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# Understanding the Determinants of Adoption and Intention to Recommend AI Technology in Travel and Transportation

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**Abstract:** The travel and transportation sectors continuously fight to stay up to date with new advancements in technology. Disruptive technologies, such as Artificial Intelligence (AI), are being used to develop businesses, enhance economic growth, revolutionize existing industries, create new opportunities, and increase productivity and efficiency. Notwithstanding the several advantages that this technology may bring, there is still little research on AI use in the travel and transportation sectors. This research contributes to this still understudied field to fill a gap in the literature by putting out a novel, thorough, and as far as we know not yet tested until now theoretical model, designed with the combination of the outcome of a literature meta-analysis study with Travel Experience and the Intention to Recommend technology constructs. A quantitative investigation using an online questionnaire was administered through social media and reached a total of 100 European participants. Structural equation modelling (SEM) was employed to test the suggested model empirically. The findings highlight that the user's attitude towards AI is strongly influenced by Performance Expectancy and that the Intention to Use this technology is significantly influenced by Initial Trust and Attitude. Theoretical and practical contributions, limitations, and future areas of research are discussed.

**Keywords:** artificial intelligence; AI; travel experience; SEM; adoption

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## 1. Introduction

We are living in a world that is constantly looking for better alternatives and better options to make processes easier and more efficient. This is in part a consequence of the fact that the world is becoming globalized at the speed of light, and this is happening especially through the impacts of the new information technologies that have enabled greater worldwide inter-connectedness (Robinson, 2019). Companies are increasingly replacing human frontline service employees with Artificial Intelligence (AI) agents to offer real-time support during purchase transactions (Elmashhara et al., 2023). Grand View Research (2023) predicts that AI will increase at an annual rate of 37.3% between 2023 and 2030, revolutionizing numerous industries. This rapid expansion underscores the growing significance of AI technologies in the future. Therefore, it is important to study AI because it can improve travel and transportation sectors' efficiency, optimizing route schedules and resource allocation. Since these sectors are directly related to consumers and their experience, chatbots and virtual assistants can help travellers with queries, bookings, and navigation (Arora et al., 2023). AI can help reduce the environmental impact of travel and transportation by optimizing routes and reducing fuel consumption (Shahedi et al., 2023).

Overall, it has the potential to revolutionize these sectors, making travel and transportation more accessible, sustainable, and convenient for people around the world.

It is known that some AI studies have often produced contradictory results, depending on multiple factors such as theoretical models employed, sample sizes, industry sectors, data collection methodologies, culture, countries, users' age and experience. Moreover, in the travel and transportation sectors, only a few studies have been conducted, requiring further research to provide a clearer and more concise view of technology determinants of adoption, a gap we hereby intend to address. For that purpose, we designed a novel theoretical framework that combines the result of a meta-analysis with specific sector insights gleaned from a thorough literature review. This study also offers a new perspective on the Intention to Recommend this technology, which is still an understudied variable in the literature. The significance of this research is underscored by the scarcity of scholarly attention devoted to the travel and transportation sectors. This work provides valuable insights into the use of AI applications in these sectors, contributing to the advancement of knowledge by exploring and discussing the direct implications for travellers and transportation users.

This research aims to understand the determinants of adoption and Intention to Recommend Artificial Intelligence (AI) technology in the travel and transportation sectors, providing whenever possible new perspectives that can help reshape the industry. Therefore, this research has the objective to answer the following questions:

- Can a previous Travel Experience influence a user to use AI on their next trip?
- What are the factors influencing the last phase of recommending AI technology in the travel and transportation sectors?
- Is there any uncertainty associated with the adoption of AI in the travel and transportation sectors?

The present study examines the primary factors that affect the implementation of AI in the travel and transportation sectors, aiming to address this gap in the literature. This study investigates and discusses the immediate implications for both travellers and transportation companies, thereby advancing knowledge in several ways and benefiting scholars.

This study is structured as follows. The next chapter provides a review of the existing literature, categorizing it into four main areas essential for understanding the subject, namely: (i) Artificial Intelligence (AI), (ii) previous studies on AI adoption, (iii) AI in the travel and transportation sectors, and (iv) current technology adoption models. Section 2 describes the research model and hypotheses formulation, while Section 3 presents the research methodology. Section 4 expands on the presentation of the results, and Section 5 discusses the key results, as well as presents the main theoretical and practical consequences and possible future directions for additional research. Finally, Section 6 presents the conclusions, which provide a summary of the work.

## 2. Literature Review

### *2.1. Artificial Intelligence*

We can say that there are multiple definitions of Artificial Intelligence (AI) in the literature, mainly due to the expansive, interdisciplinary, and perpetually advancing nature of the technology. AI encompasses a vast array of methodologies, approaches, and applications, and its definition has progressed in the same manner as our comprehension of this innovative technology has evolved. Overall, the development of Artificial Intelligence aimed to equip machines with abilities that resemble human intelligence (Theuri & Olukuru, 2022). The term Artificial Intelligence denotes the intention to create machines that are capable of emulating or duplicating human intelligence (Mccarthy, 2007). Russell and Norvig (2010) affirm that AI is a discipline within computer science and engineering that concentrates on producing intelligent machines capable of executing tasks that generally necessitate human cognition, including visual perception, speech recognition, decision-making, and language translation. AI can be used in several fields, from extensive learning and perception to implementations like playing chess, composing poetry, and diagnosing diseases. AI is pertinent to any intellectual task and is regarded as a universal field, transversal to almost all sectors. Various methods have been utilized historically to develop AI systems, and there exist several human-centred and rationality-based approaches to AI. The technological suite includes information and communication infrastructure, software (including that which employs machine learning techniques), processes, and services for data search and processing to find solutions (Atabekov, 2023). Russell and Norvig (2010) present various perspectives from different authors and categorize AI into four distinct approaches, as presented in Table 1.

**Table 1.** Artificial Intelligence definition categories identified by Russell and Norvig (2010).

| | |
|---|---|
| Thinking Humanly<br>"The exciting new effort to make computers think. . . machines with minds, in the full and literal sense" (Haugeland, 1985)<br>"[The automation of] activities that are associated with human thinking, activities such as decision-making, problem solving, learning. . ." (Bellman, 1978) | Thinking Rationally<br>"The study of mental faculties through the use of computational models" (Charniak & McDermott, 1985)<br>"The study of computations that make it possible to perceive, reason, and act" (Winston, 1992) |
| Acting Humanly<br>"The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil et al., 1990)<br>"The study of how to make computers do things at which, at the moment, people are better" (Rich & Knight, 1991) | Acting Rationally<br>"Computational Intelligence is the study of the design of intelligent agents" (Poole et al., 1998)<br>"AI. . . is concerned with intelligent behaviour in artifacts" (Nilsson, 1998) |

An AI evolution summary is presented in Table 2, according to Russell and Norvig (2010).

