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Factors Affecting the Tourist Intention to use Artificial Intelligence in United States

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Abstract

This study investigates the determinants of individuals' intention to use artificial intelligence (AI) for tourism in the United States. This study adopts a cross-sectional design, employing a convenience sampling technique. Data collection was conducted via an online survey, targeting 239 participants who have recent travel experience. Constructs including interactivity, facilitating conditions, informational support, performance expectancy, and intention to use AI for tourism were assessed using established measurement items adapted from prior literature. The analysis employed partial least squares structural equation modeling (PLS-SEM) to examine the relationships between these constructs. The results reveal that interactivity, facilitating conditions, informational support, and performance expectancy significantly influence individuals' intention to use AI for tourism. The findings offer practical implications for the tourism industry, suggesting strategies to enhance AI adoption among travelers. Additionally, this study contributes to the theoretical understanding of technology adoption in the tourism context. Future research could explore additional factors and employ longitudinal designs to further elucidate the dynamics of AI adoption in tourism. Overall, this study advances our knowledge of the factors shaping individuals' intention to use AI for tourism and lays the groundwork for continued research in this rapidly evolving field.

Keywords: artificial intelligence; information; tourism; United States

1. Introduction

Artificial Intelligence (AI) encompasses a broad spectrum of technologies designed to enable electronic systems to perform tasks that traditionally require human cognitive functions. These tasks include sensing, perceiving, interpreting, and learning (Bowen & Morosan, 2018). AI systems, such as intelligent devices, automated self-service kiosks, chatbots, and service robots, have increasingly been utilized in the provision of frontline services (Chi et al., 2020). Recent advancements in language processing, emotion recognition, and facial identification technologies have significantly enhanced the capabilities of AI devices. These advancements enable AI systems to deliver tourism-related services that involve complex social interactions, such as assisting guests in hotels and on cruise ships (Mende et al., 2019; Qiu et al., 2020), responding to travelers' inquiries, offering tailored recommendations, and guiding airline passengers at airports (Gursoy et al., 2019). As a result, the deployment of AI technologies in the travel and tourism sectors has experienced substantial growth in recent years (Prentice et al., 2020; Rafiq et al., 2022).

In an era characterized by rapid technological advancements, AI has emerged as a transformative force across various industries. From healthcare to finance, AI-powered solutions are revolutionizing traditional practices, driving efficiency, and unlocking new opportunities for innovation (Jan et al., 2023; Khan et al., 2023). In the realm of tourism, AI holds immense potential to reshape the way travelers plan, experience, and reflect on their journeys (García-Madurga & Grilló-Méndez, 2023). The tourism industry has long been at the forefront of embracing technological innovations to meet the evolving needs and preferences of travelers. From the advent of online booking platforms to the proliferation of mobile apps offering personalized recommendations, technology has played a pivotal role in shaping the modern travel experience (Ghouse & Chaudhary, 2024). However, as AI continues to permeate every aspect of our daily lives, its impact on the tourism sector is poised to be particularly profound. AI technologies encompass a wide array of applications in the tourism domain, ranging from chatbots and virtual assistants to predictive analytics and recommendation systems (Nannelli et al., 2023). These technologies have the capacity to streamline various aspects of the travel experience, from trip planning and itinerary customization to on-the-ground assistance and post-travel insights. By harnessing the power of machine learning, natural language processing, and data analytics, AI-enabled solutions can deliver personalized, contextually relevant experiences that cater to the unique preferences and interests of individual travelers (Kong et a., 2023). Despite the immense potential of AI in tourism, its adoption among travelers remains a subject of ongoing inquiry and debate. While some individuals eagerly embrace AI-driven innovations as a means to enhance their travel experiences, others may harbor reservations or skepticism about the role of technology in shaping their journeys. Understanding the factors that influence individuals' intention to use AI for tourism is therefore paramount for industry stakeholders and policymakers seeking to leverage AI to its fullest potential.

