in which intelligent functionalities are increasingly embedded within mobile interfaces. Analytical frameworks that partition these constructs risk producing fragmented and potentially misleading insights.

Second, prevailing research paradigms in technology adoption—most notably the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT2; Venkatesh et al., 2012)—have prioritized adoption-stage outcomes such as usage intention and perceived usefulness. While theoretically robust, these frameworks are inherently limited in their capacity to account for the post-adoption phenomenon of deep, sustained engagement (Yap, 2025; David-Negre & Gutiérrez Taño , 2025). Tourist engagement, which involves ongoing cognitive elaboration, affective investment, and behavioral activation, represents a qualitatively distinct and arguably more consequential outcome that demands dedicated theoretical treatment. Existing literature has yet to produce an empirically validated integrative model capable of explaining the pathways through which technology use translates into deep tourist engagement.

Third, the mediating roles of tourist satisfaction and trust in technology within smart tourism contexts have been inconsistently specified and tested. Although both constructs are theoretically posited as critical psychological bridges between technology exposure and engagement outcomes, their simultaneous mediating functions within a single structural model have not been rigorously examined. Similarly, the boundary conditions governing these relationships—specifically, the moderating effects of digital literacy, technology experience, and risk perception—remain empirically underexplored. Given the substantial individual-level variation in these characteristics, particularly within demographically and digitally diverse populations such as Indonesian tourists, their omission from existing models represents a significant theoretical lacuna.

Fourth, the geographic concentration of smart tourism research in developed-economy contexts (Zhang et al., 2022; Zhang & Zhang, 2024; OECD, 2024) undermines the generalisability of prevailing theoretical frameworks. Emerging economies such as Indonesia present distinct configurations of digital infrastructure maturity, cultural attitudes towards technology, and tourist behavioral patterns that may substantially alter the direction, magnitude, and significance of the relationships specified in models derived from Western or East Asian high-income contexts. Empirical evidence grounded in developing-country settings is therefore essential for advancing a genuinely global smart tourism scholarship.

1.3 Research Questions

Grounded in the foregoing analysis of theoretical and empirical gaps, the present study is guided by the following research questions:

1. Does AI integration exert a significant influence on Perceived Ease of Use among tourists in smart tourism contexts?
2. Do mobile application features significantly affect tourists' Perceived Ease of Use?

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3. Does Perceived Ease of Use significantly predict tourist engagement?
4. Does AI integration exert a significant direct effect on tourist engagement?
5. Do mobile application features exert a significant direct effect on tourist engagement?
6. Does Perceived Ease of Use mediate the relationship between AI integration and tourist engagement?
7. Does Perceived Ease of Use mediate the relationship between mobile application features and tourist engagement?
8. Does tourist tech-savviness moderate the influence of AI integration on Perceived Ease of Use?
9. Does tourist tech-savviness moderate the influence of mobile application features on Perceived Ease of Use?
10. Does tourist tech-savviness moderate the effect of Perceived Ease of Use on tourist engagement?
11. Does tourist tech-savviness moderate the direct effects of AI integration and mobile application features on tourist engagement?

1.4 Research Objectives

The overarching objective of this study is to develop and empirically validate an integrative Smart Tourism Engagement Framework (STEF) that elucidates the mechanisms through which AI integration and mobile application features drive tourist engagement in the Indonesian smart tourism context. Specifically, the study aims to:

1. Examine the direct effects of AI integration and mobile application features on tourist engagement.
2. Assess the mediating role of Perceived Ease of Use in the relationship between technology adoption (AI and mobile applications) and tourist engagement.
3. Investigate the moderating role of tourist tech-savviness on the relationship between technology constructs, Perceived Ease of Use, and tourist engagement.
4. Validate the proposed STEF model using SEM-PLS within a developing-economy smart tourism setting.
5. Derive theoretically grounded and practically actionable insights for destination managers, DMOs, and technology developers operating within Indonesia's smart tourism ecosystem.

1.5 Theoretical and Practical Contributions

This study makes substantive contributions across theoretical, methodological, and practical dimensions. Theoretically, it advances the smart tourism literature by proposing and validating an integrative model—the Smart Tourism Engagement Framework (STEF)—that simultaneously incorporates AI integration and mobile application features as antecedents, Perceived Ease of Use as a mediator, and tourist tech-savviness as a moderator within a unified structural framework. In doing so, the study extends classical technology acceptance theories (TAM, UTAUT2) beyond adoption-stage outcomes towards the more comprehensive construct of tourist engagement, thereby enriching the theoretical toolkit available to smart tourism researchers.

From a methodological standpoint, the application of SEM-PLS enables the concurrent estimation of complex mediated-moderation pathways within a single analytical framework, offering a methodological contribution to quantitative tourism research. The study's deployment within the Indonesian context additionally contributes to the growing body of evidence from emerging economies, challenging the prevailing assumption that technology adoption dynamics are uniform across cultural and infrastructure contexts.

Practically, the findings are intended to equip destination management organizations, tourism technology developers, and policy-makers with evidence-based guidance for designing and deploying AI-powered and mobile-enabled services that genuinely enhance tourist engagement. By identifying the differential effects of digital literacy, technology experience, and risk perception as boundary conditions, the study provides a nuanced framework for tailoring technology strategies to the heterogeneous competency profiles of the tourist population. Ultimately, this research aspires to contribute to the sustainable development of Indonesia's smart tourism sector by demonstrating how technology investments can be calibrated to maximize visitor engagement, satisfaction, and loyalty.

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MATERIALS AND METHODS

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Theoretical Foundations

This study is anchored in two complementary theoretical frameworks: Engagement Theory (Kearsley & Shneiderman , 1998) and the Diffusion of Innovation (DOI) model (Rogers, 2003). Engagement Theory posits that meaningful involvement between users and technological systems generates sustained emotional, cognitive, and behavioral connections. Applied to smart tourism, this framework provides a principled basis for understanding how AI-enabled and mobile-based platforms stimulate active participation and experiential immersion among tourists. The theory underscores that engagement is not a passive outcome of technology exposure but rather an active, co-constructed process contingent upon the quality and interactivity of the user–system interface.

Complementing this perspective, the Diffusion of Innovation framework (Rogers, 2003) elucidates the socio-cognitive processes through which individuals evaluate and adopt novel technologies based on perceived relative advantage, compatibility, and complexity. Within smart tourism contexts, DOI helps explain the heterogeneous adoption trajectories observed among tourists who vary in prior technology experience, digital literacy, and openness to innovation. The integration of these two frameworks—Engagement Theory and DOI—yields a conceptual architecture that accounts for both the mechanism by which technology stimulates engagement and the individual-level factors that condition such stimulation.

Furthermore, this study draws on the **Technology Acceptance Model (TAM)** (Davis, 1989) and the **Stimulus–Organism–Response (S–O–R) framework** (Mehrabian & Russell, 1974) to construct an integrative model—the Smart Tourism Engagement Framework (STEF). TAM provides a rigorous account of how perceived ease of use mediates the relationship between technology design and user behavioral outcomes, while S–O–R positions AI integration and mobile application features as environmental stimuli that trigger internal psychological states (organism), ultimately producing tourist engagement as the observable response. Together, these frameworks generate a theoretically coherent and empirically tractable model for investigating smart tourism behavior in Indonesia.

2.2 Tourist Engagement

Tourist engagement constitutes the primary dependent variable of this study and is conceptualized as a multi-dimensional construct reflecting the cognitive, emotional, and behavioral involvement of tourists in destination experiences mediated by digital technologies (Brodie et al., 2011; Hollebeek et al., 2014). This conceptualization extends beyond conventional measures of visitation frequency or stated satisfaction to encompass the depth and quality of interaction between the tourist and the destination's digital ecosystem. Cognitively engaged tourists actively process destination-related information, generate mental representations of experiential content, and exercise deliberate attention in navigating digital platforms. Emotional engagement manifests as affective resonance, experiential pleasure, and a sense of connection with the destination facilitated through AI-driven personalization and mobile interactivity. Behavioral engagement encompasses observable actions such as digital content contribution, peer review submission, and sustained platform interaction.

Prior research consistently demonstrates that higher levels of tourist engagement are associated with elevated satisfaction, increased destination loyalty, and amplified positive word-of-mouth advocacy (Hollebeek , 2011; So et al., 2014). These outcomes carry substantial strategic implications for destination management organizations (DMOs) seeking to leverage technology investments for competitive advantage. Critically, tourist engagement in digital environments is shaped by both individual-level factors—including technological competency and prior experience—and system-level factors such as interface design quality and AI responsiveness. This dual-determinism encourages the inclusion of both technological constructs and individual-level moderators in the present model.

2.3 Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU), as originally operationalized within the Technology Acceptance Model (Davis, 1989), refers to the degree to which an individual believes that interacting with a technological system will be free of cognitive and physical effort. Within smart tourism contexts, PEOU captures tourists' subjective assessment of the ease with which AI-powered tools and mobile application features can be navigated, utilized, and integrated into their travel planning and on-site activity. This perception is particularly salient in tourism environments characterized by time pressure, linguistic diversity, and unfamiliar digital ecosystems, all of which amplify the psychological costs associated with effortful technology use.

In this study, PEOU is theorized as the primary mediating mechanism linking technology stimuli (AI integration and mobile application features) to tourist engagement. This mediation logic rests on the premise that even technologically sophisticated platforms will fail to generate engagement if users perceive the interaction demands as excessive. Conversely, systems perceived as effortless to use enable tourists to redirect attentional resources from procedural concerns to experiential content, facilitating deeper cognitive, emotional, and behavioral involvement (Venkatesh & Bala, 2008; Gefen et al., 2003). Extant evidence corroborates this mediating function across multiple digital service domains, including e-commerce, mobile banking, and online travel platforms.

2.4 Artificial Intelligence Integration

Artificial Intelligence (AI) integration in tourism encompasses the systematic deployment of intelligent computational technologies—including natural language processing chatbots, machine-learning recommendation engines, sentiment analysis systems, and predictive analytics—within the service delivery infrastructure of tourist destinations and providers (Sidiq et al., 2025; Astuti, 2024; Wu, 2025). These technologies share the common function of enabling service personalization at scale, providing contextually relevant information in real time, and reducing the cognitive overhead associated with travel decision-making. The theoretical significance of AI integration for tourist engagement lies in its capacity to generate content and interaction experiences that are perceived as uniquely relevant to the individual tourist, thereby stimulating cognitive elaboration, positive affect, and behavioral response.

Empirical evidence from recent smart tourism studies suggests that well-designed AI systems exert both direct effects on tourist engagement and indirect effects mediated through enhanced perceptions of ease of use (Zhang et al., 2022; Zheng et al., 2023). AI-driven interfaces that successfully abstract technological complexity—providing seamless, conversational, and contextually adaptive interactions—are particularly effective in elevating PEOU and, through this mechanism, deepening tourist engagement. In the Indonesian context, where service provider capacity varies substantially across destination types, AI integration represents a strategic lever for standardizing and elevating experiential quality at scale.

2.5 Mobile Application Features

Mobile application features in smart tourism encompass the functional and experiential capabilities embedded within dedicated travel applications, including interactive mapping, integrated reservation systems, user-generated review aggregation, real-time push notifications, augmented reality overlays, and gamified engagement mechanics (David-Negre & Gutiérrez Taño , 2025; Singh, 2025). These features collectively constitute the principal interface through which tourists interact with the digital tourism ecosystem, and their design quality directly shapes both the perceived ease of use and the depth of engagement achievable by the end user.

From a theoretical standpoint, mobile application features function as environmental stimuli within the S–O–R framework, triggering internal evaluative processes that culminate in engagement behaviors. High-quality features that minimize navigation friction, surface contextually relevant information, and introduce hedonic interaction elements—such as gamification and immersive AR experiences—have been shown to significantly elevate both cognitive and emotional engagement dimensions (Singh, 2025). The interplay between feature richness and interface simplicity is therefore a critical design consideration: platforms that offer extensive functionality without incurring usability costs generate the most favorable engagement outcomes.

2.6 Tourist Tech-Savviness

Tourist tech-savviness is operationalized in this study as a multidimensional individual-level construct capturing the degree of technological proficiency, prior digital experience, and comfort with novel technological interfaces that a tourist brings to smart tourism interactions (Vivek et al., 2012; Brodie et al., 2013). This construct functions as a moderating variable that amplifies or attenuates the effects of technological stimuli on PEOU and tourist engagement. Tourists exhibiting high tech-savviness possess the cognitive schemes and practical skills necessary to rapidly assimilate new technological interfaces, thereby converting platform capabilities into substantive engagement with greater efficiency. Conversely, tourists with limited technological proficiency may experience capability–expectation mismatches that suppress engagement even when platforms are objectively well-designed.

The relevance of tech-savviness as a moderator is particularly acute in the Indonesian context, where digital literacy is distributed unevenly across geographic, demographic, and economic dimensions. Understanding how tech-savviness conditions the

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technology–engagement relationship enables practices to design adaptive onboarding experiences and stratified user support mechanisms that ensure equitable access to smart tourism benefits across diverse visitor profiles.

