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Article

Rethinking Information Quality: How Trust in ChatGPT Shapes Destination Visit Intentions

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Abstract

The present study examines the role of ChatGPT as a travel advisor in influencing tourists' decision-making in regard to destination visit intentions. Grounded in the Information Systems Success (ISS) model, this study explores three primary relationships: (1) the effect of information quality on users' trust in ChatGPT's travel recommendations, (2) the impact of trust in ChatGPT's travel recommendations on destination visit intentions, and (3) the moderating role of destination images in the relationship between information quality and trust. This research employed a quantitative research design, collecting data from 528 Indonesian ChatGPT users. The findings show that information quality does not significantly shape users' trust in ChatGPT's travel advice, contradicting the classical ISS-Model prediction. In contrast, trust in ChatGPT's travel recommendations exerts a significant positive effect on destination visit intentions, and the destination image fails to moderate the information–quality–trust link. This study provides practical guidance for Destination Management Organizations (DMOs), travel agencies, and policymakers seeking to optimize AI-driven tourism marketing by focusing on interactive storytelling and personalized engagement rather than solely focusing on information quality.

Keywords: information quality; trust; destination image; destination visit intention; ChatGPT

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1. Introduction

The tourism industry's move to digital is rapidly affecting the way people decide on their trips, largely because of advances in Artificial Intelligence (AI). Today, AI helps with everything from booking a flight to arranging itineraries, making it indispensable for many travelers (Kelleher, 2023). As the demand for personalized, real-time, and reliable information grows, AI usage continues to rise. ChatGPT, an advanced language model developed by OpenAI, is considered one of the biggest assets to the tourism industry. Statista (2023) reports that in 2023, 70 percent of travelers worldwide used AI-powered platforms during the trip-planning phase. ChatGPT alone attracts more than 1.8 billion monthly visits and serves over 180 million users globally (Similarweb, 2023).

The growing reliance on AI for travel booking suggests that many consumers prefer conversational interfaces over traditional search engines (Mostafa & Kasamani, 2022;

Dwivedi et al., 2023). Because ChatGPT can conduct human-like conversations and deliver appropriate responses quickly, it differs from conventional information systems (Whitmore, 2023; Ku, 2023). However, a heavy reliance on AI also introduces new challenges. Many users struggle to trust AI recommendations, particularly in situations of limited information or heightened cognitive bias (J. H. Kim et al., 2023; Ye et al., 2023).

Trust in AI within the travel sector has been examined mainly through online travel agencies, user-generated reviews, and chatbots (Tussyadiah et al., 2020; Ali et al., 2023). Yet much remains unknown about how trust develops with systems like ChatGPT, which rely on advanced natural language generation to provide recommendations. While the literature commonly assumes that accurate data are essential for building trust (DeLone & McLean, 2003; Shi et al., 2021), trust formation also depends on users' background beliefs and digital literacy and the manner in which a destination is framed (Afshardoost & Eshaghi, 2020; Tosyali et al., 2025).

Prior studies have largely treated trust as a static construct, overlooking how it evolves through the user interaction and contextual cues, such as the perceived destination image. A destination image can shape users' judgment about an AI system's credibility (Pham & Khanh, 2021; Gorji et al., 2023). Although past research links destination images to travel intentions, few studies test it as a moderator between information quality and trust in AI (Ali et al., 2023; Orden-Mejía et al., 2025). Addressing these gaps, the present study proposes and tests a framework centered on three relationships: (1) information quality → trust in ChatGPT's recommendations, (2) trust → the intention to visit a destination, and (3) the destination image as a moderator between the information quality and trust link. In doing so, this research advances scholarship on AI adoption in tourism and the psychology of digital trust while offering actionable guidance for destination marketers.

Based on this framework, this study addresses three research questions:

- To what extent does ChatGPT's information quality influence users' trust in its travel recommendations?
- How does trust in ChatGPT's travel recommendations affect users' destination visit intentions?
- Does the destination image moderate the relationship between information quality and trust in ChatGPT's travel recommendations?

2. Literature Review and Hypothesis Development

2.1. Previous Studies and Gap Identification

Table 1 presents an overview of prior studies examining the role of ChatGPT in tourism, with a particular focus on trust mechanisms, destination images, and travel decision-making processes.

Ali et al. (2023) showed that the level of trust in ChatGPT's travel recommendations increases when those recommendations are relevant, credible, useful, and intelligent. Yet, the study did not discuss the destination image or how it can affect the desire to visit a place, nor did it investigate factors that could alter these results. According to Solomovich and Abraham (2024), personality traits such as openness, neuroticism, and extraversion influence people's trust in—and ease of using—ChatGPT for travel planning. Although the authors identified a mediating effect of the ease of use, they did not explore the destination image or its connection to travel intentions. M. J. Kim et al. (2025) found out that the way information is structured on AI ChatGPT's interface can increase intentions to visit the destination; even so, the study overlooked how the quality of information and trust influence that decision.