Previous research on technology adoption has primarily focused on general contexts, such as the adoption of smartphones or e-commerce platforms, with limited attention to the unique dynamics of AI adoption in the tourism industry. Furthermore, existing studies often rely on theoretical frameworks or qualitative methodologies, leaving gaps in our understanding of the empirical drivers of AI adoption among travelers. This study seeks to address these gaps by investigating the determinants of individuals' intention to use AI for tourism in the United States. By examining the influence of constructs such as interactivity, facilitating conditions, informational support, and performance expectancy on individuals' intention to utilize AI technologies in their travel experiences, aim to provide valuable insights for industry practitioners, policymakers, and researchers alike.

This paper is organized into several key sections. The introduction outlines the importance of AI in tourism and identifies the research gap. The literature review discusses prior research on technology adoption, focusing on interactivity, facilitating conditions, informational support, and performance expectancy. The methodology section details the quantitative cross-sectional approach, data collection, and analysis methods. The results section presents findings from the structural equation modeling analysis. The discussion interprets these findings, highlighting theoretical and practical implications and suggesting future research directions. The conclusion summarizes the study's key insights and contributions to the tourism industry.

2. Literature Review and Hypotheses Development

2.1. Intention to use AI for Tourism

In recent years, AI service devices have seen extensive deployment across various sectors within the tourism industry. In the restaurant sector, AI robots are increasingly being used for diverse functions such as food preparation, customer service, and the management of online sales channels (Berezina et al., 2019; Lin et al., 2021). Bars have adopted sophisticated AI systems for tasks including cocktail mixing and the assessment of customers' social states, thereby refining service delivery (Foster et al., 2017). In the cruise industry, AI service devices facilitate guest interactions, disseminate service-related information, and manage booking processes, enhancing both operational efficiency and the overall guest experience (Mende et al., 2019). Similarly, in the airline industry, AI-powered assistant agents are integrated to support travelers with navigation and provide essential travel information within airport environments, thus optimizing the travel process (Gursoy et al., 2019). The hotel sector, a leading adopter of AI technology, employs interactive bellboy robots to deliver a broad range of services. These robots provide guests with information on local attractions, address various inquiries, and fulfill specific requests, demonstrating a significant advancement in enhancing guest engagement and operational productivity (Nguyen et al., 2023). This sector's adoption of AI underscores its commitment to leveraging advanced technological solutions to improve service quality and operational efficiency.

Integrating AI into the tourism industry holds significant potential for enhancing customer experience and operational efficiency. AI algorithms can analyze user preferences, past behaviors, and current trends to offer personalized travel itineraries, while AI-powered chatbots and virtual assistants handle customer inquiries and bookings around the clock (Kong et al., 2023; Ghouse & Chaudhary, 2024). AI promotes sustainable tourism by optimizing travel routes and encouraging eco-friendly practices (Nannelli et al., 2023). However, implementing AI necessitates careful consideration of data privacy, ethical use, and continuous improvement to adapt to evolving trends and maintain customer trust (García-Madurga & Grilló-Méndez, 2023). AI technology stands out from other technologies, particularly in service delivery contexts.

Although numerous studies have explored individuals' willingness to adopt AI devices in service contexts, there is growing recognition that traditional technology acceptance frameworks may not fully capture the complexities of AI device adoption due to several inherent limitations. Firstly, established technology acceptance models were initially developed for non-intelligent devices, which often require users to invest considerable effort to learn how to operate them (Gursoy et al., 2019). In contrast, AI service devices are designed to emulate human behaviors, utilize natural language, and simulate human interactions, significantly reducing the learning curve for users. Therefore, the traditional focus on "ease of use," a major factor in established technology acceptance theories, may be less relevant when assessing AI service devices (Lu et al., 2019). Secondly, the performance evaluation criteria for AI devices in service contexts require a different analytical approach (Gursoy et al., 2019). Traditional technology acceptance models typically assess whether a device can effectively perform its designated repetitive tasks. However, AI devices in service environments are engineered to handle complex tasks that involve social interactions (Fernández-Llamas et al., 2018; Vercelli et al., 2018), such as interacting with customers during service encounters (Gursoy et al., 2019). Consequently, it is essential to evaluate the performance of AI service devices not only through cognitive metrics but also through emotional and experiential criteria, reflecting their impact on user satisfaction and engagement (van Doorn et al., 2017). Thirdly, despite the advantages of AI devices in terms of performance, their application in service delivery challenges traditional service interaction paradigms. The use of AI systems reduces the extent and depth of human interaction between employees and consumers, leading to a shift in expectations regarding service delivery. This adjustment can influence individuals' acceptance of AI service devices in both positive and negative ways, as people adapt to new forms of interaction and evaluate the efficacy of AI in meeting their service needs (Huang & Rust, 2018). The integration of AI devices into service contexts calls for a reevaluation of existing technology acceptance models to account for the unique characteristics and impact of AI systems on user experiences and service interactions.