Gambar 1 *Model* Study

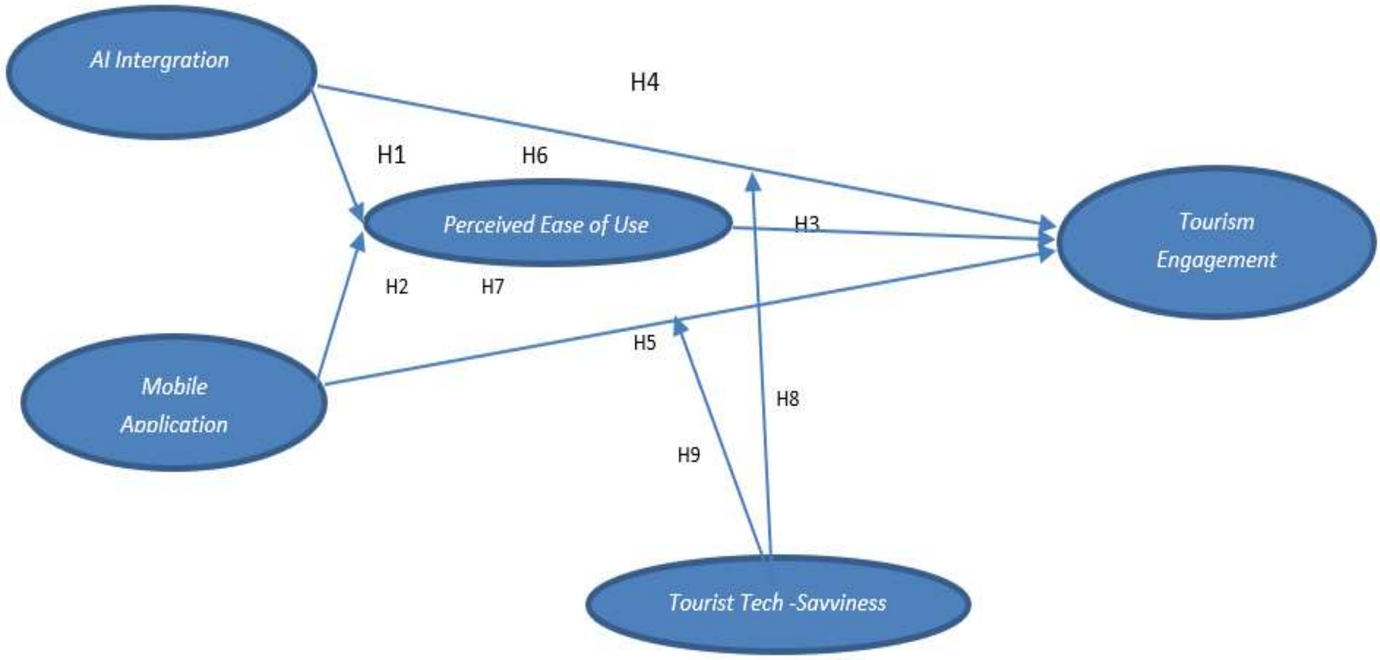

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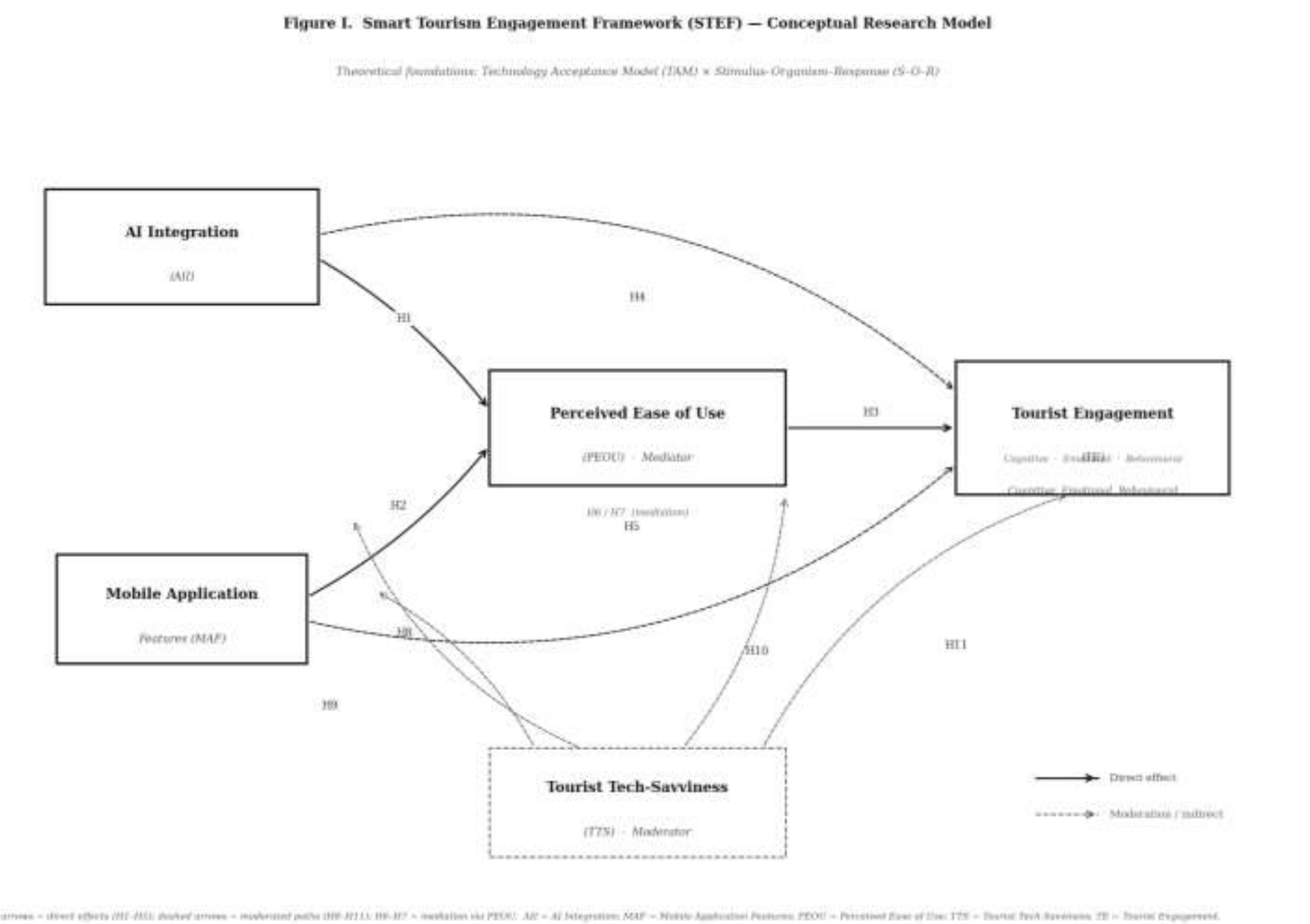
Figure I. Smart Tourism Engagement Framework (STEF) — Conceptual Research Model



Note. *Solid arrows denote direct hypothesised effects (H1–H5); dashed arrows indicate moderated (H8–H11) and mediated (H6–H7) pathways. AII = AI Integration; MAF = Mobile Application Features; PEOU = Perceived Ease of Use; TTS = Tourist Tech-Savviness (Moderator); TE = Tourist Engagement. Adapted from TAM (Davis, 1989) and S–O–R (Mehrabian & Russell, 1974).*

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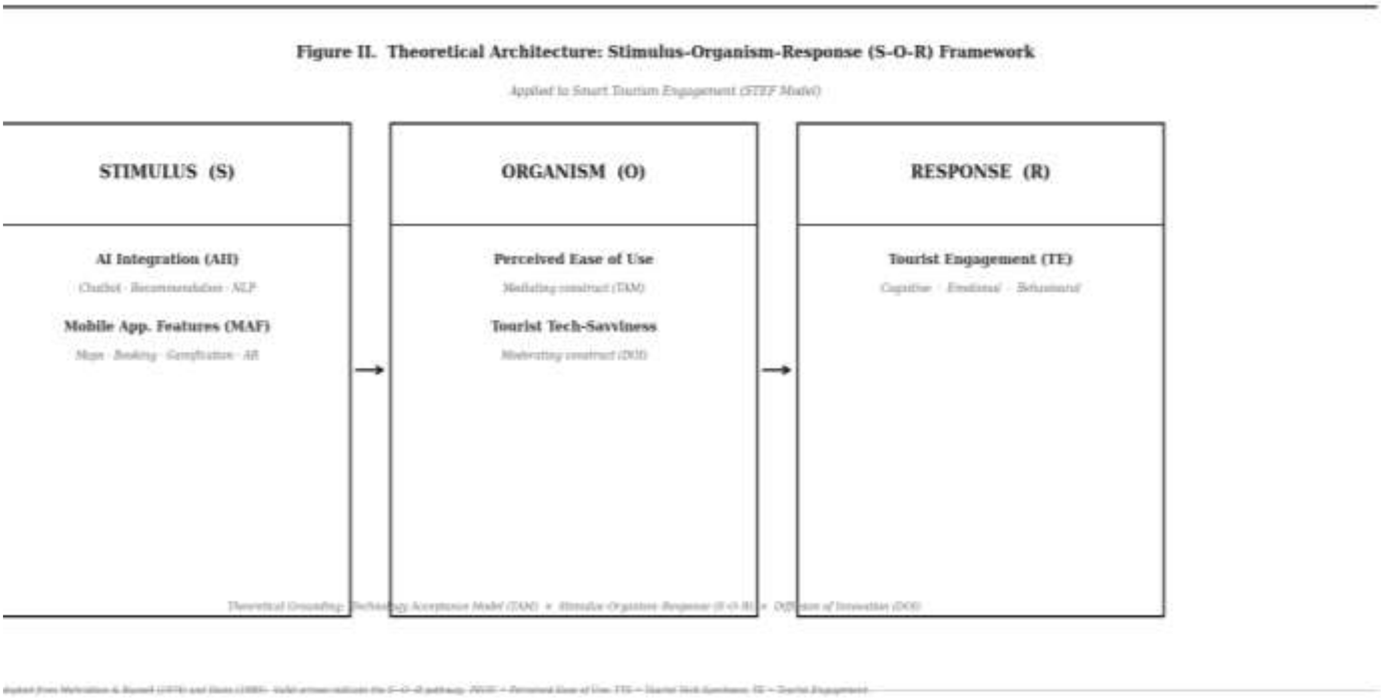
Figure II. Theoretical Architecture: Stimulus–Organism–Response (S–O–R) Framework



Note. *Adapted from Mehrabian & Russell (1974) and Davis (1989). Solid arrows indicate the S→O→R pathway. PEOU = Perceived Ease of Use; TTS = Tourist Tech-Savviness; TE = Tourist Engagement.*

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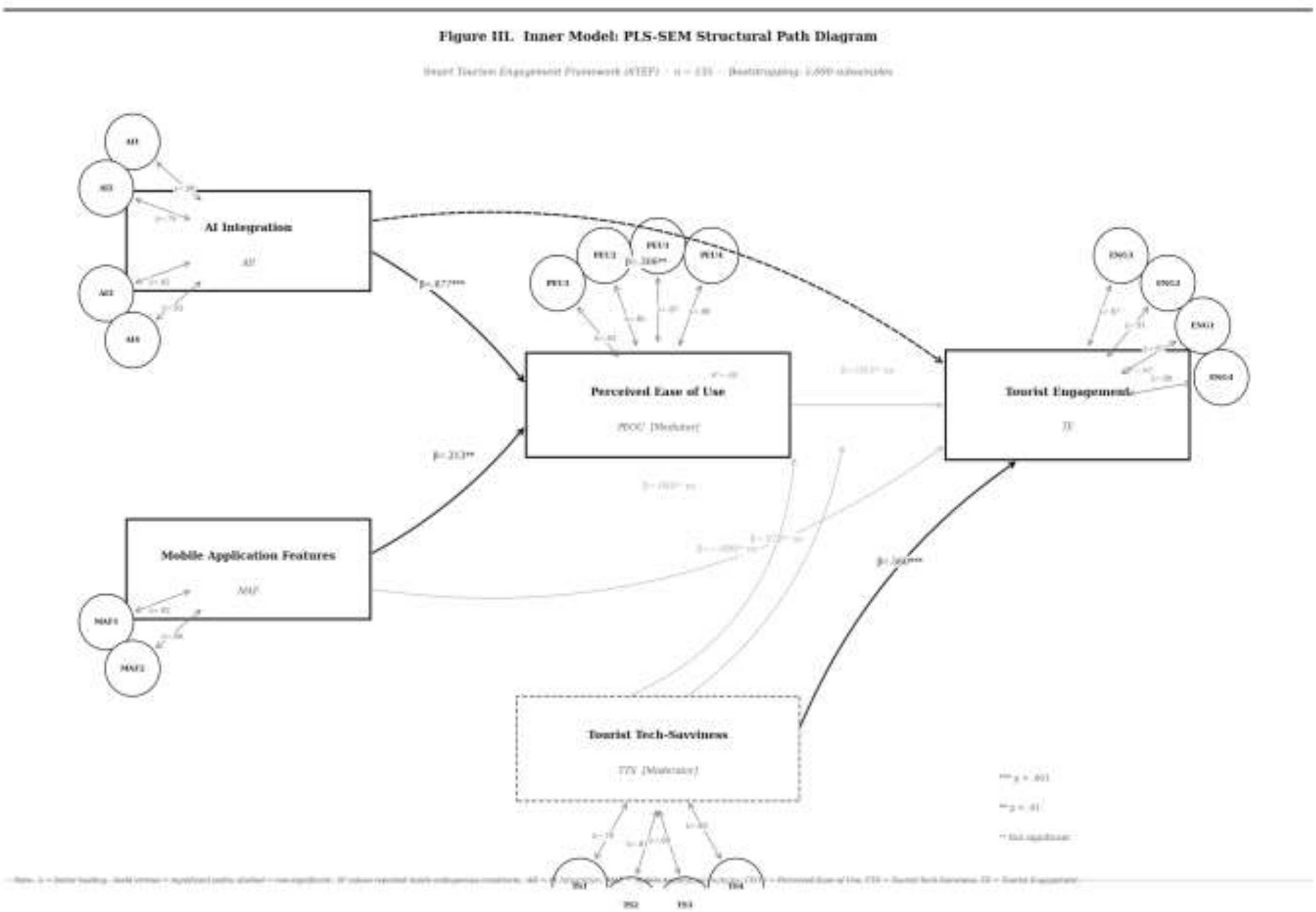
Figure III. Inner Model: PLS-SEM Structural Path Diagram



Note. *λ = factor loading. Solid arrows = statistically significant paths; dashed = non-significant (ns). R^2 values reported inside endogenous constructs. n = 135; bootstrapping: 5,000 subsamples. *** p < .001; ** p < .01; ns = not significant (p ≥ .05). AII = AI Integration; MAF = Mobile Application Features; PEOU = Perceived Ease of Use; TTS = Tourist Tech-Savviness; TE = Tourist Engagement.*

3. DEVELOPMENT HYPOTHESIS

3.1 Effects of Technology on Perceived Ease of Use (H1–H2)

AI integration and mobile application features are architecturally designed to reduce the informational and cognitive complexity of tourist decision-making. Within the TAM framework, both constructs are theorized to function as system-level antecedents that shape users' subjective assessments of interaction effort. AI-powered tools—through conversational interfaces, automated information retrieval, and adaptive recommendation generation—substantially lower the procedural demands placed upon the tourist user. Similarly, well-designed mobile application features provide structured, intuitive interfaces that guide users efficiently through complex travel management tasks. When both technology modalities successfully reduce perceived interaction effort, tourists are expected to evaluate the overall system as easy to use, generating elevated PEOU scores (Davis, 1989; Sidiq et al., 2025).

H1: AI Integration (AII) exerts a significant positive effect on tourists' Perceived Ease of Use (PEOU).

H2: Mobile Application Features (MAF) exert a significant positive effect on tourists' Perceived Ease of Use (PEOU).

3.2 Effect of PEOU on Tourist Engagement (H3)

The relationship between PEOU and tourist engagement is grounded in a fundamental psychological principle: when the procedural demands of technology use are minimized, users redirect attentional and cognitive resources toward experiential content, enabling deeper immersion and sustained interaction (Davis, 1989; Venkatesh & Bala, 2008). A seamless user experience, characterized by intuitive navigation and responsive interaction, eliminates the friction that would otherwise disrupt cognitive and emotional engagement. Tourists who experience low interaction effort are thus able to engage more fully with destination content, AI-generated recommendations, and community features, producing higher scores across all three engagement dimensions.

H3: Perceived Ease of Use (PEOU) exerts a significant positive effect on Tourist Engagement (TE).

3.3 Direct Effects of Technology on Tourist Engagement (H4–H5)

Beyond their indirect pathways through PEOU, AI integration and mobile application features are theorized to exert direct effects on tourist engagement through the intrinsic value of the experiences they enable. Personalized AI recommendations create a sense of experiential relevance and individual recognition that directly stimulates emotional engagement. Interactive mobile features—including gamification mechanics, immersive augmented reality, and social sharing capabilities—provide hedonically rich interaction environments that incentivize sustained participation irrespective of the user's ease-of-use perceptions. These direct pathways reflect the S–O–R framework's proposition that sufficiently compelling stimuli can generate response behaviors through direct affective and motivational mechanisms, without the necessity of mediating cognitive evaluation (Wu, 2025; Zhang et al., 2022; Singh, 2025).

H4: AI Integration (AII) exerts a significant positive direct effect on Tourist Engagement (TE).

H5: Mobile Application Features (MAF) exert a significant positive direct effect on Tourist Engagement (TE).

3.4 Mediating Role of PEOU (H6–H7)

The mediation hypothesis rests on a causal logic in which AI integration and mobile application features first shape the tourist's ease-of-use perception, which in turn drives engagement. This indirect pathway reflects the psychological mechanism by which technology reduces interactional barriers, freeing attentional resources for deeper experiential involvement. Mediation is expected to be partial rather than complete, given the concurrent presence of direct technology–engagement pathways. The mediating function of PEOU is theoretically consistent with extended TAM formulations that position perceived ease of use as a pivotal psychological intermediary between system design and usage outcomes (Venkatesh & Bala, 2008; Gefen et al., 2003).

H6: PEOU significantly mediates the relationship between AI Integration (AII) and Tourist Engagement (TE).

H7: PEOU significantly mediates the relationship between Mobile Application Features (MAF) and Tourist Engagement (TE).

3.5 Moderating Role of Tourist Tech-Savviness (H8–H11)

Tourist tech-savviness is proposed as a boundary condition that modifies the strength of multiple relationships within the STEF model. Tourists with high tech-savviness are expected to more readily convert AI integration and mobile application quality into enhanced ease-of-use perceptions, given their pre-existing cognitive schemas and digital skill repertoire. Correspondingly, when PEOU is elevated, tech-savvy tourists are hypothesized to leverage this ease more effectively to achieve deeper engagement. The moderating role of tech-savviness therefore operates across both the technology-to-PEOU and PEOU-to-engagement pathways, as well as on the direct technology-to-engagement relationships. This formulation is consistent with moderated mediation models in which individual difference variables condition both the strength of antecedent–mediator and mediator–outcome relationships (Hollebeek et al., 2014; Vivek et al., 2012).