Table 1. Previous studies and gap identification.

Author	Context	Variables Used	Theories Used	Main Findings	Research Gaps Identified
Ali et al. (2023)	ChatGPT (AI) in tourism industry	ChatGPT personalized travel recommendation's relevance; credibility, usefulness; and intelligence, travelers' trust, and behavioral intentions	Affordances and Actualization Theory; Trust	ChatGPT's personalized travel recommendations enhance perceived trust through relevance, credibility, usefulness, and intelligence, which in turn positively influences behavioral intentions.	No analysis of destination image, destination visit intention, and moderating mechanism
Solomovich and Abraham (2024)	ChatGPT (AI) in tourism industry	Openness, neuroticism, extraversion, perceived ease of use, behavioral intention, perceived usefulness, trust in ChatGPT	Personality Traits and TAM	Trust in ChatGPT boosts perceived usefulness, and ease of use drives chatbot adoption. Ease of use links extraversion to trust, with age influencing behavioral intentions.	No analysis of destination image, destination visit intention
M. J. Kim et al. (2025)	ChatGPT (AI) in tourism industry	ChatGPT's communication style, ChatGPT's information structure, destination familiarity, perceived informativeness, visit intention	CASA Paradigm	Communication style had no effect, but information structure boosted acceptance; explanations increased visit intention more than listings.	No analysis of ChatGPT information quality and trust
Orden-Mejía et al. (2025)	Chatbot in tourism industry	Chatbot's information quality, perceived usefulness, perceived enjoyment, user satisfaction, Chatbot's continuance intention, and destination visit intention	Technology Acceptance Model, Enterprise Content Management, and Information Systems Security Models	Information quality boosts satisfaction, enjoyment, and usefulness, which increase continuance intention and ultimately destination visits.	No analysis of ChatGPT, destination image, and trust, and no moderating mechanism
Li and Lee (2025)	ChatGPT in tourism industry	ChatGPT's communication quality (accuracy, currency, timeliness, understandability), trust, personalization, anthropomorphism, trust loyalty, and intention to use ChatGPT	The Affordance–Actualization Theory	Timeliness, personalization, and anthropomorphism build cognitive and emotional trust, leading to loyalty and usage intention.	No analysis of ChatGPT's information quality, destination image, and destination visit intention, and no moderating mechanism
Yang et al. (2024)	E-tourism platform in tourism industry	Perceived personalization, visual appearance, information quality, privacy concern, technology trust, personal tourism recommendation attitude, and visit intention	The Stimulus-Organism-Response	Information quality, personalization, and visuals boost technology trust and PTR attitudes, which affect visit intention; privacy concerns weaken the personalization–trust link.	No analysis of ChatGPT and destination image

Table 1. *Cont.*

Author	Context	Variables Used	Theories Used	Main Findings	Research Gaps Identified
This study	ChatGPT in tourism industry	ChatGPT information quality, destination image, trust in ChatGPT travel recommendations, and destination visit intention	The Information Systems Success Model	Information quality does not affect trust in ChatGPT's travel recommendation, trust in ChatGPT's travel recommendation affects destination visit intention, and destination image does not moderate information quality and trust.	It analyzes ChatGPT's information quality, trust in ChatGPT travel recommendations, and destination image as moderating variables

In Orden-Mejía et al. (2025), the chatbot satisfaction and continuance intention hinged on the perceived information usefulness, yet the authors did not examine how ChatGPT shapes destination images, trust, or the desire to visit. Li and Lee (2025) showed that accuracy, timelines, and anthropomorphism strengthen trust and loyalty toward AI assistants; however, they did not consider how ChatGPT usage might alter perceptions of a destination or lead to actual travel. Yang et al. (2024) focused on e-tourism platforms, highlighting how personalization, information reliability, and technology trust affect visit intentions but again omitted ChatGPT's potential influence on destination images or travel intentions.

Taken together, these studies indicate a fragmented understanding of how ChatGPT's information quality, user trust, and destination image interact in AI-driven tourism planning. While previous research has explored trust in AI and user behavior separately, few have traced how trust in ChatGPT emerges from the perceived information quality and how this trust translates into travel intentions. Moreover, no existing study has treated the destination image as a moderating variable, despite its documented influence on trust judgments and decision-making. Theoretical approaches—such as TAM, Affordance Theory, and CASA—offer valuable insights but have not been integrated to connect these three constructs within a single framework.