2.2. Interactivity

Perceived interactivity is a crucial element of effective online and face-to-face communication (Wei et al., 2016). The literature highlights three facets of perceived interactivity: its role as a technical feature, an information-sharing mechanism, and a user perception (Zhao & Lu, 2012). Interactivity refers to the dynamic and reciprocal nature of user interactions with AI systems, where the AI can respond in real-time and adapt to user inputs, preferences, and behaviors. Interactivity makes AI tools more engaging and immersive (Rafiq et al., 2022). When tourists interact with AI systems that provide immediate, relevant responses and personalized recommendations, they are more likely to find the experience engaging. This increased engagement can enhance their intention to use AI for various tourism-related activities, such as planning trips, booking accommodations, or discovering attractions. Interactive AI can tailor its responses and suggestions based on individual user data, preferences, and past behaviors (Wang et al., 2020). AI-powered travel assistant might recommend destinations or activities that closely align with a user's interests and previous choices. This level of personalization makes the travel planning process more appealing and relevant, thereby increasing the likelihood that tourists will use AI technologies. According to Sundar et al. (2016), both chatbots and interactive websites possess interactive media qualities that shape different aspects of perceived interactivity.

Moreover, a recent meta-analysis revealed that perceived interactivity fosters positive user attitudes (Yang & Shen, 2018). Interactivity is a fundamental feature of digital technologies (Kim et al., 2017) that significantly affects consumer experiences (Mollen & Wilson, 2010). Previous studies have shown that AI technologies enhance interactivity (Mollen & Wilson, 2019; Nikhashemi et al., 2021; Yim et al., 2017). Park and Yoo (2020) found that perceived interactivity with augmented reality influences mental imagery, leading to positive consumer attitudes. Interactivity also impacts various cognitive, emotional, and behavioral responses associated with consumer experiences (Javornik, 2016). Thus, the following hypothesis is proposed:

H1: Interactivity influences on intention to use AI for tourism.

2.3. Facilitating Conditions

Facilitating conditions refer to the perceived levels of organizational and technical support that enable the effective use of AI systems. This encompasses factors such as the availability of online tutorials, ongoing technical support, and the presence of a robust infrastructure that supports system utilization (Xian, 2021). In this context, facilitating conditions are viewed as comprising both regulatory and technical frameworks designed to enhance the adoption and effective use of technology. A facilitator, in this regard, represents a structured framework within an organization aimed at promoting the successful implementation and use of new technologies (Venkatesh et al., 2012). Facilitating conditions play a critical role in fostering greater awareness and aligning user intentions with the effective use of technology (Ghalandari, 2012). The significance of facilitating conditions is underscored by empirical evidence demonstrating their substantial impact (Onaolapo & Oyewole, 2018), with additional research highlighting their notable influence on user intentions (Vairetti et al., 2019). According to Venkatesh et al. (2003), facilitating conditions encompass the extent to which individuals perceive that both organizational and technical infrastructures are in place to support the effective utilization of a system. Interestingly, San Martín and Herrero (2012) discovered that facilitating conditions do not significantly affect the intention to engage in online shopping within rural tourism contexts. They suggest that this limited impact may be due to the absence of necessary facilitating conditions, which act as constraints. In contrast, facilitating conditions are identified as critical factors in the context of online airline ticket reservations, emphasizing their importance in various applications (Escobar-Rodríguez & Carvajal-Trujillo, 2013). A consistent body of research confirms the positive and significant effect of facilitating conditions on the intention to use technology across diverse domains (e.g., Farooq et al., 2017; Hsu et al., 2017; Abdat, 2020). Therefore, based on the existing literature, the following hypothesis is proposed:

H2: Facilitating conditions influences on intention to use AI for tourism.