**Table 2.** Artificial Intelligence phases identified by Russell and Norvig (2010).

| Years | Phases | Researchers Used. . . |
|---|---|---|
| 1050s–1960s | Early AI | formal logic and mathematical models to represent knowledge and reasoning processes. |
| 1970s–8190s | Knowledge-based AI | rule-based systems, frames, and semantic networks to represent and reason about knowledge. |
| 1980s–1990s | Machine learning | neural networks, decision trees, and genetic algorithms to build learning systems. |
| 1990s–present | Intelligent agents | reinforcement learning, deep learning, and natural language processing to build intelligent agents that can perform a wide range of tasks. |

AI technology is intended to carry out tasks such as inference, learning, and judgment, all achieved through artificial means. There are also challenges and prospects correlated to the implementation of AI, such as the necessity for fitting legal frameworks, ethical considerations, and the probable influence on the labour market and education (Atabekov, 2023).

AI has the potential to revolutionize enterprises by generating innovative business benefits, including heightened operational efficiency and scalability with smart automation, advanced real-time decision-making with predictive analysis, effortless access to expertise and knowledge via cognitive augmentation, and customization through data analysis (H. Chen et al., 2021), thereby resulting in enhanced customer satisfaction and loyalty (Arora et al., 2023). Solaimani and Swaak (2023) also affirm that AI is context-independent and has the potential to revolutionize any corporation, regardless of its magnitude and sector. Furthermore, the essential components of AI—data generation, storage, and processing—are becoming more affordable over time, and make this technology more attractive. Artificial Intelligence can be utilized to customize services and product offerings according to customers' previous purchases and inclinations, resulting in more substantial connections between customers and brands (Arora et al., 2023). Employing AI technologies and applications can ultimately lead to greater customer loyalty and profitability. This can be achieved through objective evaluation of customer feedback and preferences, leading to the provision of more tailored and personalized products and services, reducing response times and enhancing the overall customer experience (Arora et al., 2023).

H. Chen et al. (2021) defend that though AI applications have significant market potential, the present application situation remains to be explored. To deploy AI technologies and applications effectively, firms should acquire the necessary skills, particularly in management, to effectively adopt new technologies. A well-designed internal management system is crucial for the smooth implementation of new technologies. Additionally, vendors and partners can play a substantial role in aiding firms with the adoption of AI technologies. It is crucial to ensure that such services are of high quality to optimize customer experience (Arora et al., 2023). Nonetheless, AI has some problems regarding issues such as privacy, bias, and accountability. To illustrate, as per Atabekov (2023), AI systems can amass and scrutinize vast amounts of personal data to serve purposes such as targeted advertising or surveillance. This raises concerns regarding safeguarding privacy and the requirement for suitable legal structures to oversee the implementation of AI within such contexts. AI systems are also susceptible to prejudice, which could lead to unjust outcomes for specific demographic groups being attributed to data quality and algorithm designs utilized in AI training.

Some of the earliest achievements in AI research focused on problem-solving, encompassing fundamental work in learning, knowledge representation, and inference (Buchanan, 2005). Abduljabbar et al. (2019) affirm that researchers developed early AI systems based on logic and rule-based approaches. Additionally, they comprised an array of demonstration programs in language comprehension, translation, theorem proving, associative memory, and knowledge-based systems; these systems were modelled after the structure of the human brain and could learn from data. These early advancements laid the groundwork for further research in AI by establishing a basis for comprehending how machines can be programmed to execute tasks that once demanded human intelligence.

### *2.2. Prior Research on AI Adoption*

To investigate the effects of success factors on AI adoption in the telecommunications industry, H. Chen et al. (2021) combined the Technology, Organization, and Environment (TOE) framework with the Diffusion of Innovation (DOI) theory in a study conducted in China. The framework also comprised factors related to the external environment, organizational capabilities, and innovation attributes of AI. Elmashhara et al. (2023) examine methods for integrating gamification into AI systems by evaluating the impact of both utilitarian and hedonic factors, gamified chatbots promote hedonic motivations across various dimensions of customer engagement (including cognitive, emotional, and behavioural), ultimately affecting customer purchasing behaviours. Another perspective was presented by Wu et al. (2022), identifying that the amalgamation of Digital Twins (DTs) and AI technology has significant advantages in identifying transportation infrastructure and managing transportation spatial information networks. The advancement in intelligent transportation infrastructure entails functional design, intelligent development, and successful integration with new media.

The utilization of blockchain and AI technologies carries the potential to eliminate technological discrepancies in transportation systems and efficiently tackle some of the sector's current competitive challenges (Singh et al., 2022). The intermingling adoption of both technologies is expected to generate substantial benefits and establish a uniform decentralized platform for sharing data, bolstering reliability, and facilitating decision-making (Singh et al., 2022). Another revolutionary AI application in transportation is autonomous vehicles, also known as self-driving or driverless cars; this technology enables cars to operate and navigate without human intervention (Shahedi et al., 2023). Self-driving vehicles are equipped with a range of sensors, such as cameras, radar, lidar, GPS, and advanced AI algorithms, which enable them to perceive their surroundings, make decisions, and navigate (Shahedi et al., 2023). Rjab et al. (2023) defend that organizations, including smart cities, can harness the power of AI to drive innovation, improve efficiency, and create value for stakeholders and communities. Individuals who have had positive experiences with AI applications may be more inclined to adopt AI in various aspects of their lives, such as smart home devices, virtual assistants, and AI-powered services. Thøgersen and Ebsen (2019) investigated the motivational and perceptual factors contributing to the low adoption of electric cars in Denmark. They concluded that beneficial attitudes and perceptions of advantages and benefits have a beneficial impact on customers' inclinations to buy them.

### *2.3. Prior Research in the Travel and Transportation Sector*

Wang et al. (2020) developed an empirical study of consumers' intentions to use ride-sharing services, and they managed to present Perceived Risk as a construct that has a negative impact on Intention to Use ride-sharing services. In this type of service, this research has concluded that consumers are primarily motivated by the perceived value and benefits offered by ridesharing. In recent years, the notion of a "smart city" has gained significant traction in recent research on Artificial Intelligence for various reasons. Clement et al. (2023) explored this concept in 29 different countries, proposing it as a means of fostering sustainable urban development via enhanced efficiency and process optimization within the urban system. Smart city strategies are utilized to facilitate urban sustainability transitions.

There are various eco-friendly transportation options, including active and public transit, which are increasingly accessible (Mouratidis et al., 2023; Shahedi et al., 2023). Despite this fact, private cars still tend to dominate urban road traffic worldwide. Glock and Gerlach (2023) developed a study in Pankow, a district in Berlin, with the objective of developing a participatory planning process to allow everyone to be able to reach facilities catering to basic needs within 15 min. While accessibility is not consistently lower in socially deprived neighbourhoods, there is a balance between high accessibility, particularly in public transportation, and associated externalities such as noise and air pollution. Yang et al. (2018) affirm that active travel and daily transport trips decrease with age, particularly among older adults. Daily transport patterns varied depending on various factors within this age group. The relationship between the built environment and the transport habits of older adults varies depending on the specific environmental features.