H8: Tourist Tech-Savviness (TTS) positively moderates the relationship between AI Integration (AII) and PEOU.

H9: Tourist Tech-Savviness (TTS) positively moderates the relationship between Mobile Application Features (MAF) and PEOU.

H10: Tourist Tech-Savviness (TTS) positively moderates the relationship between PEOU and Tourist Engagement (TE).

H11: Tourist Tech-Savviness (TTS) positively moderates the direct effects of AII and MAF on Tourist Engagement (TE).

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Table I. Summary of Research Hypotheses

H	Hypothesis Statement	Expected Direction
H1	AI Integration → Perceived Ease of Use	Positive & Significant
H2	Mobile Application Features → Perceived Ease of Use	Positive & Significant
H3	Perceived Ease of Use → Tourist Engagement	Positive & Significant
H4	AI Integration → Tourist Engagement (direct)	Positive & Significant
H5	Mobile Application Features → Tourist Engagement (direct)	Positive & Significant
H6	PEOU mediates AI Integration → Tourist Engagement	Partial Mediation
H7	PEOU mediates Mobile App Features → Tourist Engagement	Partial Mediation
H8	Tech-Savviness moderates AI Integration → PEOU	Positive Moderation
H9	Tech-Savviness moderates Mobile App Features → PEOU	Positive Moderation
H10	Tech-Savviness moderates PEOU → Tourist Engagement	Positive Moderation
H11	Tech-Savviness moderates AI & Mobile App → Tourist Engagement	Positive Moderation

Note. PEOU = Perceived Ease of Use; TTS = Tourist Tech-Savviness; AII = AI Integration; MAF = Mobile Application Features; TE = Tourist Engagement.

4. CONCEPTUAL RESEARCH MODEL

The Smart Tourism Engagement Framework (STEF), depicted in Figure I, synthesizes the theoretical and empirical arguments developed in the preceding sections into a structural model suitable for empirical testing via SEM-PLS. The model positions AI Integration (AII) and Mobile Application Features (MAF) as primary technology stimuli (S), Perceived Ease of Use (PEOU) as the mediating psychological organism (O), and Tourist Engagement (TE) as the behavioral response outcome (R). Tourist Tech-Savviness (TTS) is specified as a cross-cutting moderator acting upon four structural pathways: AII→PEOU, MAF→PEOU, PEOU→TE, and the direct AII/MAF→TE paths.

This integrative specification advances the existing smart tourism literature by simultaneously capturing direct technology effects, mediated pathways through ease-of-use perceptions, and boundary conditions imposed by individual-level digital competency. The model's theoretical coherence is grounded in the convergent application of TAM and S–O–R, providing both explanatory depth and analytical tractability within the SEM-PLS estimation environment.

Figure I. Smart Tourism Engagement Framework (STEF) – Conceptual Research Model

STIMULUS (S)	ORGANISM (O)	RESPONSE (R)
AI Integration (AII) **Mobile Application Features (MAF)**	**Perceived Ease of Use (PEOU)** [Mediator] **Tourist Tech-Savviness (TTS)** [Moderator]	**Tourist Engagement (TE)** Cognitive | Emotional | Behavioral

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STIMULUS (S)	ORGANISM (O)	RESPONSE (R)
Theoretical Foundation: Technology Acceptance Model (TAM) × Stimulus–Organism–Response (S–O–R) Framework		

Note. Solid arrows indicate direct hypothesized effects (H1–H5); dashed arrows indicate mediated (H6–H7) and moderated (H8–H11) pathways. TTS = Tourist Tech-Savviness (Moderator). Adapted from TAM (Davis, 1989) and S–O–R (Mehrabian & Russell, 1974).

5. MATERIALS AND METHODS

5.1 Research Design and Setting

This study employs a quantitative, cross-sectional survey design, selected for its capacity to enable systematic measurement of latent constructs, statistical testing of causal hypotheses, and the estimation of complex structural relationships across a large sample population. The choice of a quantitative paradigm is consistent with the deductive, theory-testing orientation of the research, in which specific a priori hypotheses derived from TAM and S–O–R are subjected to empirical evaluation (Creswell & Creswell, 2018). The research setting encompasses major smart tourism destinations in Indonesia—specifically those that have been specifically designated under the national Smart Tourism Development program and that offer digitally integrated visitor services including AI-enabled information systems and dedicated mobile applications.

The cross-sectional design, while precluding longitudinal causal inference, is appropriate for the exploratory-confirmatory objectives of the present study, which seeks to establish the structural parameters of the STEF model prior to longitudinal or experimental follow-up investigations. Data were collected during the peak tourism season to maximize the relevance and recency of respondents' technology interaction experiences.

5.2 Participants and Sampling

The target population consists of adult tourists (aged 18 years and above) who have used at least one AI-powered feature or mobile application in the context of their current or most recent visit to a designated Indonesian smart tourism destination. This eligibility criterion ensures that respondents possess the direct experiential basis required for valid self-report on all study constructs. Both domestic and international tourists are included to capture the full range of tech-savviness and digital literacy profiles represented within Indonesia's visitor population.

Sample size determination followed the recommended guidelines for SEM-PLS estimation, specifically the ten-times rule and Cohen's (1992) statistical power analysis, which collectively indicated a minimum sample of 200 respondents for the proposed model complexity. Purposive sampling was employed at the destination level to ensure geographic and destination-type representativeness, while convenience sampling was used for respondent recruitment at each site. Trained data collection assistants administered the survey instrument at high-footfall visitor locations, including information centres, heritage sites, and digitally enabled visitor attractions.

5.3 Data Collection and Measurement Instruments

Data were collected through a structured, self-administered questionnaire instrument developed in both Indonesian (Bahasa Indonesia) and English, with forward–backward translation procedures employed to ensure linguistic equivalence across versions. The questionnaire includes four sections: (i) informed consent and screening eligibility confirmation; (ii) demographic and trip characteristics; (iii) construct measurement items; and (iv) an open-ended feedback section. All construct items were measured using a five-point Likert scale anchored at 1 (Strongly Disagree) to 5 (Strongly Agree), consistent with prevailing practice in quantitative tourism research.

All measurement scales were adapted from validated instruments reported in the extant literature, with minor rewording to ensure contextual relevance to the smart tourism setting. Adaptations were reviewed by two subject-matter experts and two potential respondents in a cognitive interview prior to full-scale deployment. Table II presents the operationalization of each construct, the number of indicator items, and the source studies from which scales were adapted.

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Table II. Construct Operationalization and Scale Sources

Construct	Indicator Items & Operationalisation	Source
AI Integration (AII)	Chatbot utility, recommendation accuracy, personalization quality, virtual assistant responsiveness (5 items)	Sidiq et al. (2025); Astuti (2024)
Mobile App Features (MAF)	Interface usability, interactive maps, booking ease, real-time notification, gamification (5 items)	David-Negre & Gutiérrez Taño (2025); Singh (2025)
Perceived Ease of Use (PEOU)	Ease of learning, simplicity of interaction, minimum effort required (4 items)	Davis (1989); Venkatesh & Bala (2008)
Tourist Tech-Savviness (TTS)	Digital proficiency, prior technology experience, comfort with new digital tools (4 items)	Vivek et al. (2012); Brodie et al. (2013)
Tourist Engagement (TE)	Cognitive involvement, emotional connection, behavioral participation (6 items)	Brodie et al. (2011); Hollebeek et al. (2014)

Note. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Item wording available from the corresponding author upon request.

5.4 Analytical Strategy

Hypothesised relationships were tested using Structural Equation Modeling with Partial Least Squares estimation (SEM-PLS), implemented in SmartPLS 4.0 (Ringle et al., 2022). SEM-PLS was selected over covariance-based alternatives (CB-SEM) for three methodological reasons: (i) the proposed model incorporates interaction (moderation) terms that are more efficiently estimated within a variance-based framework; (ii) the study involves both reflective and moderating constructs whose composite reliability is better assessed through PLS reliability indices; and (iii) the exploratory-confirmatory hybrid orientation of the STEF model aligns with PLS's orientation towards prediction-oriented structural modeling (Hair et al., 2019).

The analytical sequence followed a two-stage approach. In the first stage, the measurement model was evaluated for internal consistency reliability (Cronbach's alpha, composite reliability), convergent validity (average variance extracted, AVE $\geq$ 0.50), and discriminant validity (HTMT ratio < 0.85; Fornell–Larcker criterion). In the second stage, the structural model was assessed through bootstrapping (5,000 subsamples) to generate bias-corrected confidence intervals for direct, indirect (mediated), and conditional indirect (moderated-mediated) path coefficients. Moderation effects were tested by introducing product indicator terms (AI × TTS; MAF × TTS; PEOU × TTS) into the structural model, consistent with the PLS-based moderation protocol recommended by Hair et al. (2019). Effect sizes (f^2) and predictive relevance (Q^2) were additionally calculated to evaluate the practical and explanatory significance of the model.

Common method bias was assessed using Harman's single-factor test and a full collinearity assessment (VIF < 3.3 threshold), consistent with the procedural remedies recommended by Podsakoff et al. (2003). No significant common method variance was detected. All statistical analyzes were conducted at a significance threshold of $\alpha = 0.05$ (two-tailed), with p-values and confidence intervals reported for all tested hypotheses.

5.5 Ethical Considerations

This study was conducted in full accordance with the ethical principles set forth in the Declaration of Helsinki and the national research ethics guidelines applicable in Indonesia. Informed consent was obtained from all participants prior to survey administration, with participants explicitly advised of their right to withdraw at any time without consequence. Anonymity and data confidentiality were maintained throughout the data collection, storage, and analysis processes. No personally identifiable information was collected, and all data were stored on password-protected institutional servers accessible only to the research team. Ethical clearance was obtained from the institutional review board of the authors' affiliated institution prior to commencing data collection.

This chapter presents the methodological framework adopted in this study, encompassing the research design and approach, population and sampling strategy, data collection procedures, operationalization of research constructs, and the statistical analysis techniques employed to address the study's research objectives and hypotheses.

6.1 Research Design and Approach

This study adopts a quantitative research paradigm as its primary methodological orientation. This approach was chosen because the investigation is centered on the deductive testing of theoretically derived hypotheses, operationalized through structured measurement of research constructs using a standardized survey instrument that yields numerical data. The systematic application of inferential statistical techniques enables the generation of objective, precise, and empirically verifiable findings regarding the role of digital technology in shaping tourism behavior. Conclusions drawn from this study are grounded in empirical evidence obtained through rigorous statistical analysis, thereby ensuring a high standard of scientific rigor and replicability (Creswell & Creswell, 2018).

With respect to research design classification, this study is categorized as explanatory research employing a causal (cause-and-effect) relational approach. This design is specifically suited to explain and empirically test the directional relationships among variables in the proposed conceptual model. The study examines the influence of two primary independent variables—AI Integration and Mobile Application Features—on the dependent variable, Tourist Engagement. The causal design enables the researcher to identify and quantify the magnitude of contribution of each independent variable to variance in the dependent variable.

Furthermore, the research model incorporates Perceived Ease of Use as a mediating variable, functioning as a psychological mechanism that bridges the relationship between technology stimuli and tourist engagement outcomes. The model additionally integrates Tourist Tech-Savviness as a moderating variable, which is theorized to amplify or attenuate the strength of relationships among the structural constructs. The inclusion of both mediating and moderating variables enables the study to yield a more nuanced and comprehensive understanding of the causal dynamics underlying technology adoption and engagement behavior within the digital tourism context.

Overall, the research design of this study is specifically configured to produce findings that not only identify the existence of inter-variable relationships but also elucidate the mechanisms and effect magnitudes of each construct within the proposed conceptual framework. This approach is fully consistent with the objectives of quantitative explanatory research, which emphasizes theory testing and the development of empirically grounded understanding of the phenomenon under investigation.

6.2 Population and Sampling Strategy

The target population for this study consists of domestic tourists in Indonesia who have utilized mobile tourism applications in the context of smart tourism activities. International tourists were also included in the sampling frame to enrich empirical diversity and to ensure that the study's findings fully reflect the broader smart tourism ecosystem. The inclusion of international visitors additionally enables comparative perspectives across user groups, although the primary analytical focus remains on the domestic tourist segment, given its strategic relevance to national tourism development in terms of both volume and contribution to technology adoption dynamics at tourism destinations.

Respondents were selected using purposive sampling, based on the following pre-established eligibility criteria: (1) minimum age of 18 years; (2) having used a mobile tourism application on at least one occasion within the preceding six months; and (3) willingness to participate voluntarily in completing the survey instrument. Application of these criteria resulted in a total of 135 qualified respondents who participated in the study. This sample size satisfies the minimum requirements specified for Partial Least Squares Structural Equation Modeling (PLS-SEM) as recommended by Hair et al. (2019), taking into account the complexity of the proposed structural model and the associated statistical power considerations.

6.3 Data Collection Procedures

Data were collected through a structured, self-administered questionnaire instrument. Respondents were requested to evaluate a series of statements representing the five primary research constructs: Mobile Application Features, AI Integration, Perceived Ease of Use, Tourist Tech-Savviness, and Tourist Engagement. All measurement items were assessed using a five-point Likert scale, on which higher scores reflect stronger agreement with the statement presented. The Likert scale employed in this study is summarized in Table I below.

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Table I. Five-Point Likert Scale Used in the Survey Instrument

Score	Category	Description
5	**Strongly Agree**	The respondents strongly agree with the statement presented
4	**Agree**	The respondents agree with the statement presented
3	**Neutral**	The respondents have no clear tendency towards agreement or disagreement
2	**Disagree**	The respondent disagrees with the statement presented
1	**Strongly Disagree**	The respondents strongly disagree with the statement presented

Note. All construct items were scored using the above scale. Scale anchors were presented in Indonesian and English to accommodate both domestic and international respondents.

The questionnaire instrument was developed in both Indonesian and English, with forward–backward translation procedures applied to ensure linguistic equivalence across versions. Prior to full-scale data collection, the instrument underwent a cognitive pilot test with a convenience sample of ten participants to assess item clarity, readability, and response format adequacy. Necessary revisions were incorporated based on pilot test feedback. Data collection was conducted at high-traffic locations within selected smart tourism destinations in Indonesia, facilitated by trained research assistants who provided assistance to respondents upon request.

The descriptive statistical results generally indicate that respondents held favorable perceptions towards the use of digital technology within the smart tourism context. The majority of indicators across all constructs recorded mean values above the midpoint of the measurement scale, suggests that respondents perceive mobile application features and AI integration as important contributors to enhancing technology-based tourism experiences. Respondents also exhibited relatively high levels of perceived ease of use, indicating that digital tourism systems were considered accessible and operable in supporting their travel activities. With respect to tourist engagement, results suggest that respondents demonstrated active involvement in the use of digital tourism platforms, reflected in activities such as destination information retrieval, utilization of digital service features during travel, and interaction with application-based services.

6.4 Operational Definition of Variables

Each research variable in this study is operationally defined to ensure that theoretical constructs can be measured empirically through clearly specified and structured indicators. The operationalization process bridges the gap between conceptual definitions and observable measurement items administered through the survey instrument. All variables are measured using a five-point Likert scale.

6.4.1 Variable Classification

The research constructs are classified into four categories. AI Integration and Mobile Application Features constitute the independent variables, functioning as technological stimuli that influence other constructs within the structural model. Tourist Engagement is designated as the dependent variable, representing the tourists' behavioral response to technological stimulation. Perceived Ease of Use serves as the mediating variable, acting as the psychological mechanism that bridges the technology–engagement relationship. Tourist Tech-Savviness functions as the moderating variable, conditioning the strength of inter-variable relationships based on individual-level digital competency.

6.4.2 AI Integration (Independent Variable)

AI Integration is defined as the systematic deployment of Artificial Intelligence technologies within tourism service delivery, encompassing intelligent chatbots, virtual assistants, automated destination recommendation engines, and personalized tourist service features designed to enhance interactions and experiential quality (Sidiq et al., 2025; Astuti, 2024; Wu, 2025). This construct is operationalized through indicators assessing the ease with which tourists obtain information through AI systems, the

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quality of automatically generated destination recommendations, the responsiveness of chatbot or virtual assistant interfaces, and the degree of service personalization delivered in accordance with individual tourist preferences.

