NOVA IMS Information Management School

MDSAA

Master Degree Program in

Data Science and Advanced Analytics

Understanding the determinants of adoption and intention to recommend the AI technology in Travel and Transportation

André Figueiredo Cruz e Cunha

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

Understanding the determinants of adoption and intention to recommend the AI technology in Travel and Transportation

by

André Figueiredo Cruz e Cunha

Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Data Science.

Supervised by

Gonçalo Baptista, PhD, Universidade Nova de Lisboa

June, 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisboa, 01/06/2024]

ABSTRACT

The integration of Artificial Intelligence (AI) in the Travel and Transportation sectors represents a pivotal shift towards enhancing service quality, accessibility, and safety. This work investigates the determinants influencing the adoption and recommendation of AI technologies within these sectors. We advance the body of knowledge by proposing an innovative model combining Li et al. (2016) model, which assesses the trade-off between perceived privacy risks and benefits, with M. Camilleri et al. (2023) model, which performed an examination of the factors influencing the perceived usefulness. The research model was empirically tested using 162 responses from an on-line survey conducted in a European country. Data was analyzed using the structured equation modeling (SEM) and partial least squares (PLS). Key findings from this investigation revealed that while Information Sensitivity significantly elevates perceived privacy risks, Legislative Protection effectively mitigates these concerns. Additionally, Functionality and Information Quality were found to significantly influence perceived benefits, which in turn strongly affect both the intention to adopt and recommend AI technologies. Notably, this study highlights that despite recognizing privacy risks, these do not overwhelmingly deter users if perceived benefits are substantial, suggesting a nuanced compartmentalization of concerns, challenging conventional risk-aversion models. By addressing the existing research gap, this study contributes to both academic literature and industry practices, offering strategic guidance for stakeholders and other entities to leverage AI effectively, thus revolutionizing these sectors.

KEYWORDS

Travel and Transportation; Artificial Intelligence; Technology Adoption; Technology Recommendation

Sustainable Development Goals (SDG):

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
TAM	Technology Acceptance Model
IAM	Information Adoption Model
SEM	Structural Equation Modelling
PLS	Partial Least Squares
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor

1. INTRODUCTION

The advent of Artificial Intelligence (AI) in the travel and transportation sector signifies a pivotal shift in service delivery and user experience. Over the past decade, the rapid evolution of AI has revolutionized various sectors, including travel and transportation. AI's significance in this domain is multifaceted, addressing operational efficiency, customer experience, and environmental sustainability. Innovations such as AI-driven personalized travel planning, dynamic pricing, autonomous vehicles are redefining sector paradigms by using language processing, computer vision, and knowledge management (Lin et al., 2023). The importance of studying AI in this context is underscored by its potential to streamline complex logistical challenges, enhance customer engagement, and promote sustainable practices, not yet fully understood in earlier literature. These transformative capabilities of AI, need a comprehensive understanding of its role, influence, and future trajectory in the travel and transportation industry.

This study distinguishes itself by providing a holistic analysis of AI's impact on adoption and recommending AI technology in the travel and transportation sectors. Central to this subject are AI-powered recommender systems that employ advanced machine learning algorithms to significantly personalize user experiences (Iyer, 2021). These systems utilize vast arrays of user data to tailor suggestions for destinations, activities, and accommodations, aligning recommendations with individual preferences and behaviours. A notable implementation in this field includes a personalized tourism recommendation system that proficiently addresses user needs by analysing patterns in user data such as browsing preferences and travel habits, as demonstrated in studies like those by Nan et al. (2023) and Huda et al. (2021). These studies underscore the potential of machine learning and data mining to revolutionize service provision within tourism. Techniques like collaborative filtering and content-based filtering, integral to dynamic recommender systems, are examined for their effectiveness in enhancing the accuracy and reliability of recommendations, as highlighted by Shi et al. (2021) and Badouch & Boutaounte (2023). It is important to highlight that, combining in a single study, factors that influence positively and negatively the adoption, is not very common in literature.

Our research focuses on understanding AI's influence on user behaviour and decision-making in the travel and transportation sector. This involves examining key factors that influence individuals' perceptions of the usefulness of travel and transportation technologies and their intentions to use them. The increased market share of smartphones and advancements in high-speed wireless network technologies have escalated the industry's reliance on technologies and applications to enrich the individual experience (Yolal, 2015). A study by M. Camilleri et al. (2023) shows how the information quality, source credibility, and the functionality of travel apps significantly affect these perceptions, as the user concerns about data security significantly influence adoption rates (Miltgen et al., 2013). These factors contribute to the perceived ease of use and utility of the technologies, encouraging users to engage with them for accessing information and purchasing services with minimal effort. The compatibility of these technologies with user lifestyles, and their seamless functionality, play a critical role in enhancing user experiences and fostering willingness to engage (Oliveira et al., 2016). Previous research by Sia (2005; 2023) and Siddiqui (2022) delved deeper into the role of these technologies and their smart features in enhancing user engagement. This analysis showed how AI shapes consumer choices, affects satisfaction levels, and fosters long-term engagement. Additionally, an examination also takes place for privacy concerns, assessing how perceived risks are weighed against the substantial benefits AI technologies offer. Such an investigation is crucial, as highlighted by Li et al. (2016), because it reveals the complex dynamics influencing user decisions regarding AI adoption and recommendation in this sector. By examining the interplay between AI's capabilities and user behaviour, this exploration seeks to find a deeper understanding of the factors driving the adoption and sustained use of mobile travel apps, ultimately promoting user loyalty, and enhancing service quality in the travel and transportation sector.

This research advances the understanding of AI in the travel and transportation sectors by addressing gaps not fully explored in previous studies. While numerous studies have examined the impact of AI, few have simultaneously investigated the dual influences of both positive and negative factors on technology adoption and recommendation in these sectors, particularly within a Southern European context. Moreover, this study is unique in its comprehensive examination of both the intention to adopt and the intention to recommend technology, a variable often overlooked due to the predominant focus on adoption alone. The introduction of a model combining perceived privacy risks and benefits with the utility of AI technologies offers a robust predictive framework, as far as we know, not previously tested in literature. These elements collectively underscore the distinctive value of this thesis, aiming to provide a deeper understanding and practical guidelines for effectively leveraging AI in enhancing service delivery and user engagement.

The study begins with an Introduction that highlights AI's transformative role in service delivery and user experience for travel and transportation sectors. Following this, the Literature Review delves into existing research, discussing AI's evolution and its multifaceted implications. The Research Model chapter details the conceptual framework and hypotheses guiding the investigation. The Methodology section describes the research design, including measurement and data collection techniques. In Data Analysis and Results, the study presents the findings from the measurement model and structural model, along with hypotheses testing. The Discussion section interprets these findings, discussing theoretical implications, practical applications, and identifying study limitations while suggesting avenues for future research. The work ends with a Conclusion chapter that synthesizes the main research findings, emphasizing their significance for practitioners and for theory.

2. LITERATURE REVIEW

2.1. AI, Tools, Importance, Implications, Evolution

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions (Russell & Norvig, 1996). AI's evolution has positioned it as a transformative force across various industries and sectors, including travel and transportation. Several examples of this can be provided, such as a recent study by Zhang et al. (2023) that demonstrated the effectiveness of a stacking machine learning method in analysing travel mode choices, showing that in Jinan city, electric bikes and private cars are the primary modes of commuting, accounting for 35% and 30% of the travel modes respectively. This method outperformed the traditional multinomial logit model and other machine learning methods, with an accuracy of 0.83, underscoring the potential of AI in enhancing transportation systems. Key AI tools like machine learning, natural language processing, and robotics play a critical aspect in travel mode choice prediction, which is essential for travel demand prediction and significantly influences transport resource allocation. Chen & Cheng (2023) highlight the importance of this predictive capability in their study on using imbalanced machine learning for travel mode choices. Another example, and a notable advancement in this field, is the development of Smarter Mode of Transportation (SMT), which heavily relies on real-time traffic management. Singhal et al. (2023) discussed the implementation of a Bayesian Belief Networks (BBN) traffic control system that could be both flexible and reliable, offering a solution to the drawbacks of traditional dynamic controllers. This system, employing vision sensors like cameras for computing based on images and videos, has proven effective in gauging traffic volumes and reducing waiting times, thereby improving overall traffic management efficiency. Aghaabbasi et al. (2023) delved deeper into optimizing the hyperparameters of common machine learning models such as support vector machines, k-nearest neighbour, single decision trees, ensemble decision trees. This optimization, applied to datasets from the 2017 National Household Travel Survey in Saudi Arabia, demonstrated that Bayesian Optimization significantly improves the performance of k-nearest neighbour models, suggesting its efficacy in enhancing transportation systems.

Other AI methods, such as Artificial Neural Networks, Genetic Algorithms, Simulated Annealing, Artificial Immune Systems, the Ant Colony Optimiser, Bee Colony Optimisation, and the Fuzzy Logic Model have been brought into the travel and transport fields as well, and have had potential applications for vehicles, infrastructure, drivers, or transport users, particularly in how they dynamically interact to deliver a transport service that promotes user empowerment and supports human-machine interactions (Nikitas et al., 2020). Furthermore, specifically, neural networks and deep neural networks have been extensively applied to various railway infrastructure components such as rails, catenaries, tracks, fasteners, tunnels, turnouts, and bridges (Fox-Ivey, 2020; Oh et al., 2022). These applications focus on detection, prediction, and decision-making in the railway industry, demonstrating AI's ability to detect defects and anomalies, and to diagnose and make prognoses of railway infrastructures (Phusakulkajorn et al., 2023). Traffic flow, traffic congestion modelling, capacity analysis, mode choice analysis, and demand prediction are in between all the areas where AI is more present nowadays. However, it is important to highlight that there is a considerable gap in the application of these techniques by transportation authorities, including planners and policymakers for operations, infrastructure management, planning, sustainability, equity, accessibility, and service improvement (Behrooz & Hayeri, 2022). With this known exception, context-aware machine learning, in particular, is increasingly adopted in intelligent transportation systems, enriching data and enabling algorithms to sense dynamic changes, thereby supporting more intelligent decision-making in traffic prediction and management (Huang et al., 2023). In particular, in smart cities and automated Mobility-as-a-Service (MaaS) (Schneider et al., 2022), this technology is a significant area of development, highlighting their crucial role in advancing urban infrastructure and management (Bharadiya, 2023).