This paper aims to fill these gaps in three ways. First, it examines ChatGPT's information quality—a core determinant of trust—through the Information Systems Success (ISS) model, long recognized for explaining the system use via information credibility, satisfaction, and behavioral intention (DeLone & McLean, 2003; Petter et al., 2008). Second, it analyzes trust in ChatGPT's travel recommendations as a predictor of the destination visit intention, addressing a shortfall in the earlier work that seldom measured behavioral outcomes. Third, it introduces the destination image as a contextual moderator that could amplify or dampen the link between information quality and trust. By combining these elements, this study offers a more complete picture of AI-based tourism decision-making and extends the ISS model into the emerging domain of conversational AI systems such as ChatGPT.

2.2. The Information Systems Success Model

The Information Systems Success (ISS) model provides a robust theoretical basis for understanding the effect of information quality on user's trust and subsequent behavior when adopting technology (DeLone & McLean, 2003). Initially developed to evaluate the success of information systems, ISS has since been extended to digital platforms and artificial intelligence tools, repeatedly confirming that information quality influences a user's trust, satisfaction, and decision-making (Petter et al., 2008; Çelik & Ayaz, 2022). In AI-driven tourism services, such as ChatGPT, information quality is particularly crucial because tourists rely on such tools for pre-trip planning under uncertainty and risk. ChatGPT generates travel recommendations by drawing on vast public content, travel blogs, review websites (e.g., TripAdvisor, Google

Reviews), official tourism websites, and FAQs by users. These AI-generated responses offer conversational guidance and emerge as a substitute for conventional search engines (Sigala et al., 2024), especially among younger, tech-savvy travelers.

Information quality—defined by accuracy, relevance, completeness, clarity, and timeliness (DeLone & McLean, 2003)—increases the perceived credibility of ChatGPT, thereby fostering user trust (J. H. Kim et al., 2023; Shi et al., 2021). Trust is a critical factor in tourism behavior: it not only enhances the belief in the information provided but also influences downstream actions such as destination visit planning (Seçilmiş et al., 2022; Filieri et al., 2015). Nevertheless, trust does not form uniformly. The destination image—a traveler's cognitive and affective perception of a place—can moderate the impact of the information quality on trust. A positive image may heighten trust in destination-related recommendations, whereas a negative image can undermine trust even when the information is accurate (Afshardoost & Eshaghi, 2020; Tosyali et al., 2025).

Accordingly, this study examines three key relationships derived from the ISS model and recent AI developments: RQ1: To what extent does ChatGPT's information quality influence users' trust in its travel recommendations? RQ2: How does trust in ChatGPT's travel recommendations affect users' destination visit intentions? RQ3: Does the destination image moderate the relationship between information quality and trust in ChatGPT's travel recommendations? By addressing these questions, this study aims to deepen understandings of how AI-mediated travel information shapes tourist behavior through the interrelated effects of information quality, trust, and contextual perceptions.

2.3. Information Quality

Information quality refers to the accuracy, format, completeness, and currency of information produced by digital technologies (Lin et al., 2023). It plays a pivotal role in shaping users' trust in online platforms and decision-making systems. According to the updated ISS model, information quality significantly influences users' intentions and system use through its perceived accuracy, relevance, completeness, and timeliness (DeLone & McLean, 2003). In AI-driven applications, high-quality information is paramount in generating trust, especially when users depend on these systems for consequential decisions such as travel planning (H. Wang & Yan, 2022).

ChatGPT delivers personalized travel recommendations by synthesizing data sources and offering contextualized insights. The perceived quality of these recommendations can strongly impact users' trust. Shi et al. (2021) highlight that AI systems providing accurate, up-to-date, and relevant travel information enhance users' trust and engagement. Similarly, Casaló et al. (2020) find that the perceived informativeness and reliability of AI outputs are key antecedents of trust in AI-based travel services. Furthermore, information that is consistent and easy to understand improves user confidence and reduces uncertainty in travel decision-making (Yang et al., 2024).

Therefore, a hypothesis is proposed:

H1. *ChatGPT's information quality positively affects trust in ChatGPT's travel recommendations.*

2.4. Trust in ChatGPT Travel Recommendations

According to Rotter (1967), trust is the belief that a party's word or promise is reliable and that the party will fulfill its obligations in an exchange. Here, trust in ChatGPT recommendations denotes the extent to which a user feels assured and prepared to act on advice generated by ChatGPT (González-Rodríguez et al., 2022). Trust reduces the perceived risk and enables technology adoption in uncertain contexts such as tourism planning (Ye et al., 2023; Muliadi et al., 2024). In AI systems, trust reflects a willingness to rely on the system despite a limited understanding of its inner workings (Choung et al., 2023).

Within tourism, trust in AI-generated recommendations empowers travelers to make confident choices, sometimes selecting destinations they had not previously considered (Tussyadiah et al., 2020). Trust bridges the gap between technical functionality and behavioral intentions (Ku, 2023). ChatGPT's conversational, tailored advice mimics human interactions, further enhancing interpersonal trust dynamics (Marinchak et al., 2018). Thus, trust in ChatGPT is posited as a critical predictor of a user's intention to visit the recommended destination.