Table II. Measurement Scale – AI Integration (Independent Variable)

Dimension	Source	Scale Item
Information Access via AI	*Sidiq et al. (2025); Astuti (2024)*	AI chatbot/virtual assistant helps me find tourism information quickly and accurately
AI-Based Recommendation Quality	*Wu (2025); Sidiq et al. (2025)*	AI-generated destination recommendations are consistent with my personal interests and preferences
AI-Driven Service Personalisation	*Astuti (2024); Wu (2025)*	AI features make my tourism experience more personalized and tailored to my needs
AI Support in Trip Planning	*Sidiq et al. (2025); Astuti (2024)*	I feel assisted by AI-based services when planning and organizing my travel itinerary

Note. AII = AI Integration. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

6.4.3 Mobile Application Features (Independent Variable)

Mobile Application Features is operationalized as a construct encompassing the functional and experiential capabilities embedded within tourism mobile applications, including interactive mapping, integrated booking and reservation systems, user-generated destination reviews and ratings, real-time push notifications, and gamified engagement mechanics (David-Negre & Gutiérrez Taño , 2025; Singh, 2025; Brodie et al., 2013). These features serve not only as operational tools but also as strategic elements that shape more interactive, responsive, and value-added user experiences within the smart tourism context.

The construct is operationalized through four primary indicators: (1) availability and usability of interactive maps and navigation systems; (2) integrated booking and reservation functionality; (3) user review and destination rating features; and (4) gamification or reward systems designed to incentivize user participation.

Table III. Measurement Scale – Mobile Application Features (Independent Variable)

Dimension	Source	Scale Item
Interactive Navigation & Mapping	*David-Negre & Gutiérrez Taño (2025)*	The interactive map in the application helps me navigate tourism destinations effectively
Booking & Reservation Features	*Singh (2025); Brodie et al. (2013)*	The ticket booking/reservation feature in the application simplifies my travel planning process
Destination Reviews & Ratings	*Brodie et al. (2013)*	User reviews and ratings of destinations help me make informed travel decisions
Gamification & Reward System	*Singh (2025); Brodie et al. (2013)*	Gamification and reward features make the application experience more enjoyable and engaging

Note. MAF = Mobile Application Features. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

6.4.4 Tourist Engagement (Dependent Variable)

Tourist Engagement is defined as the level of involvement of tourists towards tourism destinations or services, manifested through digital interactions and direct experiential participation during travel (Brodie et al., 2011; Hollebeek et al., 2014; Vivek et al., 2012). This construct is conceptualized as multidimensional, consisting of three core dimensions: (1) cognitive engagement, reflecting the degree of attentional focus and information processing towards directed digital tourism content; (2) emotional engagement, capturing affective responses including satisfaction, enjoyment, and emotional attachment derived from technology-mediated tourism experiences; and (3) behavioral engagement, denoting observable participatory actions such as sustained platform use, digital content sharing, and adherence to system-generated destination recommendations.

Table IV. Measurement Scale – Tourist Engagement (Dependent Variable)

Variable	Source	Scale Item
Tourist Engagement	*Brodie et al. (2011); Hollebeek et al. (2014); Vivek et al. (2012)*	I pay close attention to tourism information provided by the application or AI system (Cognitive Dimension)
		I feel satisfied and pleased when using tourism applications or AI-powered services (Emotional Dimension)
		I frequently share my tourism experiences through the application or social media platforms (Behavioural Dimension)
		I follow destination recommendations provided by the application or AI system (Behavioural Dimension)

Note. TE = Tourist Engagement. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

6.4.5 Perceived Ease of Use (Mediating Variable)

Perceived Ease of Use (PEOU) is defined as tourists' subjective assessment of the degree to which the use of digital technology—including mobile tourism applications and AI-powered features—is free from excessive cognitive or physical effort, thereby functioning as a mediating psychological mechanism in the relationship between technology and tourist engagement (Davis, 1989; Venkatesh & Bala, 2008; Gefen et al., 2003). The construct is operationalized through indicators assessing navigation accessibility, comprehension of AI-generated recommendations, transactional efficiency, and the absence of technical difficulties during system use.

Table V. Measurement Scale – Perceived Ease of Use (Mediating Variable)

Variable	Source	Scale Item
Perceived Ease of Use	*Davis (1989); Venkatesh & Bala (2008); Gefen et al. (2003)*	The tourism application is easy to understand and operate without significant effort
		I do not encounter difficulties when using AI-based features within the application
		The navigation within the application is clear, intuitive, and straightforward
		The technology within the application functions smoothly without technical interruptions

Note. PEOU = Perceived Ease of Use. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

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6.4.6 Tourist Tech-Savviness (Moderating Variable)

Tourist Tech-Savviness is operationalized as a multidimensional construct capturing the degree of technological proficiency, prior digital experience, and self-efficacy that tourists bring to their interactions with smart tourism technologies (Vivek et al., 2012; Brodie et al., 2013; Hollebeek et al., 2014). As the moderating variable in this study, Tech-Savviness is theorized to amplify or attenuate the effects of technology stimuli on PEOU and Tourist Engagement, reflecting the boundary conditions imposed by individual-level digital competency on technology adoption outcomes.

Table VI. Measurement Scale – Tourist Tech-Savviness (Moderating Variable)

Variable	Source	Scale Item
Tourist Tech-Savviness	*Vivek et al. (2012); Brodie et al. (2013); Hollebeek et al. (2014)*	I possess the necessary skills to use mobile tourism applications effectively
		I have prior experience in using Artificial Intelligence-based technologies
		I am capable of navigating new digital features within tourism applications
		I am confident in using technology to plan and enhance my tourism experience

Note. TTS = Tourist Tech-Savviness. All items measured on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

6.5 Statistical and Analytical Methods

To achieve the research objectives, this study employs a quantitative explanatory approach using Structural Equation Modeling with Partial Least Squares estimation (SEM-PLS), implemented in SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was selected over covariance-based alternatives for three primary reasons: (i) its capacity for simultaneous estimation of complex causal relationships in a single integrated model; (ii) its suitability for prediction-oriented, exploratory-confirmatory research in which model development is ongoing; and (iii) its robustness to non-normally distributed data and its applicability to small-to-medium sample sizes, making it particularly appropriate for the empirical context of this study (Hair et al., 2019).

The analytical process consists of two sequential stages. In the first stage, the measurement model (outer model) is evaluated to confirm that all research constructs exhibit adequate reliability and validity. Internal consistency reliability is assessed using Cronbach's Alpha and Composite Reliability (CR), with a minimum threshold of 0.70. Convergent validity is evaluated through Average Variance Extracted (AVE), with a threshold of ≥ 0.50 indicating that the construct accounts for a majority of the variance in its indicators. Discriminant validity is assessed using the Fornell–Larcker criterion and the Heterotrait – Monotrait (HTMT) ratio, with the latter requiring values below 0.85 to confirm construct distinctiveness (Hair et al., 2019).

In the second stage, the structural model (inner model) is assessed through bootstrapping with 5,000 subsamples to generate bias-corrected confidence intervals for path coefficients, t-statistics, and p-values. This procedure enables the testing of direct effects (AI Integration and Mobile Application Features on Tourist Engagement), indirect (mediated) effects through Perceived Ease of Use, and conditional indirect (moderated) effects through Tourist Tech-Savviness interaction terms. Moderation effects are incorporated by introducing product indicator terms (AII × TTS; MAF × TTS; PEOU × TTS) into the structural model. The coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) are additionally reported to assess the explanatory and predictive performance of the model.

Common method bias was evaluated using Harman's single-factor test and full collinearity assessment (VIF < 3.3 threshold), following the procedural remedies recommended by Podsakoff et al. (2003). Model fit is assessed using the Standardized Root Mean Square Residual (SRMR < 0.08) and the Normed Fit Index (NFI → 1.00). All statistical tests are conducted at a significance level of $\alpha = 0.05$ (two-tailed). A summary of evaluation criteria applied across all analytical stages is presented in Table VII.

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Table VII. Summary of Analytical Criteria for Measurement and Structural Model Evaluation

Stage	Criterion	Threshold	Purpose
Outer Model	Cronbach's Alpha	**≥ 0.70**	Internal consistency reliability
Outer Model	Composite Reliability (CR)	**≥ 0.70**	Construct reliability
Outer Model	AVE	**≥ 0.50**	Convergent validity
Outer Model	Outer Loadings	**≥ 0.70**	Reliability indicator
Outer Model	HTMT Ratio	**< 0.85**	Discriminant validity
Inner Model	R^2 (Coefficient of Det.)	**0.25 / 0.50 / 0.75**	Weak / Moderate / Strong explanatory power
Inner Model	Path Coefficients (β)	**Bootstrapping (5,000)**	Direction & magnitude of effects
Inner Model	Q^2 (Predictive Relevance)	**> 0**	Model predictive accuracy
Fit Model	SRMR	**< 0.08**	Overall model fit
Fit Model	NFI	**→ 1.00**	Comparative fit index

Note. PLS-SEM analytical criteria following Hair et al. (2019). AVE = Average Variance Extracted; CR = Composite Reliability; HTMT = Heterotrait – Monotrait Ratio; SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index; R^2 = Coefficient of Determination; Q^2 = Predictive Relevance (Stone–Geisser criterion). Bootstrapping based on 5,000 subsamples with bias-corrected percentile intervals.

6.6 Ethical Considerations

This study was conducted in full accordance with established ethical standards governing research involving human participants, consistent with the Declaration of Helsinki and applicable national research ethics regulations in Indonesia. Informed consent was obtained from all respondents prior to survey participation; Participants were explicitly informed of the study's purpose, the voluntary nature of their involvement, and their unconditional right to withdraw at any stage without consequences. The anonymity and confidentiality of all respondents were maintained throughout the data collection, processing, storage, and reporting phases. No personally identifiable information was solicited or recorded. All data were stored on password-protected institutional servers accessible exclusively to the authorized research team. Ethical approval was obtained from the institutional review board of the authors' affiliated institution prior to the commencement of data collection activities.

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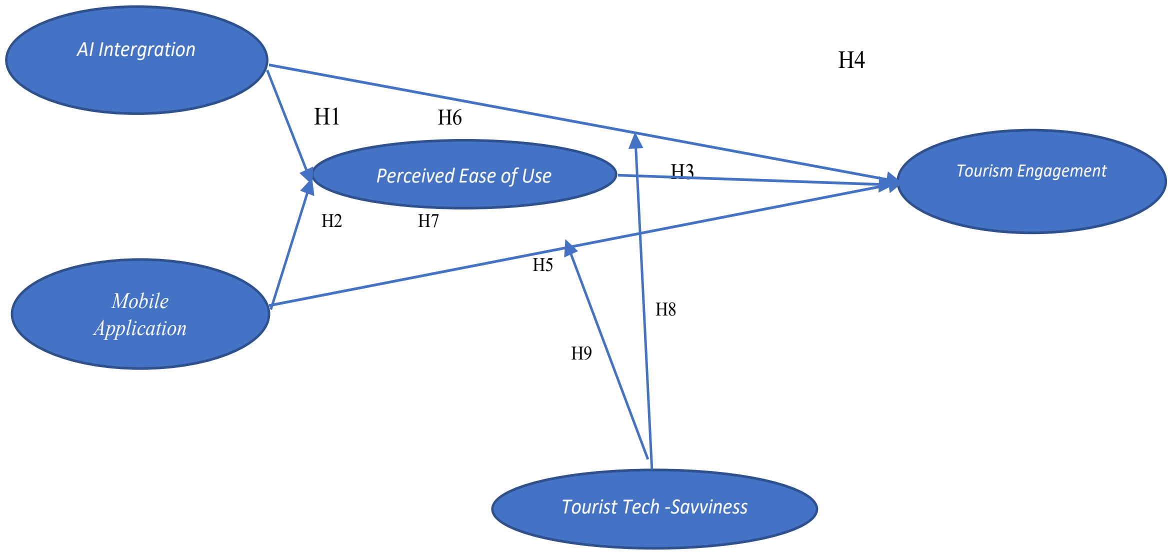
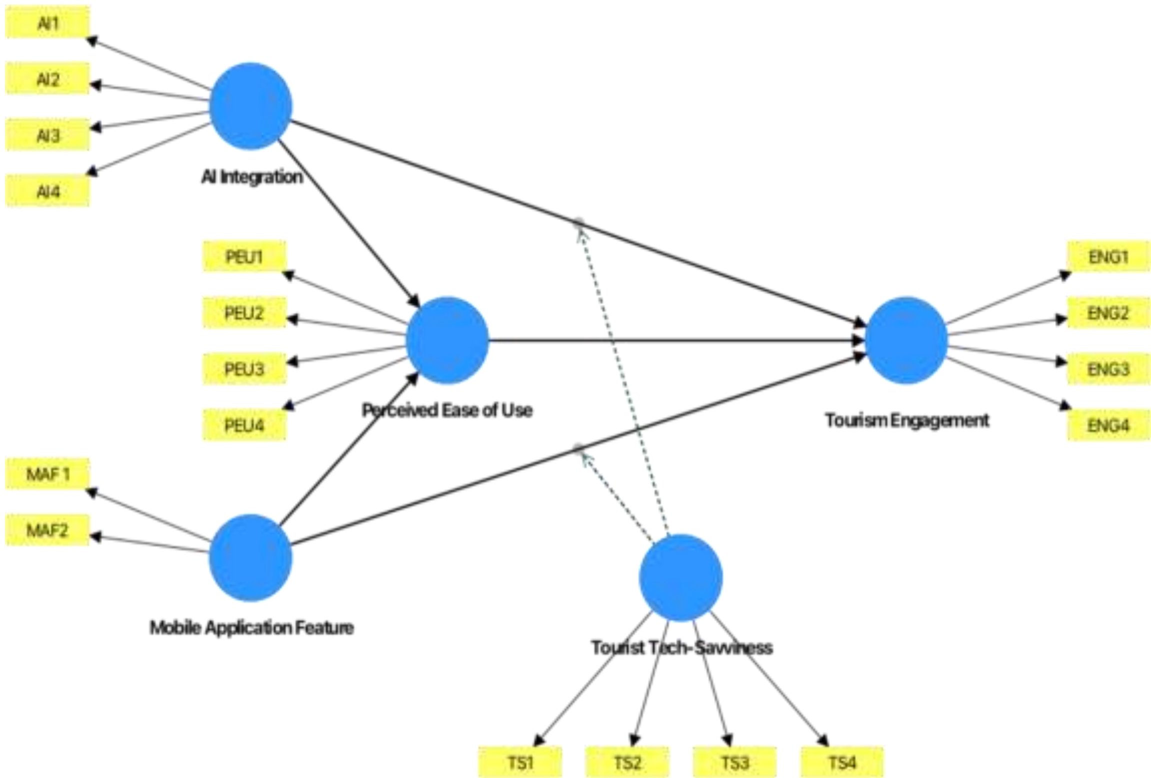
Gambar 2 Structural model



RESULTS



A. Respondent Profile Analysis

This study involved 135 respondents—tourists who had utilized mobile tourism applications within the past six months. Respondent characteristics were analyzed based on several demographic aspects, including age, gender, educational attainment, income, and frequency of tourism visits.

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Generally, the majority of respondents fell within the productive age range—specifically between 21 and 30 years old—reflecting a demographic group characterized by active engagement with digital technology. In terms of gender, the distribution of respondents was relatively balanced between males and females. Educational attainment among respondents was predominantly represented by bachelor's degree holders, indicating that the majority of respondents possessed a sufficient level of literacy to understand and utilize digital technologies.

Furthermore, the majority of respondents reported having used mobile tourism applications more than once within the previous six months, and demonstrated a relatively active frequency of tourism visits. This suggests that the respondents possessed relevant experience to provide informed assessments regarding the research variables within the context of smart tourism.