As referenced in the Introduction chapter, Li et al. (2016) provided a privacy calculus perspective in the adoption of healthcare wearable devices, highlighting a model that balances perceived privacy risks against perceived benefits. This perspective was originally created by Laufer & Wolfe (1977), who believed that individuals usually weigh the social advantages against the potential negative outcomes before revealing sensitive information. It was used again later on in several other fields, such as information systems (Culnan & Armstrong, 1999) or electronic commerce (Li et al., 2011). Li et al. (2016) model suggests that an individual's decision to adopt healthcare wearable devices is driven by a risk-benefit analysis. If the perceived benefits, such as improved healthcare management and access to health information, outweigh the perceived privacy risks associated with disclosing personal health information to the device providers, an individual is more likely to adopt the wearable device. This perspective that the decision to adopt technology is not solely based on the functionality or the perceived coolness of the innovation but that it is also deeply influenced by users' privacy concerns, can easily be brought to the context of technology adoption in the travel and transportation industry. Camilleri extends this understanding by exploring the key factors that influence individuals' perceptions of the usefulness of travel apps and predicts their dispositions to use these apps. Information quality and source credibility significantly affect the perceived usefulness of travel apps, influencing users' behavioral intentions to adopt these technologies. This suggests a critical area where travel service providers can improve their mobile apps to enhance consumer perceptions about the utility of these service technologies, leading to increased user engagement and adoption rates (M. Camilleri et al., 2023). This study is grounded in the Technology Acceptance Model (TAM), which has been extended to include constructs from the Information Adoption Model (IAM) (Sussman & Siegal, 2003), two key theoretical frameworks that suggest individuals' intentions to use a technology are influenced by their beliefs about the utility of the information provided by the technology (Davis, 1989).

These advancements highlight the potential future capabilities and opportunities of AI in transforming transportation and travel infrastructure and management. The implications of these tools are vast, ranging from predictive analytics in traffic management to personalized customer service in travel planning. The evolution of AI is charted from its early conceptual stages to its current state-of-the-art applications, highlighting its potential for future advancements in the sector.

2.2. AI IN TRAVEL AND TRANSPORTATION SECTORS

AI is playing the role of game changer in individuals that are about to travel or to make a displacement, supported in innovative solutions in the service industry which have helped to reinvent the industry in terms of enhanced quality of service and improved organizational performance (Singh et al., 2023). The industry has experienced a transformative shift due to rapid AI advancements, impacting various aspects of travel such as staying plans, travel plans, food plans, driving plans, travel route plans, and accommodation plans. This revolution underscores AI's capacity to reshape the industry to meet the needs and preferences of modern travellers (Baranidharan Subburayan, 2023). The use of AI in the hospitality industry is critical for economic development, as it helps businesses to improve customer service, to expand operational capability, to lower costs, and to quickly adapt to contemporary challenges, such as the COVID-19 crisis. With the pandemic, it has become even clearer that tourism and travelling are highly dependent on technological solutions, especially on smart technologies like AI and robotics, becoming a clear driving force in the sector. These technologies have been pivotal during the pandemic, leading to the development of new business models, customer touchpoints, and value creation opportunities, as they facilitate human experiences and support critical business processes (Koo et al., 2021). This underscores the relevance of AI in refactorizing service delivery in travel and transportation, especially in times of crisis, to ensure guest safety and satisfaction (Gretzel et al., 2015). Technological innovations such as AI-powered technologies enable businesses to transition to more digital ways of working, managing, organizing, and facilitating change in various organizational processes (Kaplan & Haenlein, 2019). This includes the implementation of AI-enhanced airport operation platform and management systems, transforming the industry into an intelligent industry. AI is also facilitating service innovation in personalized travel and transportation services, including AI-powered smart services robotics and AI-based chatbots that enhance human intelligence and physical capabilities (Jin et al., 2015). These advancements have a significant impact on employee productivity and contribute to overall service quality, influencing customer satisfaction and loyalty (Rangsit University, Thailand & Limna, 2023).

Any AI implementation is not without its risks and challenges. There are concerns about job loss in low-tech sectors, loss of control due to robot autonomy, and safety, security, and privacy concerns. Some travel and transportation businesses are apprehensive about the risks and security of implementing AI. For instance, the risk that AI-assisted robots with a certain level of autonomy may result in robot behaviour that is not controlled by humans, compromising worker safety and mental health (Ivanov & Webster, 2017). Additionally, the use of AI and automation services has the potential to enhance the demand for travel and transportation, contributing to issues such as over-bookings and overall stress on destination ecosystems (Sigala, 2018). AI systems, including the IoT - Internet of things, can also be vulnerable to security and privacy threats (Rangsit University, Thailand & Limna, 2023; Zlatanov & Popesku, 2019), leading to uncertainty and lack of trust. Among the vast array of AI subfields relevant to this sector, Ambient Intelligence (AmI) stands out. AmI refers to sensitive adaptive electronic environments that respond to the actions of persons and objects and cater for their needs. This is particularly evident in modern hospitality settings where, for instance, a hotel room may adapt the temperature, music, and light to the user’s desire, creating a personalized environment that enhances the guest experience (Bulchand-Gidumal, 2020). Expanding on this, the emergence of IoT technology supports the development of recommender systems that cater the personal preferences and professional travel recommendations, as outlined by Chen & Cheng (2023) and Ho et al. (2023). These systems can automatically generate travel itineraries, taking into account users' preferences and constraints, thereby elevating the quality of self-guided tours and reducing time costs associated with their arrangement (Ho et al., 2023; J. Zhang & Zhang, 2023). Additionally, the increasing reliance on smartphone applications within smart public transportation systems plays a crucial role in improving travel companionship and user satisfaction (Titov et al., 2022). A detailed overview of AI techniques applied worldwide revealed their impact on addressing transportation challenges, including traffic management, traffic safety, public transportation, and urban mobility (Abduljabbar et al., 2019).

3. RESEARCH MODEL

For the purpose of this work, we developed an innovative and consolidated model that combines the models of Li et al. (2016) and Camilleri et al. (2023), with an intention to recommend construct, incorporating in a single model the best of both, contributing for the advancement of knowledge, as seen in Figure 1.

Research that empirically investigates how users may perceive and react to new technologies (Miltgen et al., 2013) have been extremely helpful, but the path that sicks to investigate areas like intention to adopt technology, are not yet fully understood until now. Having that in consideration, this model was built to serve as a backbone for understanding the trade-offs users consider when deciding to adopt new technologies, particularly in sectors where privacy concerns are prominent, such as travel and transportation (Xin et al., 2019). From the constructs used in Li et al. (2016) investigation, this work incorporates Information Sensitivity, Personal Innovativeness, Legislative Protection, and Perceived Informativeness, Perceived Prestige, reflecting a consideration of privacy risks associated with technology adoption. From the constructs in Camilleri et al. (2023) investigation, this work incorporates Information Quality and Source Credibility, along with Functionality, which are the main exogenous constructs influencing the Perceived Benefit and consequently the Intention to Adopt. A final hypothesis was drawn where Intention to Adopt affects Intention to Recommend the technology (Miltgen et al., 2013).

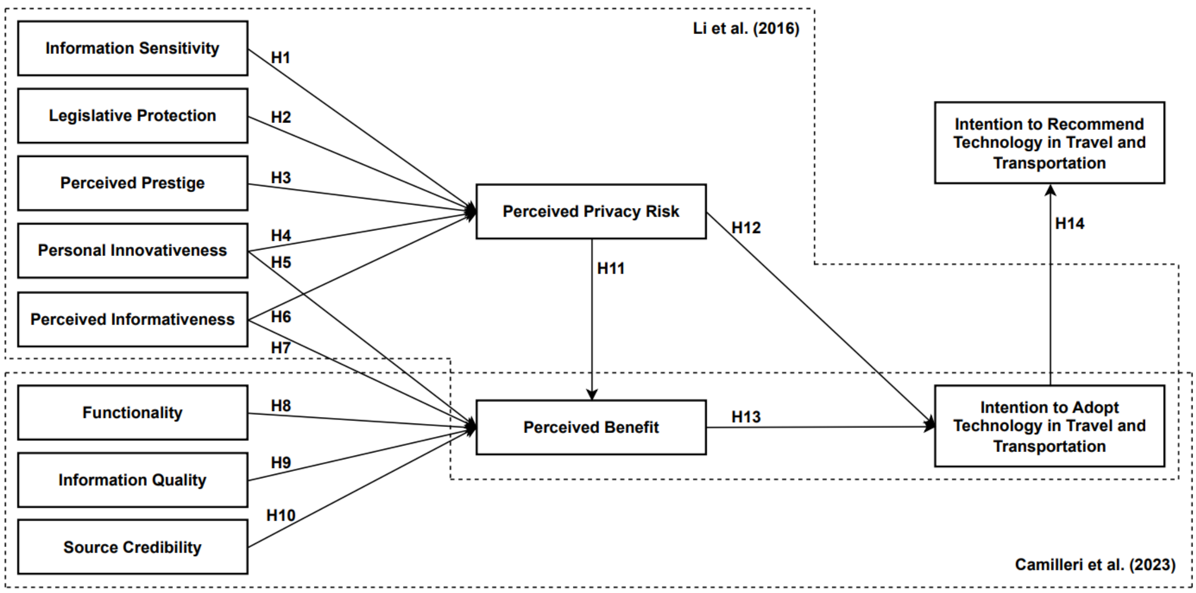

Figure 1 - Research Model

According to the privacy calculus theory, individuals assess the risks and benefits of disclosing sensitive information. In contexts like travel and transportation, sensitive data includes travel habits, locations, and payment details (Dinev et al., 2006). The sensitivity of such data heightens privacy concerns due to potential misuse, such as unauthorized tracking or financial fraud (Malhotra et al., 2004). Therefore, as the sensitivity of the information collected increases, so does the user's perception of privacy risk (Li et al., 2016). Therefore, the following hypothesis is drawn:

H1: Information sensitivity positively affects perceived privacy risk.

