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Digital Trust in Tourism: From Information Quality to Willingness to Accept

Meta Bara Berutu [1*], Dewi Agustin Pratama Sari [2], Puji Wahono [3], Ryna Parlyna [4], Nor Hafizah Abdul Rahman [5]

[1] *Lecturer at the Faculty of Economics and Business of Universitas Negeri Jakarta, Indonesia*
[2] *Lecturer at the Faculty of Economics and Business of Universitas Negeri Jakarta, Indonesia*
[3] *Lecturer at the Faculty of Economics and Business of Universitas Negeri Jakarta, Indonesia*
[4] *Lecturer at the Faculty of Economics and Business of Universitas Negeri Jakarta, Indonesia*
[5] *Lecturer at the Faculty of Accountancy, University of Teknologi MARA, Shah Alam, Selangor, Malaysia*

Abstract

Many studies discuss artificial intelligence in the education sector using the IAM (Information Adoption Model) theory, but there are still very few studies discussing AI-based IAM for tourism activities. Therefore, usage behavior is assessed not only based on technology adoption but also on the information generated. The attitude in this study is employed to determine whether AI acceptance is emotional or rational, thereby comprehensively understanding AI acceptance based on information. The study involved 450 respondents, analyzed using PLS-SEM. PLS-SEM was employed because the study aims to predict relationships among latent constructs and assess a relatively complex structural model. PLS-SEM is particularly suitable for exploratory research, theory extension, and prediction-oriented studies, while accommodating data that may not meet multivariate normality assumptions (Hair et al., 2021). Among the six hypotheses tested, four were significant, while two were not. The conclusion is that in tourism activities, AI chatbots have inconsistent usage patterns because there are results that indicate trust but not readiness to use. This is an important point for developers because optimal performance is not enough to address users' concerns about using the technology, so additional psychological encouragement is needed to overcome these issues.

Keywords

Information Adoption Model; Information Quality; Tourism; AI chatbots; Artificial Intelligence.

1. Introduction

With the development of tourism, Artificial Intelligence (AI) technology has had a significant impact on almost all aspects of human life, ranging from health, education, and e-commerce to tourism and travel. More specifically, tourist behavior began to develop into activities such as searching, choosing, and planning trips (Suanpang & Pothipassa, 2024; Wong et al., 2023). Conversational AI, or better known as AI chatbots and travel agents, is here as a solution and a consideration that can help travelers to get recommendations for destinations, tourist attractions, activities, and even travel plans quickly and more personally (Kim et al., 2024). Recent systematic studies show that AI chatbots can change the way travelers gather information and make travel decisions (Prasanna et al., 2025). More clearly, travelers are using AI as a decision support system that can save time in making the right decisions for travelers (Sigala et al., 2024).

In Indonesia, there is an innovation in the use of chatbots to encourage environmentally friendly tourism behavior on Gili Island as a form of extensification of the use of chatbots in the local context. (Majid et al., 2025). Thus, how AI chatbots are received in the context of tourism is becoming increasingly relevant, along with rising expectations for an increasingly high travel experience. However, of the many benefits offered in the previous explanation, there are still obstacles in adapting AI related to the quality of information and the trust of sources in the information generated by AI. (Shi et al., 2024). This has to do with AI hallucinations (the output of false but convincing information) (Booyse & Scheepers, 2023). In fact, while AI chatbots have benefits, travelers consider risks such as information accuracy and over-dependence. This suggests a gap between the potential benefits of AI and the rate of acceptance among tourists. Despite these technological advances, many travelers continue to hesitate to rely on AI-generated travel recommendations even when they perceive the information as useful and trustworthy. This inconsistency raises an important question regarding why trust in AI-generated information does not always translate into actual willingness to adopt AI chatbots for travel decision-making. "This paper explains why trust does not necessarily produce willingness.

Beyond information quality, recent AI adoption literature suggests that travelers' decisions are also shaped by risk perception, trust in algorithms, and resistance to intelligent systems. Even when AI-generated information is perceived as accurate, users may hesitate to rely on algorithmic recommendations because of concerns about transparency, accountability, privacy, or AI's inability to understand nuanced travel preferences. These psychological barriers may explain why trust does not automatically translate into willingness to adopt AI chatbots.