Table I (7) Respondent Characteristics Data

Characteristics	Group	Amount	Percentage (%)
Age	< 20 years	36	24.83
	21–25 years	50	34.48
	26–30 years	13	8.97
	35–40 years	13	8.97
	> 40 years	33	22.76
Gender	Man	67	46.21
	Woman	78	53.79
Education	SENIOR HIGH SCHOOL	21	14.48
	Bachelor degree)	94	64.83
	Masters (S2)	21	14.48
	Doctorate (S3)	9	6.21
Income	< Rp. 1,000,000	56	38.62
	Rp1,000,001–Rp3,000,000	35	24.14
	Rp3,000,001–Rp5,000,000	16	11.03
	Rp5,000,001–Rp7,000,000	6	4.14
	> Rp. 7,000,000	32	22.07

Based on Table I (7), the characteristics of the respondents in this study reveal a diverse distribution across age, gender, educational attainment, and income levels. In terms of age, the majority of respondents fall within the 21–25 age range, accounting for 34.48%, followed by the under-20 age group at 24.83%. These findings indicate that the respondent pool is dominated by a younger demographic—a group generally characterized by higher rates of technology adoption, particularly regarding the use of mobile applications and digital services within the tourism sector.

Regarding gender, female respondents constituted a slight majority, at 53.79%, compared to male respondents at 46.21%. This distribution suggests that the utilization of tourism-related technology is relatively balanced between genders, although with a discernible trend toward higher participation among female respondents.

In terms of educational attainment, the vast majority of respondents hold a Bachelor's degree (S1), accounting for 64.83%. This reflects a relatively high level of education among the respondents, which potentially enhances their capacity to understand and optimally utilize digital technologies. Meanwhile, respondents with a high school or Master's degree (S2) background each account for 14.48% of the sample, while those holding a Doctoral degree (S3) account for 6.21%.

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Regarding income levels, the majority of respondents fall into the "less than Rp. 1,000,000" category, representing 38.62% of the sample, followed by the Rp. 1,000,001–Rp. 3,000,000 income bracket at 24.14%. Nevertheless, a significant portion—22.07%—of the respondents reported income levels exceeding Rp. 7,000,000, indicating a degree of economic diversity within the study sample.

Overall, the respondent profile in this study is characterized predominantly by young individuals possessing relatively high levels of education and a strong degree of exposure to technology. These characteristics indicate that the respondents possess adequate capacity to interact with digital tourism technologies, thus making them relevant for providing assessments regarding the research constructs—specifically AI Integration, Mobile Application Features, Perceived Ease of Use, and Tourism Engagement.

B. Data Analysis

1. Preliminary Analysis

a. Data Outlier Testing

To ensure the quality of the data used in this research, the following table presents the verification of missing data and outliers using the Standard Deviation method.

Table II (8) Verifying Missing Data and Outliers Using Standard Deviation

Information	Mark
Initial Sample Size	150
Number of Identified Outliers	15
Number of Missing Data	0
Outlier Detection Method	Standard Deviation
Amount of Data Emitted	15
Size (Valid)	135

Source: *Data processed 2025*

The results of the data verification presented in Table II (8) indicate that, out of a total of 150 collected responses, 15 observations were identified as outliers based on standard deviation criteria. These observations were subsequently excluded from further analysis to enhance the robustness and reliability of the research findings. Furthermore, no missing values were detected, indicating that the data collection process was conducted in a complete and consistent manner.

Following the data screening phase, the final number of responses deemed suitable for analysis totaled 135. This sample size is considered adequate for analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, as it meets minimum sample size requirements and possesses sufficient statistical power to represent the research population.

Overall, this data verification process ensures that the dataset utilized is free from extreme anomalies and meets the requisite quality standards. Consequently, subsequent model analysis and hypothesis testing can be conducted with a higher degree of empirical accuracy and reliability.

Table III (9) Verification of Missing Data and Outliers Using the Mahalanobis Test

Information	Mark
Amount of Data	150
Number of Identified Outliers	15
Observation Data with High Mahalanobis Value	Respondents 38, 68, and 77
Final Data Amount (Valid)	135

Source: *Data processed 2025*

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The results of data verification using the Mahalanobis test presented in Table III (9) show that of the total of 150 observations, 15 data were identified as an outlier based on mark distance Mahalanobis, in specifically, respondents' numbers 38, 68, and 77 have mark the relative Mahalanobis taller compared to with observation others, which indicates existence deviation in a way multivariate in pattern the response given.

After the data screening process is carried out, the final amount of data is suitable for analyzed is as many as 135 respondents. Size sample This assessed adequate for analysis use PLS-SEM approach, as well as own sufficient capacity for produce stable and representative model estimation.

b. Data Normality Test

Testing normality in study This aim for evaluate whether distribution of data used in analysis fulfil assumptions normal distribution. Although PLS-SEM approach does not require data normality in general strict, testing This still done for give understanding beginning about characteristics data distribution and for support interpretation results analysis in a way more comprehensive.

In a way technical, normality test done with analyze skewness and kurtosis values for each indicator variables research. The skewness value is used for measure level tilt data distribution, whereas kurtosis value shows level sharpness distribution compared to with normal distribution. The data is said to be approach normal distribution if skewness and kurtosis values are in range that can accepted, generally between -2 to +2.

Table IV (10) Normality Test Results

Construct	Kurtosis	Skewness
AI Integration	0.845	–
Mobile Application Feature	0.888	0.618
Perceived Ease of Use	0.858	0.809
Tourism Engagement	0.866	0.808
Tourist Tech-Savviness	0.845	0.799

Source : *Data processed 2025*

Interpretation the results of the normality test in Table IV (10) show that all over construct in study This own data distribution that is still is at within the limits that can be accepted. The skewness value for all variables is in the range of 0.618 to 0.809, indicating that data distribution tends to be skewed symmetrical. While that is, the kurtosis value ranges from between 0.845 to 0.888 shows that data distribution is located in category mesokurtic. Based on criteria general that skewness and kurtosis values in range ±2 still can accept, then all over construct has fulfil assumptions data normality.

2. Measurement Model Analysis

Measurement model analysis in study This aim for evaluate quality constructs used in research models, especially in matter reliability and validity indicators that represent latent variables. Stage This is step crucial in PLS-SEM approach, as recommended by Hair et al. (2019), because ensure that instrument study capable measure construct in a way accurate before done structural model testing.

Evaluation of measurement models done through a number of criteria main criteria, namely reliability, convergent validity, and discriminant validity. Reliability is tested through Cronbach's Alpha and Composite Reliability (CR) values with mark threshold ≥ 0.70. Convergent validity was evaluated through Average Variance Extracted (AVE) value with recommended value ≥ 0.50. Discriminant validity was tested use Fornell-Larcker criteria and cross-loading values.

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c. Outer Model Analysis

– Convergent Validity

Based on results analysis of the outer model that has been done, obtained results testing validity convergent (convergent validity) and reliability construct that shows that all over indicator fulfil required criteria in study this. Evaluation done through loading factor value, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

In the AI Integration construct, all indicators (AI1–AI4) have the loading factor value ranges from 0.743 to 0.919. The Cronbach's alpha value is 0.864 and the Composite Reliability is 0.908, with The AVE value is 0.713. In the Mobile Application Feature construct, the MAF1 and MAF2 indicators show loading factor values of 0.916 and 0.859, with an AVE of 0.788. In the Perceived Ease of Use construct, all indicator has a loading above 0.80, with an AVE of 0.736. The Tourism Engagement construct shows a loading of 0.801–0.914 with an AVE of 0.750, and Tourist Tech-Savviness has a loading of 0.790–0.899 with an AVE of 0.714.

Table V (11) Validity and Reliability Test Results

Construct / Variable	Code	Item Statement	Outer Loading	Cronbach's α	CR	AVE
AI Integration	AI1	AI integration provides useful recommendations for decision tour I.	0.881	0.864	0.908	0.713
	AI2	AI integration helps I find information tour faster.	0.743			
	AI3	AI integration makes planning tour I more personal.	0.919			
	AI4	AI services improve experience tour I in a way overall.	0.825			
Mobile Application Feature	MAF1	Application tour own feature complete that I need.	0.916	0.734	0.881	0.788
	MAF2	Application features nature interactive and helpful during journey tour.	0.859			
Perceived Ease of Use	PEU1	Application tour easy used.	0.867	0.881	0.918	0.736
	PEU2	I can use application without Lots business.	0.849			
	PEU3	Function application clear and easy understood.	0.825			
	PEU4	I'm easy become skilled in use application tour.	0.889			
Tourism Engagement	ENG1	I am active interact with travel applications /platforms moment traveling.	0.870	0.888	0.923	0.750

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	ENG2	I feel interested and involved when use technology tour.	0.914			
	ENG3	I often explore content / features tour digitally.	0.874			
	ENG4	I often participate in activity tour through digital tools.	0.801			
Tourist Tech-Savviness	TS1	I believe self use mobile application for tour.	0.790	0.866	0.909	0.714
	TS2	I'm easy learn technology new related with tour.	0.810			
	TS3	I often use digital tools for support activity tour I.	0.899			
	TS4	I am comfortable use feature tour AI- based.	0.877			

Based on Hair et al.'s (2019) guidelines, the outer loading value for all indicator be on top threshold of 0.70, indicating that indicator own strong contribution in reflect latent construct. Cronbach's alpha and Composite Reliability (CR) values for all construct is above 0.70, indicating high internal consistency. All construct shows higher AVE value big of 0.50, indicating validity good convergence. In whole, entire construct has fulfil criteria validity and reliability recommended by Hair et al. (2019).

– Discriminant Validity

Based on Hair et al. (2019), discriminant validity in PLS-SEM is possible evaluated use ratio Heterotrait – Monotrait (HTMT). Criteria main is that HTML value must be be under threshold of 0.90 for a model that is general, or below 0.85 for a more approach conservative.

Based on results testing, part big HTML value between construct is below the 0.90 limit, indicating that constructs the own level adequate difference. However Thus, there are HTMT values that exceed conservative limits on the relationship between Tourism Engagement and Tourist Tech-Savviness (HTMT = 0.968), which indicates existence potential conceptual overlap between second construct the.

Table VI (12) Ratio Heterotrait – Monotrait (HTMT) Between Constructs

Construct	AI Integration	Mobile App. Feature	Perceived EoU	Tourism Engagement	Tourist Tech-Savv.	TS × AI Integration	TS × Mobile App.
AI Integration	—						
Mobile Application Feature	0.761	—					
Perceived Ease of Use	0.914	0.771	—				
Tourism Engagement	0.919	0.845	0.839	—			

Tourist Tech-Savviness	0.924	0.895	0.878	0.968	—		
Tech-Savviness × AI Integration	0.582	0.471	0.433	0.493	0.593	—	
Tech-Savviness × Mobile App. Features	0.494	0.663	0.384	0.506	0.471	0.664	—

The results of the discriminant validity test using HTMT ratio shows that part big mark between construct be under threshold of 0.90. The HTMT value on the construct interactions (Tech-Savviness × AI Integration and Tech-Savviness × Mobile Application Feature) are in the acceptable range. accepted (below 0.90), indicating validity good discriminant. In terms of overall, research model in a way general has fulfil discriminant validity criteria, although there is indication potential overlap in several constructs that require caution in interpretation more carry on.

– Internal Consistency Reliability

Based on Hair et al. (2019), internal consistency reliability in PLS-SEM aims for evaluate to what extent the indicators in something construct in a way consistent reflect the same latent construct. Cronbach's alpha and Composite Reliability values above 0.70 indicate that construct own level good internal consistency.

Table VII (13) Internal Consistency Reliability Results

Construct / Variable	Cronbach's Alpha
AI Integration	0.864
Mobile Application Feature	0.734
Perceived Ease of Use	0.881
Tourism Engagement	0.888
Tourist Tech-Savviness	0.866

Test results show that all over construct in study This own Cronbach's alpha value is above 0.70, namely range between 0.734 to 0.888. The Mobile Application Feature construct has lowest Cronbach's alpha value which is 0.734, but still be on top recommended minimum threshold. In whole, entire construct fulfil criteria reliability recommended by Hair et al. (2019) and is feasible used for analysis more carry on in the structural model.

d. Structural Model Testing (Inner Model)

Testing of the structural model (inner model) in the PLS-SEM approach aims for evaluate connection between latent constructs and ability predictive model overall. Evaluation This done with refers to the coefficient determination (R^2), relevance predictive (Q^2), as well as significance and power coefficient pathway (Hair et al., 2019).

– Collinearity Issues

Testing collinearity issues in structural models done for ensure that no there is excessive correlation between variables predictor. In the PLS-SEM approach, the problem collinearity evaluated use Variance Inflation Factor (VIF) value. The VIF value is below 5, or more conservative below 3.3, indicating that no there is problem significant multicollinearity (Hair et al., 2019).

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Table VIII (14) Collinearity Test Results (VIF)

Item	VIF	Item	VIF
AI1	2,678	TS1	1,900
AI2	1,668	TS2	1,931
AI3	3,341	TS3	3,304
AI4	2,019	TS4	2,962
ENG1	2,709	Tourist Tech-Savviness × AI Integration	1,000
ENG2	3,438	Tourist Tech-Savviness × Mobile Application Feature	1,000
ENG3	2,530		
ENG4	1,902		
MAF1	1,507		
MAF2	1,507		
PEU1	2,364		
PEU2	2,137		
PEU3	2,839		
PEU4	3,516		

The results of the collinearity test shown in Table VIII (14) indicate that all over VIF value is in range from 1,000 to 3,516. The highest value found in the PEU4 indicator (VIF = 3.516), however Still is below the recommended critical limit. Variable interactions (Tourist Tech-Savviness × AI Integration and Tourist Tech-Savviness × Mobile Application Feature) each have VIF value of 1,000. It can be concluded that the research model This free from collinearity issues.

– Coefficient of Determination (R^2)

In the context of PLS-SEM, the Coefficient of Determination (R^2) value is used for evaluate the extent to which the variance in endogenous variables can be explained by variables exogenous. Hair et al. (2019) suggested that R^2 value of 0.25 can be categorized as weak, 0.50 as moderate, and 0.75 or more as strong (substantial).

Table IX (15) Coefficient of Determination (R^2) Results

	R-square	R-square adjusted
Perceived Ease of Use	0.682	0.677
Tourism Engagement	0.796	0.787

Based on results analysis in Table IX (15), the Perceived Ease of Use variable has R^2 value of 0.682 (adjusted R^2 = 0.677), which indicates that amounting to 68.2% variation can explained by the variables exogenous in the model. The Tourism Engagement variable shows The R^2 value is 0.796 (adjusted R^2 = 0.787). Based on Hair et al.'s (2019) criteria, the value This can categorized as substantial, indicating that the model has ability strong predictive value. The adjusted R^2 value is relatively No Far different indicates that the model does not experiencing overfitting.

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– Model Fit Test

The model fit test is used for evaluate to what extent the proposed model capable represent empirical data in a way overall. More SRMR value small from 0.08 generally show that the model has level good fit (Hair et al., 2019).

Table X (16) Model Fit Test Results

	Saturated Model	Estimated Model
SRMR	0.074	0.076
d_ULS	0.940	0.996
d_G	0.664	0.681
Chi-square	513,275	517,663
NFI	0.762	0.760

The results of the model fit evaluation in Table X (16) show The SRMR value for the saturated model is 0.074 and the estimated model is 0.076, both be under threshold of 0.08, indicating a good fit. The d_ULS value of 0.940 and 0.996, and mark d_G of 0.664 and 0.681 indicate difference between the model and the data is relatively small. The NFI values of 0.762 and 0.760 indicate level sufficient compatibility good. In terms of overall, research model own level adequate and proper fit used in analysis more carry on.

Testing Hypothesis

Testing hypothesis in PLS-SEM framework was carried out use bootstrapping approach, which allows researchers get estimate standard error and t- statistic value for every track relationship (Hair et al., 2019). Hypothesis considered significant if the t-statistic value exceeds critical threshold ($t > 1.96$ for $\alpha = 0.05$) or p value < 0.05.