The utilization of AI in the travel and transportation sectors brings forth various potential benefits. Primarily, it has the capability to optimize traffic flow and lessen congestion, thus improving travel times for commuters (Abduljabbar et al., 2019). Also, AI can significantly enhance safety by promptly identifying and responding to road hazards like accidents or road damage (Abduljabbar et al., 2019; Mouratidis et al., 2023). Moreover, the implementation of AI systems can decrease emissions by improving traffic flow, thereby enhancing vehicle operation efficiency.

Regarding customer satisfaction, it is important to evaluate the perceived value of the technology and the satisfaction levels among users. These factors can have a substantial impact on the adoption, Intention to Recommend, and continuous use of the technology. Mokhtarian et al. (2015) found that pleasurable journeys were often associated with activities like travel, sightseeing, shopping, or engaging in sports and leisure. Longer-distance travel tended to receive more positive reviews. This implies that the perception of travel is influenced by the interplay between distance, travel speed, and traffic congestion. Additionally, there are numerous additional benefits of travelling to have in consideration; it can have a long-term impact on wellbeing (Bertrand, 2016), bringing satisfaction to the individual, and reinforcing one's attitude towards life, sense of control, and outlook (Tse, 2014). Traditional face-to-face chatting with fellow travellers, which was a common source of contentment in the past (Bello & Etzel, 1985), has progressively been replaced by several other types of communication such as websites, social media, applications, and active engagement with local communities (Riu & Wilson, 2024), expanding the temporal boundaries of travelling experiences.

### *2.4. Theoretical Models Used in the Literature*

#### 2.4.1. Acceptance Models

The literature analysis suggests that little is understood about the factors that impact AI adoption and how they interrelate to shape an individual's decision to adopt AI (Cao et al., 2021). In the literature exist several theoretical models and frameworks concerning technology adoption across different domains, some of the most important and most used are presented as follows.

#### 2.4.2. The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The UTAUT (Venkatesh et al., 2003) was developed based on a thorough review of eight major theories. According to this paradigm, four constructs—performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh & Davis, 2000) are expected to have a direct impact on behavioural intention and behavioural use. UTAUT has been used to explain technology adoption in organizational contexts since its inception in 2003, and it has been progressively evaluated and applied to a variety of technologies (Im et al., 2011). However, it had some limitations (Negahban & Chung, 2014) and was thus expanded to also explain acceptance in the consumer sphere (Venkatesh et al., 2012). Hedonic motivation, price value, and habit are the three new constructs, rearranging some of the existing links and creating new ones. Because of its strong theoretical underpinnings, UTAUT2 is a good option for a baseline framework in research on how technology is accepted and used (Soren & Chakraborty, 2024).

#### 2.4.3. Diffusion of Innovation (DOI)

Diffusion of Innovation focuses on the evaluation of innovations and their efficient diffusion through precise measurement of consumer behaviour (Rogers, 2003) through which scholars and professionals can explore the intricacies of technology adoption and the elements that influence it. According to Zhao and de Pablos (2011), innovation is essential, and individual inventiveness plays a significant role in influencing the outcome of technology adoption. In addition, human innovativeness is another important aspect considered in the Diffusion of Innovation theory (Yi et al., 2006). Therefore, the DOI provides a solid foundation for understanding the spread of new concepts, objects, or technological advances in a community (Oliveira et al., 2016).

#### 2.4.4. Technology Acceptance Model (TAM)

The model developed by Davis (1989) named the Technology Acceptance Model explains how users accept technology. Lim and Zhang's (2022) model offer valuable insights into forecasting customers' desire and adoption of developing technologies. This model can be very parsimonious and effective in explaining technology acceptance of different information systems (Marangunić & Granić, 2015), and it was inclusively used in several transportation studies (Thøgersen & Ebsen, 2019; Wang et al., 2020; Zhang et al., 2019) due to its facility to understand society's responses to novel transportation services.

#### 2.4.5. Theory of Planned Behaviour (TPB)

Subjective norms, perceived behavioural control, and attitudes towards behaviour can all be used to predict intentions to perform various behaviours with a high degree of accuracy (Ajzen, 1991). The TPB is an extended form of the Theory of Reasoned Action that is used to understand, explain, and predict a wide range of behaviours (Machaka-Mare et al., 2023). The TPB also states that behavioural intention is directly influenced by attitudes, subjective norms, and perceived behavioural control (Ajzen, 1991). The sense of availability of the skills, opportunities, and resources needed to perform the behaviour in question is known as perceived behavioural control (Kumari & Devi, 2023). However, the effectiveness of the theory varies according to the category of health-related activity (Godin & Kok, 1996).

## 3. Hypotheses and Research Model

Baptista and Oliveira (2016) identified an innovative research model, obtained from the results of the meta-analysis and the weight analysis study, by selecting the relationships that have been explored three or more times in the literature. This model is the foundation of our theoretical model used in this study, which we combined with the constructs of Travel Experience and Intention to Recommend the technology, providing a solid basis for future studies, as presented in Figure 1. The inclusion of these constructs in the research model allows us to reach a better understanding of the adoption impact of AI technology in the travel and transportation sectors, expectably reinforcing the significance and predictability of the results.

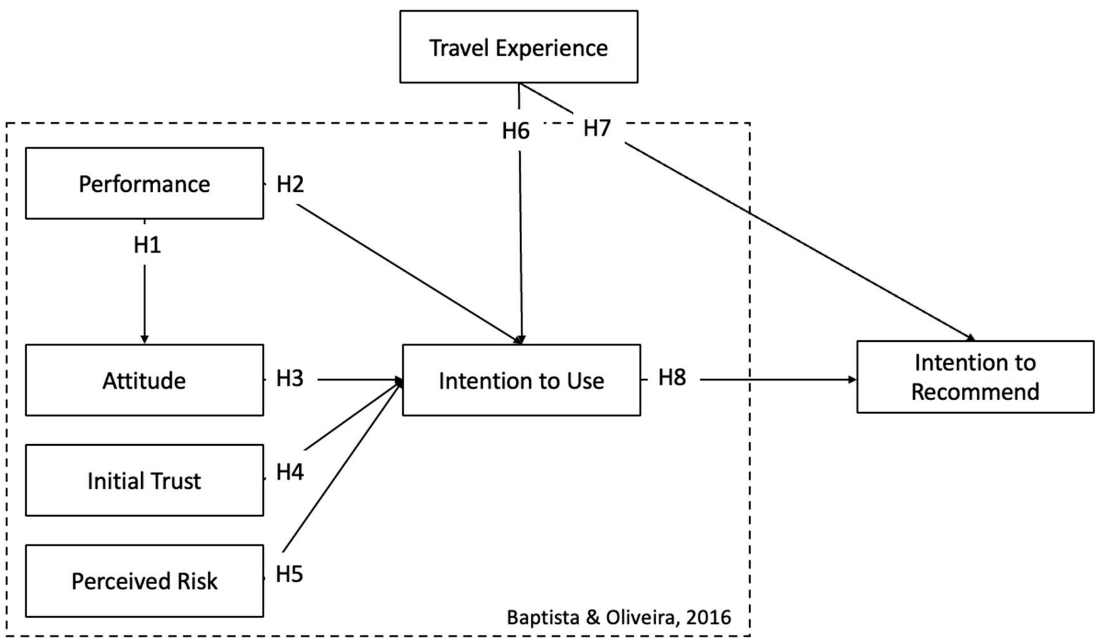


**Figure 1.** Proposed research model (from the authors).

Baptista and Oliveira's (2016) effort expectancy, structural assurance, and use variables were not included in our model due to the fact that we only intended to study the Intention to Use technology direct connections. Recommending technology to others is of great commercial interest; however, researchers have often neglected this construct due to the overwhelming emphasis on technology use (Miltgen et al., 2013); therefore, it was included in our model.