Considering that the impact of robust legal frameworks like the General Data Protection Regulation (GDPR) instill trust by setting strict standards for data handling and imposing penalties for violations, it is expected that users' perceived privacy risks significantly diminishes (Dinev et al., 2006). Studies indicate that when consumers are aware of these protections, their fear of data misuse decreases (Martin & Murphy, 2017). Therefore, legislative protection effectively reduces perceived privacy risks by reinforcing the security and proper management of personal data. Therefore, the following hypothesis is drawn:

H2: Legislative protection negatively affects perceived privacy risk.

Considering the influence that an organization's reputation may have on consumer trust and privacy concerns, combine with prestige, or a high standing perceived by customers, often implies reliability and trustworthy behavior, including on the management of sensitive data (Herbig & Milewicz, 1993). When a company is viewed as prestigious, consumers believe it upholds high standards in privacy and data security, which diminishes their perceived risks related to personal data disclosure (Eastlick et al., 2006). Research supports that perceived organizational prestige leads to reduced privacy concerns because customers associate such prestige with better privacy practices and less likelihood of data misuse (Featherman & Pavlou, 2003). Therefore, we hypothesize the following:

H3: Perceived prestige negatively affects perceived privacy risk.

Considering an individual's propensity to adopt new technologies, referred to as personal innovativeness, shapes their perception of privacy risks (Agarwal & Prasad, 1998). People who are more innovative tend to be more comfortable with new technologies and are generally less apprehensive about potential risks, including privacy concerns (Kwon et al., 2007). Personal innovativeness in technology leads individuals to be more accepting of new tech applications without as much concern for the possible privacy implications (Agarwal & Prasad, 1998). This is often because innovative individuals are more familiar with technology's mechanisms and therefore more confident in managing potential privacy threats or feel that the benefits of new technology outweigh the risks. Therefore, we hypothesize the following:

H4: Personal innovativeness negatively affects perceived privacy risk.

Personal innovativeness is a strong predictor of perceived usefulness, a key aspect of perceived benefit (Agarwal & Prasad, 1998). Innovative individuals often recognize the advantages of new technologies more readily, appreciating their potential to improve both daily activities and professional tasks (Yi et al., 2006). Thus, personal innovativeness positively influences the perceived benefits, encouraging wider adoption and positive experiences with new technologies. Therefore, the following hypothesis is drawn:

H5: Personal innovativeness positively affects perceived benefit.

When a system is perceived as highly informative, meaning it collects or provides extensive data, users may become more aware of the potential for privacy breaches due to the volume and detail of the information involved (Xu et al., 2009). When users perceive a system as providing a lot of personal or sensitive information, their awareness and concern about who can access and how this information might be used or misused increases (Culnan & Armstrong, 1999). This heightened awareness is a direct response to the increased visibility of their personal data, which amplifies perceived privacy risks. Therefore, the following hypothesis is drawn:

H6: Perceived informativeness positively affects perceived privacy risk.

When users perceive the information as comprehensive and pertinent, it enhances their understanding and utility from the technology, thereby increasing its perceived benefits (Agarwal & Karahanna, 2000). Empirical studies highlight that detailed and accurate information contributes to user satisfaction and enhances the perceived utility of technology, directly increasing its perceived benefit (Sussman & Siegal, 2003). In the context of travel technologies, the richness of content can significantly enhance the perceived usefulness (Cheung et al., 2008). Thus, the informativeness of a system, characterized by the quality and relevance of its content, is crucial for fostering perceived benefits, as it supports users in making informed decisions and effectively using the technology. Therefore, we hypothesize the following:

H7: Perceived informativeness positively affects perceived benefit.

Functionality, which includes features like ease of use, quick responses, and strong technical performance, directly increases the benefits users get from technology (Davis, 1989). The ability of technology to work efficiently and provide smooth user experiences is key in shaping how useful users think about it (M. Camilleri et al., 2023). Features that make using the technology easier, like simple navigation and thorough search options, significantly boost its perceived benefits (Venkatesh et al., 2012). This encourages users to use the technology more often and depend on it more. These insights are very important for developers and marketers in the travel and tourism sector looking to improve how much users engage with and enjoy their products (Buhalis & Law, 2008). Therefore, we hypothesize the following:

H8: Functionality can significantly affect perceived benefit.

High-quality information, characterized by accuracy, completeness, and timeliness, directly enhances user satisfaction toward the content (Petty & Cacioppo, 1986). For instance, in travel and transportation technologies, detailed and reliable information may increases user engagement and satisfaction (DeLone & McLean, 2003). Users value, such as information for making informed choices, leads to a higher perception of the technology's benefits (Petter et al., 2013). Therefore, focusing on improving information quality is essential for boosting user perception and the overall effectiveness and its perceived benefit. Therefore, the following hypothesis is drawn:

H9: Information quality can significantly affect perceived benefit.

Source credibility, encompassing the trustworthiness and expertise of the information provider, significantly impacts how users perceive the benefits of technology (Flanagin & Metzger, 2008). Credible sources are more likely to be viewed as reliable, enhancing the value and usefulness of the information they provide. Source credibility increases user trust and satisfaction, thereby enhancing the perceived benefits of using the technology (M. A. Camilleri, 2018). Users tend to rely more on technology that they believe is sourced credibly, leading to increased usage and dependency on that technology for making decisions (Sussman & Siegal, 2003). Therefore, the following hypothesis is drawn:

H10: Source credibility can significantly affect perceived benefit.

According to the Privacy Calculus theory, perceived benefit negatively affects perceived privacy risk (Dinev et al., 2006). But the other way around can be considered as well. When users perceive high privacy risks associated with a technology, their overall assessment of the technology's benefits may be overshadowed by worries about potential misuse of personal information (Xu et al., 2009). Heightened privacy concerns can lead to reduced perceptions of utility and value from a technology, as the risks begin to outweigh the perceived benefits (Featherman & Pavlou, 2003). This is particularly true in contexts where sensitive data is involved, and the consequences of a breach could be severe. Thus, when perceived privacy risks increase, the perceived benefits decrease, as users become more focused on the potential negative outcomes rather than the functionality or conveniences offered by the technology. Therefore, we hypothesize the following:

H11: Perceived privacy risk negatively affects perceived benefit.

As perceived privacy risks increase, particularly concerning to the security and confidentiality of personal information, potential users are more likely to avoid adopting new technologies (Harrison McKnight et al., 2002). This reluctance stems from fears of data breaches or misuse of sensitive information, which are paramount in sectors handling frequent and detailed user location data. Therefore, in the travel and transportation sectors, where the adoption of technology often requires sharing location and scheduling data, higher perceived privacy risks significantly reduce the intention to adopt such technologies (Xu et al., 2011). Therefore, we hypothesize the following:

H12: Perceived privacy risk negatively affects intention to adopt technology in travel and transportation sectors.

When users perceive clear benefits from a technology, they are more likely to adopt it (Cheung et al., 2008). Venkatesh and Davis (2000) supports this idea by showing that perceived usefulness, a proxy for perceived benefit, is a strong predictor of technology adoption intentions. Similarly, Buhalis & Law (2008) observed that travelers are more apt to adopt digital tools that visibly enhance their travel planning and experiences, thus reinforcing the critical role of perceived benefits in technology adoption. Therefore, the following hypothesis is drawn:

H13: Perceived benefit positively affects intention to adopt technology in travel and transportation sectors.

In the travel and transportation sectors, understanding user behavior is crucial, especially when introducing new technologies. Once users form a positive intention towards a technology, they are more likely to recommend it (Miltgen et al., 2013). This relationship is grounded in the understanding that user acceptance of technology, once established, naturally extends to endorsement behavior (Lee et al., 2011). This phenomenon occurs because acceptance often enhances the perceived value of the technology, encouraging users to share their positive experiences. As a result, the intention to adopt technology in these sectors naturally leads to a stronger intention to recommend it to others. Therefore, the following hypothesis is drawn:

H14: The intention to adopt technology in travel and transportation sectors positively influences the intention to recommend this technology to others.

4. METHODOLOGY

4.1. MEASUREMENT

Based on our research model, a detailed questionnaire in English was created. The structure of this questionnaire is thoroughly delineated in Appendix B and comprises several layers of constructs drawn from earlier prominent studies. The questionnaire is organized into four distinct sections: The first two are based on initial constructs from Li et al. (2016), covering Information Sensitivity, Legislative Protection, Perceived Prestige, Personal Innovativeness, and Perceived Informativeness. The subsequent constructs, including Functionality, Information Quality, and Source Credibility, are draw from the frameworks provided by M. Camilleri et al. (2023). The third section integrates Perceived Privacy Risk, Perceived Benefit, Intention to Adopt, and Intention to Recommend, adopted from both the initial models and by the models from Miltgen et al. (2013), Venkatesh et al. (2012), and Oliveira et al. (2016). Each item within the questionnaire was evaluated using a seven-point Likert scale, which ranges from "strongly disagree" (1) to "strongly agree" (7), allowing for nuanced responses that reflect varying degrees of agreement or disagreement. Finally, the questionnaire collects demographic information in the last section, categorizing age into groups, gender, and education level. The initial questionnaire was then translated into Portuguese, to ensure clarity and cultural relevance for respondents in Portugal, the country where the survey was administered. The questionnaire was then reverse translated into English to confirm translation equivalence.

4.2. DATA COLLECTION

The survey was deployed using a well-known platform (Qualtrics) to gather data from a broad audience engaged with technology in the travel and transportation sectors. The study sample size needed was defined before delivering the survey instrument. The sample target population were adult individuals with previous experience in travel and transportation services. Distribution channels used to get answers included social media, emails, direct requests, and online groups targeted at travel and transportation networks and professional communities (Davis, 1989). The data gathering was conducted during May 2024.

By extending the reach of the survey through these networks, a diverse range of responses was captured, reflecting varying degrees of technology adoption behaviors. A total of 162 responses were recorded, all valid responses. The majority of the participants were aged between 18-25 years, representing 65% of the sample, with the next largest age group being 26-35 years, representing 20%. Most respondents held at least a bachelor’s degree, while 34% had obtained a master’s degree, indicating a highly educated sample. The gender distribution was primarily female at 65%, with males constituting 34% of the responses, as detailed in

Table 1. Non-binary and other gender identities were also represented, though they formed a very small fraction of the sample.

