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Artificial Intelligence: Understanding the determinants of adoption and intention to recommend the technology in Travel and Transportation

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Universidade Católica Portuguesa
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Resumo

O sector das viagens e dos transportes, como qualquer outro sector, tem de se manter atualizado em relação aos avanços tecnológicos. As tecnologias disruptivas, incluindo a inteligência artificial (IA), estão a ser utilizadas para desenvolver negócios, criar oportunidades, aumentar a produtividade e a eficiência e satisfazer necessidades urgentes. Apesar das possíveis vantagens que esta tecnologia pode trazer, ainda há pouca investigação sobre a utilização da IA no sector das viagens e dos transportes. A inteligência artificial é um dos avanços técnicos mais significativos do século XXI. O seu impacto na sociedade estende-se para além do emprego e da educação, para os cuidados de saúde e os transportes. A IA tem o potencial de aumentar o crescimento económico, revolucionar as indústrias existentes e criar indústrias.

Esta investigação tenta contribuir para este campo pouco estudado, preenchendo uma lacuna na literatura, ao apresentar um modelo teórico novo, completo e, tanto quanto sabemos, ainda não testado, concebido com a combinação dos resultados de uma meta-análise da literatura com a experiência de viagem e a intenção de recomendar os constructos tecnológicos importantes. Uma investigação quantitativa realizada em vários países utilizou a modelação de equações estruturais (SEM) para testar empiricamente o modelo sugerido. Os resultados indicam que a atitude do utilizador é fortemente influenciada pela expetativa de desempenho e que a intenção de utilizar a IA é significativamente influenciada pela confiança e atitude iniciais.

Palavras-chave: Inteligência Artificial, Tecnologia, Viagens, Transportes

Abstract

The travel and transportation industry, like any other sector, must stay up to date with advancements in technology. Disruptive technologies, including Artificial Intelligence (AI), are being used to develop business, create new opportunities, increase productivity and efficiency, and to meet urgent needs. Notwithstanding the possible advantages that this technology may bring, there is still little research on AI use in the travel and transportation industry. Artificial intelligence is one of the most significant technical advancements of the twenty-first century. Its impact on society extends beyond employment and education to healthcare and transportation. AI has the potential to enhance economic growth, revolutionise existing industries, and create new ones.

This research attempts to contribute to this understudied field, filling a gap in literature, by putting out a novel, thorough, and as far as we know until now not yet tested theoretical model, designed with the combination of the outcome of a literature meta-analysis with travel experience, and intention to recommend the technology important constructs. A quantitative investigation conducted across multiple countries employed structural equation modelling (SEM) to test the suggested model empirically. The findings imply that user attitude is strongly influenced by performance expectancy, that the intention to use AI is significantly influenced by initial trust and attitude.

Keywords: Artificial Intelligence, Technology, Travel, Transportation

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1. Introduction

We are living in a world that it is constantly looking for better alternatives, better options to make processes easier and more efficient. This is in part consequence of the fact that the world is getting 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 predicts that AI will increase at an annual rate of 37.3% between 2023 and 2030, revolutionizing numerous industries (Grand View Research, 2023). 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 transportations sectors' efficiency, optimizing routes schedules, and resource allocation. Since it is a sector directly related with consumer and its 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 the industry, making travel and transport more accessible, sustainable, and convenient for people around the world.

This study addresses a gap in the literature on the travel and transportation sector by combining a novel theoretical framework result of a meta-analysis with insights gleaned from a thorough literature review. The study offers a new perspective on the intention to recommend this technology. The significance of this research is underscored by the scarcity of scholarly attention devoted to the travel and transportation sector. This work provides valuable insights into the use of AI applications in the transport sector, contributing to the advancement of knowledge by exploring and discussing the direct implications for transport users.

This research aims to understand the determinants of adoption and intention to recommend the 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 to:

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

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

The document is structured as follow. The next chapter will review 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 (T&T) industry, and (iv) current technology adoption models. The second chapter describes the research model and hypotheses formulation, while the third chapter presents the research methodology. Chapter 4 expands on the presentation of the results, and

Chapter 5 discusses the key results, as well as present the main theoretical and practical consequences, and possible future directions for additional research. Finally, Chapter 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 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 than our comprehension of it has evolved, being an innovative technology as it is. 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). Stuart J. Russell & Peter 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). Stuart J. Russell & Peter Norvig (2010) present various perspectives from different authors and categorize AI into four distinct approaches, as presented in Figure 1.