Performance Expectancy is the degree to which consumers believe that utilizing a specific technology will enable them to complete their tasks with greater effectiveness and efficiency (Venkatesh et al., 2003). Performance Expectancy is widely regarded as a crucial factor in predicting consumers' behavioural Intention to Use technology (Oliveira et al., 2014; Zhou et al., 2010). This is because it indicates how useful consumers believe the technology to be: "the degree to which using a technology will provide benefits in performing certain activities" (Oh et al., 2009; Venkatesh et al., 2012). Therefore, we hypothesize the following:

**H1.** *Performance Expectancy has a positive effect on Attitude.*

**H2.** *Performance Expectancy has a positive effect on Intention to Use.*

Attitude pertains to an individual's (un)favourable, resilient, and persistent assessment (evaluative affect) regarding performing a certain behaviour (Belanche et al., 2022), which can strongly influence and forecast human behaviour (Cheng et al., 2006; Kraus, 1995; Shanmugam et al., 2014). An individual's behaviour can be predicted by their Attitude towards how they believe others perceive them when exhibiting that behaviour, providing valuable insights for the development of innovative, user-friendly technologies that align with societal needs and values (Afrizal & Wallang, 2021; C. Chen, 2013).

**H3.** *Attitude has a positive effect on Intention to Use.*

Prior research defines Initial Trust as an individual's disposition to trust or institutional cues that enable one person to trust another without first-hand knowledge (Harrison et al., 1998). Initial Trust is critical to user behaviour, as it can be considered the level of confidence a potential user has in a technology when they have no prior experience (C. Lee et al., 2023) and various factors have been recognized to influence it, such as a website's quality, appeal, and useability; the consumer, a company's reputation, company size, and corporate image act; and third parties (Zhou, 2011). Therefore, we hypothesize the following:

**H4.** *Initial Trust has a positive effect on Intention to Use.*

Littler and Melanthiou (2006) consider that Perceived Risk is a multi-dimensional construct. The term Perceived Risk refers to the feeling of uncertainty that arises when considering the potential negative consequences of the Intention to Use a product or service (Featherman & Pavlou, 2003). It is commonly understood as the perception of implicit risk when exchanging private information over the open internet infrastructure. Perceived Risk can comprise five distinct dimensions: financial, performance, time, psychological, and security risks (Bélanger & Carter, 2008; Littler & Melanthiou, 2006). Therefore, we hypothesize the following:

**H5.** *Perceived Risk has a negative effect on Intention to Use.*

Travel Experience encompasses the entirety of a leisure or holiday trip, comprising all activities, conversations, experiences, and the general sense of fulfilment achieved from it (Stone & Petrick, 2013). It also involves the length of the stay, projected expenditure, upcoming travel arrangements, and the possibility of revisiting the same destination (Durko & Petrick, 2013). Moreover, this concept highlights the significance of the novelty of travel, explaining how the addition of new and unfamiliar encounters affects various aspects of the Travel Experience, including recreation, educational merit, and future travel aspirations (Bello & Etzel, 1985). As per Brown and Chalmers (2003), much of what is enjoyable about leisure is that it provides an opportunity to spend time with friends or family. Therefore, we hypothesize the following:

**H6.** *Travel Experience has a positive effect on Intention to Use.*

**H7.** *Travel Experience has a positive effect on Intention to Recommend.*

The Intention to Use a technology refers to an individual's or group's willingness or preparedness to accept and use a specific technology for various objectives, including communication, productivity, entertainment, and problem-solving (Teo, 2011). It is important to include this as a dependent variable because of its close link to actual behaviour, especially in what relates to AI (Dingel et al., 2024). Understanding user intentions is crucial for developers, marketers, and policymakers when implementing new technologies because it is more progressive when compared to actual use (Yi et al., 2006). This enables developers, marketers, and policymakers to create and implement technologies that are tailored to the needs and preferences of their consumers, improving the likelihood of successful acceptance and utilization (Ajzen, 1991). According to Miltgen et al. (2013) and Leong et al. (2013), consumers with a greater intention to adopt a new technology are more likely to actually Recommend it to others. Individuals are increasingly utilizing social media platforms, websites, and online forums to express their opinions on products, services, and technologies (Oliveira et al., 2016), thus increasing the importance of this construct, especially when AI services are provided to end-users (Bhatnagr et al., 2024).

**H8.** *Intention to Use has a positive effect on Intention to Recommend.*

## 4. Methods

To test the theoretical model, a quantitative survey was conducted online in several countries in Europe, targeting the adult population with transportation and travelling experience, inside or outside their country, who have at least one device that would/did allow them to use AI applications or services in their experience.

As studies of technology acceptance have traditionally been conducted using survey research (Venkatesh et al., 2003), an online survey instrument was created in English and reviewed for content validity by information system experts from a local university. As the questionnaire was also to be administered in Portugal, a version in Portuguese was also developed and translated by an expert from the original version in English. To end this process of translation, the Portuguese questionnaire was then translated back to English, to confirm translation equivalence, in order to validate the translation and ensure consistency (Brislin, 1970). Each item was measured on a seven-point Likert scale, ranging from 1 (Totally Disagree) to 7 (Totally Agree). Two demographic questions—age and gender—were also included. In order to obtain the most precise and least biased results, the questions were adapted from different authors, according to the variable included in the theoretical model, as presented in Table 3. At the beginning of the survey, an introduction to the survey objectives was presented to the respondents, informing them that this was a strictly voluntary and anonymous study on European users' behaviour and perceptions. All survey questions were defined as mandatory and incomplete answers were removed from the final dataset.

**Table 3.** Original authors of the variables' questions.

| Hypothesis | Adapted From |
|---|---|
| Travel Experience | (Bello & Etzel, 1985) |
| Performance Expectancy | (Venkatesh et al., 2003) |
| Attitude | (Rabaa'i et al., 2024) |
| Initial Trust | (C. Lee et al., 2023) |
| Perceived Risk | (Bélanger & Carter, 2008) |
| | (Featherman & Pavlou, 2003) |
| Intention to Use | (M. C. Lee, 2009) |
| Intention to Recommend | (Barta et al., 2023) |

The survey was shared multiple times between December 2023 and February 2024, with a hyperlink that could only be used once per user, through LinkedIn, WhatsApp, emails, and several survey platforms. To reinforce the sample data and possible representativeness, specific travel and transportation social network groups were used to share the survey. The first 30 answers were used as a pilot test and were not considered in the final data. The preliminary results showed that scales were reliable to continue. Direct messages were also sent to a list of contacts, encouraging them to share the survey with their own contacts. At the end of the survey period of 12 weeks, a total of 100 valid answers were obtained. The common method bias was also examined using Harman's single factor test (Podsakoff et al., 2003), obtaining a variance below the 50% threshold. And the marker variable also had a variance below the threshold of 4% (Lindell & Whitney, 2001). Hence, confirming no significant common method bias in the data.