Table 1 - Demographic Data

Gender			Education			Age		
Male	33.9%	55	Elementary School	0%	0	18 - 25	64.9%	105
Female	64.9%	105	Middle School	0%	0	26 - 35	20.3%	33
Non-binary / third gender	0.6%	1	High School	5.6%	9	36 - 45	6.2%	10
Prefer not to say	0.6%	1	Bachelor Degree	59.3%	96	46 - 55	6.8%	11
			Master Degree	33.9%	55	Above 55	1.2%	2
			Doctoral Degree	0.6%	1	Prefer not to say	0.6%	1
			Prefer not to say	0.6%	1			

To ensure that Common Method Bias (CMB) was non-existent, two different methods were used to perform the analysis. Firstly, the Harman's single-factor test was executed to ensure all variables variance was below 50%, or in other words, that no variable explained more than 50% of the model (Podsakoff et al., 2003), which was confirmed. And secondly, the Random Dependent Variable method was executed to check if the variance inflation factor (VIF) was smaller than 5, which would explain the robustness of the model against random variations (Hair et al., 2017; Kock et al., 2012), which was also confirmed.

5. DATA ANALYSIS AND RESULTS

Structural Equation Modeling (SEM) is a comprehensive statistical technique used for testing hypotheses about relationships among observed and latent variables (Gonzales, 2021). In this study, we employed Partial Least Squares (PLS), a variance-based SEM approach, supported in the SmartPLS 4.0 software (Ringle et al., 2024). PLS-SEM is preferred for its ability to handle complex models and its flexibility regarding sample size and data distribution, making it ideal for both exploratory and theory-building research (Hair et al., 2017; Henseler, 2017). The analysis comprised two phases: the assessment of the measurement model and the evaluation of the structural model. Initially, the measurement model's reliability and validity were examined to ensure the constructs were accurately measured. Then, the structural model was tested to explore the hypothesized relationships among constructs (Anderson & Gerbing, 1988). The PLS approach was particularly pertinent given the exploratory nature of some relationships in the model and the complexity arising from multiple constructs. The results, reflecting the structural model's capacity to predict and explain the relationships among variables, are detailed in the subsequent sections. These findings support the model's theoretical framework, reinforcing the suitability of PLS-SEM for this research (Anderson & Gerbing, 1988).

5.1. MEASUREMENT MODEL

The measurement model was evaluated to ensure constructs and indicators reliability, internal consistency, convergent validity, and discriminant validity. Indicator reliability was assessed by ensuring that all factor loadings were above 0.7, following the recommendation that loadings below 0.4 should be excluded to enhance model integrity, and that values between these thresholds should be evaluated (Henseler, 2017). From the constructs examined, all loadings except LP2 and LP3, met this criterion, meaning both these items were eliminated, the rest were proven to be reliable, as seen in Table 2. Internal consistency was established using composite reliability and Cronbach's alpha, both of which exceeded the 0.7 threshold across all constructs, as seen in Table 2, ensuring a strong internal consistency (Hair et al., 2017). Convergent validity was verified by measuring the Average Variance Extracted (AVE) for each construct, assuming that AVE values should exceed 0.5. (Fornell & Larcker, 1981; Hair et al., 2012), as seen in Table 2.

Table 2 - Items reliability, internal consistency, and convergent validity

Constructs	Items	Loadings	CR	AVE	Cronbach's Alpha
Functionality	FU1	0.778	0.841	0.729	0.841
	FU2	0.912			
	FU3	0.867			
Intention to Adopt	IA1	0.967	0.932	0.936	0.932
	IA3	0.968			
Information Quality	IQ1	0.895	0.918	0.851	0.918
	IQ2	0.940			
	IQ3	0.933			
Intention to Recommend	IR1	0.971	0.942	0.945	0.942
	IR2	0.973			
Information Sensitivity	IS1	0.870	0.849	0.768	0.849
	IS2	0.877			
	IS3	0.882			
Legislative Protection	LP1	1.000	N/A	N/A	N/A
Perceived Benefit	PB1	0.871	0.912	0.788	0.912
	PB2	0.896			
	PB3	0.901			
	PB4	0.883			
Perceived Informativeness	PIF1	0.855	0.830	0.714	0.830
	PIF2	0.903			
	PIF3	0.772			
Personal Innovativeness	PIN1	0.874	0.863	0.778	0.863
	PIN2	0.850			
	PIN3	0.920			
Perceived Prestige	PP1	0.896	0.898	0.811	0.898
	PP2	0.917			
	PP3	0.888			
Perceived Privacy Risk	PPR1	0.916	0.913	0.850	0.913
	PPR2	0.942			
	PPR3	0.908			
Source Credibility	SC1	0.917	0.882	0.799	0.882
	SC2	0.917			
	SC3	0.847			

Discriminant validity was rigorously tested using three methods: cross-loadings, Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT). We started with the cross-loadings criterion evaluation, where the loading of each indicator on its own construct was compared against its loadings on all other constructs. The results, according to the Annex C confirmed that all loadings are higher on their own constructs than on any other, which further validates the distinctiveness of each construct (Chin, 1998; Götz et al., 2010). Secondly, according to the Fornell-Larcker criterion, the square root of each construct's AVE was greater than its highest correlation with any other construct, which satisfies one of the key discriminant validity requirements (Fornell & Larcker, 1981), as it can be seen in Table 3.

Table 3 - Fornell-Larcker

Constructs	FU	IA	IQ	IR	IS	LP	PB	PIF	PIN	PP	PPR	SC
FU	**0.854**											
IA	0.633	**0.962**										
IQ	0.588	0.458	**0.923**									
IR	0.595	0.695	0.634	**0.972**								
IS	-0.295	-0.316	-0.450	-0.456	**0.876**							
LP	0.449	0.355	0.521	0.410	-0.425	**1.000**						
PB	0.642	0.810	0.575	0.636	-0.333	0.371	**0.888**					
PIF	0.611	0.583	0.675	0.590	-0.407	0.454	0.668	**0.845**				
PIN	0.576	0.587	0.499	0.522	-0.402	0.486	0.550	0.576	**0.882**			
PP	0.599	0.494	0.571	0.539	-0.445	0.585	0.493	0.625	0.570	**0.900**		
PPR	-0.357	-0.270	-0.476	-0.351	0.630	-0.515	-0.309	-0.465	-0.466	-0.523	**0.922**	
SR	0.470	0.396	0.716	0.612	-0.470	0.510	0.428	0.601	0.479	0.546	-0.435	**0.894**

Finally, the HTMT criterion was employed. This method compares the means of the heterotrait-heteromethod correlations to the geometric mean of the monotrait-heteromethod correlations for each pair of constructs. The HTMT values, as calculated from the correlation data, were all below the conservative threshold of 0.90, as shown in Table 4, further substantiating the discriminant validity of the constructs (Henseler et al., 2015).

Table 4 - Heterotrait-Monotrait Ratio (HTMT)

Constructs	FU	IA	IQ	IR	IS	LP	PB	PIF	PIN	PP	PPR	SC
FU												
IA	**0.728**											
IQ	0.689	**0.506**										
IR	0.687	0.735	**0.686**									
IS	0.356	0.334	0.513	**0.509**								
LP	0.504	0.380	0.546	0.423	**0.461**							
PB	0.730	0.874	0.624	0.686	0.376	**0.386**						
PIF	0.754	0.644	0.788	0.667	0.487	0.500	**0.760**					
PIN	0.679	0.639	0.563	0.576	0.470	0.522	0.617	**0.682**				
PP	0.717	0.548	0.641	0.596	0.513	0.622	0.548	0.751	**0.650**			
PPR	0.414	0.271	0.519	0.378	0.717	0.539	0.336	0.538	0.527	**0.575**		
SC	0.565	0.422	0.801	0.674	0.549	0.546	0.476	0.710	0.555	0.618	**0.487**	

5.2. STRUCTURAL MODEL AND HYPOTHESES TESTING

The collinearity among all variables was evaluated using the variance inflation factor (VIF). The results indicated that all VIF values were below the commonly accepted threshold of 5, confirming that the model is free from collinearity issues (Hair et al., 2017; Kock et al., 2012). The structural model's estimation involved calculating the coefficient of determination (Rsquared, R^2) values and analyzing the significance levels of path coefficients. The analysis of hypotheses and constructs' relationships were based on the examination of standardized paths. These model results, including the path coefficients, are depicted in Figure 2. To ensure the robustness of the path coefficients, a bootstrapping procedure with 5,000 sampling iterations was employed.