Thus, the following hypothesis is proposed:

H2. *Trust in ChatGPT's travel recommendation positively affects destination visit intentions.*

2.5. Destination Image

A destination image is a subjective interpretation of a place that influences tourist behavior (Gorji et al., 2023; Tedjakusuma et al., 2023). While information quality forms a foundation for trust, its impact is filtered through contextual factors—chief among them are consumers' pre-existing perceptions of the destination (Tosyali et al., 2025). The destination image acts as a cognitive–affective lens coloring how users interpret AI-generated information (Afshardoost & Eshaghi, 2020). When the image is positive, users are likelier to deem ChatGPT's information credible, thereby reinforcing trust (González-Rodríguez et al., 2022). Conversely, a weak or negative image can diminish trust even if the information quality is high.

This dynamic suggests that the destination image moderates the information–quality–trust relationship, either strengthening or weakening the trust-building effect. Prior studies show that people place greater trust in information aligning with their preconceived attitudes (Pham & Khanh, 2021; Rotter, 1967).

Thus, this study proposes the following:

H3. *The destination image moderates the relationship between ChatGPT's information quality and the trust in ChatGPT's travel recommendations.*

Figure 1 exhibits all the developed hypotheses above.

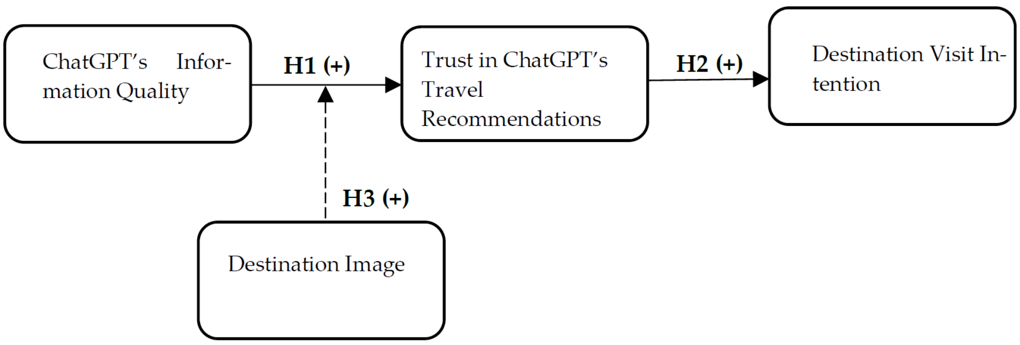

Figure 1. Research framework.

3. Methods

3.1. Operationalization and Measurement Items

The present study defines and measures key constructs to ensure internal consistency and validity. The main constructs are information quality, trust in ChatGPT's travel recommendations, destination image, and destination visit intention. All items are assessed on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). All measurement items are summarized in Table 2.

Table 2. Measurement items.

Variables	Definition	Measurement Items	Source
Information Quality	Tourist's perception of receiving relevant, reliable, and high-quality information from ChatGPT during a conversational session	1. ChatGPT provided sufficient information 2. I receive the information I need in a timely manner 3. ChatGPT presents information in a useful format 4. ChatGPT provides accurate information 5. ChatGPT provides precise information 6. ChatGPT provided up-to-date information 7. ChatGPT provided reliable information	(Orden-Mejía et al., 2025)
Destination Image	The overall cognitive and affective impressions a person holds of a place (Phelps, 1986)	1. Good climate 2. Beautiful landscape 3. A good reputation of a destination 4. Unpolluted natural environment	(Pham & Khanh, 2021)
Trust in ChatGPT's Travel Recommendations	The degree to which users perceive ChatGPT's travel advice as dependable and accurate	1. I think ChatGPT's travel recommendations are reliable 2. I think ChatGPT's travel recommendations are trustworthy 3. I think ChatGPT's travel recommendations are correct	(L. Wang et al., 2021)
Destination Visit Intention	The likelihood or willingness of a person to visit a particular destination	1. I plan to visit Bali in the future 2. I am willing to visit Bali in the future 3. I intend to visit Bali in the future	(L. Wang et al., 2021)

3.2. Sampling Technique and Data Collection

This study employs purposive non-probability sampling to recruit respondents who meet four criteria: (1) male or female, (2) at least 18 years old, (3) completion of high school education or higher, and (4) prior experience using ChatGPT. An online questionnaire built with Google Forms was used to distribute the questionnaire via social media channels, such as Line, Facebook, WhatsApp, and Instagram. The survey comprised three sections: eligibility screening, demographic information, and constructs related to behavioral intention. A seven-point Likert scale captured respondents' perceptions with greater nuance. Over a three-month period (January–March 2025), 528 valid responses were collected, providing a robust basis for analyzing destination visit intentions and the role of trust.