Upon analyzing the comprehensive sample of the respondents, the data indicate that 49% of the respondents are female, while the other 49% are male, 44% are between 18 and 24 years of age, and 56% have a bachelor's degree. In terms of country of residence, there is a normal tendency that can be considered predictable, as shown above, with 90% of respondents being Portuguese. Detailed descriptive statistics on the respondents' characteristics are shown in Table 4.

**Table 4.** Descriptive statistics of respondents' characteristics (from the authors).

| Measure | Value | Frequency | % |
|---|---|---|---|
| Gender | Female | 49 | 49.0% |
| | Male | 49 | 49.0% |
| | Other | 2 | 2.0% |
| Age | 18–24 | 44 | 44.0% |
| | 25–34 | 10 | 10.0% |
| | 35–44 | 7 | 7.0% |
| | 45–54 | 29 | 29.0% |
| | 55–64 | 8 | 8.0% |
| | 65+ | 2 | 2.0% |

**Table 4.** *Cont.*

| Measure | Value | Frequency | % |
|---|---|---|---|
| Education | High School | 10 | 10.0% |
| | Bachelor's degree | 56 | 56.0% |
| | Master's degree | 26 | 26.0% |
| | Doctorate | 3 | 3.0% |
| | Other | 5 | 5.0% |
| Country of residence | Portugal | 90 | 90.0% |
| | Belgium | 2 | 2.0% |
| | UK | 2 | 2.0% |
| | Germany | 5 | 5.0% |
| | Denmark | 1 | 1.0% |

## 5. Data Analysis and Results

Structural equation modelling (SEM) is a statistical method used to evaluate the validity of substantive theories with empirical data (Becker et al., 2023). Henseler et al. (2009) conclude that SEM is a good method to estimate the measurements. The research model was tested using variance-based techniques and partial least squares (PLSs), with SmartPLS v4.1.0.9 software (Ringle et al., 2022). PLSs is a powerful and convenient statistical technique that is appropriate for many research situations (Henseler et al., 2009) and is suitable for studying complex models with numerous constructs (Chin, 1998). PLSs is considered appropriate for this study for three main reasons because it can prove the following: firstly, the research model has not been tested in the previous literature; secondly, the research model is perceived as complex; finally, the sample size is ten times greater than the maximum number of paths directed to a variable (Gefen et al., 2005). The analysis was conducted in two steps, following Anderson et al.'s (1988) criteria. Firstly, the measurement model was used to assess the model's reliability and validity. Secondly, the structural model was used to assess the structural relationship of the model. Details for both steps are presented as follows.

### 5.1. Measurement Model

Within the measurement model step, we underwent the assessment for item reliability, internal consistency, convergence validity, and discriminant validity. Table 5 displays the average variance extracted (AVE), composite reliability (CR), Cronbach's alpha values, and loadings. Item reliability was evaluated based on the criteria that loading should be higher than 0.7 (Hair et al., 2017)—all loadings satisfy the criteria, confirming a good indicator reliability of the instrument. The table also shows that all constructs have composite reliability and Cronbach's alpha greater than 0.7 (Hair et al., 2017), confirming their internal consistency. The convergence validity was tested using AVE, and all constructs were compared positively against the minimum acceptable value of 0.50 (Fornell & Larcker, 1981; Henseler et al., 2015).

To analyze the discriminant validity, three tests were conducted and passed. The first test analyzed the cross-loadings, where the loading of each indicator should be higher than all cross-loadings (Götz et al., 2009). The Fornell–Larcker criterion was applied as the second test, which requires that the square root of all constructs' AVE should be greater than the correlation between the constructs (Fornell & Larcker, 1981). Table 6 shows that the diagonal values (square root of AVE) are greater than the off-diagonal values (correlations between the constructs), indicating that all constructs meet this criterion. The third test conducted was the heterotrait–monotrait (HTMT) ratio of correlations, with all values required to be above 0.9 (Henseler et al., 2015), as presented in Appendix A.

**Table 5.** Quality criteria and factor loadings (from the authors).

| Construct | AVE | Composite Reliability | Cronbach's Alpha | Item | Loading |
|---|---|---|---|---|---|
| Attitude | 0.903 | 0.949 | 0.893 | ATT1 <- ATT | 0.956 |
| | | | | ATT3 <- ATT | 0.945 |
| Intention to Recommend | 0.852 | 0.920 | 0.830 | IR1 <- IR | 0.949 |
| | | | | IR3 <- IR | 0.896 |
| Initial Trust | 0.916 | | 0.908 | IT1 <- IT | 0.954 |
| | | | | IT3 <- IT | 0.96 |
| Intention to Use | 0.846 | 0.943 | 0.909 | IU1 <- IU | 0.911 |
| | | | | IU2 <- IU | 0.925 |
| | | | | IU3 <- IU | 0.923 |
| Performance Expectancy | 0.804 | 0.943 | 0.918 | PE1 <- PE | 0.92 |
| | | | | PE2 <- PE | 0.915 |
| | | | | PE3 <- PE | 0.908 |
| | | | | PE4 <- PE | 0.842 |
| Perceived Risk | 0.820 | 0.948 | 0.927 | PR1 <- PR | 0.892 |
| | | | | PR2 <- PR | 0.929 |
| | | | | PR3 <- PR | 0.91 |
| | | | | PR4 <- PR | 0.892 |
| Travel Experience | 0.644 | 0.878 | 0.818 | TE1 <- TE | 0.771 |
| | | | | TE2 <- TE | 0.791 |
| | | | | TE3 <- TE | 0.853 |
| | | | | TE4 <- TE | 0.792 |

**Table 6.** Fornell–Larcker (from the authors).

| | ATT | IR | IT | IU | PE | PR | TE |
|---|---|---|---|---|---|---|---|
| ATT | 0.944 | | | | | | |
| IR | 0.765 | 0.923 | | | | | |
| IT | 0.782 | 0.766 | 0.955 | | | | |
| IU | 0.744 | 0.783 | 0.746 | 0.920 | | | |
| PE | 0.813 | 0.742 | 0.704 | 0.701 | 0.897 | | |
| PR | −0.327 | −0.375 | −0.441 | −0.361 | −0.236 | 0.906 | |
| TE | 0.475 | 0.414 | 0.449 | 0.308 | 0.392 | −0.172 | 0.802 |

Legend: ATT—Attitude; IR—Intention to Recommend; IT—Initial Trust; IU—Intention to Use; PE—Performance Expectancy; PR—Perceived Risk; and TE—Travel Experience.