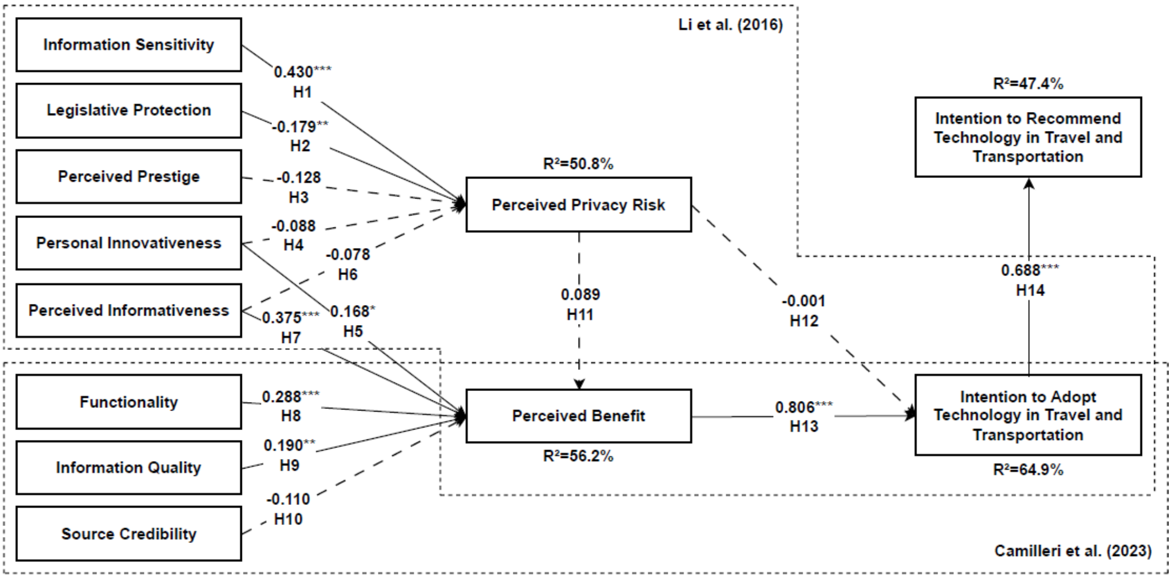

Figure 2 - Structural Model

Legend: *** $p<0.01$; ** $p<0.05$; *$p<0.1$

The model explains 50.8% of variance in Perceived Privacy Risk. Information Sensitivity ($\hat{\beta}$ = 0.430; $p < 0.01$) and Legislative Protection ($\hat{\beta}$ = -0.179; $p < 0.05$) were found to be statistically significant in explaining Perceived Privacy Risk. However, the effects of Perceived Prestige, Personal Innovativeness, and Perceived Informativeness on Perceived Privacy Risk were found not statistical significance. Therefore, H1 and H2 are supported whereas H3, H4 and H6 are not supported. Regarding Perceived Benefit, which explains 56.2% of the variance, statistically significant influences were found from Personal Innovativeness ($\hat{\beta}$ = 0.168; $p < 0.1$), Perceived Informativeness ($\hat{\beta}$ = 0.375; $p < 0.01$), Functionality ($\hat{\beta}$ = 0.288; $p < 0.01$) and Information Quality ($\hat{\beta}$ = 0.190; $p < 0.05$). However, Source Credibility was not statistically significant, leading to H5, H7, H8 and H9 being supported, and H10 being not supported. In terms of behavioral intentions constructs, the model predicts 64.9% of the variance in Intention to Adopt Technology in Travel and Transportation, with its predominant driver being Perceived Benefit ($\hat{\beta}$ = 0.806; $p < 0.01$), however, Perceived Privacy Risk did not reach statistical significance, both for its influence on Intention to Adopt and Perceived Benefit. Intention to Recommend Technology in Travel and Transportation was explained with a variance value of

47.4% which was explained by the Intention to Adopt construct ($\hat{\beta} = 0.688$; $p < 0.01$). Hence, H13 and H14 are true, while H11 and H12 are not supported.

Table 5 - Hypotheses Test Results

Hypotheses		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypotheses Statistically Supported
H1	IS -> PPR	0.430	0.428	0.080	5.358	0.000	Supported
H2	LP -> PPR	-0.179	-0.176	0.071	2.518	0.012	Supported
H3	PP -> PPR	-0.128	-0.135	0.087	1.464	0.143	Not Supported
H4	PIN -> PPR	-0.088	-0.085	0.090	0.977	0.328	Not Supported
H5	PIN -> PB	0.168	0.161	0.090	1.872	0.061	Supported
H6	PIF -> PPR	-0.078	-0.079	0.086	0.903	0.367	Not Supported
H7	PIF -> PB	0.375	0.379	0.082	4.572	0.000	Supported
H8	FU -> PB	0.288	0.286	0.087	3.310	0.001	Supported
H9	IQ -> PB	0.190	0.183	0.088	2.152	0.031	Supported
H10	SC -> PB	-0.110	-0.095	0.097	1.127	0.260	Not Supported
H11	PPR -> PB	0.089	0.094	0.064	1.385	0.166	Not Supported
H12	PPR -> IA	-0.001	-0.001	0.045	0.014	0.989	Not Supported
H13	PB -> IA	0.806	0.802	0.045	17.877	0.000	Supported
H14	IA -> IR	0.688	0.690	0.092	7.522	0.000	Supported

Legend: IS (Information Sensitivity), LP (Legislative Protection), PP (Perceived Prestige), PIN (Personal Innovativeness), PIF (Personal Informativeness), FU (Functionality), IQ (Information Quality), SC (Source Credibility), PPR (Perceived Privacy Risk), PB (Perceived Benefit), IA (Intention to Adopt), IR (Intention to Recommend).

6. DISCUSSION

This study delves into the dynamics of Artificial Intelligence's impact on user behavior and decision-making within the travel and transportation sectors, focusing specifically on the dual factors of technology adoption and recommendation. This analysis aligns with some existing studies and presents some other insights, and incorporates an innovative integration of variable relations, assessing both the positive and negative influences on these processes.

The predictive strength of our research model is compelling, especially when compared against similar studies within the domain of technology adoption. For instance, the model's predictive capability is significantly stronger than those reported by Davis (1989) and Venkatesh et al. (2012), where R-square values often hovered around 0.50 for predicting user acceptance and usage intentions of technologies. Furthermore, in the study by Morosan & DeFranco (2016), which specifically explored technology acceptance in the tourism sector, the R-square values reported were slightly lower than what we achieved, reinforcing the robustness of our model. This enhancement in predictive power transitions seamlessly into our findings. Starting with Information Sensitivity, this significantly showed to raise Perceived Privacy Risks (H1). This result is supported by similar conclusions found in studies on digital services adoption, such as those by Laukkanen (2016). On the other hand, Legislative Protection appears to mitigate these risks effectively (H2), echoing findings from Morosan & DeFranco (2016) that robust legal frameworks can indeed reduce privacy concerns and boost user trust. However, other variables such as Perceived Prestige (H3), Personal Innovativeness (H4), and Perceived Informativeness (H6), which were anticipated to impact Perceived Privacy Risk based on studies like those by Cho (2016), did not show significant effects in this context. This indicates a possible shift in how these variables influence privacy concerns, suggesting that the impact of these factors may be more context-dependent or influenced by evolving user perceptions and technological advancements than previously understood.

Perceived Benefit emerged as a crucial determinant in our model. Functionality (H8) and Information Quality (H9) significantly influenced Perceived Benefits, relating to theories proposed by Davis (1989) and Venkatesh et al. (2011), who emphasized the impact of Perceived Usefulness and Information Quality on technology acceptance. To join these constructs, Perceived Informativeness (H7) and Personal Innovativeness (H5) significantly contributed to Perceived Benefit, aligning with the findings from Venkatesh et al. (2011). On the other side of the spectrum, Source Credibility did not show a significant impact on Perceived Benefit (H10), suggesting that while trust in the information source is important, it may not be as critical in this context. This observation aligns with the work of Wathieu et al. (2002), who argued that while Source Credibility influences consumer perceptions, its impact may be overshadowed by the direct experience of the product's functionality and the quality of information provided.

This study's results also showed that privacy concerns do not necessarily dampen the perceived advantages that technologies may offer, as the relationship between Perceived Privacy Risk and Perceived Benefit (H11) was not significant. This suggests that users might compartmentalize their privacy worries apart from the functional benefits of technology, aligning with findings from Acquisti & Grossklags (2005). This perspective is a departure from traditional models emphasizing risk aversion, such as those discussed by Kim et al. (2008), where Perceived Privacy Risk did not significantly influence the Intention to Adopt (H12), suggesting a broader acceptance of inherent risks in modern technological solutions. This nuanced understanding of user behavior extends into the strong influence that Perceived Benefit has on users' Intention to Adopt (H13), often outweighing concerns about risks. Once users decide to adopt a technology, they are likely to recommend it to others (Oliveira et al., 2016), demonstrating a cascade effect where adoption leads to recommendation that this study's model showed to be statistically significant (H14). This pattern, also highlighted by Morosan & DeFranco (2016), showed how user satisfaction and adoption can significantly drive advocacy behaviors, enriching our comprehension of technology acceptance dynamics.

6.1. THEORETICAL IMPLICATIONS

This study on technology adoption within the travel and transportation sector offers several significant contributions to the existing body of literature by integrating privacy calculus with technology acceptance models. By examining both perceived privacy risks and perceived benefits together, the research provides a more nuanced understanding of how these factors interact to influence adoption and recommendation decisions. This dual-focus approach, as far as we know, is rare in earlier studies, enhances significantly our comprehension of user behavior in technology-rich environments where privacy concerns are paramount. Additionally, the research extends theoretical models like Li et al. (2016) and M. Camilleri (2023) to include specific elements such as legislative protection and information sensitivity, making them more relevant to the travel and transportation sectors. Importantly, the findings suggest that users may compartmentalize privacy concerns when considering the benefits of technology, indicating that perceived advantages often outweigh privacy risks in their decision-making processes. This challenges traditional risk-averse models and offers a new perspective on user behavior in technology adoption. This work also explores the direct relationship between the intention to adopt technology and the intention to recommend it, showing the predictive power of adoption intentions for recommendation behaviors within this sector, a relationship not yet fully explored in literature. Researchers can use this study to further refine technology adoption and recommendation models at the individual level. The effectiveness of the model should be validated across a diverse range of demographic factors, including different age groups, countries and cultures, to explore how these variables may further enrich this model and understanding of global user behaviors.

6.2. Practical Implications

Our study provides several practical implications for the travel and transportation sectors, important nature industry stakeholders, especially those developing and deploying technologies such as AI-driven systems and smart travel and transportation solutions. By highlighting key areas for strategic application, businesses and policymakers can significantly enhance technology adoption and effectiveness. A balance between perceived privacy risks and perceived benefits in technology design, services and application development, and communication is crucial. Although privacy concerns are significant, they do not overwhelmingly deter users if the perceived benefits are substantial. Focusing on enhancing the functional benefits and user-friendliness of technologies, and clearly communicating how this technology serve users' needs can help mitigate privacy concerns and encourage adoption (Agarwal & Karahanna, 2000; Venkatesh & Bala, 2008). Integrating legislative protections and sensitivity to information privacy into technology designs can significantly influence user trust and acceptance. Robust regulatory frameworks and strong legal protections effectively assuage user concerns about privacy risks (Laukkanen, 2016). Technology developers and policymakers should collaborate to ensure these protections are not only in place but also prominently communicated to users and stakeholders. Users tend to compartmentalize privacy risks and perceived benefits, indicating that traditional models of risk aversion may not fully capture user behavior in the context of modern technology adoption (Johnston & Warkentin, 2010). By designing offerings, applications, and services that emphasize the benefits and directly incorporate user feedback into continuous improvement processes, companies can better align their products with user expectations and enhance adoption rates. The direct link between the intention to adopt and the intention to recommend underscores the importance of user satisfaction in fostering organic growth through recommendations (Gefen & Straub, 2004). Strategies that encourage existing users to share their positive experiences, such as referral incentives or social sharing features integrated within the technology, are for sure very beneficial.