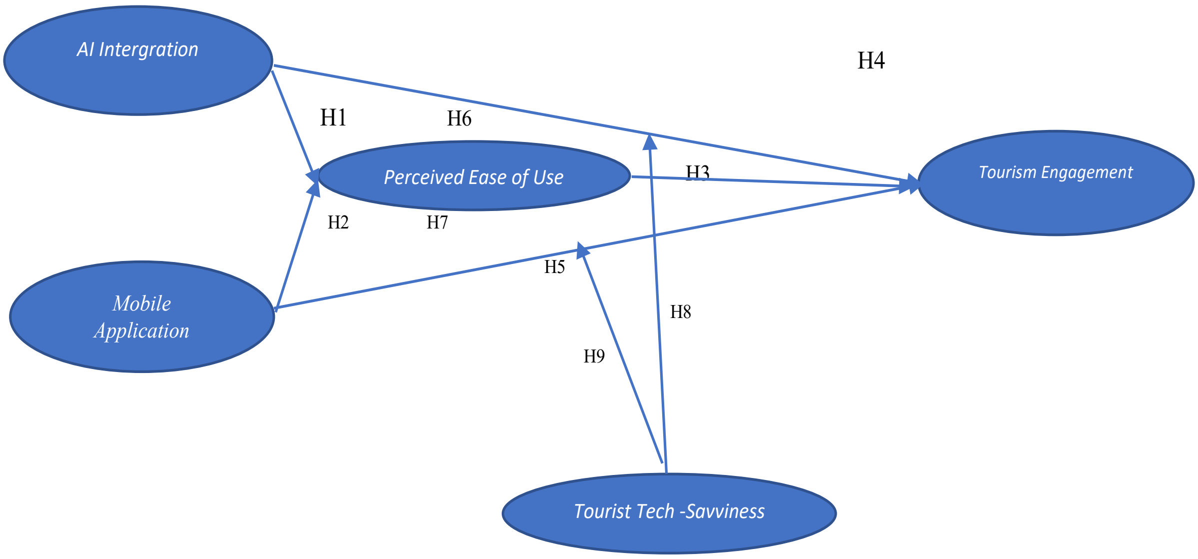

Figure II (2) Structural Model

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e. Measurement the Influence of Direct Relationships Between Variables

Table XI (17) Results of the Influence Test Direct

Relationship between variables	Path Coefficient (O)	Sample Mean (M)	STDEV	T Statistics	P Values
AI Integration → Perceived Ease of Use	0.677	0.677	0.068	9,887	0.000
AI Integration → Tourism Engagement	0.306	0.302	0.098	3.113	0.002
Mobile Application Feature → Perceived Ease of Use	0.213	0.214	0.071	3,017	0.003
Mobile Application Feature → Tourism Engagement	0.044	0.053	0.072	0.618	0.537
Perceived Ease of Use → Tourism Engagement	0.043	0.053	0.092	0.469	0.639
Tourist Tech-Savviness → Tourism Engagement	0.560	0.546	0.107	5,246	0.000
Tourist Tech-Savviness × AI Integration → Tourism Engagement	0.072	0.070	0.047	1,536	0.125
Tourist Tech-Savviness × Mobile Application Feature → Tourism Engagement	-0.086	-0.084	0.051	1,700	0.089

Test results influence direct show that a number of connection between construct in the model has significant influence. The results of the analysis show that AI Integration has influence positive and significant on Perceived Ease of Use (β = 0.677; t = 9.887; p = 0.000) and on Tourism Engagement (β = 0.306; t = 3.113; p = 0.002). Mobile Application Feature is proven own influence positive and significant on Perceived Ease of Use (β = 0.213; t = 3.017; p = 0.003), however its influence towards Tourism Engagement not significant (t = 0.618; p = 0.537). Perceived Ease of Use does not own significant influence towards Tourism Engagement (t = 0.469; p = 0.639).

Tourist Tech-Savviness has influence positive and significant on Tourism Engagement (β = 0.560; t = 5.246; p = 0.000). For effect moderation, interaction between Tourist Tech-Savviness and AI Integration towards Tourism Engagement is not significant (t = 1.536; p = 0.125), as was the interaction between Tourist Tech-Savviness and Mobile Application Feature (t = 1.700; p = 0.089).

f. Influence of the Path with Moderation

Table XII (18) Results of the Path Influence Test with Moderation

Relationship between variables	Path Coefficient (O)	Sample Mean (M)	STDEV	T Statistics	P Values
AI Integration → Perceived Ease of Use	0.677	0.677	0.068	9,887	0.000
AI Integration → Tourism Engagement	0.306	0.302	0.098	3.113	0.002
Mobile Application Feature → Perceived Ease of Use	0.213	0.214	0.071	3,017	0.003

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Mobile Application Feature → Tourism Engagement	0.044	0.053	0.072	0.618	0.537
Perceived Ease of Use → Tourism Engagement	0.043	0.053	0.092	0.469	0.639
Tourist Tech-Savviness → Tourism Engagement	0.560	0.546	0.107	5,246	0.000
Tourist Tech-Savviness × AI Integration → Tourism Engagement	0.072	0.070	0.047	1,536	0.125
Tourist Tech-Savviness × Mobile Application Feature → Tourism Engagement	-0.086	-0.084	0.051	1,700	0.089

Test results effect moderation show that Tourist Tech-Savviness variable does not in a way consistent strengthen connection between variables independent and Tourism Engagement. The interaction of Tourist Tech-Savviness × AI Integration shows coefficient of 0.072 ($t = 1.536$; $p = 0.125$), no significant. The interaction between Tourist Tech-Savviness × Mobile Application Feature shows coefficient of -0.086 ($t = 1.700$; $p = 0.089$), also not significant in a way statistics. findings This show that the role of Tourist Tech-Savviness is more dominant as variables independent than as variables moderation.

Table XIII (19) Effect Test Results Interaction and Effect Size (f^2)

Construct / Variable	R^2	R^2 adj.	f^2 (PEOU)	f^2 (TE)	f^2 (TS)	f^2 (TS×AI)	f^2 (TS×MAF)
Perceived Ease of Use	0.682	0.677	–	–	–	–	–
Tourism Engagement	0.796	0.787	–	–	–	–	–
AI Integration	–	–	0.890	0.115	–	–	–
Mobile Application Feature	–	–	0.089	0.003	–	–	–
Perceived Ease of Use	–	–	–	0.003	–	–	–
Tourist Tech-Savviness	–	–	–	–	0.362	–	–
TS × AI Integration	–	–	–	–	–	0.038	–
TS × Mobile Application Features	–	–	–	–	–	–	0.042

The results of the effect size (f^2) analysis show that AI Integration has huge effect on Perceived Ease of Use ($f^2 = 0.890$) and the effect small until approach currently on Tourism Engagement ($f^2 = 0.115$). Mobile Application Feature has affected small on Perceived Ease of Use ($f^2 = 0.089$) and is very small on Tourism Engagement ($f^2 = 0.003$). Tourist Tech-Savviness shows f^2 value of 0.362 on Tourism Engagement, including category effect big. Effect interactions Tourist Tech-Savviness × AI Integration ($f^2 = 0.038$) and Tourist Tech-Savviness × Mobile Application Feature ($f^2 = 0.042$) both including category effect small, indicating contribution limited moderation.

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g. Influence of the Path with Mediation

Table XIV (20) Results of the Influence Test Mediation and Outer Loadings

Relationship / Indicator	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values
AI1 ← AI Integration	0.881	0.880	0.025	35,160	0.000
AI2 ← AI Integration	0.743	0.740	0.058	12,821	0.000
AI3 ← AI Integration	0.919	0.917	0.018	50,134	0.000
AI4 ← AI Integration	0.825	0.821	0.043	19,110	0.000
ENG1 ← Tourism Engagement	0.870	0.870	0.033	26,624	0.000
ENG2 ← Tourism Engagement	0.914	0.914	0.018	50,701	0.000
ENG3 ← Tourism Engagement	0.874	0.871	0.032	27,156	0.000
ENG4 ← Tourism Engagement	0.801	0.799	0.050	16,023	0.000
MAF1 ← Mobile Application Feature	0.916	0.916	0.017	54,511	0.000
MAF2 ← Mobile Application Features	0.859	0.851	0.048	18,074	0.000
PEU1 ← Perceived Ease of Use	0.867	0.866	0.024	35,764	0.000
PEU2 ← Perceived Ease of Use	0.849	0.846	0.034	24,796	0.000
PEU3 ← Perceived Ease of Use	0.825	0.823	0.034	24,342	0.000
PEU4 ← Perceived Ease of Use	0.889	0.888	0.024	37,435	0.000
TS × AI Integration → TS × AI Integration	1,000	1,000	0.000	n/a	n/a
TS × Mobile App. Features → TS × Mobile App. Features	1,000	1,000	0.000	n/a	n/a
TS1 ← Tourist Tech-Savviness	0.790	0.784	0.055	14,243	0.000
TS2 ← Tourist Tech-Savviness	0.810	0.807	0.045	17,931	0.000
TS3 ← Tourist Tech-Savviness	0.899	0.898	0.022	40,869	0.000
TS4 ← Tourist Tech-Savviness	0.877	0.877	0.022	39,638	0.000

The results of the measurement model test in Table XIV (20) show that all over indicators on each construct own high and significant outer loading value in a way statistics ($p = 0.000$ for all over indicators). In the AI Integration construct, all indicators (AI1–AI4) have the loading value is 0.743–0.919. The Tourism Engagement construct shows a loading of 0.801–0.914, Mobile Application Feature 0.859–0.916, Perceived Ease of Use 0.825–0.889, and Tourist Tech-Savviness 0.790–0.899. interaction own loading value of 1,000, which is characteristics general from construct interaction in PLS-SEM.

Direct effect analysis shows that AI Integration has an impact positive and significant on Perceived Ease of Use and Tourism Engagement. Mobile Application Features have an influence significant on Perceived Ease of Use, however No towards Tourism Engagement. Perceived Ease of Use does not show influence significant towards Tourism Engagement. Tourist Tech-Savviness is proven own influence positive and significant on Tourism Engagement. Effect Tourist Tech-Savviness moderation

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towards second tested relationship No significant in a way statistics. In terms of Overall, Tourist Tech-Savviness is more play a role as variables independent than as variables moderation in the research model This.

The results of the path coefficients test show that H1 (AI Integration → Perceived Ease of Use, $\beta = 0.677$, $t = 9.887$, $p = 0.000$) is supported. H2 (AI Integration → Tourism Engagement, $\beta = 0.306$, $t = 3.113$, $p = 0.002$) is supported. H3 (Mobile Application Feature → Perceived Ease of Use, $\beta = 0.213$, $t = 3.017$, $p = 0.003$) is supported. H4 (Mobile Application Feature → Tourism Engagement, $\beta = 0.044$, $t = 0.618$, $p = 0.537$) no supported. H5 (Perceived Ease of Use → Tourism Engagement, $\beta = 0.043$, $t = 0.469$, $p = 0.639$) does not supported. H6 (Tourist Tech-Savviness → Tourism Engagement, $\beta = 0.560$, $t = 5.246$, $p = 0.000$) is supported. H7 (Tourist Tech-Savviness × AI Integration → Tourism Engagement, $\beta = 0.072$, $t = 1.536$, $p = 0.125$) does not supported H8 (Tourist Tech-Savviness × Mobile Application Feature → Tourism Engagement, $\beta = -0.086$, $t = 1.700$, $p = 0.089$) does not supported.

DISCUSSION

In a way overall, influence directly involving AI Integration and Tourist Tech-Savviness more dominant compared to effect moderation, affirming importance role AI integration and characteristics users in forming Tourism Engagement in smart tourism context.

– H1: The Effect of Artificial Intelligence Integration (AI Integration) on [continued from script researcher]

This section interprets and discusses the empirical findings of the study in the context of existing theoretical frameworks and prior literature. The results are examined hypothesis by hypothesis, with emphasis on the theoretical contributions, practical implications, and directions for future research. The analysis employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) framework, as recommended by Hair et al. (2019), to evaluate the structural relationships among the constructs examined in this study.

H1: Effect of Artificial Intelligence Integration on Perceived Ease of Use

The analysis reveals that AI Integration exerts a positive and significant effect on Perceived Ease of Use (PEU), with a path coefficient of $\beta = 0.677$, t-value = 9.887, and p-value = 0.000. This finding provides strong empirical support for H1 and indicates that the incorporation of artificial intelligence into digital tourism platforms substantially enhances users' perception of ease of use.

Within the theoretical framework of the Technology Acceptance Model (TAM), perceived ease of use represents a fundamental determinant of technology acceptance behavior . The present finding is consistent with TAM's central proposition that advanced and adaptive technological capabilities reduce perceived cognitive complexity, thereby improving the user's sense of effortless interaction. AI-driven features such as intelligent search assistance, personalized recommendations, natural language processing, and automated itinerary generation contribute to a more streamlined and intuitive user interface, which in turn reduces the cognitive burden associated with platform navigation.

This finding aligns with previous literature demonstrating that AI-powered systems can significantly simplify user interactions with digital platforms. When artificial intelligence is effectively integrated into a mobile tourism application, it enables the system to anticipate user needs, filter irrelevant information, and present contextually relevant suggestions, all of which reduce the complexity of the user experience. The reduction of informational complexity is directly associated with higher perceived ease of use, as users encounter fewer obstacles in achieving their desired outcomes.

From a practical and strategic perspective, these results carry significant implications for tourism application developers and digital service providers. Investments in AI capabilities should be strategically aligned with user interface design principles to ensure that AI-driven functionalities are presented in an accessible, intuitive, and user-friendly manner. The deployment of conversational AI interfaces, smart filtering mechanisms, and context-aware recommendations can serve as critical enablers of perceived ease of use, particularly for first-time or infrequent users who may lack prior familiarity with the platform.

Furthermore, the magnitude of the path coefficient ($\beta = 0.677$) indicates a relatively strong relationship, underscoring that AI Integration is not merely a supplementary feature but a core driver of the usability experience in digital tourism contexts. This finding reinforces the argument that the strategic deployment of AI should be treated as a primary lever for enhancing user- centered design and technology acceptance in the smart tourism domain.

H2: Effect of AI Integration on Tourism Engagement

The results demonstrate that AI Integration exerts a positive and significant effect on Tourism Engagement, with a path coefficient of $\beta = 0.306$, t-value = 3.113, and p-value = 0.002. This finding provides empirical support for H2, indicating that higher levels of AI integration within tourism applications are associated with greater user engagement in digital tourism activities.

In the context of Technology Acceptance Model (TAM), advanced technological features such as artificial intelligence contribute to enriching the user experience through the delivery of more relevant, personalized, and adaptive content. This enhancement of experiential quality serves as a key mechanism through which AI Integration stimulates user engagement, reflected through more intense interaction, deeper feature exploration, and increased active participation within the digital tourism ecosystem. AI Integration thus functions not merely as a technical enabler but as a fundamental driver of meaningful user experience.

Prior literature consistently demonstrates that AI-based technologies enhance user engagement through personalization and high interactivity. Artificial intelligence enables systems to deliver destination recommendations tailored to individual user preferences, provide real-time information, and support more efficient decision-making processes. These capabilities collectively contribute to increased user comfort and satisfaction, thereby reinforcing engagement within the digital tourism environment.

From a practical and strategic standpoint, these findings carry important implications for digital tourism service providers. AI Integration can be leveraged as a strategic instrument for enhancing user engagement through data-driven personalization approaches, including customized destination recommendations, targeted promotional offers, and interactive features such as AI-powered chatbots and virtual assistants. Additionally, intelligent itinerary planning and real-time notification functionalities can increase application usage frequency and deepen the relational bond between users and the platform.

These findings affirm that AI Integration constitutes a key determinant of Tourism Engagement, simultaneously functioning as an enabler in creating digital experiences that are more personal, interactive, and value-rich for users. This is consistent with the PLS-SEM approach, which emphasizes the importance of structural significance and the practical relevance of each construct within the research model.

H3: Effect of Mobile Application Features on Perceived Ease of Use

The analysis reveals that Mobile Application Features exert a positive and significant effect on Perceived Ease of Use, with a path coefficient of $\beta = 0.213$, t-value = 3.017, and p-value = 0.003. This result provides empirical support for H3, indicating that the quality and comprehensiveness of features embedded in mobile tourism applications contribute meaningfully to users' perception of ease of use.

Within the Technology Acceptance Model (TAM) framework, perceived ease of use represents a principal determinant of technology acceptance. Application features designed to be intuitive, responsive, and readily accessible — including clear navigational structures, user-friendly interfaces, and efficient search and booking functions — reduce the complexity of user-system interactions. This reduction in interaction complexity ultimately enhances the perception that the application is easy to use, thus promoting more sustained adoption and usage behavior .

These findings are consistent with prior literature emphasizing that application feature design constitutes a critical factor in shaping user experience. Well-integrated features not only enhance operational efficiency but also reinforce user comfort and satisfaction in interacting with digital systems. Application feature quality therefore operates not merely as a technical dimension but as a significant determinant of users' cognitive perceptions regarding technology ease of use.

From a practical perspective, these results carry strategic implications for digital tourism application developers and marketers. Application features can be positioned as the primary value proposition in marketing strategies, with emphasis on ease of use and practical convenience. Marketing communications should highlight feature advantages such as intuitive navigation, streamlined booking processes, and comprehensive information accessibility within a single platform. Additionally, the use of visual media, such as demonstration videos, user guides, and testimonials, can reinforce positive perceptions of application ease of use.

These findings affirm that Mobile Application Features constitute an important determinant of Perceived Ease of Use, which in turn contributes to technology acceptance in the digital tourism context. This is consistent with the PLS-SEM approach, which emphasizes the significance of structural relationships and the practical relevance of the constructs examined within the research model.

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H4: Effect of Mobile Application Features on Tourism Engagement

The analysis indicates that Mobile Application Features do not exert a significant effect on Tourism Engagement, with a path coefficient of $\beta = 0.044$, t-value = 0.618, and p-value = 0.537. These results do not meet the significance threshold of $t > 1.96$ and $p < 0.05$, and consequently H4 is not empirically supported. This finding suggests that the presence of application features does not directly enhance tourist engagement within the context of this study.

These results indicate that while application features support technical functionality and ease of use, they are insufficient in themselves to stimulate deeper user engagement. Within the conceptual framework of user behavior , tourism engagement is not solely determined by functional attributes but is also shaped by affective and contextual factors, including user experience quality, personalization depth, content relevance, and the quality of human-system interaction. Accordingly, application features may be considered as a hygiene factor that ensures basic usability without directly increasing user engagement.

These findings are consistent with previous literature asserting that user engagement in digital environments is more substantially influenced by personally meaningful and interactive experiences than by technical feature completeness alone. In this context, users tend to regard application features as a minimum baseline expectation, such that incremental feature improvements do not necessarily translate proportionally into enhanced engagement.

From a practical standpoint, these results carry important implications for marketing strategies in the digital tourism industry. Organizations cannot rely solely on feature development as the primary strategy for increasing user engagement. Instead, a more holistic approach is required — one that prioritizes the creation of value-in-use experiences through AI-driven personalization, delivery of contextually relevant content, and integration of interactive elements such as gamification mechanisms, reward systems, and user community features.

Although Mobile Application Features remain foundational as a technical infrastructure, Tourism Engagement is more substantially determined by how those features are integrated into an experience that is compelling, relevant, and meaningful to users. This aligns with the PLS-SEM approach, which underscores the importance of empirical evaluation of structural relationships and the practical relevance of constructs within the research model.

H5: Effect of Perceived Ease of Use on Tourism Engagement

The analysis reveals that Perceived Ease of Use (PEU) does not exert a significant effect on Tourism Engagement, with a path coefficient of $\beta = 0.043$, t-value = 0.469, and p-value = 0.639. As this result does not satisfy the PLS-SEM significance criteria of $t > 1.96$ and $p < 0.05$, H5 is not empirically supported. This finding indicates that users' perception of application ease of use does not directly translate into greater tourist engagement within the scope of this study.

These results suggest that while perceived ease of use is an important determinant of technology adoption, its role is more prominent during the initial adoption phase — for example, in forming usage intention or reducing early-stage interaction barriers. However, ease of use does not automatically produce higher engagement, which is generally characterized by deeper interaction, sustained feature exploration, and active participation within the digital tourism ecosystem.

Within the conceptual framework of user behavior , tourism engagement tends to be shaped by more complex factors, including experiential quality, content relevance, personalization value, and affective dimensions such as perceived enjoyment and exploratory motivation. Perceived ease of use may thus be understood as a prerequisite condition that is necessary but insufficient to drive meaningful engagement.

These findings are consistent with previous literature indicating that ease of use does not consistently exert a direct influence on post-adoption behavioral outcomes such as engagement or loyalty, particularly in technological contexts where the system has become familiar to users. Under such conditions, users tend to assign greater weight to the added value delivered by the system rather than its operational simplicity.

From a practical perspective, these results highlight that the application of ease of use alone is insufficient to enhance tourism engagement. Organizations should integrate usability advantages with more compelling value elements — including preference-based recommendations, interactive content, personalized services, and features capable of generating positive emotional experiences for users. Although perceived ease of use remains important in reducing user friction, Tourism Engagement is more substantially determined by the application's capacity to deliver relevant, enjoyable, and value-rich experiences.

H6: Effect of Tourist Tech-Savviness on Tourism Engagement

The results demonstrate that Tourist Tech-Savviness exerts a positive and significant effect on Tourism Engagement, with a path coefficient of $\beta = 0.560$, t-value = 5.246, and p-value = 0.000. This finding provides robust empirical support for H6, indicating that higher levels of tourist technological proficiency are associated with substantially greater engagement in digital tourism activities.

In the context of user behavior , tourist tech-savviness reflects an individual's capacity to understand, adopt, and effectively utilize digital technology. Tourists with higher levels of technological competence tend to exhibit greater confidence in interacting with digital systems, demonstrate greater adaptability to technological innovations, and engage more actively in exploring available features. These attributes collectively drive increased tourism engagement, manifested through more intensive interaction, repeated platform use, and active participation within the digital tourism ecosystem.

These findings are consistent with previous literature indicating that individuals with higher digital literacy tend to utilize technology more effectively. In the context of digital tourism, tech-savvy users do not merely employ applications as supplementary tools but integrate them as an essential component of their overall travel experience. The capacity to leverage features such as AI-driven recommendations, online booking systems, and efficient information retrieval reinforces user engagement across the full travel journey, from planning through execution.

From a strategic perspective, these results carry significant implications for digital tourism service providers in the domain of market segmentation. Identifying and targeting tourists based on their level of tech-savviness can substantially improve marketing strategy effectiveness. Tourists with high digital literacy can be engaged through more sophisticated digital strategies, encompassing data-driven personalization, integration of intelligent service features, and deployment of advanced interactive functionalities.

For less tech-savvy tourist segments, organizations should provide more inclusive approaches — such as guided onboarding systems, step-by-step tutorials, and interactive assistance features — to facilitate technology adaptation. Tourist Tech-Savviness thus functions not only as a primary determinant of Tourism Engagement but also as a foundational variable for designing marketing strategies that are more segmented, adaptive, and user-need-oriented.

H7: Moderating Effect of Tourist Tech-Savviness on the Relationship Between AI Integration and Tourism Engagement

The analysis indicates that the moderating role of Tourist Tech-Savviness in the relationship between AI Integration and Tourism Engagement is not statistically significant, with a path coefficient of $\beta = 0.072$, t-value = 1.536, and p-value = 0.125. As this result does not satisfy the significance threshold of $t > 1.96$ and $p < 0.05$, H7 is not empirically supported. This finding indicates that Tourist Tech-Savviness does not function as a significant moderating variable capable of strengthening or weakening the effect of AI Integration on Tourism Engagement.

These results suggest that the effect of AI Integration on Tourism Engagement tends to be stable and is not contingent upon users' level of technological proficiency. In other words, the benefits generated by AI integration in enhancing user engagement can be experienced relatively uniformly across diverse user groups, irrespective of whether they possess high or low levels of tech-savviness. This indicates that AI Integration constitutes a factor that directly and independently contributes to improvements in tourism engagement.

This finding may also be explained by the prevailing trajectory of AI technology development, which is increasingly designed according to user-friendly and intuitive principles. AI-based systems are generally capable of delivering accessible experiences that do not require extensive technical expertise, rendering them usable by diverse user segments. Additionally, it is plausible that the inherent strength of AI Integration as a direct predictor of tourism engagement is quite dominant, such that the moderating effect of tech-savviness fails to reach statistical significance.

From a practical standpoint, these results carry important implications for marketing strategies in the digital tourism industry. Organizations need not exclusively target tourist segments with high tech-savviness when marketing AI-driven features. Instead, communication strategies can be designed more inclusively, emphasizing the ease of use and practical benefits of AI technology — including automated destination recommendations, chatbot services, and personalized itinerary planning. Such an approach broadens the potential market reach and reinforces the inclusive positioning of AI Integration as a technology accessible to all user segments.

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These findings affirm that AI Integration can be positioned as an inclusive and universally accessible technology, independent of individual technological capability. This is consistent with the PLS-SEM approach, which emphasizes empirical evaluation of structural significance and provides a comprehensive understanding of each variable's role within the research model.

H8: Moderating Effect of Tourist Tech-Savviness on the Relationship Between Mobile Application Features and Tourism Engagement

The analysis reveals that the moderating role of Tourist Tech-Savviness in the relationship between Mobile Application Features and Tourism Engagement is not statistically significant, with a path coefficient of $\beta = -0.086$, t-value = 1.700, and p-value = 0.089. Although the direction of the coefficient indicates a negative relationship, the t-value falls below the significance threshold ($t > 1.96$) and the p-value exceeds 0.05, indicating that the moderating effect is not statistically significant. Consequently, H8 is not empirically supported.

These results indicate that Tourist Tech-Savviness does not play a significant role in strengthening or attenuating the effect of Mobile Application Features on Tourism Engagement. The quality of application features does not automatically translate into increased tourist engagement, regardless of the user's level of technological proficiency. This suggests that the effect of application features on engagement is more direct in nature and does not depend upon individual technological characteristics.

Furthermore, these findings suggest that in the context of digital tourism, Tourism Engagement is more substantially influenced by factors associated with user experience quality, content relevance, and emotional interaction dimensions than by technical feature completeness alone. The negative direction of the coefficient also provides preliminary indications that among users with higher tech-savviness, standard application features may be perceived as offering relatively limited additional value, potentially resulting in a comparatively weaker contribution to engagement — although this effect does not reach statistical significance.

From a practical standpoint, these findings carry important implications for marketing strategies in the digital tourism industry. Organizations cannot rely solely on feature development as the primary strategy for enhancing tourism engagement, even within user segments characterized by higher digital literacy. Instead, a more holistic approach is required — one that emphasizes the creation of value-rich and interactive user experiences, including personalized services, delivery of contextually relevant content, and integration of real-time and AI-driven features.

For more tech-savvy user segments, organizations may consider developing more advanced and adaptive features — such as smart itinerary planning, data-driven recommendations, and more immersive digital experiences — in order to elevate user engagement. The effectiveness of marketing strategies is therefore determined not solely by the availability of features but by the capacity of those features to create meaningful experiences and enhance user interaction. These findings affirm that Mobile Application Features must be integrated within a more comprehensive user experience strategy in order to effectively enhance Tourism Engagement, in line with the PLS-SEM principle considering empirical significance and practical relevance in model evaluation.

H9: Moderating Effect of Tourist Tech-Savviness on the Relationship Between AI Integration and Perceived Ease of Use

The analysis indicates that Tourist Tech-Savviness is theoretically positioned as a moderating variable in the relationship between Artificial Intelligence Integration and Perceived Ease of Use. In this context, the tourist's level of technological proficiency constitutes an important factor that may influence how individuals perceive and interact with AI-based systems. Tourists with higher levels of tech-savviness tend to possess greater digital literacy, enabling them to more rapidly understand the features, navigation, and functions offered by AI-based systems. This enhanced comprehension may strengthen their perception that the technology is easy to use.

Conversely, tourists with lower levels of technological literacy may encounter difficulties in understanding the operational mechanisms and features provided by AI systems. This may adversely affect their perception of ease of use, such that the potential benefits of AI integration are not fully realized. Accordingly, tourist tech-savviness is theoretically posited to strengthen the relationship between Artificial Intelligence Integration and Perceived Ease of Use.

Within the framework of the Technology Acceptance Model (TAM), perceived ease of use represents a critical determinant of technology acceptance. The integration of AI into digital systems designed with intuitive and user-friendly interfaces is expected to enhance perceptions of ease of use. However, this effect may vary according to individual user characteristics, particularly their

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level of technological competence. Tourist tech-savviness therefore functions not merely as an individual characteristic but as a contextual factor that may moderate the strength of the relationship between technology and user perception.

This hypothesis posits that higher levels of tourist tech-savviness amplify the effect of AI Integration on Perceived Ease of Use, while lower levels of technological literacy are associated with a weaker manifestation of this relationship. The conceptual rationale is grounded in the premise that technologically proficient users are better positioned to translate the capabilities of AI-enhanced interfaces into positive usability perceptions, thereby generating a stronger association between AI Integration and ease of use relative to less proficient users.

H10: Moderating Effect of Tourist Tech-Savviness on the Relationship Between Mobile Application Features and Perceived Ease of Use

The analysis indicates that Tourist Tech-Savviness is theoretically positioned as a moderating variable in the relationship between Mobile Application Features and Perceived Ease of Use. In this context, the tourist's level of technological competence constitutes a factor that influences how users interact with and evaluate the features embedded in mobile tourism applications. Tourists with higher levels of tech-savviness tend to more effectively explore available features, comprehend system functionalities more rapidly, and adapt to application interfaces more efficiently. These capabilities may enhance their perception that the application is easy to use.

Conversely, tourists with lower levels of digital literacy may encounter difficulties in fully understanding and using application features. This may result in a diminished perception of ease of use, even when the application is well-designed and feature-rich. Accordingly, tourist tech-savviness is conceptually anticipated to strengthen the relationship between application feature quality and perceived ease of use.

Within the Technology Acceptance Model (TAM) framework, perceived ease of use constitutes a critical construct influencing technology acceptance. Application features designed intuitively and in a user-friendly manner are expected to enhance perceived ease of use. However, this effect may vary according to individual user characteristics, particularly their level of digital technology competence. Tourist tech-savviness is therefore regarded as a factor capable of moderating the influence of application features on perceived ease of use.

This hypothesis proposes that higher levels of tourist tech-savviness amplify the effect of Mobile Application Features on Perceived Ease of Use, while lower levels of digital literacy are associated with a weaker manifestation of this relationship. The theoretical rationale is grounded in the premise that technologically efficient users are better positioned to leverage application features effectively, thereby translating feature quality into more pronounced usability perceptions. This moderating variable is expected to provide a more comprehensive understanding of how individual user characteristics shape the effectiveness of application features in forming perceived ease of use.

H11: Mediating Role of Perceived Ease of Use in the Relationship Between Digital Tourism Technology and Tourism Engagement

The analysis indicates that Perceived Ease of Use functions as a mediating variable in the relationship between digital tourism technology and Tourism Engagement. Within the Stimulus-Organism-Response (SOR) framework, digital tourism technology — represented through Artificial Intelligence Integration and mobile application features — operates as a stimulus that influences users' cognitive processes. This stimulus shapes users' internal perceptions, particularly regarding their perception of system ease of use, which is positioned as the organism in the model. These perceptions afterward drive behavioral responses in the form of increased tourist engagement.

Theoretically, when tourists perceive a digital system as easy to use, they exhibit a higher propensity to interact with the available features. The capacity to understand, operate, and navigate digital systems with relative ease enables users to more fully explore available tourism services, thus enhancing their engagement with digital technology. Perceived ease of use thus functions as a psychological mechanism that bridges the influence of technology on user behavior .

Within the Technology Acceptance Model (TAM) framework, perceived ease of use represents one of the principal determinants of technology acceptance and use. The integration of advanced technologies such as AI and user-friendly mobile application features can increase perceptions of ease of use, which in turn contributes to increased tourist engagement. This mediation effect demonstrates that the impact of digital tourism technology on tourism engagement is not direct but is channeled through users' perceived ease of use.