The results of the measurement model suggest that the model has good construct reliability, indicator reliability, convergence validity, and discriminant validity. This ensures that the constructs are statistically distinct and can be used to test the structural model. The standardized root mean square residual (SRMR) goodness of fit was also calculated, obtaining the values of 0.065 (saturated model) and 0.086 (estimated model); these values are acceptable according to Henseler et al. (2014), confirming the model fitness.

### *5.2. Structural Model and Hypotheses Testing*

The evaluation of the structural model and subsequent hypotheses testing rely on the examination of standardized paths. The significance levels of these paths were determined using the bootstrapping resampling technique with 5000 iterations of resampling (Chin, 1998). The findings are summarized and illustrated in Figure 2.

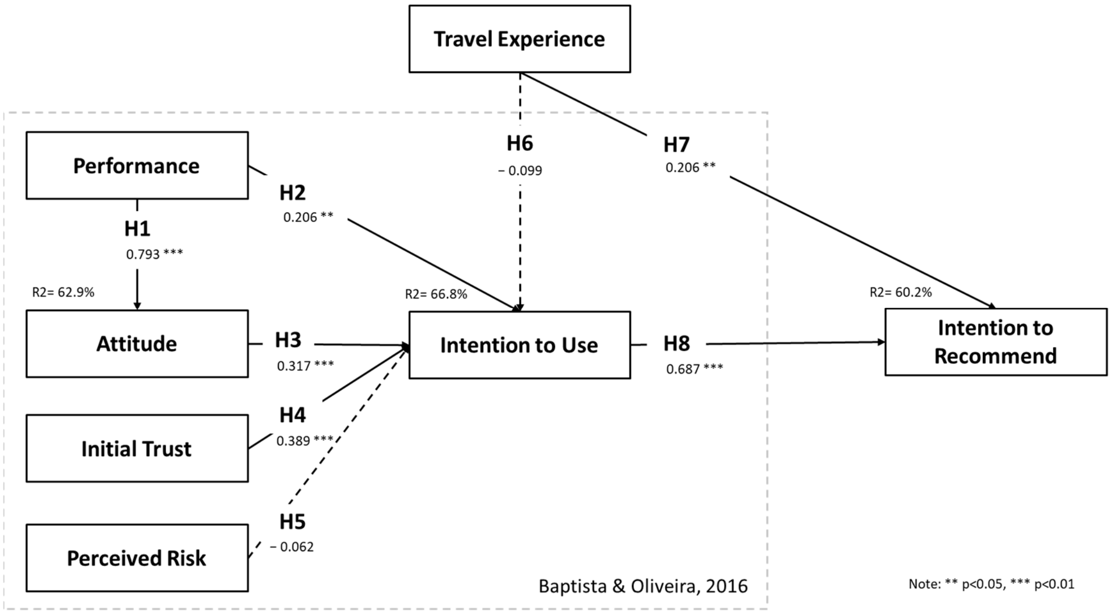


**Figure 2.** Structure model results (from the authors).

To avoid multicollinearity, it was necessary to ensure that all constructs had a Variance Inflation Factor (VIF) below the threshold of 5 (Ringle et al., 2022), as confirmed in Table 7.

**Table 7.** Variance Inflation Factor (VIF) test (from the authors).

| ITEMS | VIF | ITEMS | VIF |
|---|---|---|---|
| ATT1 | 2.871 | PE3 | 3.307 |
| ATT3 | 2.871 | PE4 | 2.180 |
| IR1 | 2.016 | PR1 | 3.751 |
| IR3 | 2.016 | PR2 | 4.856 |
| IT1 | 3.246 | PR3 | 3.314 |
| IT3 | 3.246 | PR4 | 3.080 |
| IU1 | 2.770 | TE1 | 1.715 |
| IU2 | 3.121 | TE2 | 1.978 |
| IU3 | 3.273 | TE3 | 1.961 |
| PE1 | 4.161 | TE4 | 1.493 |
| PE2 | 4.262 | | |

The model explains a 62.9% variation in Attitude, 66.8% in Intention to Use, and 60.2% in Intention to Recommend, as shown in Table 8.

**Table 8.** Coefficient of determination values (from the authors).

| | $R^2$ | $R^2$ Adjusted |
|---|---|---|
| ATT | 0.629 | 0.625 |
| IR | 0.602 | 0.594 |
| IU | 0.668 | 0.651 |

Legend: ATT—Attitude; IR—Intention to Recommend; and IU—Intention to Use.

Performance Expectancy was found to be statistically significant in explaining Attitude and Intention to Use, due to $\hat{\beta}$ = 0.793 and $p < 0.01$ and $\hat{\beta}$ = 0.206 and $p < 0.05$, respectively, therefore supporting hypotheses H1 and H2, which are presented in Table 9. In line with that, Attitude ($\hat{\beta}$ = 0.317) and Initial Trust ($\hat{\beta}$ = 0.389) were found to be statistically significant in explaining Intention to Use, both with $p < 0.01$, thus supporting hypotheses H3 and H4. Also, Intention to Use and Travel Experience were found to be statistically significant in explaining Intention to Recommend, due to $\hat{\beta}$ = 0.687 and $p < 0.01$ and $\hat{\beta}$ = 0.206 and $p < 0.05$, respectively, therefore supporting hypotheses H7 and H8. The effect of Perceived Risk in Intention to Use was not found to be statistically significant, thus not supporting hypothesis H5. In line, the effect of Travel Experience on Intention to Use was not found to be statistically significant, thus not supporting hypothesis H6.

**Table 9.** Structural model decision (from the authors).

| Structural Paths | Path Coefficients | *p*-Values | Conclusion |
|---|---|---|---|
| PE -> ATT | 0.793 | 0.000 | H1 supported |
| PE -> IU | 0.206 | 0.046 | H2 supported |
| ATT -> IU | 0.317 | 0.007 | H3 supported |
| IT -> IU | 0.389 | 0.000 | H4 supported |
| PR -> IU | −0.062 | 0.346 | H5 not supported |
| TE -> IU | −0.099 | 0.080 | H6 not supported |
| TE -> IR | 0.206 | 0.011 | H7 supported |
| IU -> IR | 0.687 | 0.000 | H8 supported |

Legend: ATT—Attitude; IR—Intention to Recommend; IT—Initial Trust; IU—Intention to Use; PE—Performance Expectancy; PR—Perceived Risk; and TE—Travel Experience.

## 6. Discussion

The theoretical model presented in this study is unique, integrating one model developed by Baptista and Oliveira (2016) with the construct of Travel Experience, introduced by Bello and Etzel (1985), and the construct of Intention to Recommend, introduced by Oliveira et al. (2016). This framework offers a comprehensive perspective on the factors that affect the adoption and recommendation of AI in the travel and transportation sectors.

The research model explains 62.9% of the variation in Attitude, 66.8% in Intention to Use, and 60.2% in Intention to Recommend. Regarding the individual predicting power of each construct, the results indicate that Attitude, with 62.9%, has a significant effect on Intention to Use, being higher when compared to a previous study (Cheng et al., 2006) but lower when compared to 76% of M. C. Lee's (2009) study. This research model explains 66.8% of Intention to Use, registering a higher power when compared to Yi et al.'s (2006) study, however being lower when compared to a previous study (M. C. Lee, 2009). The model explained substantial variance in Intention to Recommend, with 60.2%, in line with a previous study (Oliveira et al., 2016), and the findings validate the influence of Intention to Use over it.