As technology evolves, so may the factors influencing technology adoption and recommendation. The foundation provided by this study supports ongoing research and development efforts that track these changes (Bhattacherjee, 2001). Businesses should remain agile, continuously testing and adapting their strategies to meet changing user needs and to leverage new technological advancements. By applying these insights effectively, companies in the travel and transportation sector can enhance the adoption and utility of new technologies, leading to improved user satisfaction and business performance. The framework provided by this study for developing user-centered technology solutions aligns with users' expectations and privacy concerns, paving the way for innovative and effective technology implementations.

6.3. LIMITATIONS AND FURTHER RESEARCH

Although some very important conclusions were drawn, it also highlights several limitations that pave the way for future research opportunities. The focus primarily on the intention to adopt and recommend, without a deeper exploration of how demographic variables such as age, cultural background, and education level influence technology adoption and recommendation patterns, suggests areas for further investigation. Future research could extend this work to include more diverse geographic samples to understand global user behaviors and preferences in technology adoption within the sector, as supported by the work of Walsh et al. (2010). Additionally, comparing how technology adoption varies between developed countries and those in development could offer deeper insights into contextual influences on technology uptake (Yi et al., 2006). Including more variables in the model could potentially increase its predictive power. The same could be said on exploring additional factors such as trust, and user engagement could deepen our understanding of technology adoption in the travel and transportation sector. Trust plays a crucial role in shaping technology adoption decisions amid privacy concerns and could significantly interact with constructs like Information Sensitivity and Legislative Protection, as discussed by Pavlou & Gefen (2004). User engagement, reflecting how actively users interact with technology, might also be reflected on variations in user acceptance and utilization of new technologies, supporting insights similar to those proposed by O'Brien & Toms (2008). Moreover, considering samples from other European countries could help determine whether behavioral responses to technology are consistent across different cultural contexts (Arpaci, 2015). Studying the longitudinal impact of these factors would yield insights into the evolution of user perceptions over time. Such an approach, recommended by Venkatesh et al. (2016), would allow researchers to detect trends and shifts in attitudes that aren't visible in snapshot studies.

Addressing these limitations through future research could significantly enhance our understanding of the dynamics influencing technology adoption in the travel and transportation sector, contributing to more effective and user-centered technology solutions.

7. CONCLUSION

This study on technology adoption in the travel and transportation sector enriches our understanding of how perceived benefits and privacy risks shape user intentions to adopt and recommend AI technologies. The analysis revealed that while Information Sensitivity significantly raises perceived privacy risks, Legislative Protection effectively mitigates them. Additionally, Functionality and Information Quality notably enhance perceived benefits, which robustly influence both intentions to adopt and to recommend technologies. The findings of our model indicate that despite privacy concerns, their impact does not overwhelmingly deter adoption when the perceived benefits of the technology are substantial. This suggests that users may compartmentalize their concerns about privacy when they perceive significant benefits. The strong linkage between the intention to adopt and the intention to recommend highlights the importance of satisfaction with technology, further suggesting that adoption significantly predicts recommendation behaviors, a relationship less explored in existing literature. This dual influence is captured within a novel and innovative model that surpasses the predictive capabilities of previous models. The theoretical implications of this study enhance the existing frameworks by integrating privacy calculus with technology acceptance models, highlighting how users balance perceived risks and benefits in their decision-making processes. This contribution provides a new perspective on user behavior, suggesting that traditional risk-averse models may not fully capture the nuances of modern technology adoption. For industry stakeholders, the research underscores the importance of improving perceived benefits and addressing privacy concerns through effective communication and robust legal protections to enhance technology adoption and recommendation rates.

In summary, by developing a comprehensive and innovative model not previously explored in the literature, this study offers actionable guidelines for enhancing technology uptake and recommendations in the travel and transportation sector. It emphasizes that user-friendly technologies that clearly articulate their benefits can foster widespread user acceptance and implementation. The conclusion of this research not only advances theoretical knowledge but also provides practical strategies for industry stakeholders aiming to optimize the integration and utility of new technologies, leading to improved user satisfaction and business performance.

BIBLIOGRAPHICAL REFERENCES

Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. *Sustainability*, *11*(1), 189. https://doi.org/10.3390/su11010189

Acquisti, A., & Grossklags, J. (2005). Privacy and rationality in individual decision making. *IEEE Security and Privacy Magazine*, *3*(1), 26–33. https://doi.org/10.1109/MSP.2005.22

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, *24*(4), 665. https://doi.org/10.2307/3250951

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of Information Technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Aghaabbasi, M., Ali, M., Jasiński, M., Leonowicz, Z., & Novák, T. (2023). On hyperparameter optimization of machine learning methods using a bayesian optimization algorithm to predict work travel mode choice. *IEEE Access*, *11*, 19762–19774. https://doi.org/10.1109/ACCESS.2023.3247448

Anderson, J. C., & Gerbing, D. W. (1988). *Structural equation modeling in practice: A review and recommended two-step approach*.

Arpaci, I. (2015). A comparative study of the effects of cultural differences on the adoption of mobile learning. *British Journal of Educational Technology*, *46*(4), 699–712. https://doi.org/10.1111/bjet.12160

Badouch, M., & Boutaounte, M. (2023). Personalized travel recommendation systems: A study of machine learning approaches in tourism. *Shu Ju Cai Ji Yu Chu Li/Journal of Data Acquisition and Processing*, *38*, 867–877.

Baranidharan Subburayan. (2023). *The artificial intelligence (AI) odyssey: Redefining travel and tourism for modern explorers*. https://doi.org/10.13140/RG.2.2.22816.15362

Behrooz, H., & Hayeri, Y. M. (2022). Machine learning applications in surface transportation systems: A literature review. *Applied Sciences*, *12*(18), 9156. https://doi.org/10.3390/app12189156

Bharadiya, J. (2023). Artificial intelligence in transportation systems a critical review. *American Journal of Computing and Engineering*, *6*(1), 34–45. https://doi.org/10.47672/ajce.1487

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, *25*(3), 351. https://doi.org/10.2307/3250921

Buhalis, D., & Law, R. (2008). Progress in information technology and tourism management: 20 years on and 10 years after the Internet—The state of eTourism research. *Tourism Management*, *29*(4), 609–623. https://doi.org/10.1016/j.tourman.2008.01.005

Bulchand-Gidumal, J. (2020). Impact of artificial intelligence in travel, tourism, and hospitality. In Z. Xiang, M. Fuchs, U. Gretzel, & W. Höpken (Eds.), *Handbook of e-Tourism* (pp. 1–20). Springer International Publishing. https://doi.org/10.1007/978-3-030-05324-6_110-1

Camilleri, M. A. (2018). The promotion of responsible tourism management through digital media. *Tourism Planning & Development*, *15*(6), 653–671. https://doi.org/10.1080/21568316.2017.1393772

Camilleri, M., Troise, C., & Kozak, M. (2023). Functionality and usability features of ubiquitous mobile technologies: The acceptance of interactive travel apps. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4320926

Chen, H., & Cheng, Y. (2023). Travel mode choice prediction using imbalanced machine learning. *IEEE Transactions on Intelligent Transportation Systems*, *24*(4), 3795–3808. https://doi.org/10.1109/TITS.2023.3237681

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research*, *18*(3), 229–247. https://doi.org/10.1108/10662240810883290

Chin, W. W. (1998). *The partial least squares approach to structural equation modelling. In Marcoulides G. A. (Ed.). Modern Methods for Business Research, 295(2), 295–336*.

Cho, J. (2016). The impact of post-adoption beliefs on the continued use of health apps. *International Journal of Medical Informatics*, *87*, 75–83. https://doi.org/10.1016/j.ijmedinf.2015.12.016

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization Science*, *10*(1), 104–115.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

DeLone, & McLean. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I., & Colautti, C. (2006). Privacy calculus model in e-commerce – A study of Italy and the United States. *European Journal of Information Systems*, *15*(4), 389–402. https://doi.org/10.1057/palgrave.ejis.3000590

Eastlick, M. A., Lotz, S. L., & Warrington, P. (2006). Understanding online B-to-C relationships: An integrated model of privacy concerns, trust, and commitment. *Journal of Business Research*, *59*(8), 877–886. https://doi.org/10.1016/j.jbusres.2006.02.006

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Flanagin, A. J., & Metzger, M. J. (2008). The credibility of volunteered geographic information. *GeoJournal*, *72*(3–4), 137–148. https://doi.org/10.1007/s10708-008-9188-y

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Fox-Ivey, R. (2020). *Deep learning for railroad inspection*.