2.4. Informational Support

Informational support refers to the provision of helpful and relevant information to individuals facing challenges or seeking guidance in various aspects of their lives. This form of support aims to provide knowledge, advice, and resources that empower individuals to make informed decisions, solve problems, and cope effectively with their circumstances (Lee et al., 2022). Informational support can be delivered through various channels, such as verbal communication, written materials, online resources, or personal interactions (Tutunea, 2021). It plays a crucial role in enhancing individuals' understanding, confidence, and ability to navigate complex situations, ultimately promoting their well-being and success (Lin & Lee, 2023). Informational support encompasses a range of resources including opinions, ideas, guidelines, or advice, all aimed at facilitating problem resolution and providing solutions (Cohen & Wills, 1985). Within the context of this research, informational support is specifically focused on the role of AI chatbots in delivering actionable guidance and advice to address user inquiries and challenges. AI chatbots, particularly those endowed with advanced cognitive capabilities, such as computer vision, sophisticated information retrieval systems, and adaptive learning mechanisms, are positioned to meet users' informational needs with greater efficacy. Computer vision enables chatbots to process and interpret visual data, while information retrieval systems allow them to access and provide relevant information from vast databases. Adaptive learning algorithms further enhance their ability to tailor responses based on individual user interactions and preferences. These advanced features collectively contribute to improving the quality of informational support by ensuring that users receive accurate, contextually relevant guidance in a timely manner. The capacity of AI chatbots to deliver immediate and pertinent feedback is thus significantly enhanced, making them a valuable tool in addressing and resolving user issues more efficiently (Shum et al., 2018). Based on this understanding, the following hypothesis is proposed:

H3: Informational support influences on intention to use AI for tourism.

2.5. Performance Expectancy

Performance expectancy refers to the extent to which individuals believe that AI systems are capable of executing tasks with accuracy and consistency that meets or exceeds the performance of human employees (Gursoy et al., 2019). This perception encompasses the belief that AI technologies can not only match but potentially surpass human capabilities in terms of precision and reliability. The level of performance expectancy associated with AI service devices is anticipated to vary across different service contexts. This variability arises from the diverse applications and environments in which AI technologies are deployed. For example, the performance expectancy of AI in healthcare may differ significantly from that in financial services or retail, depending on the specific tasks and the expected outcomes within each context. Performance expectancy is fundamentally linked to the expectation that adopting a particular technology will yield tangible benefits and enhance effectiveness in performing specific tasks. This includes improvements in efficiency, quality of work, and overall productivity. As a result, individuals and organizations are likely to evaluate AI systems based on their perceived ability to deliver superior performance and achieve desired outcomes in their specific operational settings. In the context of AI for tourism, performance expectancy plays a crucial role in determining travelers' intention to adopt and use AI technologies. Travelers are increasingly seeking personalized and efficient services that can enhance their overall travel experience. AI technologies are designed to meet these expectations by offering a range of capabilities, from personalized recommendations to efficient service delivery. Since performance expectancy emphasizes the utilitarian value of AI service devices, tourists are likely to rate AI performance higher in airline services, where the focus is on utilitarian aspects such as safe and efficient travel from point A to point B (Overby & Lee, 2006). In contrast, tourists in the hospitality sector are generally less inclined to prefer AI service devices, as they place greater emphasis on hedonic benefits, such as enjoyment and memorable experiences, compared to those in the airline industry (Miao et al., 2014). Moreover, interactions between staff and tourists in hospitality services are usually more comprehensive and immersive than those in airline services (Pizam & Shani, 2009). Consequently, the following hypothesis is proposed.

H4: Performance expectancy influences on intention to use AI for tourism.

Figure 1 depicts the proposed research model.