3.3. Analysis Technique

Structural equation modeling (SEM) with SmartPLS 4.0. tested the measurement and structural models. SEM is appropriate for exploratory settings that examine complex variable relationships (Hair et al., 2017). Common Method Variance (CMV) was first assessed to ensure that any bias stemming from self-report data remained minimal. Convergent validity was confirmed when average variance extracted (AVE) values $\geq$0.5 were reached, and indicator loadings were also >0.7 (Baumgartner & Weijters, 2021). Reliability was demonstrated with Cronbach's alpha and composite reliability (CR) scores of $\geq$0.7 (Hair et al., 2017). Discriminant validity was verified using the Fornell–Larcker criterion—requiring each construct's AVE square root to surpass its inter-construct correlations—and by confirming that every indicator loaded more strongly on its own construct than on others (Henseler et al., 2015). Finally, model quality was assessed through Goodness of Fit (GoF) and R-squared values, yielding a step-by-step evaluation that enhances this study's robustness.

4. Results

4.1. Sample Demographics

The present study analyzed 528 respondents who had tried ChatGPT; 56.82% were men and 43.18 women, indicating a balanced uptake across genders. Most respondents were millennials or young professionals aged 30–39 (51.89%) and individuals in their twenties (27.84%), suggesting that digital-native cohorts adopt ChatGPT for practical tasks such as travel planning. The majority held a bachelor's degree (61.93%), with 11.74% possessing a master's degree. Regarding occupations, private employees (25%) and civil servants (22.54%) predominated, while 17.05% were entrepreneurs—which is evidence of ChatGPT's cross-sector appeal. Notably, 31.82% worked in information technology, reflecting the tech-savvy nature of early AI adopters. The usage tenure was varied: 31.06% had used ChatGPT for 6–9 months and 27.27% for 3–6 months. The primary motive was academic work (28.41%) followed by professional support and travel information (21.21% and 18.56%, respectively). These demographics align with this study's focus on information quality, trust, and destination images because respondents are experienced, educated, and motivated users. Full details appear in Table 3.

Table 3. Sample demographics.

Measure	Items	Frequency	Percentage
Gender	Female	228	43.18%
	Male	300	56.82%
Age group	>18 yo	32	6.06%
	20–29 yo	147	27.84%
	30–39 yo	274	51.89%
	40–49 yo	62	11.74%
	>50 yo	13	2.46%
Education level	High school or equivalent	81	15.34%
	Diploma	44	8.33%
	Bachelor	327	61.93%
	Master's degree	62	11.74%
	Doctoral	14	2.65%
Occupation	Lecturer	30	5.68%
	Private employee	132	25.00%
	Entrepreneur/business owner	90	17.05%
	Teacher	21	3.98%
	Students	79	14.96%
	Civil servant	119	22.54%
	Freelancer	44	8.33%
	Job seeker	13	2.46%
Job fields	Education	112	21.21%
	Engineering	52	9.85%
	Information technology	168	31.82%
	Social science	62	11.74%
	Marketing/business	44	8.33%
	Others	90	17.05%

Table 3. *Cont.*

Measure	Items	Frequency	Percentage
How long they have used ChatGPT	<1 month	11	2.08%
	1–3 month(s)	64	12.12%
	3–6 months	144	27.27%
	6–9 months	164	31.06%
	10–12 months	89	16.86%
	>1 year	56	10.61%
Main objective of using ChatGPT	For academic reasons (studying, writing, research)	150	28.41%
	To support professional work	112	21.21%
	To make content (video, writing, etc.)	69	13.07%
	For entertainment or chatting	40	7.58%
	For travel information research	98	18.56%
	To answer general questions or explore knowledge	59	11.17%

4.2. Common Method Variance (CMV)

The CMV was assessed with Harman's single-factor test. The first factor accounted for 33.7% of the variance—well below the 50% threshold—indicating that common method bias is unlikely to compromise the findings (Baumgartner & Weijters, 2021).

4.3. Validity and Reliability Assessment

The structural equation modeling in SmartPLS 4.0 evaluated the measurement quality. All indicator loadings exceeded 0.7 (Hair et al., 2017), as shown in Table 4, confirming the item reliability. Average variance extracted (AVE) values were above 0.50, demonstrating convergent validity. Cronbach's alpha and composite reliability both surpassed 0.70, indicating strong internal consistency.

Table 4. Convergent validity and reliability.

Construct	Items	FL	CA	CR	AVE
Information quality	IQ4	0.846	0.878	0.924	0.803
	IQ5	0.954			
	IQ6	0.913			
Trust in travel recommendation	TR1	0.702	0.811	0.909	0.833
	TR2	0.940			
	TR3	0.818			
Destination visit intention	DVI1	0.823	0.815	0.890	0.731
	DVI2	0.946			
	DVI3	0.788			
Destination image	DI3	0.868	0.760	0.864	0.701
	DI4	0.955			

The discriminant validity was tested in three ways. First, Fornell–Larcker results (Table 5) showed that each construct's AVE square root exceeded its correlations. Second, heterotrait–monotraitn ratios (Table 6) were all below 0.85 (Henseler et al., 2015). Third, cross-loadings (Table 7) revealed that every indicator loaded higher on its intended construct than on others. These statistics confirm that the constructs are distinct.

Table 5. Fornell–Larcker criterion.

Constructs	IQ	DI	DVI	TR
Information Quality (IQ)	0.896			
Destination Image (DI)	−0.193	0.913		
Destination Visit Intention (DVI)	0.104	0.131	0.855	
Trust (TR)	−0.084	0.240	0.363	0.855

Notes: The diagonal values are the square roots of the AVE.

Table 6. Heterotrait–monotrait ratio (HTMT).

Constructs	IQ	DI	DVI	TR
Information Quality (IQ)	0.245			
Destination Image (DI)	0.211	0.176		
Destination Visit Intention (DVI)	0.163	0.298	0.441	
Trust (TR)	0.186	0.379	0.164	0.149

Notes: The HTMT values, with <0.85 being strong, <0.90 being moderate, and <0.95 being weak.

Table 7. Cross-loadings matrix.

Constructs	IQ	DI	DVI	TR
IQ4	0.816	−0.191	0.052	−0.054
IQ5	0.954	−0.165	0.100	−0.081
IQ6	0.913	−0.172	0.115	−0.085
DI3	−0.220	0.868	0.061	0.155
DI4	−0.152	0.955	0.157	0.260
DVI1	−0.075	0.016	0.823	0.338
DVI2	0.126	0.149	0.946	0.342
DVI3	0.275	0.201	0.788	0.232
TR1	−0.183	0.237	0.177	0.702
TR2	−0.104	0.230	0.316	0.940
TR3	0.050	0.139	0.382	0.818

4.4. Model Robustness Testing

The process began by analyzing the R^2 of every endogenous construct to find out how much variation in the outcome variables was caused by the predictors. Falk and Miller (1992) note that a model is viable when the R^2 value is above 0.1. Based on the findings, both the destination visit intentions ($R^2 = 0.132$) and trust in ChatGPT travel recommendations ($R^2 = 0.105$) can be greatly explained by the information quality and destination image. These results confirm that the model can illustrate the relationships between variables and is effective in explaining what leads to destination visit intentions in the tourism industry. In the second step, tests were performed to ensure the model accurately fits the data. Hu and Bentler (1999) suggest that a model is well-fitted when the SRMR is lower than 0.05 or 0.08. Furthermore, the Normed Fit Index (NFI) is taken as acceptable when it gets very close to 0.95. By using bootstrap results for the fit indices, the authors accurately interpret the values for d_ULS and d_G. The value found for the SRMR was 0.107, which falls over the suggested thresholds of 0.05 or 0.08, so the SRMR could not be accepted. Nevertheless, the NFI value of 0.736 is quite similar to 0.95, so it remains within a suitable range.

To measure how reliable and effective this study's research model was, the Goodness of Fit (GoF) was used. GoF merges the model's R^2 and AVE into a single total. It is calculated by multiplying the average R^2 and the average AVE together and then taking the square root. By using this approach, one can confidently judge if the model is reliable and fits the relationships among the constructs. The formula used for the GoF is as follows:

$$GoF = \sqrt{\overline{AVE}} \times \sqrt{\overline{R^2}} = \sqrt{0.762 \times 0.237} = 0.426 \tag{1}$$

To evaluate the Goodness of Fit (GoF), specific cut-off values are used: thresholds under 0.10 mean no fit; values between 0.10 and 0.25 indicate a small fit; values from 0.25 to 0.36 show a moderate fit; and those surpassing 0.36 mean a high fit (Tenenhaus et al., 2005; Wetzels et al., 2009). The GoF value computed in this study is 0.426, so it is regarded as a high fit. Here, the results underline that the research model performs very well and accurately represents the relationships among all the constructs.

4.5. Hypothesis Testing

Table 8 exhibits the results of the hypothesis testing of this study. Hypothesis H1, stating that ChatGPT's information quality significantly affects trust in ChatGPT travel recommendations, is unsupported as its result is statistically insignificant, with a path coefficient of −0.060 and a T-value of 1.073. Meanwhile, Hypothesis H2, stating that trust in ChatGPT travel recommendations significantly affects destination visit intentions, is supported as it meets both statistical and theoretical expectations with a path coefficient of 0.363 and a T-value of 6.554. Hypothesis 3, stating that the destination image moderates the relationship between the ChatGPT information quality and trust in ChatGPT travel recommendations, is unsupported because even though it is statistically significant (T-value = 2.573), the direction of the path coefficient (−0.152) contradicts the hypothesized positive effect. A hypothesis summary can be seen in Figure 2.

Table 8. The results of the hypothesis testing.

Hypothesis	Path Coefficients	T-Statistics	Bootstrapping 97.5%		Remarks
			Min	Max	
H.1 IQ → TR	−0.060 ***	1.073	−0.172	0.070	Unsupported
H.2 TR → DVI	0.363 ***	6.554	0.280	0.450	Supported
H.3 IQ → DI → TR	−0.152 ***	2.573	−0.234	−0.021	Unsupported

Notes: Significance level with *** $p < 0.001$.

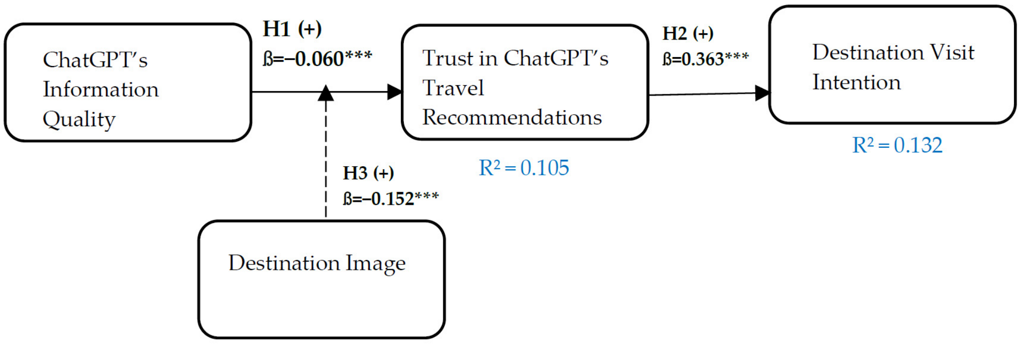

Figure 2. Hypothesis summary. Notes: Significance level with *** $p < 0.001$.

5. Discussion

The present study investigated the effect of ChatGPT's information quality on destination visit intentions, with the destination image serving as a moderating variable. The hypothesis testing reveals several key findings. First, the information quality does not significantly affect users' trust in ChatGPT's travel recommendations (H1 unsupported). Users appear willing to rely on ChatGPT even when its accuracy, completeness, or timeliness vary.

Prior work indicates that design cues such as personalization and anthropomorphism wield a greater influence over trust. For example, Shin et al. (2025) show that how much users trust ChatGPT's travel suggestions relies more on its narrowing options and suggesting personalized plans than on the quality of the data itself. Similarly, J. H. Kim et al. (2023) mention that if users are still given incorrect information, they might trust the service as long as the app is enjoyable and flexible. These insights suggest that tourism marketers should produce marketing content and messages that are customized and important to consumers and encourage interaction by paying attention to popular travel topics, like eco-tourism, cultural heritage, and different types of food experiences frequently highlighted by ChatGPT.

Second, trust in ChatGPT travel recommendations positively influences destination visit intentions (H2 supported). This signifies that when users trust ChatGPT travel recommendations, they are more likely to accept the recommendations and form intentions to visit the suggested destinations. This finding is in line with Batouei et al. (2025), who posit that users' trust in ChatGPT can increase their willingness to act on the travel advice provided by ChatGPT as long as such advice is perceived as credible and personalized. Shin et al. (2025) propose a similar point, that when ChatGPT can narrow down travel options, this can not only reduce users' decision fatigue but also strengthen the user's intent to travel. These insights suggest that the more users believe in the credibility and personalization of ChatGPT's suggestions, the more likely they are to move from consideration to commitment in their travel decisions. Meanwhile, H3's findings show that the destination image does not moderate the relationship between ChatGPT's information quality and the trust in its travel recommendations. This suggests that even when users have a favorable image of a destination, such affective perceptions do not enhance the impact of ChatGPT's information quality on trust formation. This aligns with previous studies that propose that moderating variables like destination images tend to have a more substantial impact on final behavioral intentions than on intermediary cognitive constructs such as trust (Artigas et al., 2015).

In addressing the research questions, this study finds that trust in ChatGPT's travel recommendations significantly drives users' intentions to visit suggested destinations. However, information quality alone does not significantly impact trust, suggesting that users value personalized and engaging interactions over purely informational content. Additionally, the destination image does not enhance or weaken the relationship between information quality and trust, indicating its limited moderating role. These insights provide practical recommendations for developers and marketers, highlighting the importance of focusing on personalization and interactive features in AI travel recommendation systems to effectively foster user trust and boost travel intentions.