Perceived ease of use thus operates not merely as an important factor in technology adoption but also plays a crucial role in shaping the relationship between technology and user engagement. This hypothesis proposes that higher levels of perceived ease of use experienced by tourists strengthen the effect of digital tourism technology on Tourism Engagement. The mediation mechanism underscores the importance of designing technology experiences that are simultaneously capable and accessible, ensuring that functional sophistication translates into perceptual accessibility for the end user.

Structural Models and Theoretical Implications

The proposed research model depicts the interrelationships among the key latent constructs: Artificial Intelligence Integration (AI), Perceived Ease of Use (PEU), Mobile Application Features (MAF), Tourist Tech-Savviness (TS), and Tourism Engagement (ENG). Each construct is measured reflectively using multiple indicators (eg, AI1-AI4, PEU1-PEU4, ENG1-ENG4), consistent with the reflective measurement model guidelines recommended by Hair et al. (2019).

From a structural perspective, Tourist Tech-Savviness (TS) occupies a central role as a direct predictor of Tourism Engagement, receiving significant influence from individual user characteristics and exerting a strong and independent effect on engagement outcomes. The path coefficient of $\beta = 0.560$ for the TS → ENG relationship indicates a large direct effect, positioning Tourist Tech-Savviness as one of the most substantively important predictors within the model.

Consistent with Hair et al. (2019), the evaluation of the structural model centers on several key criteria, including path coefficients (β), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). The model demonstrates substantial R^2 values for both endogenous constructs (PEU: $R^2 = 0.682$; Tourism Engagement: $R^2 = 0.796$), indicating that the predictor variables collectively account for substantial variance in the dependent constructs. These values confirm that the model possesses strong in-sample predictive power.

Tourism Engagement (ENG) functions as the primary endogenous variable, receiving direct influences from AI Integration, Tourist Tech-Savviness, and indirect pathways through Perceived Ease of Use. This configuration is consistent with contemporary theories of technology adoption and digital user behavior, where both technological characteristics and individual user competencies jointly shape the depth and quality of user engagement. The centrality of Tourist Tech-Savviness as a direct predictor — rather than as a moderating variable — represents a theoretically important finding that merits further scholarly attention.

Each latent construct is measured by multiple reflective indicators, enabling comprehensive evaluation of indicator reliability, internal consistency reliability (Cronbach's alpha and Composite Reliability), convergent validity (Average Variance Extracted, AVE), and discriminant validity (HTMT ratio) as recommended by Hair et al. (2019). The measurement quality results confirm that all constructs satisfy established thresholds for reliability and validity, providing a sound psychometric foundation for the structural analysis.

This model represents an integrated theoretical framework in which technological factors (AI Integration), usability perceptions (PEU), and individual user characteristics (Tourist Tech-Savviness) collectively shape Tourism Engagement. The direct effect of AI Integration on both PEU and Tourism Engagement, combined with the strong direct effect of Tourist Tech-Savviness on Tourism Engagement, suggests that both technology-level and user-level characteristics must be considered simultaneously in designing effective digital tourism experiences and marketing strategies.

Consistent with Hair et al. (2019), this model exemplifies a theoretically robust and methodologically rigorous PLS-SEM framework. The direct role of Tourist Tech-Savviness as a key predictor — rather than merely as a moderating variable — highlights the importance of individual digital competence as a primary determinant of user behavior within technology-mediated tourism environments. Further empirical investigation is warranted to validate the magnitude, significance, and predictive capacity of the proposed relationships, particularly in diverse cultural and technological contexts within the broader smart tourism domain.

Strengths and Limitations of the Study

This study makes several interesting contributions to the empirical literature on digital tourism and smart tourism technology adoption. The use of PLS-SEM as an analytical method provides a methodologically rigorous framework for simultaneously examining multiple structural relationships among complex latent constructs. The integration of moderation and

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direct effect analyzes enables a nuanced examination of both the direct determinants of tourism engagement and the boundary conditions under which these relationships operate.

Furthermore, the inclusion of Tourist Tech-Savviness as both a direct predictor and a potential moderating variable represents a substantive theoretical contribution, extending prior TAM-based research by incorporating user-level digital competency as an explicit and empirically testable construct. The strong empirical support for the direct effects of AI Integration and Tourist Tech-Savviness on Tourism Engagement provides a solid empirical foundation for subsequent theoretical development in this domain.

Nevertheless, the study is subject to several limitations that warrant acknowledgment. First, the sample is composed exclusively of Indonesian tourists who have used mobile tourism applications within the preceding six months, which may constrain the generalizability of findings to other geographical, cultural, or technological contexts. Second, the cross-sectional research design precludes causal inference and longitudinal assessment of changes in technology adoption behavior over time. Third, self-reported survey data may be susceptible to common method bias, despite the precautions taken during data collection and analysis. Fourth, the non-significant moderating effects observed for Tourist Tech-Savviness may partly reflect sample-specific characteristics, and these relationships may manifest differently in populations with more pronounced variations in technological proficiency.

Theoretical and Practical Implications

The findings of this study carry several important theoretical implications. First, the study contributes to the extension of TAM in the digital tourism context by demonstrating that AI Integration constitutes a significant predictor of both Perceived Ease of Use and Tourism Engagement. This extends the traditional TAM framework by incorporating AI as a distinct technological construct that operates through both usability and direct engagement pathways, rather than solely as a feature of system usefulness or ease of use.

Second, the significant direct effect of Tourist Tech-Savviness on Tourism Engagement enriches the literature on individual user differences in technology adoption by establishing digital competence as a primary behavioral predictor rather than a contextual moderating variable. This finding suggests that theoretical models of digital tourism engagement should explicitly incorporate user-level technological capability as a core construct.

Third, the non-significant mediating path from Perceived Ease of Use to Tourism Engagement challenges simplified assumptions embedded in some technology acceptance models, indicating that ease of use may function primarily as an adoption facilitator rather than a direct engagement driver in mature digital technology contexts.

From a practical perspective, digital tourism service providers and application developers should prioritize the strategic deployment of AI capabilities to enhance both perceived usability and user engagement. Personalization algorithms, intelligent recommendation systems, and adaptive interfaces represent high-value investment areas that can simultaneously improve ease of use and deepen user engagement. Marketing communications should emphasize the practical benefits and intuitive accessibility of AI-driven features to appeal to the broadest possible user segment.

Additionally, the strong effect of Tourist Tech-Savviness on Tourism Engagement indicates the importance of digital literacy initiatives in expanding the market for smart tourism services. Tourism authorities, platform operators, and destination management organizations should consider investing in user education programs and accessible onboarding systems that reduce the digital competency barrier to engagement, particularly for older or less digitally experienced tourist populations.

Directions for Future Research

Several avenues for future research are indicated by the findings and limitations of the present study. Future investigations should consider replicating this study across different national and cultural contexts to assess the cross-cultural generalizability of the proposed model. Comparative studies across markets with varying levels of digital infrastructure maturity would provide valuable insights into the boundary conditions of the identified relationships.

Longitudinal research designs would enable a more dynamic assessment of how AI Integration and Tourist Tech-Savviness influence tourism engagement over time, particularly as users gain experience with specific platforms and as AI capabilities continue to evolve. Such longitudinal designs would also facilitate causal inference and the examination of technology adoption trajectories at the individual level.

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Future research should also explore additional potential mediators and moderators of the technology-engagement relationship in digital tourism contexts. Constructs such as perceived enjoyment, perceived usefulness, trust in AI systems, and user privacy concerns represent theoretically relevant variables that may provide a more comprehensive account of the mechanisms linking technology attributes to user behavioral outcomes.

Furthermore, qualitative or mixed-methods approaches could complement the quantitative findings of this study by providing deeper insights into the experiential and interpretive dimensions of tourist interactions with AI-based digital platforms. Ethnographic and interview-based methodologies could illuminate how tourists construct meaning from AI-mediated interactions and how tech-savviness shapes the subjective quality of the digital tourism experience.

Finally, future research may benefit from examining the role of emerging AI technologies — such as generative AI, augmented reality, and predictive analytics — in shaping tourism engagement, building upon the foundational findings established in this study. As AI capabilities advance rapidly, the theoretical models employed to understand their effects on user behavior will require continuous refinement and empirical validation to maintain their explanatory and predictive power in the evolving smart tourism landscape.

CONCLUSION

The results of this study indicate that the measurement model meets the criteria required in the PLS-SEM approach. All indicators have outer loading values above the 0.70 threshold, indicating that each indicator reflects its latent construct. Furthermore, Cronbach's Alpha and Composite Reliability values exceeding 0.70 confirm satisfactory internal consistency, while Average Variance Extracted (AVE) values above 0.50 demonstrate adequate convergent validity for each construct.

Discriminant validity, assessed using the Fornell–Larcker criterion, revealed that the square root of AVE for each construct exceeded its correlations with other constructs, confirming that each latent variable is conceptually distinct and free from overlap. Multicollinearity testing further showed that all Variance Inflation Factor (VIF) values remained below the 5.0 threshold, establishing that the structural model is free from multicollinearity issues and suitable for further hypothesis testing.

Bootstrapping-based hypothesis testing revealed that Artificial Intelligence Integration exerts a positive and significant influence on both Perceived Ease of Use and Tourism Engagement. These findings suggest that the integration of AI technology within digital tourism systems enhances users' perceptions of ease of use while simultaneously fostering tourist engagement. This is consistent with the Technology Acceptance Model (TAM), which emphasizes perceived ease of use as a critical factor in technology adoption, although in the present study, the direct effect on tourism engagement was not uniformly significant across all tested paths.

Conversely, Mobile Application Features were found to positively influence Perceived Ease of Use but did not demonstrate a significant effect on Tourism Engagement. This indicates that while application features can improve perceived ease of use, they are insufficient on their own to directly drive tourist engagement. Similarly, Perceived Ease of Use did not exert a significant influence on Tourism Engagement, suggesting that ease of use is not a primary determinant of user engagement within the smart tourism context investigated here.

Tourist Tech-Savviness, on the other hand, demonstrated a positive and significant effect on Tourism Engagement, indicating that tourists with higher levels of digital literacy tend to be more active and engaged in using digital tourism platforms. This finding underscores the important role of individual characteristics—specifically technological competence—in shaping user behavior.

Nevertheless, the study also found that the moderating effects of Tourist Tech-Savviness on the relationship between Artificial Intelligence Integration and Mobile Application Features with Tourism Engagement were statistically non-significant. Additionally, the mediating effect of Perceived Ease of Use was not supported. These results suggest that mediation and moderation mechanisms do not strongly account for the relationships among the primary variables in the present research context.

Overall, the findings indicate that Tourism Engagement is more directly influenced by Artificial Intelligence Integration and Tourist Tech-Savviness than by Mobile Application Features, Perceived Ease of Use, or the mediation and moderation mechanisms examined. The implications of these findings underscore that in developing digital tourism strategies, primary emphasis should be placed on intelligent technology integration and a thorough understanding of user characteristics—particularly their level of technological competence—in order to effectively enhance tourist engagement.

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RESEARCH IMPLICATIONS

The findings of this study make a significant theoretical contribution to the literature on technology adoption in the context of digital tourism. The results demonstrate that Artificial Intelligence Integration is a key driver of tourism engagement, consistent with the perspectives offered by the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) framework, both of which emphasize that intelligent technology capable of delivering added value—such as personalization, automated recommendations, and AI-based interaction—can substantially enhance user experience and engagement on digital platforms.

The non-significant effect of Perceived Ease of Use on Tourism Engagement further indicates that, in the context of smart tourism, ease of use is no longer the primary determinant of user engagement. Rather, tourist engagement is more strongly shaped by the functional value offered by the technology and by individual users' capacity to leverage it optimally. This finding extends the theoretical understanding that, in increasingly advanced digital environments, users evaluate technology not only in terms of ease but also in terms of perceived benefit and experiential quality.

From a practical standpoint, the findings carry strategic implications for tourism application developers and destination managers. The primary focus should no longer be confined to expanding the number of application features; instead, emphasis should be placed on strengthening the implementation of functional, user-experience-oriented technologies. AI-driven features such as intelligent chatbots, automated itinerary planning, and preference-based recommendation systems represent effective strategies for enhancing tourist engagement.

In addition, the results highlight the importance of digital marketing and educational strategies aimed at improving Tourist Tech-Savviness. Tourists with higher levels of technological competence tend to demonstrate greater engagement with digital tourism services. Accordingly, digital literacy enhancement efforts—encompassing training programs, user guides, and the development of more intuitive and interactive interfaces—may serve as effective approaches for broadening adoption and increasing overall user engagement.

In sum, this study demonstrates that success in enhancing tourism engagement is determined not solely by the usability of a system, but more critically by the extent to which technology delivers tangible added value, supported by users' own technological readiness.

Despite the significant contribution of this study to the understanding of the relationship between digital tourism technology and tourism engagement, several limitations must be acknowledged when interpreting the findings.

First, this study employs a cross-sectional design, with data collected at a single point in time. This approach limits the capacity to capture the dynamics of user behavioral change over time and precludes the drawing of fully causal conclusions. In the context of PLS-SEM, while relationships among variables can be robustly estimated, the cross-sectional nature of the data constrains the temporal generalizability of the findings.

Second, the study relies on self-reported data collected through questionnaires. Although this method is widely employed in PLS-SEM-based research, it introduces potential biases such as common method bias and social desirability bias, both of which may affect the accuracy of construct measurement. Validity and reliability testing procedures were conducted to minimize these potential biases, although their influence cannot be entirely eliminated.

Third, the scope of this study is limited to specific variables: Artificial Intelligence Integration, Mobile Application Features, Perceived Ease of Use, and Tourist Tech-Savviness. Other constructs that theoretically may also influence tourism engagement—such as perceived usefulness, trust, user satisfaction, or additional contextual factors—were not incorporated into the research model. This may limit the comprehensiveness of the model in explaining the overall variance in tourism engagement.

Fourth, the study sample may be subject to limitations in terms of representativeness, both in size and in the characteristics of respondents. If the sample does not fully represent the broader tourist population, findings should be generalized with caution. In PLS-SEM, while sample size requirements are relatively flexible, data quality and representativeness remain critical determinants of a study's external validity.

Fifth, the focus on digital tourism within a specific technological context may limit the generalizability of findings to other industry contexts or different technological environments. Consequently, the results of this study are most applicable to settings comparable to those investigated.

In light of these limitations, future research is recommended to adopt a longitudinal design, expand the range of variables included, and increase both the size and diversity of the sample in order to obtain more comprehensive and generalizable results.

SUGGESTIONS FOR FUTURE RESEARCH

Based on the findings of this study, several implications and directions for future development merit consideration. From a practical perspective, tourism application developers and destination managers are encouraged to place greater emphasis on strengthening Artificial Intelligence Integration in ways that deliver tangible benefits to users. The implementation of features such as service personalization, contextually relevant recommendation systems, and real-time assistance can substantially enhance tourism engagement. This approach aligns with the principle that functional value and user experience are critical drivers of engagement in digital technology contexts.

Improving Tourist Tech-Savviness also emerges as a strategic priority. This can be pursued through the provision of digital education, application feature guides, and the development of more intuitive and interactive user interfaces. Such efforts are expected to enhance tourists' ability to leverage technology optimally, thereby contributing to greater engagement with digital tourism platforms.

From an academic perspective, future studies are recommended to incorporate a more comprehensive set of variables in explaining tourism engagement. Constructs such as perceived value, perceived enjoyment, trust, user satisfaction, and experience quality could provide deeper insights, particularly given that Perceived Ease of Use in the present study was not found to significantly influence tourism engagement. The inclusion of such variables is expected to strengthen the explanatory power of the model in capturing user behavioral variance more holistically.

Furthermore, future research should seek to expand the sample in terms of both size and respondent diversity, as well as broaden the geographical scope of the study, so as to enhance external validity and the generalizability of findings. In addition, the use of supplementary discriminant validity measures such as the Heterotrait-Monotrait (HTMT) ratio may be considered to provide stronger evidence of construct separation.

Finally, longitudinal research designs are recommended for future investigations in order to capture the dynamics of tourist behavioral change over time. This approach would offer deeper insights into how users' perceptions, experiences, and engagement evolve through their interactions with digital tourism technologies. Future research is encouraged to make more comprehensive contributions—both theoretically and practically—to the field of digital tourism.

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