(i) Thinking humanly: The cognitive modelling approach

(ii) Thinking rationally: The "laws of thought" approach

(iii) Acting humanly: The Turing Test approach

(iv) Acting rationally: The rational agent approach

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

Figure 1 - AI definitions, organized into categories

Regarding the evolution of AI, bellow it is presented a table of its evolution by Stuart J. Russell and Peter Norvig (2010).

Table 1 - Artificial Intelligence - Phases

Years	Phases	Researchers used…
50s – 60s	Early AI	formal logic and mathematical models to represent knowledge and reasoning processes

Years	Phases	Researchers used…
70s – 80s	Knowledge-based AI	rule-based systems, frames, and semantic networks to represent and reason about knowledge
80s – 90s	Machine learning	neural networks, decision trees, and genetic algorithms to build learning systems
90s - 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; Stuart J. Russell & Peter Norvig, 2010).

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).

Chen, Li, and Chen (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, Chen, Li, and Chen, (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 amalgamation of Digital Twins (DTs) and AI technology have 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 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 the Transportation are the autonomous vehicles, also known as self-driving or driverless cars; technology that enables them 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 & Ebsen (2019) investigated the motivational and perceptual factors contributing to the low adoption of electric cars in Denmark. They have 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 travel and transportation sector

Wang et al. (2020) developed an empirical study of consumers' intention 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 services, 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, Ruysschaert, and Crutzen (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 the urban sustainability transitions.

There are various eco-friendly transport options, including active and public transit, which are increasingly accessible (Mouratidis et al., 2023; Shahedi et al., 2023), despite that fact, private cars still tend to dominate the 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 transport, and associated externalities such as noise and air pollution. Yang et al. (2018) affirm that active travel and daily transport trips decreased 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 varied depending on the specific environmental features.

Virtual traveling, although it is unfamiliar to most tourists, is a concept that is recently growing, due to covid-19 pandemics, and it is becoming popular, due to travel convenience, travel cost, and travel motivation (S. N. Zhang et al., 2022). The utilization of AI in the transport industry 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, chatting with fellow travellers was a common source of contentment. Bello & Etzel (1985) emphasize that individuals' motivation to travel is to seek new experiences that differ from their everyday routine. While traveling, individuals participate in different activities that include shopping, outdoor activities, cultural experiences, or relaxation.

2.4. Theoretical models used in literature

2.4.1. Acceptance models

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

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

The UTAUT (Venkatesh et al., 2003) was developed based on 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 on 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 it has been expanded to explain acceptance also in a 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 a precise measurement of consumer behaviour (Rogers, 2003), and with so scholars and professionals can explore the intricacies of technology adoption and the elements that influence it. According to Zhao & 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, 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 & Zhang, 2022) model offers valuable insight into forecasting customers' desire and adoption of developing technology. This model can be very parsimonious and effective in explaining technology acceptance of different information systems (Marangunić & Granić, 2015), and it was inclusive used in several transport studies (Thøgersen & Ebsen, 2019; Wang et al., 2020; T. Zhang et al., 2019) due to its facility to understand society's responses to novel transport services.

2.4.5. Theory of Planned Behaviour (TPB)

Subjective norms, perceived behavioural control and attitudes towards the behaviour can all be used to predict intentions to perform various behaviours with a high degree of accuracy (Ajzen, 1991). TPB is an extended form of the Theory of Reasoned Action, 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 & 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 that we will within our study, that we combine with a travel experience and intention to recommend the technology constructs, providing a solid basis for your study, 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 the AI technology in the travel and transportation sectors, expectably reinforcing the significance and predictably of the results.

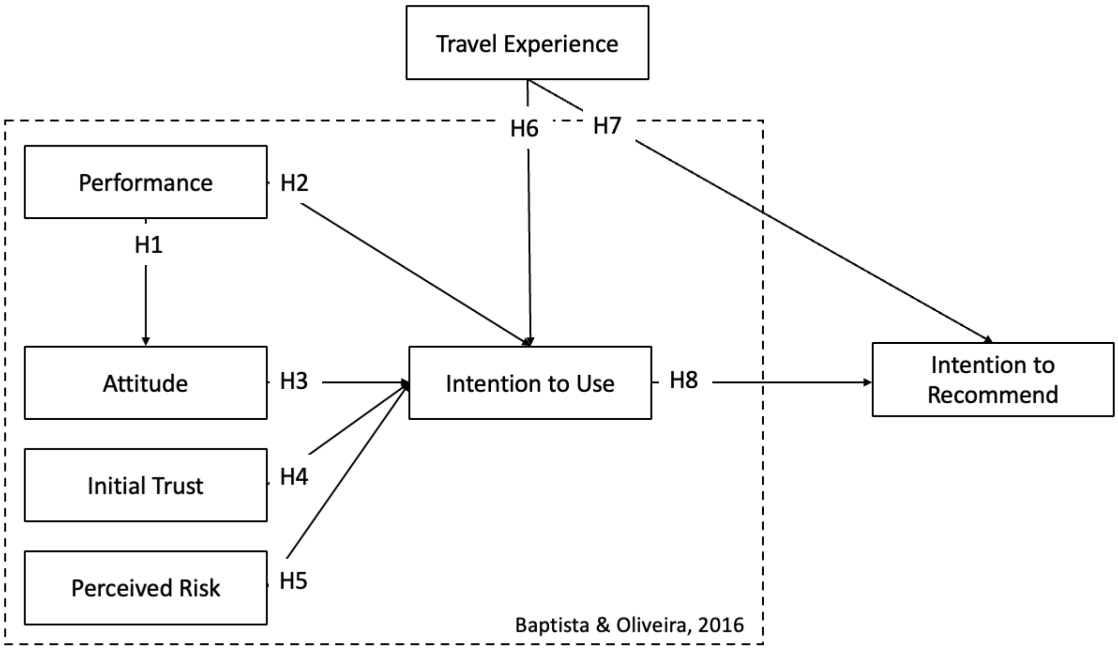

Figure 2 – Proposed Research Model

Baptista & Oliveira (2016) Effort expectancy and Structural Assurance, and Use variables were not included in our model due to the fact that we only intend to study the intention to use the technology and their direct relations. Recommending technology to others is of great commercial interest, however, researchers often neglected this construct due to the overwhelming emphasis on technology use (Miltgen et al., 2013), and 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).

Attitude pertains to an individual's (un)favourable, resilient, and persistent assessment (evaluative affect) regarding performing a certain behaviour (Belanche et al., 2022), that can strongly influence and forecast human behaviour (Cheng et al., 2006; Kraus, 1995; Shanmugam et al., 2014). The 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). Therefore, we hypothesize:

H1: *Performance expectancy has a positive effect on Attitude.*

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

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

Prior research defines **Initial Trust** as an individual's disposition to trust or on 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 – website's quality, appeal, and useability; consumer; company's reputation, company size, and corporate image act; third parties (Zhou, 2011). Therefore, we hypothesize:

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

Littler & 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 on 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:

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

Travel Experience encompasses the entirety of a leisure or holiday trip, comprising of all activities, conversations, experiences, and 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 & 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:

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** 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 (M. C. Lee, 2009; Teo, 2011). It is important to include this as a dependent variable, because of its close link to actual behaviour (Hu et al., 2003; Kiraz & Ozdemir, 2006). 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 them 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 Lancelot Miltgen et al.

(2013) & Leong et al. (2013), consumers with a greater intention to adopt a new technology are more likely to actually do so and to **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).

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, and that have at least one device that would/did allow them to use AI applications or service 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, 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 have 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 2.

Table 2 – Original authors of the variables' questions

Hypothesis	Adapted from
Travel Experience (TE)	(Bello & Etzel, 1985)
Performance Expectancy (PE)	(Venkatesh et al., 2003)
Attitude (ATT)	(Rabaa'i et al., 2024)
Trust (IT)	(C. Lee et al., 2023)
Perceived Risk (PR)	(Bélanger & Carter, 2008)
	(Featherman & Pavlou, 2003)
Intention to Use (IU)	(M. C. Lee, 2009)
Intention to Recommend (IR)	(Barta et al., 2023)

The survey was shared multiple times between December 2023 and February 2024, throughout LinkedIn, WhatsApp, emails, and several survey platforms. The first 30 answers were used as pilot-test and were not considered in the final data. 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 period of 12 weeks, a total 100 valid answers were obtained. The common method bias was also examined using the Harman's single factor test (Podsakoff et al., 2003), obtaining a variance below the 50% threshold. And also, the marker variable has also variance below the threshold of 4% (Lindell & Whitney, 2001). Hence, confirming no significant common method bias in the data.

Upon analysing the comprehensive sample of the 100 individuals, the data indicates that 49% of the respondents are female, while the other 49% are male, 44% are between 18-24 years, 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 below in Table 3.

Table 3 – Descriptive statistics of respondents' characteristics

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%
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) concludes that SEM is a good method to estimate the measurements. The research model was tested using a variance-based techniques, partial least squares (PLS), with SmartPLS4 software (Ringle et al., 2022). PLS 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). PLS 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 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., 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 follow.