Furthermore, AI chatbots, which are digital applications, are important for measuring their performance in terms of the benefits offered and ease of use. In this case, performance expectations and effort expectations are the strongest predictors for measuring a person's intention in adopting technology. (Khechine et al., 2016; Magsamen-Conrad et al., 2015; Miah et al., 2023). According to Solomovich and Abraham (2024), If travelers feel that AI can provide accurate, relevant, and personalized information, then travelers will judge that AI can improve performance expectations and effort expectations. (Kim et al., 2025; Kim et al., 2024). The context of utilitarian tourism will be considered a high performance expectation if it can generate value for money and efficiency (García-Milon et al., 2021). Meanwhile, to measure the level of expected effort in tourism activities, the use of AI should not impose an additional burden. But in reality, even though AI chatbots are considered to provide benefits in providing travel recommendations, according to Shi et al (2024), the accuracy of the information and the over-reliance on AI suggest that there is a gap between the benefits of AI and the actual level of acceptance from travelers. This paper explains why trust does not necessarily produce willingness.

Previous studies have demonstrated that information quality and source trustworthiness significantly influence AI adoption (Khan & Azam, 2023; Shi et al., 2024). Likewise, technology acceptance studies based on TAM and UTAUT have consistently identified perceived usefulness, performance expectancy, and effort expectancy as key determinants of adoption intentions. However, these studies generally assume that higher trust naturally leads to greater adoption intentions. Little attention has been paid to situations in which travelers acknowledge AI-generated information as trustworthy but remain reluctant to rely on it for actual travel decision-making. This unresolved inconsistency represents an important theoretical gap that this study seeks to address.

To explain this phenomenon, this study integrates the Information Adoption Model (IAM) with the Technology Acceptance Model (TAM) and UTAUT perspectives. While IAM focuses on the adoption of information based on its quality and credibility, TAM and UTAUT explain how users evaluate technology in terms of usefulness and ease of use. Integrating these theories enables a more comprehensive understanding of why trustworthy AI-generated information does not always result in travelers' willingness to adopt AI chatbots. By integrating these complementary perspectives, this study provides a more comprehensive explanation of how information characteristics and technology acceptance mechanisms jointly shape travelers' willingness to use AI-generated tourism recommendations.

This research is important to carry out for several reasons: first, the emergence of AI chatbots, which is increasingly massive, and literature studies that test psychological factors in their use. (Ding & Najaf, 2024; Gkinko & Elbanna, 2022). Second, previous studies have demonstrated that information quality and source trustworthiness are strong determinants in AI chatbot systems. Khan & Azam (2023). However, these findings have rarely been examined within the tourism context, where travelers require highly contextualized information such as destination recommendations, itineraries, and local experiences. Third, Indonesia's tourism sector increasingly depends on digital innovation to remain competitive, making it important to identify the factors that encourage tourists to accept AI chatbot technologies.

Accordingly, this study aims to investigate the factors influencing travelers' willingness to accept AI chatbots in tourism by integrating Information Quality and Source Trustworthiness from the Information Adoption Model (IAM) with Performance Expectancy and Effort Expectancy from technology acceptance theories. In particular, this study seeks to explain the observed inconsistency between travelers' trust in AI-generated information and their actual willingness to rely on AI chatbots for travel decision-making.

Theoretically, this study aims to validate and extend the integration of IAM, TAM, and UTAUT in the context of AI chatbot tourism by emphasizing the relative role of information quality and source trustworthiness. Next, this research can provide instructions to chatbot developers and tourism agencies (tourism offices and destination management) to design features, communication strategies, and information delivery so that chatbots are more useful for tourists. For example, if the research finds that source reliability (source trustworthiness) strongly influences willingness to accept, then the destination party can display an official label or certification on the chatbot so that users feel more assured. Third, the results of the research are expected to help accelerate the adoption of digital innovations in Indonesian tourism so that local destinations can compete amid the global digital revolution. Fourth, this research can open up further research pathways, for example, adding moderation variables (such as traveler characteristics, previous technological experience, or the level of complexity of questions) or extending the context to other AI applications in tourism. Thus, this research is not only an academic study, but also part of efforts to digitally transform Indonesian tourism to face future challenges and opportunities.

2. Literature Review

As for being more comprehensive, each variable is described as follows (see **Figure 1**):

Integrating IAM, TAM, and UTAUT in AI Tourism Adoption

The adoption of AI chatbots in tourism cannot be adequately explained by a single theoretical perspective because travelers' decisions involve both information evaluation and technology acceptance processes. The Information Adoption Model (IAM) explains how users assess the quality and credibility of AI-generated information before deciding whether to rely on it. However, information credibility alone may not be sufficient to encourage adoption, as travelers also evaluate whether AI chatbots are useful and easy to use when supporting travel planning. These cognitive evaluations are captured by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasize perceived usefulness, performance expectancy, and effort expectancy as key determinants of technology acceptance. By integrating IAM with TAM and UTAUT, this study provides a more comprehensive framework that explains how information-related factors (Information Quality and Source Trustworthiness) interact with technology acceptance factors (Performance Expectancy and Effort Expectancy) to shape travelers' willingness to accept AI-generated tourism recommendations. This integrated perspective is particularly relevant for addressing the observed inconsistency between travelers' trust in AI-generated information and their actual willingness to adopt AI chatbots, thereby offering a more holistic explanation of AI adoption behavior in tourism.

Unlike previous studies that primarily examined information adoption or technology acceptance separately, this study argues that understanding AI chatbot adoption in tourism requires integrating both perspectives to explain why trust in AI-generated information does not always translate into travelers' willingness to use AI for travel decision-making.

2.2. Information Quality

Information quality is one of the important dimensions used to measure the Information System Success Model developed by DeLone and McLean (2003). Information quality refers to the extent to which the information provided by a system. (Miller, 1996; Stawowy et al., 2021), which will affect the user's intention to use or adopt the system. In the context of AI, information quality refers to recommendations for destinations, activities, and culinary activities that suit tourists' needs. According to Kim et al. (2025) The urgency of using information quality variables lies in the fact that travelers will trust and start using AI chatbots because the information generated can provide benefits tailored to travelers' preferences. The dimensions used in this study are based on the source of the Sussman & Siegal, (2003) which includes accuracy, relevance, completeness, timeliness, and comprehensiveness. In more detail, accuracy and relevance refer to the information provided, displaying facility information with details, ticket prices, and activities that can be done by tourists. (Gao et al., 2020; Zhang et al., 2020). Completeness and fluency refer to the response that is produced thoroughly and well-organized. Timeliness refers to the information generated being up-to-date to ensure it is in accordance with the conditions and activities that are taking place. Overall information quality includes the suitability of the information produced and supports the sustainability of the use of AI chatbots in tourism activities.

2.3. Source Trustworthiness

Trust is one of the essential components of communication and persuasion related to the acceptance or rejection of results. (Hovland, 1953). In this study, source trust is related to the level of trust of users in the information provided (Filieri et al., 2015; Sbaffi & Rowley, 2017; Yi et al., 2013). Information includes perceptions of honesty, credibility, personalization, and perceived integrity. In the context of AI for tourism activities, travelers need to believe that the information generated is unbiased, non-misleading, and reliable. Travelers tend to avoid chatbot services that provide ambiguous information or cast doubt on the legitimacy of the source. The right information can help tourists make their activities easier because tourists tend to easily receive information that is considered reliable. (Solomovich & Abraham, 2024). More specifically, transparency and credibility include how transparent AI is in providing reliable information and avoiding imitation by humans. Personalization is a response that is in line with user preferences and cultural expectations by creating appropriate closeness and trust.

2.4. Attitudes Towards Use

Attitude is a psychological factor formed from individual beliefs and perceptions that impacts actual intentions and behaviors (Fishbein & Ajzen, 1977). Attitudes towards use refer to the positive or negative evaluation of the user towards the use of a particular technology (Dwivedi et al., 2017; Liesa-Orús et al., 2022). This attitude reflects how individuals rate the desire, acceptance, or refusal to use a particular application or information system in work or daily life. If a person has a positive attitude towards the use of a technology, they are likely to support, use, and continue to use it, while a negative attitude leads to resistance or rejection of the technology. In the context of tourism, if travelers have a good experience, for example, AI information is found useful, easy to use, and trustworthy, then a positive attitude will be formed that encourages them to continue using AI in travel activities (Au & Enderwick, 2000; Dwivedi et al., 2017; Liesa-Orús et al., 2022). The urgency of researching attitudes is because these variables act as a psychological bridge between technical perceptions (quality of information, trust, expectations) and real use intentions. In addition, attitude can evaluate the success of a system use. These dimensions include cognitive (rational) and affective (emotional) attitudes (Davis et al., 1989).

2.5. Performance Expectancy

Performance expectations are the extent to which a person believes that using technology will improve their performance or effectiveness. In the context of AI, performance expectancy is one of the important factors that need to be researched. Recent research shows that performance expectancy is often the most significant predictor in technology adoption models involving AI (Acosta-Enriquez et al., 2024; Camilleri, 2024; Cornelissen et al., 2022). This confirms that the success of AI implementation depends largely on the extent to which users see the practical benefits offered. As such, understanding performance expectancy is critical for developers and organizations that want to adopt AI effectively.

In the context of tourism, performance expectations mean the extent to which travelers judge that AI (such as ChatGPT or Gemini) actually helps them choose destinations, create itineraries, save costs, and improve the travel experience, as AI chatbots allow travelers to get instant and accurate information. If the chatbot meets the expected performance expectations, then the possibility of using it will occur. (Jenneboer et al., 2022; Nguyen et al., 2021).

However, the level of performance expectancy can also be influenced by user trust in the quality of technology. (Lee et al., 2019). The urgency of research on these variables lies in the utilitarian nature of tourism; tourists want to get real benefits from the technology used. Its dimensions can include perceived usability, effectiveness, and improved yields (Venkatesh et al., 2012).

2.6. Effort Expectancy

Effort expectancy is the level of ease felt when using a technology, including the ease of learning and interacting with it, such as a user-friendly interface and natural conversation mechanisms. In the context of AI, this variable plays an important role because the perception of convenience will determine whether users are willing to try and continue using the technology. (Dwivedi et al., 2021). When AI is designed with a simple, intuitive, and user-friendly interface, the user's effort expectancy will increase. (Costa et al., 2024; Kelly et al., 2022).

Research shows that the lower the effort required to understand and operate AI, the higher the user's intention to adopt it. (Dwivedi et al., 2017). For example, AI-based chatbots that are easily accessible through popular messaging apps can increase the perception of convenience compared to systems that require complex procedures. (Liu, 2020). In addition, effort expectancy is also influenced by the user's level of digital literacy and previous experience with similar technology. (Getenet et al., 2024). This factor is particularly relevant in developing countries, where there is still a gap in digital technology capabilities among people (Dwivedi et al., 2021)

For travelers, AI is more likely to be adopted if it is considered easy to use, for example, being able to understand natural language, provide quick answers, and present information in a simple, non-confusing format. Recent studies confirm that the easier AI is to use, the more likely users are to get comfortable and adapt quickly to AI chatbots that don't confuse or require a lot of complicated steps (Topsakal and Çuhadar, 2025), and the higher the intention of tourists to use it repeatedly in planning trips(To & Yu, 2025).

2.7. Willingness to Accept

It refers to the extent to which individuals are willing to accept and adopt new technologies in their daily activities despite risks or uncertainties (Davis, 1989). This concept is often used in technology adoption studies as a final indicator that describes the readiness of users to actually use technology after considering cognitive and affective factors (Venkatesh et al., 2003). Intention of use (*Behavioral intent*) is the main predictor of actual behavior in using technology. In the context of Artificial Intelligence (AI), willingness to accept is important because the adoption of AI often raises concerns related to privacy, reliability, and the replacement of human roles (Dwivedi et al., 2021). Research shows that users who have a high level of trust in AI are more likely to have a strong willingness to accept (Shankar, 2020).

Researching willingness to accept is important because it serves as a bridge between perception and real behavior. Variables such as information quality, trust, performance expectations, business expectations, and attitudes toward use ultimately come down to how willing users are to actually adopt the technology. Willingness to accept. This emphasizes that willingness to accept is not only a matter of technical readiness, but also psychological and social readiness. As such, understanding the willingness to accept is critical for AI developers and marketers to make implementation strategies more effective. In AI-based tourism research, willingness to accept is also important because it can show the potential for sustainability (*sustainability*) of the use of technology, not just a momentary trend.

3. Materials and Methods

To test the relationship between constructions, empirical studies were conducted, and questionnaires were created specifically for this purpose. The surveys used to collect data are described below.

3.1 Data Collection

The sampling method of non-probability objectives is used in the data collection process. This method is used because certain attributes, such as whether the user is a college student or has used an AI application, are identified in the research sample. The survey, which was conducted in Jakarta between February 2025 and May 2025, was used to collect responses from participants, totaling 450 respondents (see **Table 1**).

Table 1. Descriptive Analysis.