6. Implications

6.1. Theoretical Implications

This study challenges traditional assumptions within the ISS model, which typically asserts that high information quality leads directly to increased user trust in technology-based recommendations. Contrary to these assumptions, this study's findings reveal that information quality alone does not significantly influence trust in AI-mediated travel recommendations provided by ChatGPT. This suggests that tourists may evaluate ChatGPT's travel advice based on factors beyond only quality indicators, such as relevance, accuracy, and completeness. This aligns with recent expansions of technology acceptance models—specifically in Human–Computer Interaction (HCI) and AI-driven technologies—which propose that anthropomorphic characteristics, personalization, and conversational experiences enhance social presence and user engagement, thereby influencing trust in interactive AI systems.

In addition, the present study repositions the role of destination images in the trust-building process. The findings of this study demonstrate that the destination image does not moderate the effect of information quality on trust, contradicting established beliefs that positive mental representations of a destination can enhance trust in AI-provided information. This indicates that even when tourists hold favorable views of a destination, it does not necessarily improve their trust in ChatGPT's travel suggestions if the perceived information quality does not meet their expectations. This suggests that trust formation in AI contexts may be more dependent on the interactive and experiential quality of the AI communication rather than the traditional cognitive evaluations of content quality and destination familiarity.

Meanwhile, trust in ChatGPT's travel recommendations significantly affects destination visit intentions, affirming the theoretical argument that trust remains a critical predictor of behavioral intentions in digital tourism contexts. This is in line with Trust Theory, which postulates that in situations where there is some degree of uncertainty, such as travel planning, the willingness to act based on the information provided by ChatGPT is greatly encouraged by trust in the platform. Since ChatGPT has multiple functions that simulate natural human-like conversations, the perceived risk is likely to decrease, thereby influencing users' willingness to visit the recommended destinations.

6.2. Practical Implications

The present work provides practical insights for key stakeholders in the tourism industry, including Destination Management Organizations (DMOs), travel agencies, and policymakers, on how to utilize ChatGPT to increase destination visit intentions. The findings of this work assert that trust in ChatGPT travel recommendations is a primary driver of tourists' willingness to visit suggested destinations. In contrast to the conventional tourism marketing channels, ChatGPT's conversational and interactive delivery design provides a unique channel to deliver personalized travel recommendations in real time, thereby increasing tourists' engagement and trust in travel decisions.

For DMOs, they can create storytelling devices and attract experiential value in the digital context. Having a dialog-based response, the DMOs should focus on the narrative-based content—plunging descriptions of local experiences, unheard cultural bits, and detailed descriptions of landmarks that can be accessed through various online resources. For example, they may generate fascinating narratives about local festivals, unknown spots, and genuine local experiences that are appealing to travelers' imagination and pull them towards travel intentions. This style of narrative is more likely to be recorded and imitated by ChatGPT in its interactions with users because a rich depth and experiential depth are key to engaging users.

For travel agencies, they can focus on personalized travel engagement. Since the effectiveness of ChatGPT's efficiency is associated with its conversational and interactive tendencies, travel agencies can develop interactive chatbot solutions on their websites that have the conversational style of ChatGPT. These chatbots may provide more immediate itinerary suggestions, travel tips, and local information through an interactive and dynamic approach. In addition, they can generate live chat support, where the travelers can ask particular questions and receive immediate personalized responses, which resembles the conversational trust-forming experienced with ChatGPT. This transformation from static information to real-time live conversations could increase user confidence and stimulate destination visit intentions.

For policymakers, they can support the creation of official tourism storytelling platforms that provide immersive, interactive content about local destinations, which could be referenced by ChatGPT. Moreover, policymakers could incentivize the production of virtual experiences and interactive cultural showcases that are digitally accessible, enhancing tourists' engagement and travel intentions through enriched, experiential information. This approach would align with how tourists interact with ChatGPT—favoring narrative depth and authenticity over purely factual descriptions.

7. Conclusions

The present work examines the effect of ChatGPT's travel recommendations on destination visit intentions through the lens of the Information Systems Success (ISS) model. This work's findings show that ChatGPT's information quality does not significantly affect trust in ChatGPT's travel recommendations, trust in ChatGPT's travel recommendations significantly affects destination visit intentions, and the destination image does not moderate the relationship between information quality and trust in ChatGPT's travel recommendations.

Limitations and Future Research

This study has two primary limitations. First, it is geographically limited to Indonesia, potentially restricting the generalizability of the findings to other cultural contexts where digital trust mechanisms may differ. Future research should expand its geographic scope to validate these findings across diverse tourism markets. Second, this study focuses exclusively on trust and visit intentions, leaving the role of user satisfaction and loyalty underexplored. Future studies could investigate how continuous interactions with ChatGPT not only affect initial trust and travel intentions but also influence long-term user loyalty and repeated usage in travel planning. Understanding these longitudinal impacts would provide richer insights into ChatGPT's role as a sustainable digital travel companion.

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