5.1. Measurement model

Within the measurement model step, we underwent the assessment for items reliability, internal consistency, convergence validity, and discriminant validity. Table 4 displays the average variance extracted (AVE), composite reliability (CR), Cronbach’s alpha values, and loadings. Items 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).

Table 4 – Quality criteria and factor loadings

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

To analyse the discriminant validity, three tests were conducted and passed. The first test analysed 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 5 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 made was the heterotrait-monotrait (HTMT) ratio of correlations was measured, with all values required to be above 0.9 (Henseler et al., 2015), as presented in Annex C.

Table 5 – Fornell-Larcker

	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**

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.

5.2. Structural model and Hypothesis Testing

The evaluation of the structural model and subsequent hypothesis testing relies 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.

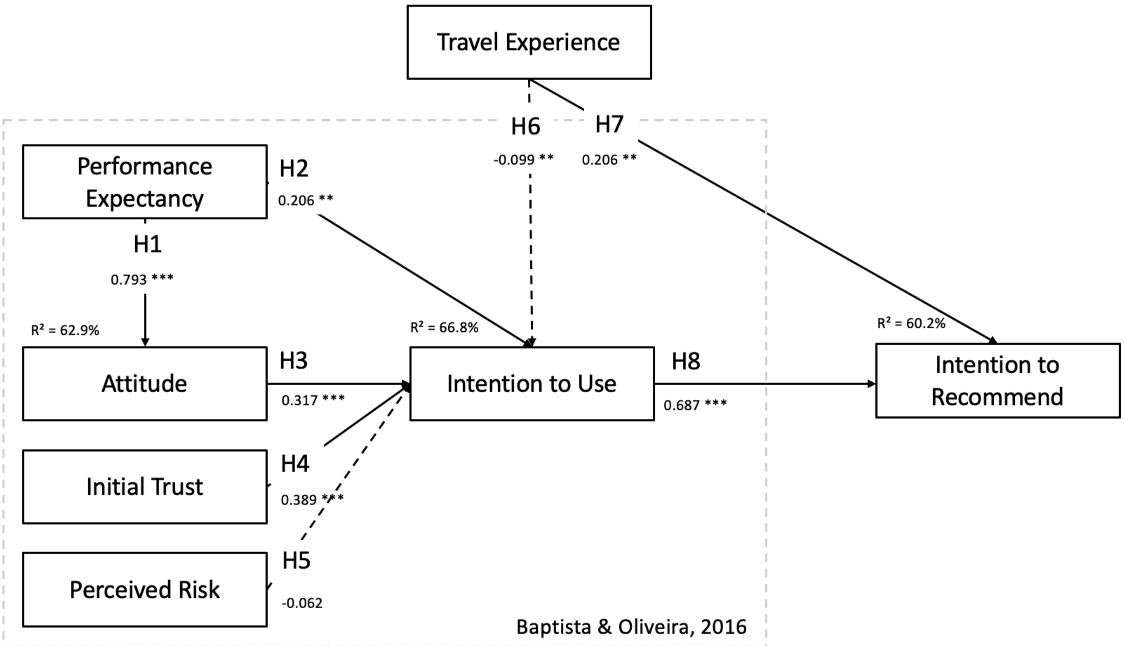

Figure 3 – Structure Model Results

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 6.

Table 6 – Variance Inflation Factor (VIF) test

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% of variation in Attitude, 66.8% in Intention to Use, and 60.2% in Intention to Recommend, as seen in Table 7.

Table 7 – Coefficient of determination values

	R^2	R^2 adjusted
ATT	0.629	0.625
IR	0.602	0.594
IU	0.668	0.651

Performance Expectancy was found to be statistically significant in explaining Attitude and Intention to Use, due to =0.793 & $p<0.01$ and =0.206 & $p<0.05$, respectively, therefore supporting hypothesis **H1** and **H2**, presented in Table 8. In line with that, Attitude (=0.317) and Initial Trust (=0.389) were found to be statistically significant in explaining Intention to Use, both with $p<0.01$, thus supporting **H3** and **H4**. Also, Intention to Use and Travel Experience were found to be statistically significant in explaining Intention to Recommend, due to =0.687 & $p<0.01$ and =0.206 & $p<0.05$, respectively, therefore supporting hypothesis **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 in Intention to Use was not found to be statistically significant, thus not supporting hypothesis **H6**.

Table 8 – Structural Model Decision

Structural Paths	Path coefficients	P-values	Conclusion
PE -> ATT	0.793	0.000	H1 Supported
PE -> IU	0.206	0.086	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

6. Discussion

This theoretical model presented is unique, integrating one model developed by Baptista & Oliveira (2016), with the construct Travel Experience, introduced by Bello & Etzel (1985), and the construct 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 transporting sector.