Profile	Description	Frequency	Percentage
Occupation	Student	379	84%
	Civil Servant/State-Owned Enterprise	41	9%
	Entrepreneur	13	3%
	Freelancer	13	3%
	Unemployed	4	1%
Duration of Use	Daily	209	47%
	Twice a Week	191	43%
	Four Times a Month	50	11%

At the education level, AI use for tourism-related activities is predominantly concentrated among students, who represent 379 respondents (84%) of the sample. This finding aligns with the report by Chegg, (2025), which revealed that 95% of Indonesian students use AI, placing Indonesia among the leading countries in AI adoption across 15 surveyed nations. The high prevalence of AI use among students can be attributed to their frequent exposure to AI-powered tools in academic settings, where these technologies have become integral to learning, information retrieval, and problem-solving. Such continuous interaction with AI is likely to enhance users' familiarity, confidence, and perceived usefulness of the technology, encouraging its application beyond educational contexts, including tourism-related information search, destination exploration, itinerary planning, and travel decision-making. Furthermore, the finding that most respondents use AI daily suggests that AI has become embedded in their everyday digital routines. This habitual use may reduce psychological barriers to adoption and strengthen individuals' willingness to rely on AI when making tourism-related decisions, thereby reinforcing its role as a trusted source of travel information and assistance.

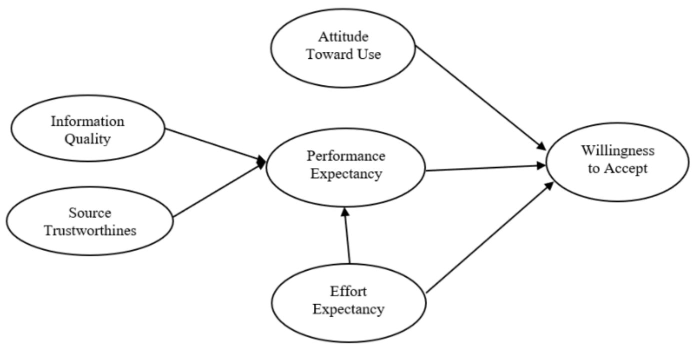

Figure 1. Conceptual Framework.

3.2 Measurement

Online surveys are used in this research. The survey is modified from technical innovation research. It contains a request and assurance that the information provided will be kept confidential and anonymous. For each construct, a 6-point Likert scale is used. The ratings range from 1 (strongly disagree) to 6 (strongly agree). The selection of an even Likert scale aims to encourage respondents to provide clearer attitudinal tendencies. (Chyung et al., 2017). Items are modified to fit the circumstances of the study. "Have you ever used AI for tourism activities?" is a dichotomy filtering question used to weed out irrelevant forms.

3.3 Measurement model: validity and reliability

According to Taherdoost (2016) and Lawshe (1975) The basis for the validity test was a minimum value of 0.6. The criteria used for the reliability test were 0.5 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1978). **Table 2** shows the findings of the validity and reliability tests. Each score is higher than what is considered acceptable. AVE is greater than 0.5, and composite reliability is greater than 0.7. The value of a set of variables is higher than the value of other variables when the value of discriminant validity is determined. Measurements of discriminant validity, convergent validity, and reliability were found to meet all established criteria.

Table 2. Convergent Reliability and Validity.

Factor	Item	Loading factor	AVE	Cronbach Alfa	Composite Reliability
Information Quality	The information provided by GenAI is easy to understand (clear).	0.795	0.738	0.881	0.918
	The information provided by GenAI is accurate for travel planning.	0.877			
	The information provided by GenAI is always up to date and aligned with current conditions in the tourism industry.	0.866			
	The information provided by GenAI is reliable in supporting my travel decisions.	0.896			
Source Trustworthiness	I trust GenAI's recommendations	0.835	0.765	0.898	0.929
	GenAI is more reliable than other media outlets, such as social media and television, for travel information.	0.883			
	The travel information I get from GenAI is always up-to-date and timely.	0.890			
	GenAI is more influential than other media outlets in my final decision to choose a travel destination.	0.889			
Attitudes Towards Use	Using GenAI for tourism purposes is effective.	0.880	0.786	0.909	0.936
	I find using GenAI in tourism planning helpful.	0.872			
	GenAI is a practical tool to support my tourism activities.	0.887			
	I consider GenAI to be a highly valuable tool in the context of tourism planning.	0.907			
Performance Expectancy	I find using GenAI beneficial for planning my travels.	0.866	0.779	0.906	0.934