The relationship between Performance Expectancy and Attitude and Intention to Use is consistent with previous studies (Oliveira et al., 2014; Zhou et al., 2010). According to the respondents, Performance Expectancy is one of the most important predictors of intention behaviour to adopt AI technology, confirming the results of studies (Oh et al., 2009; Venkatesh et al., 2012). Attitude relationship with Intention to Use findings is consistent with previous studies (Cheng et al., 2006; M. C. Lee, 2009; Shanmugam et al., 2014). Therefore, evaluating and considering that Attitude in advance can help anticipate how people behave, it is important to develop useful technologies and applications to facilitate processes in different areas, for instance, related to the travel and transportation sectors, which can have a positive effect on Intention to Use. Furthermore, respondents consider Performance Expectancy as one of the most important antecedents of Attitude, therefore confirming prior studies (Ajzen, 1991). In line with the conclusions of previous studies, Initial Trust was also confirmed to have a positive effect on Intention to Use, which is crucial to consider for users without experience (C. Lee et al., 2023), thus giving importance to the diverse factors mentioned by Zhou (2011).

The construct of Travel Experience was also evaluated, and the findings are similar to those presented by Brown and Chalmers (2003), reinforcing the importance of designing technologies for tourists that can give them better experiences, such as platforms where they can share their experiences, electronic guides, and maps, or supporting pre- and post-visiting (Brown & Chalmers, 2003). Also, the Intention to Use followed the same pattern as previous AI studies (Dingel et al., 2024), confirming its link to actual behaviour, thus giving developers one crucial construct to focus on attention while implementing new technologies.

The Intention to Recommend was also evaluated, and the findings validate the influence of Intention to Use and Travel Experience over it. In line with the results of previous studies on the adoption of new technologies (Barta et al., 2023; Oliveira et al., 2016), the significant value obtained confirms the propensity of users to recommend AI-based devices while travelling, in social networks, and other means of communication. It also highlights the importance and relevance of including the recommendation construct in this and future studies on the adoption of new technologies (Miltgen et al., 2013).

Lastly, Perceived Risk was also studied, but the model did not confirm the statistical relationship to Intention to Use, contrary to some earlier studies that achieved this (Bélanger & Carter, 2008; Littler & Melanthiou, 2006). This can be explained by an emerging paradigm that is related to newer generations' habits and resistance to risk. Even though Gen Y and Gen Z are more up-to-date regarding risks and their consequences, they do not recognize these risks as a barrier in their decision-making process regarding the use of AI technologies in the travel and transportation sectors.

### *6.1. Implications for Research and Practice*

This study and its results have implications for researchers and practitioners. For researchers, this study provides a solid and novel basis for further refinement of individual acceptance models to explore with other technologies, other sectors, other countries, or other generations. The development and use of AI technologies in the travel and transport sectors can be influenced by understanding travellers' beliefs about the effectiveness and efficiency of using a specific technology to complete their tasks. To improve the user experience, research can focus on specific areas such as increased productivity, tailored suggestions, and better decision-making.

Examining passengers' perceptions of AI technologies can aid transport companies in identifying and overcoming barriers to adoption and levels of acceptance. To inform tactics for promoting favourable attitudes towards AI adoption, researchers can examine elements that influence attitudes, such as perceived utility, usability, and ethical considerations. To instil confidence in passengers, it is imperative to investigate the importance of Initial Trust in AI systems. The development of trust can be influenced by several elements, such as system reliability, transparency, and security measures. The knowledge gained can guide actions aimed at building trust in AI-based travel services. Research into Perceived Risks associated with the use of AI in travel and transport can help transport companies identify problems and remove potential barriers. Research can assess different aspects of risk, including data security, privacy, and reliability issues, to inform communication and risk management plans.

Research into the impact of AI technologies on Travel Experience can provide opportunities for innovation and uniqueness in the industry. Service suppliers can explore how AI-driven enhancements, such as tailored suggestions, easy booking processes, and real-time support, improve the quality of Travel Experiences. Identifying travellers' Intention to Use AI-powered devices and applications can help guide resource allocation and decision-making for technology development and implementation. To improve adoption techniques, research could examine elements that influence Intention to Use, such as perceived benefits, convenience of use, and social impact.

### *6.2. Limitations and Future Research*

There are several limitations to this study that require further investigation and research. Although Baptista and Oliveira's model was created through a meta-analysis and our study obtained solid results, it can be considered as not being sufficiently tested to be a solid model to study all technologies, therefore requiring further investigation. One of the main limitations of this study is the relatively low number of respondents, which leaves room to repeat this with more people from different backgrounds and perceptions. Even though this research included different nationalities, they were all from developed countries. Exploring this model in developing countries, with different cultural behaviours, may provide different and interesting perspectives, even more because many of these countries have less access to technology and less access to good communication infrastructures. The age factor may be also another interesting path to follow, which is directly related to the results, for example, of Perceived Risk, as mentioned previously. Future research can attempt to extend the work to more generations or even target specific generations to see how they react to the use of AI in the travel and transportation sectors.

Exploring how the construct of Travel Experience affects the Intention to Recommend opens the door to the suggestion of exploring how the trip itself can be improved, what factors are most relevant to the user, or what the outcomes of a trip are. In line with this, it may be interesting to explore what are the best methods or platforms for recommending AI, as this has not been explored in this research. Moreover, as this research only targeted individuals, it would be beneficial to investigate whether the implementation of this technology results in increased productivity and performance gains for companies. Such research could provide valuable insights into the impact of this technology on organizational performance and contribute to a deeper understanding of its broader implications.

## 7. Conclusions

The use of Artificial Intelligence in travel and transportation is very promising, receiving growing attention globally. Based on earlier technology adoption studies, this research conducted an analysis using a novel model that extended previous literature models with past (Travel Experience) and future (Intention to Recommend) constructs, identifying relevant aspects of the Intention to Use and Intention to Recommend AI technology in the travel and transportation sectors. In terms of work, all the objectives were fully achieved, with the relevance of our extended model being highlighted by our results, which show convergences and divergences with previous findings, confirming the specificities of these important sectors. According to the findings, the proposed model has a strong ability to explain consumers' intentions and is robust in predicting whether they will accept AI in these sectors and recommend the technology.

Performance Expectancy, Attitude, and Initial Trust have significant direct and indirect effects on the adoption of AI in the travel and transportation sectors and the Intention to Recommend this technology. The relevance of Travel Experience on Intention to Recommend was also confirmed, supporting the importance of investing in AI-based infrastructures, devices, and platforms, giving users good experiences, contributing to spreading their good experiences via social networks or websites and recommending its use. For researchers, this study provides a basis for further refinement of individual acceptance models. For practitioners, understanding the key constructs is critical to designing, refining, and implementing AI-based services, applications, and products that achieve high levels of consumer acceptance, value, and positive social network recommendations in the travel and transportation sectors.

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**Data Availability Statement:** The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** Survey.

| Construct | Items | Questions | Adapted From |
|---|---|---|---|
| Travel Experience (TE) | TE1 | Travel is always a unique experience for me. | (Bello & Etzel, 1985) |
| | TE2 | Travel is always a new experience for me. | |
| | TE3 | While travelling, I do new and unfamiliar things. | |
| | TE4 | Travel is very restful. | |
| Performance Expectancy (PE) | PE1 | I would find AI-based devices useful in my travel. | (Venkatesh et al., 2003) |
| | PE2 | Using AI-based devices enables me to accomplish tasks more quickly when I travel. | |
| | PE3 | Using AI-based devices increases my productivity when travelling. | |
| | PE4 | If I use AI-based devices, I will increase my chances of getting better travel. | |

**Table A1.** *Cont.*

| Construct | Items | Questions | Adapted From |
|---|---|---|---|
| Attitude (ATT) | ATT1 | I like the idea of using travel AI-based devices, services, and applications. | (Belanche et al., 2022) |
| | ATT2 | I have a good opinion about using travel AI-based devices, services, and applications. | |
| | ATT3 | Using AI-based devices, services, and applications is pleasant. | |
| Initial Trust (IT) | IT1 | AI-based devices, services, and applications seem dependable. | (Kim et al., 2009) |
| | IT2 | AI-based devices, services, and applications seem secure. | |
| | IT3 | AI-based devices, services, and applications seem reliable. | |
| Perceived Risk (PR) | PR1 | The decision of whether to use AI-based devices, services, and applications is risky. | (Bélanger & Carter, 2008) |
| | PR2 | In general, I believe using AI-based devices, services, and applications is risky. | |
| | PR3 | Using AI-based devices, services, and applications subjects my personal information to potential fraud. | (Featherman & Pavlou, 2003) |
| | PR4 | Using AI-based devices, services, and applications will cause me to lose control over the privacy of my travel information. | |
| Intention to Use (IU) | IU1 | I would use AI-based services for my travelling and transportation needs. | (Cheng et al., 2006) |
| | IU2 | Using AI-powered travel assistants for managing my travel arrangements is something I would consider. | |
| | IU3 | I would see myself using AI-driven travel apps for managing my travel itineraries and transportation arrangements. | |
| Intention to Recommend (IR) | IR1 | I will probably make positive comments about the experience of using AI-based devices, services, and applications. | (Casaló et al., 2017) |
| | IR2 | I will recommend these AI-based devices, services, and applications to those of my family and friends who are interested in travelling. | |
| | IR3 | I would seldom miss a chance to tell others interested in travelling about these AI-based devices, services, and applications. | |

**Table A2.** Cross-loadings (from the authors).

| | ATT | IR | IT | IU | PE | PR | TE |
|---|---|---|---|---|---|---|---|
| ATT1 | 0.941 | 0.742 | 0.727 | 0.766 | 0.771 | −0.317 | 0.425 |
| ATT2 | 0.955 | 0.725 | 0.765 | 0.676 | 0.796 | −0.301 | 0.452 |
| ATT3 | 0.937 | 0.698 | 0.724 | 0.654 | 0.735 | −0.307 | 0.472 |
| IR1 | 0.766 | 0.955 | 0.739 | 0.782 | 0.738 | −0.349 | 0.464 |
| IR2 | 0.75 | 0.958 | 0.77 | 0.782 | 0.722 | −0.436 | 0.378 |
| IR3 | 0.58 | 0.852 | 0.593 | 0.574 | 0.576 | −0.227 | 0.281 |
| IT1 | 0.739 | 0.69 | 0.937 | 0.698 | 0.639 | −0.365 | 0.391 |
| IT2 | 0.755 | 0.76 | 0.966 | 0.691 | 0.707 | −0.465 | 0.471 |
| IT3 | 0.746 | 0.742 | 0.96 | 0.747 | 0.672 | −0.432 | 0.424 |

**Table A2.** *Cont.*

| | ATT | IR | IT | IU | PE | PR | TE |
|---|---|---|---|---|---|---|---|
| IU1 | 0.736 | 0.692 | 0.734 | 0.912 | 0.654 | −0.319 | 0.313 |
| IU2 | 0.696 | 0.758 | 0.698 | 0.925 | 0.676 | −0.322 | 0.284 |
| IU3 | 0.61 | 0.708 | 0.623 | 0.923 | 0.599 | −0.356 | 0.25 |
| PE1 | 0.75 | 0.672 | 0.628 | 0.621 | 0.919 | −0.215 | 0.354 |
| PE2 | 0.758 | 0.656 | 0.669 | 0.618 | 0.916 | −0.275 | 0.479 |
| PE3 | 0.703 | 0.688 | 0.599 | 0.64 | 0.908 | −0.235 | 0.264 |
| PE4 | 0.703 | 0.643 | 0.629 | 0.633 | 0.841 | −0.122 | 0.313 |
| PR1 | −0.304 | −0.293 | −0.372 | −0.316 | −0.208 | 0.892 | −0.087 |
| PR2 | −0.271 | −0.294 | −0.396 | −0.305 | −0.192 | 0.929 | −0.153 |
| PR3 | −0.333 | −0.379 | −0.463 | −0.343 | −0.258 | 0.91 | −0.239 |
| PR4 | −0.272 | −0.383 | −0.362 | −0.34 | −0.196 | 0.892 | −0.138 |
| TE1 | 0.328 | 0.259 | 0.286 | 0.246 | 0.288 | −0.044 | 0.768 |
| TE2 | 0.297 | 0.23 | 0.286 | 0.193 | 0.219 | −0.107 | 0.791 |
| TE3 | 0.405 | 0.421 | 0.444 | 0.224 | 0.363 | −0.207 | 0.856 |
| TE4 | 0.455 | 0.366 | 0.384 | 0.307 | 0.357 | −0.16 | 0.791 |

Legend: ATT—Attitude; IR—Intention to Recommend; IT—Initial Trust; IU—Intention to Use; PE—Performance Expectancy; PR—Perceived Risk; and TE—Travel Experience.

**Table A3.** Heterotrait–monotrait ratio (HTMT) (from the authors).

| | ATT | IR | IT | IU | PE | PR | TE |
|---|---|---|---|---|---|---|---|
| ATT | | | | | | | |
| IR | 0.835 | | | | | | |
| IT | 0.842 | 0.806 | | | | | |
| IU | 0.828 | 0.843 | 0.829 | | | | |
| PE | 0.874 | 0.814 | 0.750 | 0.765 | | | |
| PR | 0.360 | 0.352 | 0.453 | 0.393 | 0.255 | | |
| TE | 0.535 | 0.467 | 0.478 | 0.349 | 0.438 | 0.185 | |

Legend: ATT—Attitude; IR—Intention to Recommend; IT—Initial Trust; IU—Intention to Use; PE—Performance Expectancy; PR—Perceived Risk; and TE—Travel Experience.

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