The research model explains a 62.9% of 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 previous study (Cheng et al., 2006), but lower when compared to 76% of M. C. Lee (2009) study. This research model explains 66.8% in Intention to Use, registering a higher power when compared to Yi et al. (2006) study, however being lower when compared to previous study (M. C. Lee, 2009). The model explained substantial variance in intention to recommend, with 60.2%, in line with 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 the AI technology, confirming the results of studies (Oh et al., 2009; Venkatesh et al., 2012). Attitude relationship with Intention to Use finding is consistent with previous studies (Cheng et al., 2006; M. C. Lee, 2009; Shanmugam et al., 2014). Therefore, evaluating and considering attitude in advance can help anticipating how people behave, being important to develop useful technologies and applications to facilitate processes in different areas, for instance, related with travel and transporting sector, having 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, being crucial to consider it for users without experience (C. Lee et al., 2023), giving importance to diverse factors mentioned by Zhou (2011).

The construct Travel experience was also evaluated, and the findings are similar to those presented in Brown & Chalmers (2003), reinforcing the importance of designing technologies for tourists, that can give them better experiences, such as platforms where to share the visit, electronic guides, and maps, or supporting pre- and post-visiting (Brown & Chalmers, 2003). Also, Intention to Use has followed the same pattern as previous studies (Hu et al., 2003; Kiraz & Ozdemir, 2006), confirming its link to actual behaviour, giving developers one crucial construct to focus on attention while implementing new technologies.

The Intention to Recommend has also been 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 in 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 (Lancelot Miltgen et al., 2013).

Lastly, Perceived Risk was also studied, but the model did not confirm the statistically relationship to Intention to Use, contrary to some earlier studies that have been able to do it (Bélanger & Carter, 2008; Littler & Melanthiou, 2006). This can be explained by an emerging paradigm, related to newer generations' habits and resistance to risk. With so, even though Gen Y and Gen Z are more up to date regarding risks and its consequences, they do not recognize these risks as a barrier in their decision-making process of AI in travel and transporting sector.

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 travel and transport 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 to identify and overcome 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 to 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 the 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 & Oliveira's model was created through a meta-analysis, and although 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, with different background and perceptions. Even this research included different nationalities, they were all from developed countries. Exploring this model in developing countries, within 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, directly related to the results, for example, of perceived risk, as mentioned before. Future research can try to extend the work to more generations, or even try to target specific generations to see how they react to the use of AI in the T&T sector.

Exploring how the 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. This research targeted individuals. In addition, 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 the travel and transport industry is very promising, receiving growing attention globally. Based on previous studies of technology adoption, this research conducted an analysis using a novel model that extended earlier literature models with past (Travel Experience) and future (Intention to Recommend) constructs in the same model, identifying relevant aspects on the intention to use and to recommend the AI technology in the travel and transportation sector. 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 this sector and recommend the technology.

Performance Expectancy, Attitude, and Initial Trust have a significant direct and indirect effects over the adoption of AI in T&T sector and the intention to recommend this technology. The relevance of Travel Experience on Intention to Recommend was also confirmed, supporting the importance to invest in AI-based infrastructures, devices, and platforms, giving users' good experiences, contributing to spreading their good experiences via social networks or websites, 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.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used chat.openai.com to generate topics to explore this theme. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Appendices

Annex A – Survey

Construct	Items	Questions	Adapted from
Travel Experience (TE)	TE1	Travel is always a unique experience for me.	(Bello and Etzel, 1985)
	TE2	Travel is always a new experience for me.	
	TE3	While traveling, 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 the AI based devices enable me to accomplish tasks more quickly when I travel.	
	PE3	Using the AI based devices increases my productivity when travelling.	
	PE4	If I use AI based devices, I will increase my chances of getting better travel.	
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.	(Afshan and Sharif 2016)
	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 the AI based services for my traveling and transporting needs.	Cheng et al., 2006
	IU2	Using the 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 traveling.	
	IR3	I would seldom miss a chance to tell others interested in travelling about these AI based devices, services and applications.	

Annex B – Cross-Loadings

	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
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**

Note: ATT – Attitude; IR – Intention to Recommend; IT – Initial Trust; IU – Intention to Use; PE – Performance Expectancy; PR – Perceived Risk; TE – Travel Experience

Annex C – Heterotrait-monotrait ratio (HTMT)

	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	

Note: ATT – Attitude; IR – Intention to Recommend; IT – Initial Trust; IU – Intention to Use; PE – Performance Expectancy; PR – Perceived Risk; TE – Travel Experience