Factor	Item	Loading factor	AVE	Cronbach Alfa	Composite Reliability
	Using GenAI helps me complete travel-related tasks more quickly.	0.900			
	Using GenAI can increase my productivity in planning my travels.	0.897			
	Using GenAI increases my chances of achieving important milestones in my travel planning.	0.868			
Effort Expectancy	I feel that learning how to use GenAI for travel purposes will be easy for me.	0.899	0.779	0.906	0.934
	My interactions with GenAI when searching for travel information will be clear and easy to understand.	0.900			
	I feel that using GenAI for travel purposes will not be difficult for me.	0.862			
	I feel that it will be easy for me to become proficient in using GenAI for travel planning.	0.871			
Willingness to Accept	I would be willing to use GenAI to help with travel needs or tourist information.	0.914	0.806	0.880	0.926
	I would be happy to interact with GenAI when planning a trip.	0.901			
	I would most likely use GenAI to find travel information or recommendations.	0.878			

Each construct in the model meets the recommended thresholds of reliability and validity. All items have a load factor of more than 0.70 (Hair et al., 2021) which indicates that the indicator is reliable. The convergent validity is confirmed by the Average Variance Extracted (AVE) value for each construct above the minimum requirement of 0.50 (Fornell & Larcker, 1981). Internal consistency is considered acceptable when the Alpha Cronbach value falls between 0.723 and 0.853 (Nunnally & Bernstein, 1978). The reliability of the construct is further supported by the Composite Reliability (CR) rating, which is all above 0.70 (Hair et al., 2021).

3.4 Factor loading

The value of the burden in this study is shown through several things, as shown in **Table 2**. The path coefficients of the PLS-SEM path coefficients are described in **Table 3** below.

Table 3. COEFASIA SEM-Path.

Regression Coefficients			Statistics T	P value	Result
H1	IQ→PE	0.317	5.447	0.000	Supported
H2	ST →PE	0.087	1.623	0.105	Not Supported
H3	AtU →WtA	0.606	8.937	0.000	Supported

Regression Coefficients			Statistics T	P value	Result
H4	PE→WtA	0.084	1.217	0.224	Not Supported
H5	EE→WtA	0.243	3.385	0.001	Supported
H6	EE→PE	0.565	11.880	0.000	Supported

Based on the results of the path analysis, the first hypothesis in the model is statistically significant, as shown by the p-value of less than 0.05 and the t-statistic greater than 1.96. However, only the second hypothesis and the hypothesis of four beliefs about perceived expectations and willingness to accept are insignificant.

Furthermore, to determine the strength of the model built in this study, it is illustrated by the value of R^2 where the result of R^2 (R squared) on performance expectations is found to be 0.762 or 76.2%, which means that the variables of information quality, source reliability, and effort expectations can explain their influence on performance expectations by 76.2%, the remaining 23.8% is explained by other variables that are not explained in this study. Meanwhile, the variables that were willing to accept were obtained an R^2 of 0.765 or 76.5%, which means that the variables of information quality, trust of sources, attitudes towards use, business expectations, and perceived expectations were able to explain 76.5% of the effect; the remaining 23.5% was explained by other variables that were not explained in this study. Broadly speaking, the model framework described in this study has a good level of explanation because the closer the value of R^2 is to the number 1, the better the model**.**

4. Discussion

In the first hypothesis, the quality of information has a significant influence on performance expectations; the results of this study are in line with (Camilleri, 2024; Kim et al., 2024; Orden-Mejía et al., 2025). This means that the more relevant, useful, and accurate the information provided by AI, the more it impacts travelers' belief that AI chatbots can improve travel effectiveness. The quality of the information here includes accuracy, relevance, completeness, and up-to-date information. This confirms that travelers tend to evaluate the usefulness of AI based on the extent to which the information they receive corresponds to their practical needs in planning trips. Travelers who receive relevant, complete, and accurate information from AI chatbots find the technology useful for improving the effectiveness of travel decision-making, including in choosing destinations, activities, and travel services. In addition, the study also found that informative content not only increases the perception of usability. These findings reinforce the argument that information quality is a key determinant in shaping perceptions of the benefits of AI in the tourism sector. Without accurate and relevant information, AI will not be seen as useful, even if it is technologically advanced. Conversely, when AI can provide recommendations for destinations that suit their preferences, the right itinerary, or interesting local culinary options, travelers will feel that these technologies are truly improving the effectiveness and efficiency of their trips.

Furthermore, the relationship between source confidence and performance expectations shows that these influences bring insignificant results. Further explanation related to destination recommendations and tourist information: sometimes users judge whether the information produced is relevant without first trusting the source, so the relationship built in this study is not correct. This means that users judge a chatbot's performance more by its immediate usefulness and user experience than by trust in its source separately (Alagarsamy & Mehrolia, 2023). AI chatbot users are more focused on assessing the quality of the chatbot's information, services, and usability than who the source is. Even in studies, design and interface aspects do not always have a significant effect on the trustworthiness of chatbots if the interface is considered simple enough and easy to use. In addition, research that uses the trust variable is more powerful in predicting satisfaction, attitudes, or sustainability intentions compared to performance expectations (Alagarsamy & Mehrolia, 2023), who demonstrate that the role of trust in a relationship can be a mediator, not a direct relationship. This explains why the direct relationship between source trustworthiness and performance expectancy is not significant (Camilleri, 2024; Su et al., 2025).

Next is the relationship between attitude toward use and effort expectancy and willingness to accept, which gives significant results. This means that the more positive the attitude of tourists towards AI, the higher their readiness or willingness to adopt(Marikyan & Papagiannidis, 2021). If tourists feel positive benefits such as being useful and fun when using AI chatbots in tourism activities, then they are willing to accept or use it (Dwivedi et al., 2021). Furthermore, the discovery that effort expectancy has a significant effect on the willingness to accept, which emphasizes the UTAUT model that ease of use is one of the important factors that affect the acceptance of a technology (Venkatesh et al., 2003). Furthermore, tourists feel that the use of AI chatbots does not require a great effort, which results in a reduction in psychological obstacles to accepting it (Pei et al., 2020). This further strengthens that tourism activities are fun activities that aim to improve the quality of life by giving rise to a feeling of happiness by being free from various complicated things. Of course, this is supported by the presence of AI chatbots, which also provide ease of use. These two positive findings suggest that positive attitudes provide emotional and cognitive boosts that reinforce acceptance, while the perception of ease reduces the technical barriers that users may face. The combination of the two creates optimal psychological conditions for individuals to accept AI in tourism. Thus, AI organizations and developers need to pay attention to the design aspects of user-friendly technology while building a positive image of AI, so that willingness to accept can continue to increase.

Next are the findings that are different or insignificant between performance expectancy and willingness to accept. While AI is believed to be able to improve performance or provide functional benefits, it does not directly encourage an individual's willingness to accept technology. One possible cause is that travelers are more focused on emotional experiences and attitudes than functional benefits (Zhang et al., 2023). This may be especially true if travelers become more accustomed to using AI and make its "usability" more familiar to them. In other words, even if AI is considered useful, if users are not comfortable or have a positive attitude towards its use, they will not immediately accept it. Since travelers are driven more by emotional attitudes and affective experiences than functional benefits or convenience alone, emphasize that the success of tourism chatbots lies in their ability to build enjoyable, positive experiences(Liao et al., 2021;Jeong et al., 2020; Lin & Kuo, 2016; Orden-Mejia & Huertas, 2022). Additionally, in the context of new technologies such as AI, many users still have a limited level of confidence in AI's ability to completely replace or improve human performance. Some studies show that users often doubt the accuracy of AI-provided recommendations or outcomes, especially when it comes to important decisions (Heersmink et al., 2024; Marikyan & Papagiannidis, 2021; Shankar, 2020). This doubt can reduce the relevance of the performance benefits offered by AI to willingness to accept, because trust and perceived risk factors are more dominant in influencing acceptance. Therefore, although performance expectancy is often a strong predictor of intention to use (Venkatesh et al., 2003), in the case of willingness to accept, the results can be different because they are more related to emotional readiness and attitude than to performance considerations alone. Thus, these findings indicate that AI developers must not only highlight performance benefits but also build trust, comfort, and positive user attitudes for acceptance to be realized.

The results of the study further showed that business expectations have a significant influence on performance expectations. This means that the easier it is for tourists to experience the use of AI-based chatbots, the higher their belief that the technology is useful in supporting tourism activities. (Huang & Rust, 2018). Further explanation is that if travelers find the chatbot easy to understand, does not require high technical skills, and is able to provide quick and relevant answers, they will find this technology effective in helping with trip planning, destination selection, and local culinary recommendations. Therefore, it can be concluded that the perception of comfort (EE) is an important catalyst in improving the perception of usability (PE), thus ensuring that tourism chatbots are not only easy to use but also seen as very useful in the tourism decision-making process.

5. Conclusion

This study examined the factors influencing the acceptance of AI chatbots in tourism by integrating the Information Adoption Model (IAM) and the AI Device Use Acceptance (AIDUA) model. The findings indicate that information quality significantly enhances tourists' performance expectancy, demonstrating that accurate, relevant, complete, and up-to-date information strengthens users' perceptions of the usefulness of AI chatbots in supporting tourism decision-making. In contrast, source credibility does not significantly influence performance expectancy, suggesting that users tend to evaluate AI chatbots based on the quality and usefulness of the information provided rather than on the credibility of the information source itself.

The study also reveals that performance expectancy does not directly influence tourists' willingness to accept AI chatbots. This finding suggests that perceived functional benefits alone are insufficient to encourage AI adoption in tourism, as users' acceptance is also shaped by emotional readiness, trust, and positive user experiences. Furthermore, business expectancy significantly influences performance expectancy, indicating that AI chatbots that are easy to use, responsive, and capable of providing efficient assistance strengthen users' perceptions of AI usefulness.

Overall, this study contributes to the AI tourism literature by demonstrating that information quality remains the primary driver of performance expectancy, whereas source credibility plays a less prominent role in the context of generative AI. The findings further suggest that the pathway from perceived usefulness to AI acceptance is more complex than traditional technology acceptance models propose, highlighting the importance of incorporating emotional and psychological factors into future AI acceptance research.

5.1 Practical Recommendation

Based on the findings, AI chatbot developers should prioritize improving the quality of information generated by AI systems. Travel recommendations should be accurate, up-to-date, personalized, and contextually relevant so that users perceive AI as genuinely useful in supporting travel planning and decision-making.

Tourism organizations and Destination Management Organizations (DMOs) should also ensure that AI chatbots provide simple, intuitive, and efficient interactions. Features such as personalized itinerary planning, real-time travel information, multilingual communication, and fast response times can enhance users' performance expectancy and overall experience.

Since performance expectancy alone does not directly increase tourists' willingness to accept AI, developers should focus not only on functional performance but also on building user trust and positive emotional experiences. Providing transparent AI-generated recommendations, clearly communicating information sources, protecting user privacy, and incorporating more natural and human-like interactions may strengthen users' confidence and increase their willingness to adopt AI in tourism services.

5.2 Future Research Suggestions

Future studies are encouraged to investigate additional factors that may explain tourists' willingness to accept AI beyond performance expectancy. Variables such as trust, perceived risk, privacy concerns, perceived humanness, anthropomorphism, AI transparency, emotional attachment, and hedonic motivation may provide a more comprehensive explanation of AI acceptance in tourism.

Future research should also examine the mediating or moderating mechanisms that explain why performance expectancy does not directly translate into willingness to accept AI. Understanding these mechanisms would contribute to the refinement of technology acceptance theories in AI-enabled tourism.

In addition, future studies should involve more diverse respondent groups across different age categories, occupations, cultural backgrounds, and travel experiences to improve the generalizability of the findings. Longitudinal studies and cross-country comparative research are also recommended to capture changes in AI acceptance over time and across different tourism contexts.

6. Recommendations

This research provides an opportunity for academic study of tourism technology. The findings indicate that the insignificant influence of performance expectations on willingness to adopt can be explored by examining other variables, such as perceived pleasure or social pleasure, used as mediating variables. Furthermore, it can practically be recommended that AI-based chatbot service providers should provide quality information, as it is the strongest predictor for using chatbot applications. In addition, attitudes towards positive use or communication for tourists can be a positive response so that they can be widely used by tourists. In addition, the greatest significance value is found in the effort expectancy-perceived expectancy relationship, which means that tourists strongly consider the level of ease of use, which is the main reason for assessing the benefits of the application. In the future, developers need to provide a minimum level of ease for all age levels.

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Ethics approval

The study protocol adhered to the principles outlined in the Declaration of Helsinki, which provides guidelines for ethical research involving human participants. Ethical considerations in this study were that participation was entirely optional. This study was reviewed and approved by the Ethical Committee of the Research and Community Service Institute (LP2M), Universitas Negeri Jakarta, Indonesia (Ref. No. B/197/UN39.14/PT/III/2025)

Conflict of interest

The author(s) declare(s) that there is no competing interest.

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