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: Experiments in e-Products and e-Services. *Omega*, *32*(6), 407–424. https://doi.org/10.1016/j.omega.2004.01.006

Gonzales, J. E. (2021). Structural equation modeling with JMP® Pro. *Measurement: Interdisciplinary Research and Perspectives*, *19*(1), 80–92. https://doi.org/10.1080/15366367.2020.1809231

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2010). Evaluation of structural equation models using the partial least squares (PLS) approach. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 691–711). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-32827-8_30

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: Foundations and developments. *Electronic Markets*, *25*(3), 179–188. https://doi.org/10.1007/s12525-015-0196-8

Hair, J. F., Hult, G., Ringle, C., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). *International Journal of Research & Method in Education*, *38*(2), 220–221. https://doi.org/10.1080/1743727X.2015.1005806

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Harrison McKnight, D., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems*, *11*(3–4), 297–323. https://doi.org/10.1016/S0963-8687(02)00020-3

Henseler, J. (2017). Partial least squares path modeling. In P. S. H. Leeflang, J. E. Wieringa, T. H. A. Bijmolt, & K. H. Pauwels (Eds.), *Advanced Methods for Modeling Markets* (pp. 361–381). Springer International Publishing. https://doi.org/10.1007/978-3-319-53469-5_12

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Herbig, P., & Milewicz, J. (1993). The relationship of reputation and credibility to brand success. *Journal of Consumer Marketing*, *10*(3), 18–24. https://doi.org/10.1108/EUM0000000002601

Ho, C.-L., Chen, W.-L., & Ou, C.-H. (2023). Constructing a personalized travel itinerary recommender system with the Internet of Things. *Wireless Networks*. https://doi.org/10.1007/s11276-023-03453-y

Huang, G.-L., Zaslavsky, A., Loke, S. W., Abkenar, A., Medvedev, A., & Hassani, A. (2023). Context-aware machine learning for intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems*, *24*(1), 17–36. https://doi.org/10.1109/TITS.2022.3216462

Huda, C., Ramadhan, A., Trisetyarso, A., Abdurachman, E., & Heryadi, Y. (2021). Smart tourism recommendation model: A systematic literature review. *International Journal of Advanced Computer Science and Applications*, *12*(12). https://doi.org/10.14569/IJACSA.2021.0121222

Ivanov, S., & Webster, C. (2017). *Adoption of robots, artificial intelligence, and service automation by travel, tourism, and hospitality companies – A cost-benefit analysis*.

Iyer, L. S. (2021). AI enabled applications towards intelligent transportation. *Transportation Engineering*, *5*, 100083. https://doi.org/10.1016/j.treng.2021.100083

Jin, X., Wah, B. W., Cheng, X., & Wang, Y. (2015). Significance and challenges of big data research. *Big Data Research*, *2*(2), 59–64. https://doi.org/10.1016/j.bdr.2015.01.006

Johnston & Warkentin. (2010). Fear appeals and information security behaviors: An empirical study. *MIS Quarterly*, *34*(3), 549. https://doi.org/10.2307/25750691

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544–564. https://doi.org/10.1016/j.dss.2007.07.001

Kock, N., Lynn, G., & Stevens Institute of Technology. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580. https://doi.org/10.17705/1jais.00302

Koo, C., Xiang, Z., Gretzel, U., & Sigala, M. (2021). Artificial intelligence (AI) and robotics in travel, hospitality and leisure. *Electronic Markets*, *31*(3), 473–476. https://doi.org/10.1007/s12525-021-00494-z

Kwon, O., Choi, K., & Kim, M. (2007). User acceptance of context-aware services: Self-efficacy, user innovativeness and perceived sensitivity on contextual pressure. *Behaviour & Information Technology*, *26*(6), 483–498. https://doi.org/10.1080/01449290600709111

Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: A Multidimensional developmental theory. *Journal of Social Issues*, *33*(3), 22–42. https://doi.org/10.1111/j.1540-4560.1977.tb01880.x

Laukkanen, T. (2016). Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. *Journal of Business Research*, *69*(7), 2432–2439. https://doi.org/10.1016/j.jbusres.2016.01.013

Lee, K., Yan, A., & Joshi, K. (2011). Understanding the dynamics of users’ belief in software application adoption. *International Journal of Information Management*, *31*(2), 160–170. https://doi.org/10.1016/j.ijinfomgt.2010.07.009

Li, H., Sarathy, R., & Xu, H. (2011). The role of affect and cognition on online consumers’ decision to disclose personal information to unfamiliar online vendors. *Decision Support Systems*, *51*(3), 434–445. https://doi.org/10.1016/j.dss.2011.01.017

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals’ adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics*, *88*, 8–17. https://doi.org/10.1016/j.ijmedinf.2015.12.010

Lin, H., Yan, Y., & Cheng, Q. (2023). Future role of artificial intelligence in advancing transportation electrification. *Journal of Intelligent and Connected Vehicles*, 1–4. https://doi.org/10.26599/JICV.2023.9210020

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users’ information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research*, *15*(4), 336–355.

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4

Miltgen, L., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the “Big 3” of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114. https://doi.org/10.1016/j.dss.2013.05.010

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management*, *53*, 17–29. https://doi.org/10.1016/j.ijhm.2015.11.003

Nan, X., Parthasarathy, R., & Wang, C. (2023). Personalized travel recommendation system based on data mining technology. In G. Grigoras & P. Lorenz (Eds.), *Frontiers in Artificial Intelligence and Applications*. IOS Press. https://doi.org/10.3233/FAIA230840

Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability*, *12*(7), 2789. https://doi.org/10.3390/su12072789

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, *59*(6), 938–955. https://doi.org/10.1002/asi.20801

Oh, K., Yoo, M., Jin, N., Ko, J., Seo, J., Joo, H., & Ko, M. (2022). A review of deep learning applications for railway safety. *Applied Sciences*, *12*(20), 10572. https://doi.org/10.3390/app122010572

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404–414. https://doi.org/10.1016/j.chb.2016.03.030

Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, *15*(1), 37–59. https://doi.org/10.1287/isre.1040.0015

Petter, S., DeLone, W., & McLean, E. R. (2013). Information systems success: The quest for the independent variables. *Journal of Management Information Systems*, *29*(4), 7–62. https://doi.org/10.2753/MIS0742-1222290401

Petty, R. E., & Cacioppo, J. T. (1986). *The elaboration likelihood model of persuasion (pp. 1-24). Springer New York.* 1–24.

Phusakulkajorn, W., Núñez, A., Wang, H., Jamshidi, A., Zoeteman, A., Ripke, B., Dollevoet, R., De Schutter, B., & Li, Z. (2023). Artificial intelligence in railway infrastructure: Current research, challenges, and future opportunities. *Intelligent Transportation Infrastructure*, *2*, liad016. https://doi.org/10.1093/iti/liad016

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rangsit University, Thailand, & Limna, P. (2023). Artificial intelligence (AI) in the hospitality industry: A review article. *International Journal of Computing Sciences Research*, *7*, 1306–1317. https://doi.org/10.25147/ijcsr.2017.001.1.103

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4. Bönningstedt: SmartPLS. Retrieved from https://www.smartpls.com*.

Russell, S., & Norvig, P. (1996). *Artificial intelligence: A modern approach*.

Schneider, M., Kutila, M., & Höß, A. (2022). Applications of AI in transportation industry. In O. Vermesan, *Artificial Intelligence for Digitising Industry – Applications* (1st ed., pp. 355–362). River Publishers. https://doi.org/10.1201/9781003337232-29

Shi, S., Gong, Y., & Gursoy, D. (2021). Antecedents of trust and adoption intention toward artificially intelligent recommendation systems in travel planning: A heuristic–systematic model. *Journal of Travel Research*, *60*(8), 1714–1734. https://doi.org/10.1177/0047287520966395

Sia, P. Y. H. (2005). *A conceptual model of emerging mobile travel apps for smart tourism among Gen X, Gen Y & Gen Z*.

Sia, P. Y.-H., Saidin, S. S., & Iskandar, Y. H. P. (2023). Systematic review of mobile travel apps and their smart features and challenges. *Journal of Hospitality and Tourism Insights*, *6*(5), 2115–2138. https://doi.org/10.1108/JHTI-02-2022-0087

Siddiqui, B. (2022). *Adoption of artificial intelligence in smart travel and tourism: A conceptual framework*.

Sigala, M. (2018). New technologies in tourism: From multi-disciplinary to anti-disciplinary advances and trajectories. *Tourism Management Perspectives*, *25*, 151–155. https://doi.org/10.1016/j.tmp.2017.12.003

Singh, P. K., Wierzchoń, S. T., Tanwar, S., Rodrigues, J. J. P. C., & Ganzha, M. (Eds.). (2023). *Proceedings of third international conference on computing, communications, and cyber-security: IC4S 2021* (Vol. 421). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-1142-2

Singhal, P., M. P., K., & Faujdar, P. K. (2023). The development of a smarter mode of transportation using ai to reduce travel and waiting times. *Multidisciplinary Science Journal*, *5*, 2023ss0117. https://doi.org/10.31893/multiscience.2023ss0117

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, *14*(1), 47–65. https://doi.org/10.1287/isre.14.1.47.14767

Titov, W., Ayoubi, S., Friedrich Gerlach, C., & Schlegel, T. (2022). *Evaluation of a mobile and seamless travel companionship in smart public transport*. Human Interaction & Emerging Technologies (IHIET 2022): Artificial Intelligence & Future Applications. https://doi.org/10.54941/ahfe1002753

Venkatesh, Thong, & Xu. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Thong, J., Hong Kong University of Science and Technology, Xu, X., & The Hong Kong Polytechnic University. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., Hu, P. J.-H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context: Context, expectations and IS continuance. *Information Systems Journal*, *21*(6), 527–555. https://doi.org/10.1111/j.1365-2575.2011.00373.x

Walsh, I., Kefi, H., & Baskerville, R. (2010). Managing culture creep: Toward a strategic model of user IT culture. *The Journal of Strategic Information Systems*, *19*(4), 257–280. https://doi.org/10.1016/j.jsis.2010.09.002

Wathieu, L., Brenner, L., Carmon, Z., Chattopadhyay, A., Wertenbroch, K., Drolet, A., Gourville, J., Muthukrishnan, A. V., Novemsky, N., Ratner, R. K., & Wu, G. (2002). Consumer control and empowerment: A primer. *Marketing Letters*, *13*(3,), 297–305.

Xin, F. Z., Hang, H. X., Jie, N. H., En, N. Q., & Jun, S. K. (2019). *A contemporary paradigm of the travel industry: Determinants of sharing economy adoption*.

Xu, H., Luo, X. (Robert), Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. *Decision Support Systems*, *51*(1), 42–52. https://doi.org/10.1016/j.dss.2010.11.017

Xu, H., Teo, H.-H., Tan, B. C. Y., & Agarwal, R. (2009). The role of push-pull technology in privacy calculus: The case of location-based services. *Journal of Management Information Systems*, *26*(3), 135–174. https://doi.org/10.2753/MIS0742-1222260305

Yi, M. Y., Jackson, J. D., Park, J. S., & Probst, J. C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management*, *43*(3), 350–363. https://doi.org/10.1016/j.im.2005.08.006

Yolal, M. (2015). *The 5th advances in hospitality & tourism marketing and management (AHTMM) Conference, 18-21 June 2015, Beppu, Japan*.