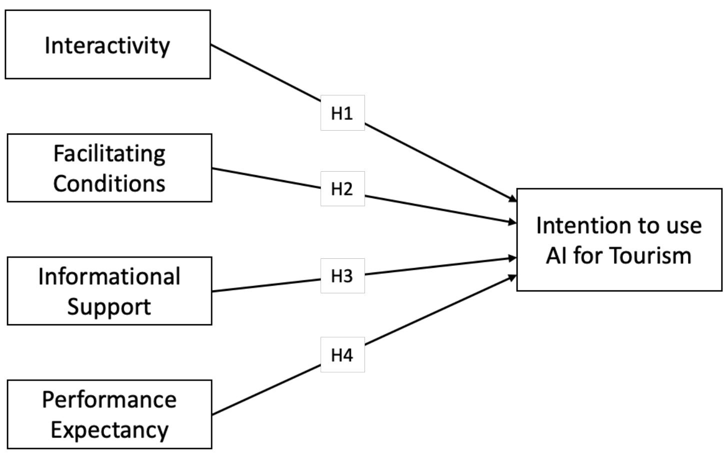

Figure 1. Proposed model.

3. Methodology

The methodology utilized in this research was carefully designed to investigate the factors influencing the intention to use AI for tourism among individuals residing in the United States with recent travel experience. A convenience sampling technique was employed to recruit 239 participants, reflecting a diverse range of backgrounds and travel preferences. This study adopted a cross-sectional quantitative approach, leveraging the power of online surveys to collect data efficiently and comprehensively from February to March 2024.

Measurement items for the various constructs were derived from well-established sources in the literature. Interactivity, facilitating conditions, and performance expectancy constructs were operationalized with four items each, drawing upon the works of Arghashi and Yuksel (2022), Xian (2021), and Lu et al. (2019), respectively. Informational support, meanwhile, was assessed with three items adapted from the seminal research of Cutrona and Suhr (1992). Intention to use AI for tourism was gauged using a set of four items adapted from the insightful contributions of Melián-González et al. (2021). To ensure robustness and validity, all measurement items were rated on a 7-point Likert scale, enabling respondents to express their opinions across a spectrum of agreement levels, from "strongly disagree" to "strongly agree". This comprehensive approach to measurement facilitated nuanced insights into participants' perceptions and attitudes towards AI utilization in the tourism domain.

Data analysis was conducted using partial least squares structural equation modeling (PLS-SEM), a widely recognized and versatile statistical technique suitable for exploring complex relationships in smaller sample sizes and non-normal data distributions. PLS-SEM allowed for the simultaneous assessment of the measurement model and the structural model, thereby ensuring the validity, reliability, and significance of the hypothesized relationships.

4. Results

Table 1 presents the demographic characteristics of the 239 respondents in the study. Among the respondents, 59% are male (141 individuals) and 41% are female (98 individuals). In terms of age distribution, the largest group consists of individuals aged 26-35, comprising 51% of the sample (123 respondents). This is followed by the 36-45 age group at 28% (66 respondents), those above 45 years at 11% (26 respondents), and the 18-25 age group at 10% (24 respondents). Regarding education, the majority of respondents hold a bachelor's degree, accounting for 60% (144 individuals). Those with a master's degree make up 23% of the sample (56 respondents), while 14% have a higher secondary school education (33 respondents), and 3% possess a doctoral degree (6 respondents). This demographic profile indicates that the sample is predominantly male, primarily aged between 26 and 35 years, and largely holds a bachelor's degree.

Table 2 provides an overview of the measurement model's reliability and validity for various constructs in the study, as assessed by Cronbach's alpha, composite reliability, and average variance extracted (AVE). Additionally, item loadings above the 0.7 threshold for each construct indicate strong factor loadings, supporting the constructs' validity. Interactivity has a Cronbach's alpha of 0.761, a composite reliability of 0.862, and an AVE of 0.677. These values indicate good internal consistency and reliability, with AVE above the recommended threshold of 0.5, suggesting that the construct explains a high proportion of variance in its indicators. Facilitating conditions shows a Cronbach's alpha of 0.796, a composite reliability of 0.775, and an AVE of 0.613. This construct also demonstrates good reliability and adequate validity, with all values meeting or exceeding acceptable standards. Informational support has a Cronbach's alpha of 0.716, a composite reliability of 0.751, and an AVE of 0.603. These metrics suggest satisfactory internal consistency and construct validity. Performance expectancy records the highest Cronbach's alpha at 0.87, indicating excellent internal consistency. Its composite reliability is 0.9, and its AVE is 0.563, both of which support the construct's reliability and validity. Finally, intention to use AI for tourism has a Cronbach's alpha of 0.816, a composite reliability of 0.857, and an AVE of 0.583. These values indicate strong internal consistency and reliability, with an AVE above 0.5, suggesting good convergent validity.

Table 3 presents the discriminant validity of the constructs using the Fornell-Larcker criterion. Discriminant validity is established when the square root of the average variance extracted (AVE) for each construct is greater than its correlations with other constructs. For facilitating conditions, the square root of the AVE is 0.692, which is greater than its correlations with other constructs, indicating good discriminant validity. Informational support shows a square root of AVE of 0.751, also higher than its correlations with other constructs, supporting its discriminant validity. Intention to use AI for tourism has a square root of AVE of 0.766, which is higher than its correlations with any other construct, indicating strong discriminant validity. Interactivity has a square root of AVE of 0.671, greater than its correlations with other constructs, confirming its discriminant validity. Lastly, performance expectancy has a square root of AVE of 0.720, which is higher than its correlations with other constructs, indicating good discriminant validity.

Table 1. Respondents Characteristics (n=239).

	Frequency	Percent
Gender		
Male	141	59%
Female	98	41%
Age		
18-25	24	10%
26-35	123	51%
36-45	66	28%
Above 45	26	11%
Education		
Higher Secondary School	33	14%
Bachelor degree	144	60%
Master degree	56	23%
Doctoral degree	6	3%

Table 2. Measurement model.

Constructs	Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Interactivity		0.761	0.862	0.677
IT1: I was in control of my conversation through the AI for tourism	0.717			
IT2: I had some control over the results of the AI for tourism that I wanted to see	0.729			
IT3: I was in control over the pace to get information	0.81			
IT4: AI for tourism had the ability to respond to my specific needs quickly	0.71			
Facilitating Conditions		0.796	0.775	0.613
FC1: I have the resources necessary to use AI	0.758			
FC2: I have the knowledge necessary to use AI	0.797			
FC3: AI is compatible with my other technologies	0.816			
FC4: I can get help from others when having difficulties of using AI	0.821			
Informational support		0.716	0.751	0.603
IS1: AI gives me suggestions and advice about how to cope with problems	0.781			
IS2: AI tells me what she did in a situation similar to mine	0.729			
IS3: AI tells me where I can go to get help	0.739			
Performance Expectancy		0.87	0.9	0.563
PE1: AI devices are more accurate than human beings	0.733			
PE2: AI devices are more accurate with less human errors	0.771			

Constructs	Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
PE3: AI devices provide more consistent service than human beings	0.779			
PE4: Information provided by AI devices are more consistent	0.711			
Intention to use AI for Tourism		0.816	0.857	0.583
INT1: I intend to use or to continue using AI for tourism in the future	0.761			
INT2: When required, I will use AI for tourism	0.791			
INT3: I intend to use AI for tourism in the future	0.858			
INT4: I think that more and more people will use AI for tourism	0.818			

Table 3. Discriminant validity (Fornell-larcker criterion).

	Facilitating Conditions	Informational Support	Intention to use AI for Tourism	Interactivity	Performance Expectancy
Facilitating Conditions	0.692				
Informational Support	0.568	0.751			
Intention to use AI for Tourism	0.59	0.608	0.766		
Interactivity	0.614	0.615	0.587	0.671	
Performance Expectancy	0.514	0.625	0.783	0.582	0.72

Table 4 presents the path coefficients for the hypothesized relationships between various constructs and the intention to use AI for tourism. Each path coefficient (beta) is accompanied by its standard deviation, T statistics, P values, and the results indicating whether the hypothesis is supported. Interactivity has a path coefficient of 0.404, with a standard deviation of 0.108, T statistics of 5.041, and a P value of 0.002. These values indicate that interactivity significantly influences the intention to use AI for tourism, thus supporting H1. Facilitating conditions show a path coefficient of 0.565, with a standard deviation of 0.109, T statistics of 4.595, and a P value of 0.00. This indicates that facilitating conditions significantly influence the intention to use AI for tourism, supporting H2. Informational support has a path coefficient of 0.449, with a standard deviation of 0.143, T statistics of 6.345, and a P value of 0.01. These values suggest that informational support significantly influences the intention to use AI for tourism, supporting H3. Performance expectancy records the highest path coefficient at 0.723, with a standard deviation of 0.104, T statistics of 6.967, and a P value of 0.00. This indicates that performance expectancy significantly influences the intention to use AI for tourism, thus supporting H4. Additionally, the R-square value for the intention to use AI for tourism is 0.619 as mentioned in Figure 2. This indicates that 61.9% of the variance in the intention to use AI for tourism is explained by interactivity, facilitating conditions, informational support, and performance expectancy combined. This relatively high R-square value suggests that the model has good explanatory power.

Table 4. Path coefficients.

Paths	Beta	Standard deviation	T statistics	P values	Results
Interactivity -> Intention to use AI for Tourism	0.404	0.108	5.041	0.002	H1 is supported
Facilitating Conditions -> Intention to use AI for Tourism	0.565	0.109	4.595	0.00	H2 is supported
Informational Support -> Intention to use AI for Tourism	0.449	0.143	6.345	0.01	H3 is supported
Performance Expectancy -> Intention to use AI for Tourism	0.723	0.104	6.967	0.00	H4 is supported

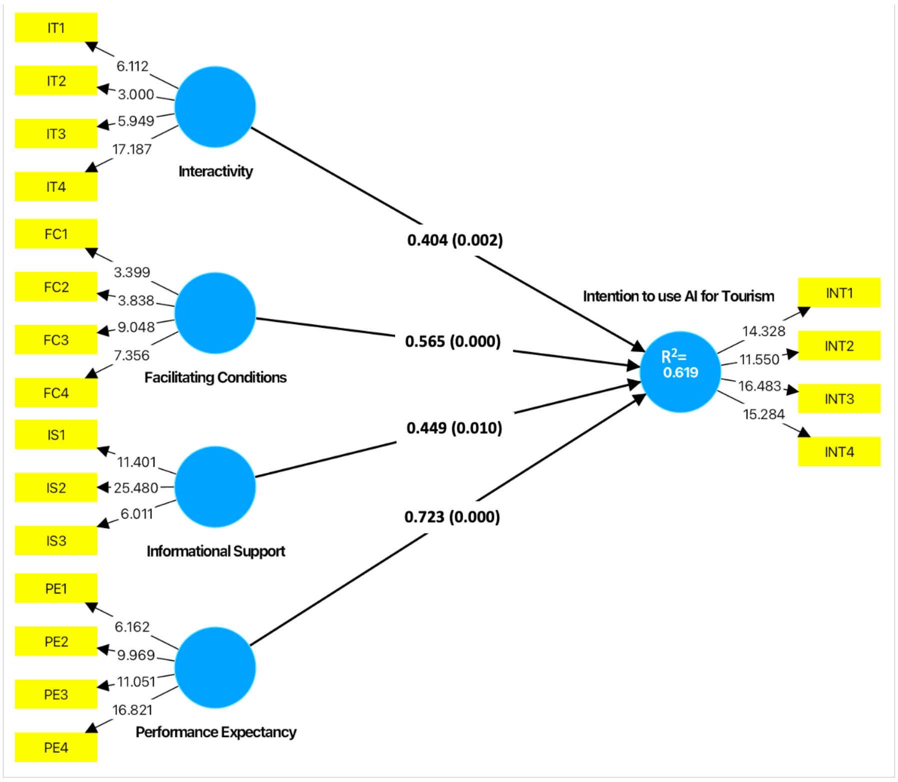

Figure 2. Structural model.

5. Discussion

The findings of this study shed light on the factors influencing individuals' intention to use AI for tourism. The results indicate that interactivity, facilitating conditions, informational support, and performance expectancy significantly influence individuals' intention to use AI for tourism. Specifically, participants who perceive higher levels of interactivity, such as user-friendliness and responsiveness in AI systems, are more likely to express an intention to utilize AI technologies in their travel experiences (Jan et al., 2023). Moreover, the presence of facilitating conditions, such as accessible and supportive environments for AI adoption, positively impacts individuals' intention to use AI for tourism (García-Madurga & Grilló-Méndez, 2023). Informational support, encompassing the availability of relevant and reliable information about AI-enabled tourism services, also plays a crucial role in shaping individuals' intentions. Participants who feel adequately informed and supported in their interactions with AI technologies exhibit a stronger inclination towards utilizing them in their travel activities (Nannelli et al., 2023). Additionally, performance expectancy, reflecting individuals' beliefs about the effectiveness and utility of AI in enhancing their tourism experiences, emerges as a significant predictor of intention to use AI for tourism.

Further analysis of the results reveals interesting nuances in the relationships between constructs. For instance, while performance expectancy emerged as a strong predictor of intention to use AI for tourism, its influence may be mediated by individual differences in perceived risk or trust in AI technologies (Arghashi & Yuksel, 2022). Similarly, the role of informational support may vary depending on the quality and source of information, suggesting potential moderating effects that warrant exploration in future research (Kong et al., 2023). These insights underscore the complexity of the decision-making process surrounding AI adoption in tourism and highlight the need for a nuanced understanding of individual perceptions and preferences (Melián-González et al., 2021).

These findings hold important implications for practitioners and policymakers in the tourism industry. Understanding the determinants of individuals' intention to use AI for tourism can guide the development and implementation of AI-driven innovations in travel services. Businesses can focus on enhancing the interactivity and user experience of AI-powered platforms to encourage adoption among travelers. Furthermore, efforts to improve facilitating conditions, such as infrastructure support and regulatory frameworks, can facilitate smoother integration of AI technologies into the tourism ecosystem. From a theoretical perspective, this study enhances the expanding body of knowledge on technology adoption within the tourism sector. By empirically examining the relationships between core constructs and the intention to utilize Artificial Intelligence (AI) in tourism, this research enriches our understanding of the factors that influence technology acceptance and implementation in the travel industry.

However, the study has certain limitations. The use of convenience sampling and reliance on self-reported data may introduce potential biases and restrict the generalizability of the findings. Future research could address these limitations by employing more rigorous sampling methods and longitudinal approaches to validate the results and investigate the evolution of AI adoption in tourism over time. Furthermore, exploring the moderating effects of individual characteristics, such as demographic variables and travel preferences, could offer more nuanced insights into the specific drivers of AI adoption in the tourism sector.

6. Conclusion

This study has provided valuable insights into the factors influencing individuals' intention to use AI for tourism. The results indicate that interactivity, facilitating conditions, informational support, and performance expectancy significantly influence individuals' intention to use AI for tourism. Participants who perceive higher levels of interactivity and facilitating conditions, along with adequate informational support and positive performance expectancy, are more likely to express an intention to utilize AI technologies in their travel experiences. These findings have important implications for both academia and industry. For practitioners in the tourism industry, understanding the drivers of AI adoption can inform the development and implementation of AI-driven innovations in travel services. By focusing on enhancing user experience, improving infrastructure support, and providing relevant and reliable information about AI-enabled services, businesses can encourage adoption among travelers and enhance the overall tourism experience. From a theoretical perspective, this study advances the existing body of research on technology adoption within the tourism sector. By empirically validating the correlations between principal constructs and the intent to utilize Artificial Intelligence (AI) for tourism, this research enhances our comprehension of the determinants influencing technology acceptance and deployment in the travel industry. Future research directions could include an examination of additional variables affecting AI adoption in tourism, such as individual attributes, situational contexts, and cultural variations. Longitudinal studies might offer valuable insights into the evolution of AI adoption over time, while qualitative methodologies could provide a deeper understanding of the intrinsic motivations and decision-making processes of travelers.

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