Zhang, H., Zhang, L., Liu, Y., & Zhang, L. (2023). Understanding travel mode choice behavior: Influencing factors analysis and prediction with machine learning method. *Sustainability*, *15*(14), 11414. https://doi.org/10.3390/su151411414

Zhang, J., & Zhang, J. (2023). Artificial intelligence applied on traffic planning and management for rail transport: A review and perspective. *Discrete Dynamics in Nature and Society*, *2023*, 1–17. https://doi.org/10.1155/2023/1832501

Zlatanov, S., & Popesku, J. (2019). Current applications of artificial intelligence in tourism and hospitality. *Proceedings of the International Scientific Conference - Sinteza 2019*, 84–90. https://doi.org/10.15308/Sinteza-2019-84-90

APPENDIX A – ETHICS COMMITTEE APROVAL

This is to certify that
Project No.: **INFSYS2024-4-169276**
Project Title: **Understanding the determinants of adoption and intention to recommend the technology in Travel and Transportation**
Principal Researcher: **André Figueiredo Cruz e Cunha**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 4/16/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 4/16/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

APPENDIX B - SURVEY

Constructs	#	Items	Source
		In Travel and Transportation sector:	
Information sensitivity	IS1	I do not feel comfortable with the type of information that AI enabled devices, services, and applications request from me.	(Li et al, 2016)
	IS2	I feel that AI enabled devices, services, and applications gather highly personal information about me.	
	IS3	The personal information I should provide to the AI enabled devices, services, and applications is very sensitive to me.	
		In Travel and Transportation sector:	
Legislative protection	LP1	I believe that I would be protected from the misuse of my personal data.	(Li et al, 2016)
	LP2	I believe that the practices of how AI enabled devices, services, and applications providers collect, use, and protect my private information should be governed and interpreted.	
	LP3	I believe that the violation of the personal information I provided AI enabled devices, services, and applications should be able to be addressed.	
Perceived prestige	PP1	People in my community think highly of AI enabled devices, services, and applications in travel and transportation.	(Li et al, 2016)
	PP2	The use of AI enabled devices, services, and applications in travel and transportation has a good reputation in my community.	
	PP3	It is considered positive in the community to adopt AI enabled devices, services, and applications in travel and transportation.	
Personal innovativeness	PIN1	If I heard about a new AI enabled device, service, or applications, I would look for ways to experiment with it.	(Li et al, 2016)
	PIN2	Among my peers, I am usually the first to try out new AI enabled devices, services, or applications.	
	PIN3	In general, I like to experiment with new AI enabled devices, services, or applications.	
		In Travel and Transportation sector:	
Perceived informativeness	PIF1	AI enabled devices, services, and applications supplies relevant information on products or services.	(Kim & Ham, 2014)
	PIF2	AI enabled devices, services, and applications are a good source of information.	
	PIF3	AI enabled devices, services, and applications are a good source of up-to-date products or services information.	
		In Travel and Transportation sector:	
Functionality	FU1	AI enabled devices, services, and applications offers a good selection of functionalities.	(Camilleri et al, 2023)
	FU2	AI enabled devices, services, and applications works well.	
	FU3	It is quick and easy to use AI enabled devices, services, and applications.	
		In Travel and Transportation sector:	
Information quality	IQ1	The information in AI enabled devices, services, and applications is complete.	(Sussman & Siegal, 2003)
	IQ2	The information in AI enabled devices, services, and applications is accurate.	
	IQ3	The information in AI enabled devices, services, and applications is consistent.	
		In Travel and Transportation sector:	

Constructs	#	Items	Source
Source credibility	SC1	I trust the content that is presented in AI enabled devices, services, and applications.	(Camilleri et al, 2023)
	SC2	The content that is featured in AI enabled devices, services, and applications is truthful.	
	SC3	The curators of the AI enabled devices, services, and applications are skilled.	
		In Travel and Transportation sector:	
Perceived privacy risk	PPR1	It would be risky to disclose my personal information to the AI enabled devices, services, and applications vendors.	(Li et al, 2016)
	PPR2	There would be high potential for loss associated with disclosing my personal information to vendors providing AI enabled devices, services, and applications.	
	PPR3	There would be too much uncertainty associated with giving my personal information to vendors providing AI enabled devices, services, and applications.	
		In Travel and Transportation sector:	
Perceived benefit	PB1	The AI enabled devices, services, and applications improves my performance in searching for information I need.	(Y. Li, 2014)
	PB2	The AI enabled devices, services, and applications enables me to search for information faster.	
	PB3	The AI enabled devices, services, and applications enhances my effectiveness in information search.	
	PB4	The AI enabled devices, services, and applications increases my productivity in information search.	
		In Travel and Transportation sector:	
Intention to adopt	IA1	I intend to continue using AI enabled devices, services, and applications in the next months.	(Venkatesh et al, 2012)
	IA2	I plan to continue using AI enabled devices, services, and applications in the next months.	
	IA3	I will continue using AI enabled devices, services, and applications in the next months.	
		In Travel and Transportation sector:	
Intention to recommend	IR1	Based on availability, would you recommend that your friends subscribe to AI enabled devices, services, and applications?	(Oliveira et al, 2016)
	IR2	Based on your experience, would you recommend that your friends subscribe to AI enabled devices, services, and applications?	

ANNEX C – CROSS LOADING

Items	FU	IA	IQ	IR	IS	LP	PB	PIF	PIN	PP	PPR	SC
FU1	**0.778**	0.440	0.527	0.532	-0.245	0.409	0.426	0.478	0.404	0.530	-0.286	0.417
FU2	**0.912**	0.592	0.560	0.600	-0.296	0.437	0.591	0.588	0.559	0.579	-0.336	0.495
FU3	**0.867**	0.572	0.437	0.411	-0.218	0.320	0.603	0.498	0.497	0.443	-0.294	0.306
IA1	0.613	**0.967**	0.433	0.659	-0.303	0.339	0.783	0.555	0.555	0.470	-0.235	0.335
IA3	0.628	**0.968**	0.469	0.673	-0.274	0.371	0.777	0.545	0.559	0.490	-0.249	0.405
IQ1	0.511	0.412	**0.895**	0.607	-0.437	0.477	0.498	0.637	0.405	0.524	-0.376	0.650
IQ2	0.563	0.429	**0.940**	0.570	-0.412	0.490	0.570	0.620	0.462	0.514	-0.497	0.653
IQ3	0.553	0.426	**0.933**	0.583	-0.400	0.476	0.518	0.613	0.513	0.544	-0.438	0.681
IR1	0.565	0.671	0.613	**0.971**	-0.465	0.384	0.606	0.538	0.507	0.516	-0.348	0.569
IR2	0.591	0.680	0.620	**0.973**	-0.421	0.414	0.630	0.608	0.509	0.531	-0.335	0.621
IS1	-0.342	-0.378	-0.441	-0.486	**0.870**	-0.417	-0.377	-0.419	-0.451	-0.467	0.557	-0.455
IS2	-0.242	-0.208	-0.405	-0.371	**0.877**	-0.358	-0.248	-0.369	-0.343	-0.358	0.543	-0.395
IS3	-0.191	-0.242	-0.338	-0.340	**0.882**	-0.342	-0.250	-0.284	-0.261	-0.343	0.557	-0.385
LP1	0.449	0.355	0.521	0.410	-0.425	**1.000**	0.371	0.454	0.486	0.585	-0.515	0.510
PB1	0.598	0.701	0.619	0.571	-0.328	0.371	**0.871**	0.707	0.528	0.492	-0.306	0.440
PB2	0.476	0.725	0.409	0.553	-0.223	0.263	**0.896**	0.486	0.395	0.351	-0.202	0.299
PB3	0.600	0.747	0.523	0.598	-0.335	0.361	**0.901**	0.580	0.512	0.478	-0.302	0.405
PB4	0.596	0.703	0.475	0.534	-0.289	0.312	**0.883**	0.585	0.510	0.417	-0.281	0.368
PIF1	0.524	0.613	0.507	0.478	-0.247	0.401	0.659	**0.855**	0.541	0.520	-0.341	0.421
PIF2	0.544	0.484	0.672	0.600	-0.478	0.426	0.596	**0.903**	0.524	0.525	-0.492	0.630
PIF3	0.482	0.352	0.528	0.392	-0.294	0.309	0.403	**0.772**	0.371	0.559	-0.333	0.465
PIN1	0.514	0.580	0.460	0.527	-0.338	0.403	0.536	0.556	**0.874**	0.483	-0.382	0.467
PIN2	0.457	0.401	0.408	0.351	-0.335	0.375	0.407	0.466	**0.850**	0.480	-0.409	0.378
PIN3	0.547	0.560	0.451	0.491	-0.388	0.500	0.505	0.499	**0.920**	0.544	-0.442	0.417
PP1	0.527	0.336	0.496	0.477	-0.400	0.544	0.356	0.484	0.468	**0.896**	-0.483	0.499
PP2	0.532	0.521	0.496	0.451	-0.402	0.525	0.489	0.622	0.587	**0.917**	-0.519	0.488
PP3	0.568	0.478	0.563	0.542	-0.401	0.512	0.493	0.582	0.475	**0.888**	-0.395	0.489
PPR1	-0.326	-0.279	-0.443	-0.337	0.579	-0.479	-0.310	-0.425	-0.450	-0.478	**0.916**	-0.403
PPR2	-0.378	-0.236	-0.453	-0.356	0.564	-0.497	-0.312	-0.432	-0.447	-0.509	**0.942**	-0.406
PPR3	-0.282	-0.231	-0.420	-0.277	0.602	-0.447	-0.231	-0.430	-0.389	-0.459	**0.908**	-0.393
SC1	0.418	0.380	0.652	0.561	-0.378	0.455	0.415	0.601	0.410	0.525	-0.389	**0.917**
SC2	0.420	0.352	0.715	0.563	-0.444	0.480	0.379	0.543	0.407	0.511	-0.402	**0.917**
SC3	0.426	0.326	0.549	0.516	-0.446	0.433	0.352	0.458	0.474	0.421	-0.376	**0.847**

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa