UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

SEYEDEH KIANA HOSSEINI

AN EXTENSION OF THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGIES IN TRAVEL-RELATED MOBILE APPLICATIONS

DOCTORAL DISSERTATION

Ljubljana, 2026

AUTHORSHIP STATEMENT

The undersigned Seyedeh Kiana Hosseini, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title "An extension of the unified theory of acceptance and use of technologies in travel-related mobile applications", prepared under supervision of Assist. Prof. dr. Daša Farčnik

D E C L A R E

1. this doctoral dissertation to be based on the results of my own research;
2. the printed form of this doctoral dissertation to be identical to its electronic form;
3. the text of this doctoral dissertation to be language-edited and technically in adherence with the SEB LU's Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this written final work of studies in accordance with the SEB LU's Technical Guidelines for Written Works;
4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;
5. to be aware of the consequences a proven plagiarism charge based on this doctoral dissertation could have for my status at the SEB LU in accordance with the relevant SEB LU Rules;
6. to have obtained all the necessary permits to use the data and works of other authors which are (in written or graphical form) referred to in this doctoral dissertation and to have clearly marked them;
7. to have acted in accordance with ethical principles during the preparation of this doctoral dissertation and to have, where necessary, obtained permission of the Ethics Committee;
8. my consent to use the electronic form of this doctoral dissertation for the detection of content similarity with other written works, using similarity detection software that is connected with the SEB LU Study Information System;
9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this doctoral dissertation in the electronic form, the right of its reproduction, as well as the right of making this doctoral dissertation available to the public on the World Wide Web via the Repository of the University of Ljubljana;
10. my consent to publication of my personal data that are included in this doctoral dissertation and in this declaration, when this doctoral dissertation is published;
11. that I have verified the authenticity of the information derived from the records using artificial intelligence tools.

Ljubljana, September 28th, 2026 Author's signature: _____

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Assistant Professor Dr. Daša Farčnik, for her kind guidance, support, and invaluable feedback throughout this thesis. Her mentorship has been essential to the completion of my work.

I am also thankful to my committee members, Professor Dr. Darko Prebežac, Professor Janne Liburd, D.Phil, PhD, and Professor Dr. Tomaž Turk for their time, insights, and constructive suggestions, which helped improve the quality of this research.

To my husband, Ahoura, thank you for your endless support, love, patience, and belief in me. I am also deeply grateful to my family for their constant support and encouragement throughout this journey.

Lastly, I would like to thank the University of Ljubljana, School of Economics and Business for providing the environment and resources that made this research possible.

SUMMARY

This doctoral dissertation examines the factors that drive users' intention to accept and use Travel Mobile Apps (TMAs) specifically during the pre-travel phase. Building on the Unified Theory of Acceptance and Use of Technology (UTAUT2) model, the study integrates perceived Trust as an additional construct and explores the moderating effects of user experience. The objective is to understand how functional, social, and Trust-related factors shape users' Behavioural Intention in a context where mobile tourism technologies are rapidly expanding but remain under-researched, particularly in emerging markets.

A comprehensive literature review identified key gaps in technology-adoption research in tourism, especially regarding privacy, security, and information quality as antecedents of Trust. To address these gaps, a conceptual model was developed and tested using a multi-phase approach. Using partial least squares structural equation (PLS-SEM) modelling on data from 424 respondents, demonstrated the reliability and validity of the measurement model. Among all the constructs in the model, Habit is the most influential driver of Behavioural Intention to use TMAs, followed closely by Perceived Trust and Social Influence. When predicting actual Use Behaviour, the strongest determinant is Behavioural Intention itself, supported to a lesser extent by Habit and Facilitating Conditions. Together these findings highlight that cultivating habitual engagement, reinforcing social cues, and building Trust are central to forming intention, while a firm intention is the critical gateway to turning planned use into real adoption.

This dissertation advances technology-adoption research in tourism through four key contributions: (1) integration of the UTAUT2 model extended by Perceived Trust and empirically validating its relevance in the tourism context; (2) highlighting the importance of privacy and security perceptions, as well as information quality, in shaping Trust and Behavioural Intention; (3) providing evidence from a non-technologically advanced setting, thereby broadening the geographical scope of mobile-app adoption research; and (4) offering practical guidance for tourism app developers and service providers to enhance Trust, usability, and customer engagement.

KEY WORDS: digital behaviour, travel mobile apps, TMAs, technology adoption, UTAUT2, Trust, privacy, security, tourism.

POVZETEK

Doktorska disertacija preučuje dejavnike, ki vplivajo na namen in uporabo mobilnih aplikacij za potovanja (angl. Travel Mobile Apps – TMAs) turistov, predvsem v obdobju pred potovanjem. Na podlagi razširjenega modela UTAUT2 delo vpelje zaznano zaupanje kot dodaten konstrukt ter preučuje interakcijske učinke uporabniške izkušenosti. Namen raziskave je razumeti kako funkcionalni, socialni in na zaupanju temelječi dejavniki oblikujejo vedenjski namen turistov v kontekstu, kjer se mobilne turistične tehnologije hitro razvijajo, a ostajajo premalo raziskane.

Sistematičen pregled literature je pokazal pomembne vrzeli v raziskavah sprejemanja tehnologije v turizmu s strani turistov, zlasti glede zasebnosti, varnosti in kakovosti informacij kot elementov zaznanega zaupanja. Za zapolnitev teh vrzeli je bil razvit konceptualni model, ki je bil empirično preverjen v več fazah. Analiza s pomočjo modeliranja strukturnih enačb z metodo delnih najmanjših kvadratov (PLS-SEM) na podatkih 424 respondentov potrjuje zanesljivost in veljavnost merilnega modela. Med vsemi konstrukti se je kot najmočnejši napovednik vedenjskega namena uporabe TMAs izkazala navada, sledita zaznano zaupanje in socialni vpliv. Pri napovedovanju dejanske uporabe pa je najpomembnejši dejavnik vedenjski namen, ki mu v manjši meri sledita navada in omogočitveni pogoji. Rezultati poudarjajo, da so spodbujanje rabe, krepitev socialnih signalov in gradnja zaupanja ključni za oblikovanje namena, medtem ko je jasen namen bistvena povezava med načrtovano in dejansko uporabo.

Disertacija prispeva k raziskavam sprejemanja tehnologije v turizmu v naslednjih štirih področjih: (1) razširi okvir UTAUT2 z vključitvijo zaznanega zaupanja ter empirično potrdi njegov pomen v turističnem kontekstu; (2) izpostavi pomembnost zaznav zasebnosti, varnosti in kakovosti informacij pri oblikovanju zaupanja in namena uporabe; (3) prinaša empirične dokaze iz tehnološko manj naprednega okolja ter s tem širi geografski obseg raziskav sprejemanja mobilnih aplikacij; in (4) nudi praktične smernice razvijalcem aplikacij in turističnim ponudnikom glede krepitve zaupanja, uporabnosti in zavzetosti uporabnikov.

KLJUČNE BESEDE: Digitalno vedenje, mobilne aplikacije za potovanja (TMAs), sprejemanje tehnologije, model UTAUT2, zaupanje, zasebnost, varnost, turizem

TABLE OF CONTENTS

1 INTRODUCTION 1

1.1 Research problem and research gaps 2

1.2 Aim of the research and research questions 4

1.3 Methodology and data 7

1.4 Structure of the dissertation 8

2 THE TOURISTS' MULTI-FACETED EXPERIENCES 8

2.1 Conceptualizing the pre-travel phase as a multi-stage process 11

2.1.1 Dreaming 11

2.1.2 Decision-making and Planning 12

2.1.3 Booking 13

2.1.4 Transactions 13

2.1.5 Expectation formation 14

2.2 Integration of TMAs in pre-travel phase 14

3 THEORIES IN ACCEPTANCE AND USE OF TECHNOLOGY 16

3.1 Early theoretical models in technology acceptance 16

3.2 Unified Theory of Acceptance and Use of Technology (UTAUT) 17

3.3 UTAUT2: extension for consumer contexts 17

3.4 UTAUT2 and Perceived Trust 18

3.5 UTAUT2's relevance to TMAs 18

3.6 Research context: Iran 19

4 HYPOTHESES Development 21

4.1 Performance Expectancy 21

4.2 Effort Expectancy 22

4.3 Social Influence 23

4.4 Facilitating Conditions 24

4.5 Hedonic Motivation 25

4.6 Price Value 25

4.7 Habit 26

4.8 Behavioural Intention 27

4.9 The extension of UTAUT2 with Perceived Trust 28

4.10 Perceived Trust and the underlying key antecedents 32
4.10.1 Perceived Privacy and Perceived Trust 32
4.10.2 Perceived Security and Perceived Trust 33
4.10.3 Perceived Security and Perceived Quality of Information 33
4.11 The moderating role of Experience 34
5 CONCEPTUAL MODEL 35
6 METHODOLOGY 38
6.1 Measurement of constructs 38
6.2 Questionnaire development and structure 44
6.3 Data collection and sampling 45
6.4 Sample description 46
6.5 Methods 48
7 RESULTS 49
7.1 Descriptive analysis of study variables 50
7.2 Measurement model assessment 51
7.2.1 Factor Loadings and Variance Inflation Factor (VIF) 51
7.2.2 Cronbach's Alpha (α) 53
7.2.3 Composite Reliability (ρA and ρC) 53
7.2.4 Average Variance Extracted (AVE) 54
7.2.5 Fornell–Larcker Criterion 55
7.2.6 Heterotrait–Monotrait Ratio (HTMT) 57
7.3 Structural model assessment 63
7.3.1 Hypotheses testing 64
7.4 Control variables 69
7.5 Importance–Performance Matrix Analysis (IPMA) 70
7.5.1 Importance–Performance Matrix Analysis (IPMA)– Behavioural Intention 70
7.5.2 Importance–Performance Matrix Analysis (IPMA)–Use Behaviour 72
8 DISCUSSION 75
8.1 Direct effects on Behavioural Intention, Perceived Trust and Use Behaviour 75
8.1.1 Behavioural Intention 75
8.1.2 Perceived Trust 77

8.1.3 Use Behaviour 78
8.2 Indirect effects on Use Behaviour 79
8.3 Role of demographic, temporal, and situational factors 82
8.4 Importance–Performance Matrix Analysis (IPMA) 82
8.5 Implications and limitations 86
8.5.1 Theoretical implications 86
8.5.2 Managerial implications 88
8.6 Research limitations 89
8.7 Directions for future research 90
9 CONCLUSION 92
REFERENCE LIST 94
APPENDICES 113

LIST OF TABLES

Table 1: Summary of Hypotheses 35
Table 2: Measurement items 41
Table 3: Profile of the respondents 47
Table 4: Descriptive Statistics 50
Table 5: The results of factor loadings and the collinearity index 52
Table 6: Reliabilty and Convergant validity 54
Table 7: The Fornell–Larcker Matrix 56
Table 8: The Heterotrait-Monotrait Ratioo (HTMT) 58
Table 9: Cross Loading 60
Table 10: Structural Equation Modelling (Hypothesis Testing) 68
Table 11: Control Variables 69
Table 12: Results of the Importance–Performance Matrix Analysis (IPMA)- Behavioural Intention 71
Table 13: Results of the Importance–Performance Matrix Analysis (IPMA)- Use Behaviour 73

LIST OF FIGURES

Figure 1: Conceptual Framework: The Extended UTAUT2 37
Figure 2: Structural Model with Standardized Path Coefficients (t-values) and R^2 Values. 64
Figure 3: Importance–Performance Map (IPMA) for Behavioural Intention 72
Figure 4: Importance–Performance Map (IPMA) for Use Behaviour 74

LIST OF APPENDICES

Appendix 1: Questionnaire in English 1
Appendix 2: Questionnaire in Persian 10
Appendix 3: Measurement model with standardized factor loadings 19
Appendix 4: Daljši povzetek 21

LIST OF ABBREVIATIONS

AI – Artificial Intelligence

App – Application

AVE – Average Variance Extracted

BI – Behavioral Intention

CAGR – Compound Annual Growth Rate

CFA – Confirmatory Factor Analysis

HTMT – Heterotrait–Monotrait Ratio

ICT – Information and Communication Technology

IoT – Internet of Things

IPMA – Importance–Performance Map Analysis

IS – Information System

ML – Machine Learning

PLS-SEM – Partial Least Squares Structural Equation Modeling

sl. – Slovene

SPSS – Statistical Package for the Social Sciences

TMA – TMAslication

UB – Use Behavior

UTAUT2 – Unified Theory of Acceptance and Use of Technology 2

VIF – Variance Inflation Factor

1 INTRODUCTION

In today's digital era, technological advancements are accelerating at an exponential pace, transforming societies, industries, and individuals' daily lives (Jiao et al., 2025). Among these, rapid progress in mobile technologies and applications–as software programs specifically designed to operate on mobile devices such as smartphones, tablets, or smartwatches (Sharma et al., 2023)–has created new opportunities and innovative business models across various sectors (Mariano et al., 2022). The tourism industry is no exception to this digital transformation, as travel mobile apps (hereafter TMAs) have become indispensable tools for both tourism suppliers and users (Birenboim et al., 2023).

For tourism businesses and destination management organizations (DMOs), TMAs play a prevailing role in the formation of destination marketing and branding (Tran & Rudolf, 2024). Companies increasingly leverage TMAs not only to provide access to products and services but also to strengthen customer relationships and build lasting brand loyalty (Tian et al., 2021). From the consumer perspective, given the inherently mobile and dynamic nature of tourism, and particularly after COVID-19, TMAs have become essential tools, accelerated the digital transformation of travel experiences and significantly shift tourist behaviour (Dias & Afonso, 2021).

This shift in adoption driven by the growing reliance on mobile technologies, has provided travellers with greater independence from traditional intermediaries and increased freedom and flexibility in planning and managing their trips (Jamal & Habib, 2020). TMAs now play a vital role in fulfilling the diverse needs of modern travellers (Sia et al., 2024). Therefore, due to their growing popularity among both tourism suppliers and users, the global revenue of TMAs has tripled, surpassing 1.2 billion U.S. dollars in 2023 (Statista, 2024) and rank among the most widely used categories of active mobile applications (Hamouda, 2022).

Due to this growing popularity, TMAs have attracted increasing scholarly attention within the broader technology adoption literature (Gera et al., 2025). Within tourism research specifically, studies have vigorously examined the factors influencing the acceptance and use of these applications (Li et al., 2024). As TMAs continue to evolve and are updated daily with novel integrated features (e.g., location-based services, artificial intelligence, augmented reality), the determinants of their use remain a dynamic area of inquiry, requiring continuous investigation to keep pace with technological changes (Şeker et al., 2023). This persistent scholarly interest underscores the need to consistently refine the understanding of user behaviour in this rapidly changing digital ecosystem.

To examine these evolving behavioural patterns, researchers have increasingly investigated the adoption of TMAs through established technology-acceptance theoratical models, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT) model and its extension, UTAUT2 model (Tran et al., 2024). Developed by Venkatesh et al. (2012), the

UTAUT2 model incorporates the constructs of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Price Value, Hedonic Motivation, and Habit. UTAUT2 provides a strong foundation for analysing consumer technology adoption across diverse contexts (Venkatesh et al., 2016), and its comprehensive, consumer-centric structure has led to its widespread application in the technology adoption literature within tourism.

For instance, Rayun et al. (2025) employed UTAUT2 to investigate factors influencing the adoption of mobile wallets (m-wallets) for cashless transactions within the tourism sector, finding that Performance Expectancy, and Effort Expectancy, significantly influenced adoption intentions. Similarly, Foroughi et al. (2025) applied an extended UTAUT2 model to assess the drivers of user intentions to utilize AI-powered tools (ChatGPT) for travel planning, identifying Hedonic Motivation, Performance Expectancy, And Habit as key predictors. Furthermore, Gupta and Dogra (2017) used the UTAUT2 framework to examine factors influencing tourist adoption of mapping apps for navigation during travel within the destination context, revealing that Habit, Facilitating Conditions, Performance Expectancy, And Hedonic Motivation were significant antecedents of Behavioural Intention. These studies demonstrate the model's adaptability and relevance across different tourism technologies and stages of the traveller journey.

While the chronological division of the tourist experience into pre-, during-, and post-travel phases provides a useful structural framework (Tung & Ritchie, 2011; Clawson & Knetsch, 1966), recent research suggests that tourist experience is increasingly dynamic and multifaceted. A distinction has been made between “the tourist experience” as a structured process and “tourists’ experiences” as subjective and context-dependent phenomena (Volstad & Font, 2020). In digitally connected environments, these stages may overlap, as anticipation and recollection can occur simultaneously through ongoing engagement with digital platforms. However, for the purpose of this study, tourist experience is treated as a holistic construct, with a specific focus on the pre-travel phase, providing a consistent basis for empirical analysis.

1.1 Research problem and research gaps

Even though TMAs have become an established topic in tourism research, existing studies predominantly examine their overall adoption as generic tools (Asif & Fazel, 2024). Tourists’ experiences, however, are multifaceted and multistage processes encompassing activities before, during, and after travel–commonly referred to as the pre-travel, travel, and post-travel phases (Tung & Ritchie, 2011). Among the three phases, the on-site phase has received the most attention, with nearly five times more studies, revealing a clear research imbalance in the literature (Eletxigerra et al., 2021). Even in the technology adoption literature, the pre-travel phase remains comparatively underexplored. For instance, research by Khalilzadeh et al. (2017), investigated mobile payment adoption in restaurants, or Kebab et al. (2025) focused on the factors influencing international tourists' intentions to adopt

TMAs in an emerging market specifically for the during-travel phase and within the destination context, but did not delineate the specific sub-stages of planning and booking. Similarly, several studies have focused primarily on post-travel outcomes, such as Agag and El-Masry (2016), explored how attitudes formed during the travel experience influence post-travel behaviours such as positive word-of-mouth and future intentions.

This highlights a notable gap in the literature regarding a targeted, in-depth analysis of user acceptance specifically within the detailed, multi-stage pre-travel phase. This phase is critical because it lays the groundwork for the actual trip and involves key activities manageable through TMAs, including information searching, itinerary planning, and decisions related to destinations, accommodations, transportation, and budgets, as well as the booking and payment of tourism products (Eletxigerra et al., 2021).

Moreover, the existing studies often originate from technologically advanced countries where digital literacy is high and internet infrastructure is robust (e.g., Sánchez-Torres et al., 2021), thereby introducing a geographical bias into the literature. This overrepresentation overlooks important cultural and infrastructural differences, particularly in developing countries or regions where users' behaviours toward TMAs adoption might differ substantially (Gretzel, 2015).

The current understanding of TMAs adoption behaviour by Iranian users is subject to both contextual and geographical limitations. At the contextual level, research within Iran has identified Iran as a developing country with structural challenges–such as technological readiness and regional inequalities (Nafchi & Mohelska, 2018; Kazemi & Amini, 2024), yet limited attention has been given to how these conditions influence TMA use and user behavior. On the other hand, at the geographical level, existing literature is largely dominated by studies conducted in technologically advanced countries with well-developed infrastructure (Sánchez-Torres et al., 2021). This overrepresentation overlooks important cultural and infrastructural differences, particularly in developing countries or regions where users' behaviours toward TMAs adoption might differ substantially (Gretzel, 2015).

Even though the UTAUT2 model has been successfully applied in technology adoption literature in tourism, there is a critical gap as one crucial construct, namely Perceived Trust, is notably absent from the original UTAUT2 model (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Therefore, they extended UTAUT2 by integrating perceived Trust as an additional antecedent of Behavioural Intention in their study of online ticket purchasing on low-cost carrier websites. In their model, Trust captured users' beliefs in the platform's security, reliability, and integrity–factors that were found to significantly strengthen intention to use the airline's online services.

In fact, this concept is highly important in the context of TMAs (Tran & Vu, 2024) and is especially critical within the pre-travel phase, where users continuously share sensitive personal data, execute financial transactions, and evaluate crucial destination information

via mobile platforms (Ioannou et al., 2020). Trust, shaped by users' perceptions of data security, service reliability, and app transparency (Baruah & Sarma, 2024), is a critical determinant of whether TMA users will ultimately be used or abandoned during the pre-travel phase, yet it remains largely overlooked in both current research and existing technology-adoption models in tourism employing UTAUT2 model.

1.2 Aim of the research and research questions

Building on the identified research gap, this study first conceptualizes the pre-travel phase as a sequence of dynamic and interconnected stages: dreaming, decision-making planning, booking, transaction, and expectation formation. This framework offers a structured approach for analysing the tourists' experiences and the role of TMAs in shaping this process.

Second, this study employes the extended versiom of UTAUT2 model with the incorporation of the construct of Perceived Trust. The Perceived Trust is operationalized based on three foundational antecedents: Perceived Privacy, Perceived Security, and perceived Information Quality to study users' acceptance and use of TMAs. These specific factors were selected due to their theoretical and empirical salience in the formation of Perceived Trust (Escobar-Rodríguez & Carvajal-Trujillo, 2014). The application of this extended model is particularly relevant in the Iranian context, which serves as the case of study for this research.

As in Iran, despite the growing adoption of TMAs (Morabi Jouybari et al., 2023), inadequate digital infrastructure, insufficient legal frameworks, and limited resource allocation continue to impose significant supply- and demand-side constraints on technological development (Amiri & Sangar, 2023). Furthermore, in this collectivist culture, where social norms and Trust heavily shape user decisions (Esfandiar et al., 2023), the extended UTAUT2 model provides deeper insights into how cultural, technological, and institutional factors influence adoption behaviour beyond advanced economies. This study also assesses the moderating effects of prior user experience. Specifically, it investigates how this experience moderates the hypothesized relationships between two key UTAUT2 constructs: Habit and Behavioural Intention, as well as Habit and actual Use Behaviour.

Third, this study promotes the inclusion of Iran as a developing-country context (Nafchi & Mohelska, 2018; Kazemi & Amini, 2021) in tourism technology research, by studying Iranian users as a representative case. This approach helps counterbalance the dominance of studies conducted in technologically advanced regions and captures the unique cultural, infrastructural, and trust-related factors that influence technology adoption differently in such settings.

Fourth, the study delivers both theoretical and practical contributions. From a theoretical perspective, the research strengthens the academic literature through the extension of the UTAUT2 model. From a practical perspective, the findings provide actionable insights for

app developers, tourism service providers, and policymakers. These contributions aim to bridge the gap between academic theory and real-world application, fostering improved development strategies within the travel technology sector.

To ensure the research objectives are systematically addressed, this dissertation is guided by a set of main research questions. These questions are designed to explore the key factors influencing the acceptance and use of TMAs across the specific sub-stages of the pre-travel phase, integrate the construct of perceived Trust into the UTAUT2 model, examine the moderating role of prior experience, and consider the unique contextual factors inherent in a developing-country market. The main goal of this dissertation is to provide answers to the following research questions:

The pre-travel phase is a multi-stage process (Gretzel, 2021) and is recognised as a foundational component of the tourist journey (Tung & Ritchie, 2011); however, its internal structure and the role of TMAs across its sub-stages remain insufficiently examined. Pre-travel planning receives significantly less scholarly attention than the on-site stage (Eletxigerra et al., 2021), resulting in limited understanding of how users engage with TMAs before departure. To address this gap, the first research question examines how TMAs are used within the distinct sub-stages of the pre-travel phase as:

RQ1. What are the key stages that define the pre-travel phase, and how do users interact with TMAs during each stage?

While existing studies identify a range of determinants influencing technology adoption, few examine these factors specifically within the pre-travel context, where user motivations and barriers differ significantly from on-site or post-travel behaviour (Gretzel et al., 2020). Additionally, the rapidly evolving features of TMAs mean that the determinants of their use remain dynamic and require continuous reassessment (Şeker et al., 2023). Therefore, this research question focuses on identifying the factors influencing TMA acceptance during pre-travel:

RQ2. What factors positively or negatively influence users' acceptance and use of TMAs throughout the pre-travel phase?

Although UTAUT2 is widely used in technology-adoption research, it does not include Perceived Trust, despite the central role Trust plays in consumer context where privacy, security, and information quality strongly influence user decision-making (Hartono et al., 2014; Kim et al., 2008). Prior work by Escobar-Rodríguez and Carvajal-Trujillo (2014) demonstrated that incorporating Trust into UTAUT2 significantly improved its ability to explain online purchasing behaviour; however, their focus was limited to transactional airline websites rather than the broader, information-rich interactions typical of TMAs during the pre-travel phase. Given that Trust is particularly important when users evaluate data reliability, security, and privacy before a trip, examining its integration into UTAUT2 is essential for strengthening the model's explanatory power in this context. Therefore:

RQ3. How does integrating the construct of Perceived Trust (and its antecedents of Perceived Privacy, Perceived Security, and Perceived Information Quality) enhance the explanatory power of the extended UTAUT2 model in this specific context?

Technology adoption is shaped by cultural norms, socio-economic conditions, and institutional environments, yet most studies on TMAs have been conducted in digitally advanced, Western contexts (Sánchez-Torres et al., 2021). Consequently, there is a need to better understand how users in developing countries–with different infrastructural realities, privacy expectations, and social norms–perceive and use TMAs. Within this broader context, the case of Iran is particularly noteworthy, as Trust emerges as a critical factor due to limited institutional safeguards, low consumer familiarity with digital transactions, and insufficiently transparent data-protection practices, especially when personal or financial information is required (Hanafizadeh et al., 2014). These contextual characteristics highlight the importance of examining how cultural and environmental factors shape Iranian users' perceptions and behaviours toward TMAs. Therefore,

RQ4. How do cultural and contextual factors specific to Iranian users shape their perceptions of and behaviours toward TMAs within a developing-country setting?

Although UTAUT2 identifies prior user experience as a key moderating variable, empirical studies report mixed and often inconsistent findings regarding its moderating effects in different technological contexts. Some research indicates that experience strengthens relationships such as Habit and Behavioural Intention (Chang et al., 2019), while others demonstrate no meaningful moderation, suggesting that its influence may be highly context-dependent (Nikolopoulou et al., 2021). Given that TMAs vary in complexity, frequency of use, and familiarity across user groups, understanding whether experience shapes core behavioural pathways within an extended UTAUT2 model is essential for clarifying its theoretical role. Therefore:

RQ5. To what extent does prior user experience moderate the relationships between Habit, Behavioural Intention, and actual Use Behaviour within the extended UTAUT2 model?

While theoretical models such as UTAUT2 offer valuable insights into the determinants of technology acceptance, there remains a need to translate these findings into practical guidance for developers, tourism organisations, and policymakers. This is particularly important in developing-country contexts, where infrastructural limitations, privacy concerns, and varying levels of digital literacy can hinder the effective design and deployment of TMAs (Amiri & Sangar, 2023; Gretzel et al., 2015). By deriving actionable recommendations from the empirical findings, research can support the development of more Trustworthy, user-centred, and contextually appropriate TMAs. Therefore:

RQ6. What practical design and policy recommendations can be drawn to improve the Trustworthiness, usability, and contextual relevance of TMAs for users in developing countries?

1.3 Methodology and data

This study employs a quantitative, cross-sectional research design to examine the determinants of TMA acceptance and use during the pre-travel phase within an extended UTAUT2 model. Given the model's complexity–comprising multiple latent constructs, mediating pathways, and a moderating variable–Partial Least Squares Structural Equation Modelling (PLS-SEM) is selected as the primary analytical method due to its suitability for this research. The measurement instrument is developed by adapting validated items from prior UTAUT2 model and digital-Trust studies, with all constructs operationalised as reflective latent variables measured through Likert-type scales. Perceived Trust and its antecedents (Perceived Privacy, Perceived Security, and Perceived Information Quality) are incorporated alongside traditional UTAUT2 constructs, while Experience is included as a moderator and measured reflectively to capture familiarity, frequency, and confidence in using TMAs. Data are collected through an online survey targeting Iranian TMA users, using non-probability convenience and purposive sampling, yielding 424 valid responses, which exceed recommended minimum thresholds for PLS-SEM. Analysis follows the standard two-step procedure, first assessing the measurement model for reliability and validity, and then evaluating the structural model, including direct, indirect, and moderating effects. Bootstrapping is used to assess the significance of path coefficients, and model performance is evaluated using R^2, Q^2, f^2, and SRMR using SmartPLS.

This dissertation contributes to the field of knowledge in several ways. First, theoretical understanding of tourism digital technology, particularly TMA adoption, is advanced by conceptualising the pre-travel phase as a structured, multi-stage process and by examining how users engage with TMAs within each of these stages. While existing studies frequently treat TMA use as a generalised behaviour, this research offers a more comprehensive, stage-specific perspective that reflects the complexity of users' decision-making processes prior to departure.

Second, the study employs the UTAUT2 model with the integrated Perceived Trust and its key antecedents of Perceived Privacy, Perceived Security, and Perceived Information Quality. This provides a more comprehensive model for explaining user behaviour in digital tourism environments, particularly those in which Trust, risk, and information reliability play central roles. By testing this extended model empirically, the dissertation enhances the theoretical applicability and explanatory power of UTAUT2 model within mobile tourism contexts.

Third, the research contributes new insights into tourism digital technology, in particular TMAs adoption in a developing-country setting, an area that remains underrepresented in the tourism and information-systems literature. By examining the perceptions and behaviours of Iranian TMA users, the study highlights the contextual influences of cultural norms, infrastructural conditions, and institutional Trust environments, offering evidence

that adoption patterns may differ substantially from those observed in digitally advanced economies.

Finally, the dissertation contributes methodologically by applying a comprehensive structural model that incorporates direct, indirect, and moderating effects, tested through Partial Least Squares Structural Equation Modelling (PLS-SEM). The operationalisation of Experience as a measurable construct further enables a more precise examination of its role in technology adoption processes. These methodological contributions support future research aiming to refine behavioural models and adapt them to diverse digital and cultural contexts.

1.4 Structure of the dissertation

This dissertation is composed of nine chapters. chapter 1 introduces the research topic by outlining the research problem and research gaps, presenting the aim of the study and the research questions, and providing an overview of the methodology and data. Chapter 2 presents a review of the existing literature and addresses the identified research gaps, including the conceptualisation of the pre-travel phase and the role of TMAs across its sub-stages. Chapter 3 outlines the theoretical foundation of the study, introducing the UTAUT2 model and its extension through the inclusion of Perceived Trust and prior Experience, and further establishes the research context by examining the digital and cultural landscape of Iran as the case of this study, thereby justifying its selection as a representative case for TMA adoption in a developing economy. Chapter 4 develops the study's hypotheses by discussing each UTAUT2 construct, outlining the antecedents of Perceived Trust (Perceived Privacy, Perceived Security, and Perceived Information Quality), and explaining the moderating role of Experience. Chapter 5 presents the conceptual model that synthesises the proposed hypotheses. Chapter 6 describes the research methodology, including construct measurement, questionnaire development, data collection procedures, sampling strategy, sample characteristics, and analytical methods. Chapter 7 reports the empirical results, covering descriptive analyses, measurement model assessment, structural model assessment, hypothesis testing, analysis of control variables, and the Importance–Performance Matrix Analysis (IPMA). Chapter 8 discusses the findings in relation to the research questions and existing literature, and presents the theoretical and managerial implications, study limitations, and directions for future research. Chapter 9 concludes with a summary of the overall research process, the main findings, and the key insights derived from the study.

2 THE TOURISTS' MULTI-FACETED EXPERIENCES

Tourist experience is commonly defined as tourists' interactions with, and responses to, the products, systems, and services offered across the travel journey (Guerreiro et al., 2025). Existing literature has predominantly conceptualised the tourist experience as a structured, unified, and chronologically ordered phenomenon, typically divided into pre-travel, during-

travel, and post-travel phases (Guerreiro et al., 2025; Tung & Ritchie, 2011). While this phase-based perspective provides a useful analytical framework, it often reflects a singular and relatively homogenised understanding of tourist experience.However, this dominant perspective has been increasingly challenged. The concept of the tourist gaze (Urry & Larsen, 2011) marks a significant shift away from earlier functionalist and ethnocentric assumptions, emphasising that experiences are subjective, socially constructed, and context-dependent. This shift highlights an important limitation of traditional approaches, which tend to treat tourist experience as a uniform process, thereby overlooking its inherent diversity and variability.

In response to this limitation, this study adopts a pluralistic perspective, distinguishing between "the tourist experience" as a structured process and "tourists' experiences" as heterogeneous, multifaceted, and context-dependent phenomena. This distinction enables a more nuanced understanding of how experiences unfold across individuals and situations, rather than assuming a single, standardised trajectory.

At the same time, the conceptualisation of tourism as a multi-stage process remains relevant. Foundational work by Clawson and Knetsch (1966) introduced a staged model of outdoor recreation, later extended by Killion (1992) and Craig-Smith and French (1994), who conceptualised tourism as a cyclical and interconnected process. Despite variations in terminology and granularity, these models consistently highlight the processual nature of tourism experiences.

Therefore, this study integrates both perspectives by conceptualising tourism as a structured, multi-stage process, while simultaneously recognising that experiences within each stage are diverse, subjective, and context-dependent.

Pre-travel refers to before travel: occurring or existing prior to travelling (Merriam-Webster, 2025). The pre-travel phase constitutes a critical foundation for the formation of actual travel behaviour (Eletxigerra et al., 2021). The pre-travel phase mainly involves actively searching for information to identify personal needs, assess risks, compare options, and make decisions about destinations, budgets, safety, and travel logistics, as travellers use both internal and external sources to shape their choices and expectations (Björk & Kauppinen-Räisänen, 2015; Eletxigerra et al., 2021).

The during-travel phase–also commonly referred to as the on-site stage–is the point at which the actual consumption of the tourism product takes place, expectations shaped during the pre-travel phase are realised and evaluated shaping the perceived value of the on-site trip experience (Prebensen et al., 2013). However, contemporary perspectives challenge the traditional notion that value is created solely through consumption. Pine and Gilmore's Experience Economy argue that value emerges through travellers' immersion in memorable experiences (Pine & Gilmore, 1999), while Customer-Dominant Logic emphasises that value is formed across the customer's wider experiential journey rather than at a single point

of use (Heinonen et al., 2010). These perspectives suggest that on-site experiences contribute to value creation not only through consumption but also through engagement. This implies that upon visiting a destination, travellers develop a more intricate and multilayered image based on their direct experiences and interactions with the environment, which further shapes destination image formation during the travel phase (Wang et al., 2023). At the destination, travellers participate in diverse activities, many of which centre on touristic attractions– places, people, events, and objects that draw travellers and influence how they experience the destination (Benckendorff, 2014). This phase remains important, as a positive destination image enhances intentions to revisit and recommend the destination (De Nisco et al., 2015).

The post-travel phase, also known as the reflective phase, encompasses the recollection of experiences, evaluation of satisfaction or dissatisfaction, and the subsequent sharing of memories and recommendations (Shen et al., 2020). This phase is particularly influential, as experience sharing has become highly significant for travellers and has greatly shaped tourism demand and destination reputation (Kim & Fesenmaier, 2017). Moreover, the post-travel stage plays a critical role in shaping the pre-travel phase, as prospective travellers are strongly motivated to seek suggestions, reviews, and insights from others' shared experiences in order to reduce perceived risks and uncertainties (Cheng et al., 2019). This reliance on others' reflections is especially pronounced because tourism products and services are intangible and cannot be physically examined or evaluated prior to purchase, unlike traditional material goods (Kirilenko et al., 2021).

Among these three phases, this study is aiming to explore the pre-travel phase as the focal period of analysis because, despite its importance, more studies examining on-destination experiences than the pre-travel phase and this phase remain underrepresented in tourism research (Eletxigerra et al., 2021). Moreover, as foundation and subsequently formation of actual travel behaviour (Eletxigerra et al., 2021), consumers' experiences during this initial phase can significantly increase the likelihood of a positive overall experience and generate valuable post-vacation word-of-mouth (WOM) (Andersen et al., 2025).

The pre-travel phase has evolved also into a digitally mediated decision space, deeply shaped by the rapid integration of emerging technologies and supported by substantial infrastructure investment across the tourism and technology sectors. For instance, the full-scale penetration of AI-driven features–such as predictive pricing, recommendation engines, and chatbots–enable personalized, data-informed itinerary construction, while augmented and virtual reality reshape users' perceptions of value, risk, and authenticity through immersive simulations (Foroughi et al., 2025; Tekin, 2025). This "try-before-you-buy" approach supports travellers by making more informed decisions when it comes to planning their trips and stimulates interest in less conventional or emerging destinations (Tekin, 2025). Accordingly, this study is also technology-oriented research and aims to analyse consumer digital behaviour associated with the acceptance and use of TMAs. Therefore, the pre-travel phase constitutes a critical unit of analysis in contemporary tourism behaviour studies.

2.1 Conceptualizing the pre-travel phase as a multi-stage process

Historically, earlier studies in tourism have examined the pre-travel phase primarily through the lenses of decision-making (Xiang & Gretzel, 2010) and travel motivation (Yoon & Uysal, 2005), consequently offering a rather fragmented framework that overlooks other psychological and contextual factors shaping travellers' early-stage behaviours. In contrast, more recent research advances that view with a more dynamic, multi-stage process (Gretzel, 2021) acknowledging pre-travel phase through a sequence of interconnected cognitive, emotional, and evaluative steps rather than a single, isolated decision point. While acknowledging that travellers do not experience a singular, linear, or uniform process (Urry & Larsen, 2011), the present study adopts an integrative perspective, conceptualising the pre-travel phase as comprising five interrelated stages–dreaming, decision-making and planning, booking, transaction, and expectation formation–to better capture the multidimensional mechanisms of tourists' experiences underlying this phase.

2.1.1 Dreaming

The travel journey typically begins with the dreaming a stage in which prospective travellers seek inspiration and begin to imagine destinations and experiences that appeal to them (Gretzel, 2021). Dreaming stage is characterized as a motivational state characterized by a two-stage process: "inspired-by" and "inspired-to" (Thrash & Elliot 2004). The first stage, inspired-by, refers to the spontaneous and passive reception of ideas triggered by external stimuli, such as exposure to appealing travel-related content. This process generates cognitive and emotional arousal (evocation). The second stage, inspired-to, follows by creating a sense of expanded possibility (transcendence) and activating an approach-oriented motivation to act upon the newly formed idea (Thrash & Elliot 2004).

This model has been studied by Dai et al. (2022) who demonstrate that inspired-by occurs when individuals encounter evocative stimuli–such as visually compelling destination images on social media or narratives shared by peers–without actively seeking them. This passive exposure subsequently transitions into the inspired-to phase, where individuals develop an intention to act, such as initiating information search, exploring travel options, or mentally incorporating the destination into future plans. Through this process, abstract inspiration is transformed into early-stage behavioral intentions**,** effectively bridging the dreaming stage and subsequent planning activities (Dai et al., 2022).

Importantly, the dreaming stage is increasingly digitally mediated, as travellers are continuously exposed to large volumes of inspirational content across online environments. Such inspiration often emerges through serendipitous digital encounters, defined as unplanned and unexpected exposure to content that evokes new travel desires (Chen et al., 2019; Dai et al., 2022). These encounters play a critical role in shaping initial travel motivations without requiring active search behavior. In this stage, digital solutions such as TMAs act as key catalysts for imagination and early travel intentions (Li & Jiang, 2024).

Empirical evidence further highlights the structured nature of dreaming as a pre-planning activity. Through a netnographic study of Pinterest boards titled “Places I’d Like to Go,” Gretzel (2021) demonstrates that users engage in non-transactional, exploratory information behavior aimed at curating and organizing future travel aspirations. Rather than reflecting abstract imagination, this behavior represents a systematic accumulation of inspiration, which forms a cognitive and visual repository that supports later decision-making stages.

Building on this perspective, this study positions the dreaming stage as a digitally enabled entry point into the travel decision process, where technological platforms, particularly TMAs, play a central role in shaping exposure to inspiration and facilitating the transition toward intention formation.

2.1.2 Decision-making and Planning

What begins as an imaginative dreaming gradually transforms into making concrete decisions and practical plannings in this stage (Tan, 2017). In this stage, travellers’ thoughts often transition from imaginative ideas to practical considerations. This process is effectively explained through the lens of Crompton's (1979) push and pull motivations theory. Push factors, which are largely intrinsic and socio-psychological in nature–such as the fundamental need for escape, the pursuit of self-discovery, or the desire for social bonding–generate the initial impetus to travel and determine the general type of experience sought. Concurrently, external "pull" factors begin to shape the selection of a specific locale. These destination attributes, which might include unique cultural attractions, favourable climate, or specific leisure facilities, attract the potential traveller to a particular location (Crompton, 1979). The decision-making process at this stage is fundamentally about the traveller aligning their internal needs with the extrinsic opportunities offered by various potential destinations.

In line with this phenomenon, a year-long study of Belgian households confirmed that the decision-making process for the vacations evolves from fantasy to reality, as participants in the early stages were often influenced by dream-like imagination, which gradually diminished and moved toward practical considerations and more concrete plannings (Decrop & Snelders, 2004).

During the planning and decision-making stage, travellers make crucial, interlinked decisions that shape their entire trip experience. Krešić and Prebežac (2011) demonstrate that tourists evaluate multiple destination attributes–such as natural features, safety, accommodation quality, cultural heritage, activities, and destination marketing–when forming their pre-travel decisions and destination preferences. Recent literature highlights that this process, though increasingly complex results in choices about the fundamental "five A's" of tourism: attractions, accessibility, accommodation, amenities, and affordability (Mangali et al., 2021). These decisions are informed by an active search for information, where individuals evaluate alternatives based on factors like price, safety, social media

reviews, and personal interest, ultimately leading to a set of planned behaviours (Zarezadeh et al., 2023).

2.1.3 Booking

Once the traveller has decided on key elements of the trip, the booking stage begins (Vaz et al., 2024). Scholars argue that booking intention itself is a refined decision point, distinct from earlier planning, which directly precedes the act of reservation (Pérez-Ricardo & García-Mestanza, 2023). Dual-system theory by Kahneman (2011) provides a critical lens for understanding tourist behaviour during the complex, information-rich booking stage, highlighting the constant interplay between the fast, intuitive System 1 and the slower, analytical System 2. Tourists often rely on System 1 for rapid evaluations based on visual appeal, brand familiarity, and simple heuristics (e.g., star ratings) to manage cognitive overload when presented with vast options. Conversely, high-involvement decisions, such as comparing detailed itineraries or assessing cancellation policies, trigger the effortful analysis characteristic of System 2. Recognizing this dual processing enables online platforms to optimize the user experience by catering to both intuitive engagement and deliberate information seeking, ultimately facilitating the progression from initial interest to a confirmed booking intention (Lindberg & Stemmer, 2022; McCabe et al., 2016; Stylos, 2022).

The scope of the booking is wide-range, encompassing structural, supportive, and experiential services. Core bookings such as flights, trains, buses, and accommodation form the backbone of the trip (Maric & Zoroja, 2019). Supportive bookings, including travel insurance, local transportation, and visa arrangements, ensure safety and compliance, while experiential bookings such as guided tours, cultural events, and culinary workshops reflect the growing demand for immersive and personalized travel (Navalón-García & Mínguez, 2021). Add-ons such as seat upgrades, in-flight meals, and flexible check-in options further enhance convenience and comfort (Li et al., 2022). Together, these choices demonstrate how booking has expanded from a purely functional activity into a multidimensional stage that influences the quality of the overall journey. Nowadys, E-booking platforms have revolutionized how users book their travel, offering convenience, cost-efficiency, and the ability to access real-time information (Vlahović et al., 2024).

2.1.4 Transactions

The transaction stage follows planning and booking where consumers make a tangible commitment of resources–both time and money–to a selected itinerary, reflecting their final Behavioural Intention to proceed with the trip (Cheung & Lee, 2007). Aligned with Theory of Planned Behaviour (TPB) (Ajzen, 1991), this commitment is driven by three key factors: attitude toward the behaviour (e.g., perceptions of value and satisfaction), subjective norms

(e.g., social or peer influence), and perceived behavioural control (e.g., confidence in using booking systems).

This stage is notable for requiring users to disclose highly sensitive personal data, including precise location and billing information– which in turn–increases their vulnerability to significant privacy and security risks during the data exchange process (Madlmayr et al., 2008). Studies have confirmed that, complex online platforms users remain hesitant to finalise monetary transactions through such platforms, as this reluctance often stems from perceived risks–including concerns about payment security, limited Trust in vendors, or the unavailability of preferred payment methods (Xu & Lu, 2020). Conversely, ease of use, truthful information, and security of payment systems strongly influence users' confidence, underscoring the importance of website design, security and privacy protections, and reliable fulfilment in Trust and Behavioural Intentions (Lacity et al., 2024).

2.1.5 Expectation formation

Drawing on the concept of Anticipatory Feelings (Stefanova et al., 2020)–which defined as feelings related to anticipation in regards to future events–the Expectation Formation stage involves a complex integration of cognitive, emotional, and physiological processes that prepare individuals for future events. These feelings are not passive; they influence pre-travel behaviour such as information-seeking, itinerary adjustments, and reassurance efforts (Stefanova et al., 2020).

Complementing this, Expectancy Theory (Vroom, 1964) offers a motivational framework for understanding how tourists weigh the value and likelihood of anticipated travel outcomes. According to this view, expectations function as forward-looking evaluations that motivate action: tourists engage in preparation or behaviour regulation based on how desirable they perceive the expected experience to be (valence), how likely it is to occur (expectancy), and whether it will lead to valued outcomes (instrumentality) (Vroom, 1964). Together, these frameworks underscore that the post-booking period is not a passive waiting stage, but an active, dynamic phase involving emotional anticipation and motivational reasoning that significantly shapes subsequent travel behaviour.

In expectation formation, digital content such as user-generated media and influencer posts enhances information quality, co-creating vivid destination images and enriching anticipatory feelings (Lam et al., 2020).

2.2 Integration of TMAs in pre-travel phase

The global economy is undergoing profound transformation driven by the 4th Industrial Revolution (Castagnoli et al., 2022). This shift was notably accelerated by the COVID-19 pandemic, which, through lockdowns and social distancing measures, drove widespread

adoption of digital tools for accessing goods and services (Hall et al., 2020). As digital technologies become more embedded in everyday life, their impact extends to the tourism sector, reshaping how users plan, book, and experience travel (Abashidze, 2024). Travellers now enjoy greater autonomy from traditional travel agencies, gaining more freedom and flexibility in organizing their trips (Jamal & Habib, 2020). In this context, ranked among the top downloaded app categories, TMAs have emerged as vital tools that empower users to customize and manage their travel experiences (Dias & Afonso, 2021).

Given the inherently mobile and dynamic nature of tourism, TMAs are designed for continuous, location-independent use, leveraging built-in smartphone features such as GPS, cameras, motion sensors, and biometric tools to deliver a seamless, personalized, and context-aware user experience (Li et al., 2023). This evolution is further driven by the rapid integration of artificial intelligence (AI) and machine learning (ML) technologies into TMAs (Sia et al., 2024). From the supplier perspective: AI, particularly through ML, has enabled new forms of data-driven personalization and strategic decision-making. For example, ML is used to segment tourists based on their behaviours and preferences, supporting more targeted service delivery (Egger, 2022). It is also applied in sentiment analysis of user reviews to improve offerings and to build models that forecast demand and sustainability trends (Jahani, 2020). On the consumer side: AI enhances mobile apps by enabling real-time itinerary updates, tailored suggestions, and predictive alerts that respond to user context and preferences (Egger, 2022; Ganesan, 2022). These features are typically powered by ML algorithms trained on behavioural data. Additionally, natural language processing (NLP)–a form of AI–allows users to interact with apps through voice commands, creating more seamless and personalized experiences (Knani et al., 2022).

As tourism becomes increasingly digitalized, TMAs are not merely tools for booking and navigation but have become fully integrated platforms that support users across all stages of the pre-travel phase. For instance, during Dreaming Stage, TMAs have become key tools for initiating early travel interest by offering visually rich, personalized, and easily accessible content (Gretzel, 2021). Many TMAs also incorporate immersive technologies like augmented and virtual reality to simulate destination experiences, helping users form emotional connections with places before any concrete decisions are made (Bretos et al., 2023). During Planning and Decision Making Stage, TMAs are becoming more integrated with artificial intelligence to deliver personalized itineraries and real-time recommendations (Parmar et al., 2025). This shift marks a move toward more data-driven and user-centric planning behaviours (Tussyadiah, 2016). During the booking phase, TMAs can consolidate transportation, accommodation, and activities within a single interface, improving usability and satisfaction (Hamouda, 2022). In the transaction phase, as tourists rely more on mobile payments, Trust, convenience, and security become crucial in shaping experiences (Dias & Afonso, 2021; Putrevu & Mertzanis, 2024). Finally, in expectation formation, TMAs digital content such as user-generated media and influencer posts enhances information quality, co-creating vivid destination images and enriching anticipatory feelings (Lam et al., 2020).

Despite the growing penetration of TMAs into the pre-travel phase supported by features such as personalization, automation, and real-time responsiveness (Parmar et al., 2025), the factors impacting their acceptance and continued use remain multifaceted. Among these, Perceived Trust has emerged as a critical determinant concern particularly around data privacy, algorithmic transparency, and ethical AI usage continue to influence user attitudes (Maldonado-Canca et al., 2024).

Therefore, this study aims to investigate the factors affecting the acceptance and use of technology, particularly by integrating Perceived Trust, as it is one of the critical factors to be considered in TMAs in the pre-travel phase–from accuracy of information, to secure transactions, privacy protection, platform reliability, and user interface design (Hua et al., 2021).

3 THEORIES IN ACCEPTANCE AND USE OF TECHNOLOGY

Research on technology adoption draws on several theoretical frameworks, many of which have been applied to understand tourists' use of digital tools, including TMAs. This chapter provides an overview of these theories, to demonstrate the evolution of technology-acceptance research and to justify the selection of UTAUT2 as the theoretical foundation for this study.

3.1 Early theoretical models in technology acceptance

Over the past several decades, numerous theoretical models have been developed to explain why individuals adopt or reject new technologies, each offering distinct perspectives on the psychological, social, and contextual factors shaping user behaviour. Early foundational models include the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991), both of which emphasise attitudes, social norms, and perceived behavioural control as determinants of intention. Building on these cognitive foundations, the Technology Acceptance Model (TAM) (Davis, 1989) highlights perceived usefulness and perceived ease of use as key predictors of adoption, while later models such as C-TAM-TPB (Taylor & Todd, 1995) integrate attitudinal and control-related components to provide a more comprehensive explanation of behaviour. Additional frameworks contribute motivational, experiential, and contextual elements: the Motivational Model (MM) (Davis et al., 1992) distinguishes between intrinsic and extrinsic drivers of technology use; the Model of PC Utilisation (MPCU) (Thompson et al., 1991) incorporates complexity, job fit, and long-term consequences; Social Cognitive Theory (SCT) (Bandura, 2001) emphasises self-efficacy and environmental influence; and Innovation Diffusion Theory (IDT) (Rogers, 1962) examines how characteristics of innovations–such as relative advantage, compatibility, and trialability–shape adoption over time. Collectively, these models form the conceptual foundation for understanding the mechanisms underlying user

acceptance and technology-related behaviour across diverse contexts, including digital tourism.

3.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was developed through the systematic integration of core constructs originating from these eight foundational technology-acceptance theories, combining their most influential components into a unified framework (Venkatesh et al., 2003). From TRA and TPB, UTAUT incorporates the central role of Behavioural Intention, subjective norm, and elements of perceived behavioural control. TAM contributes perceived usefulness and perceived ease of use, which evolve into Performance Expectancy and Effort Expectancy. The Motivational Model provides the foundation for extrinsic motivation captured within Performance Expectancy, while the Model of PC Utilisation (MPCU) contributes constructs such as complexity, job fit, and Facilitating Conditions, informing both Effort Expectancy and Facilitating Conditions. Social Cognitive Theory (SCT) enriches the model through outcome expectations and self-efficacy, which influence Performance and Effort Expectancy. Finally, Innovation Diffusion Theory (IDT) adds concepts such as relative advantage, compatibility, and observability, which are reflected mainly in Performance Expectancy and Facilitating Conditions. By synthesising overlapping constructs from these theories, UTAUT provides a parsimonious yet comprehensive framework for explaining technology acceptance.

Ultimately, UTAUT was developed with four core determinants: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, moderated by gender, age, experience, and voluntariness (Venkatesh et al., 2003). The model was developed for organisational, mandatory-use environments–an important limitation when studying voluntary consumer technologies.

3.3 UTAUT2: extension for consumer contexts

While UTAUT (Venkatesh et al., 2003) provides a strong foundation for explaining technology acceptance, it was originally designed for organizational environments, where technology use is often mandatory and influenced by workplace structures. Such contexts differ substantially from consumer settings, where individuals voluntarily choose whether to adopt and use technologies based on personal preferences, perceived value, enjoyment, and habitual behaviour. Recognising these differences, Venkatesh et al. (2012) introduced UTAUT2 as an extension of the original model to better capture the complexities of consumer decision-making. To achieve this, UTAUT2 incorporates three additional constructs–Hedonic Motivation, Price Value, and Habit. All in all, UTAUT2 comprises a total of seven constructs: the original four from UTAUT (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions), together with the three newly added consumer-oriented constructs (Hedonic Motivation, Price Value, and Habit). This

expanded structure reflects motivational, experiential, and value-related drivers that are more relevant to consumer behaviour than to organizational technology use (Al-Adwan et al., 2024).

This integrated structure provides UTAUT with exceptional explanatory power, which was further enhanced in UTAUT2 through the inclusion of additional constructs, increasing the variance explained in Behavioural Intention from 56% to 74% and in actual technology use from 40% to 52% (Venkatesh et al., 2012).

3.4 UTAUT2 and Perceived Trust

Despite its strong explanatory power in consumer technology contexts (Venkatesh et al, 2016), UTAUT2 does not explicitly incorporate Perceived Trust, a construct widely recognised as essential in online and mobile environments (Lin et al., 2013) where privacy, security, and information reliability shape user decisions (Escobar-Rodríguez & Carvajal-Trujillo, 2014). In digital tourism contexts, Trust becomes particularly salient because users often disclose personal and financial information, rely on the accuracy of destination-related content, and evaluate the credibility of unfamiliar service providers (Gupta et al., 2018). Prior studies demonstrate that Perceived Privacy, Perceived Security, and Perceived Information Quality are key antecedents of Trust that significantly influence technology adoption in tourism and e-commerce settings (D. J. Kim et al., 2008; Kim et al., 2011). This relevance is further amplified in developing-country contexts such as Iran, where institutional safeguards, data-protection mechanisms, and user familiarity with digital transactions are less established (Hanafizadeh et al., 2014).

3.5 UTAUT2's relevance to TMAs

UTAUT2 has demonstrated strong relevance and applicability to the adoption of TMAs, which are voluntary, consumer-driven technologies used to support pre-travel. Several studies highlight the model's suitability for this context. For example, Gupta and Dogra (2017) applied UTAUT2 to examine tourists' adoption of mobile mapping applications, showing that constructs such as Performance Expectancy, Effort Expectancy, and Habit significantly influenced users' Behavioural Intention in tourism settings. Foroughi et al. (2025) extended UTAUT2 to analyse users' intention to use ChatGPT for travel planning, demonstrating that personal innovativeness and risk aversion further enrich the model when applied to emerging AI-based tools. Similarly, Sia et al. (2024) examined the factors influencing the adoption of smart mobile tourism apps (SMTAs) that integrate augmented reality (AR) and big data analytics (BDA), using an extended UTAUT2 framework combined with Privacy Calculus Theory (PCT). Recognizing gaps in understanding user acceptance of privacy-sensitive tourism technologies, the authors incorporated Personal Innovativeness, Privacy Concern, Privacy Risk, and Privacy Information Disclosure into the traditional UTAUT2 model.

These studies collectively demonstrate that UTAUT2 is well positioned to explain consumer adoption of TMAs due to its incorporation of motivational, experiential, and habitual factors that shape individual use patterns. Its flexibility and demonstrated success across various tourism technologies make it an appropriate theoretical foundation for analysing TMA acceptance and use in the pre-travel phase, including in developing-country contexts such as Iran.

Considering the fact that Iran is a developing country in adoption of novel technologies …. they are not really aware of the benefits and advantages

Iran is generally characterized as a collectivist society, where individuals tend to prioritize group norms and social relationships over individual preferences (Hofstede, 2001). In such contexts, decision-making is strongly influenced by social networks, including family, peers, and community members. This cultural orientation has important implications for technology adoption, as individuals are more likely to rely on recommendations, shared experiences, and social validation when engaging with digital platforms.

Iran is commonly classified as an upper-middle-income economy by the World Bank (2023), a category widely associated with developing countries, and is frequently examined in the literature as a developing-country context characterized by structural economic constraints and ongoing institutional development (Amirahmadi, 1990; Pesaran, 2011). This classification is also reflected in studies of digital technology adoption in Iran, which analyze ICT use within the conditions typical of developing economies, including infrastructural limitations and institutional factors (Hanafizadeh et al., 2014; Sadeghi & Farokhian, 2011).

3.6 Research context: Iran

This study focuses on Iran as the empirical context. Although the classification of Iran varies across academic disciplines, a body of literature–particularly within development studies, technology adoption, and market research–commonly characterizes Iran as a developing country (Nafchi & Mohelska, 2018; Kazemi & Amini, 2024). For instance, in the context of industrial transformation and market dynamics, Iran is described as a developing economy facing structural challenges, including limitations in technological infrastructure, research capacity, and innovation systems (Nafchi & Mohelska, 2018). Similarly, studies on digital transformation and the adoption of digital technologies, such as e-learning, consider Iran as a developing country and highlight barriers related to insufficient governmental support, limited public awareness, infrastructural constraints (e.g., low internet speed), and broader socio-political conditions (Kazemi & Amini, 2024).

At the same time, according to the World Bank, Iran is classified as an upper-middle-income economy based on income indicators (Metreau et al., 2024). This dual characterization reflects the coexistence of relatively developed economic structures with persistent institutional, technological, and infrastructural constraints. Such conditions make Iran a

particularly relevant context for examining technology adoption, as they may shape user behaviour in ways that differ from technologically advanced economies.

Iran demonstrates a relatively high level of digital engagement and rapid growth in mobile technology adoption. Mobile penetration exceeds the total population, reaching approximately 166%, while internet penetration stands at 79.6%, with the majority of connections relying on broadband networks (Kemp, 2025). This has contributed to the emergence of a "mobile-first" environment, in which domestic digital platforms such as Snapp and Alibaba.ir play a central role in facilitating everyday digital interactions (Hamidi & Bidi, 2018). However, this digital engagement occurs within a complex infrastructural and regulatory environment. The National Information Network (NIN) enables domestic traffic routing, while international sanctions and internal filtering mechanisms impose constraints on access to global digital platforms (Dadabayeva et al., 2025; European University Institute, 2023).

Although empirical research on TMAs in Iran remains limited, insights from related domains–particularly mobile banking–provide insights for understanding technology adoption behavior in this setting. These studies are especially relevant, as both mobile banking and TMAs are infrastructure-dependent, internet-based services involve digitally mediated transactions, personal data exchange, and user reliance on platform credibility making trust and risk central determinants of usage (Jadil et al., 2021; Geupta et al., 2018). For instance, Mollajafari (2018) identifies for Iranian users (1) Perceived Trust, shapes primarily by users' concerns regarding data security and transaction safety; (2) Facilitating Conditions, reflectes in infrastructural constraints such as low internet speed, unstable connectivity, and limited technological resources that may hinder adoption; (3) Effort Expectancy, as limited digital literacy and lack of user awareness reduce the perceived ease of using mobile systems; and (4) Perceived Risk, arising from multiple sources of uncertainty, including cybersecurity threats and transaction vulnerabilities, which negatively affect user confidence. A key integrative insight of this study is the sequential relationship between security, trust, and usage: enhanced security increases trust, which in turn promotes adoption behavior. This mechanism is also relevant to TMAs, where perceived platform security may shape users' trust in travel-related transactions and, consequently, their willingness to engage with mobile applications.

These findings are further supported by the study of Mohammadi (2015), which provides additional insight into the determinants of mobile technology adoption in Iran. The results indicate that (1) system compatibility–reflecting the degree to which mobile services align with users' needs, existing infrastructure, and lifestyle–represents a primary driver of user attitudes; (2) resistance, associated with security concerns, uncertainty, and distrust, exerts a significant negative effect on both perceived ease of use and perceived usefulness; and (3) perceived usefulness plays a mediating role between ease of use and user attitudes, reinforcing its central importance in adoption behavior. Furthermore, the study highlights the moderating role of perceived image, suggesting that social and cultural perceptions

influence how users evaluate the usefulness of mobile technologies–as Iran characterized as a collectivistic society, where individuals tend to rely on group norms, social expectations, and peer evaluations in decision-making processes (Tavakoli & Tavakoli, 2010).

These findings are also relevant to the context of TMAs. In particular, system compatibility can be related to how well travel mobile applications align with users' travel planning needs and digital habits, while resistance reflects concerns related to trust, risk, and uncertainty in travel-related transactions. The mediating role of perceived usefulness suggests that even if TMAs are easy to use, their adoption ultimately depends on the extent to which Iranian users perceive them as beneficial for travel decision-making. Moreover, the influence of perceived image indicates that social and cultural factors–such as peer perceptions and societal attitudes–may shape how users evaluate and adopt TMAs, particularly in collectivistic contexts.

These characteristics highlight the relevance of Iran as a context for examining technology adoption. The coexistence of high digital engagement and structural constraints provides a unique setting in which contextual factors may shape user behavior in ways that differ from those observed in technologically advanced economies. As a result, localized digital ecosystems and domestically developed applications play an important role within this context often better aligned with local user needs and contextual conditions in Iran (Barzegari et al., 2022).This is especially important in light of prior research emphasizing the role of context-aware information in supporting user decision-making in mobile technologies adoption (Lamsfus et al., 2013)

4 HYPOTHESES DEVELOPMENT

Drawing on the UTAUT2, this study develops a set of hypotheses to examine the key determinants influencing users' Behavioural Intention and Use Behaviour of TMA users. While UTAUT2 provides a well-established foundation by integrating constructs such as Performance Expectancy, Effort Expectancy, and Hedonic Motivation, this research further expands the model by incorporating Perceived Trust and its antecedents–Perceived Privacy, Perceived Security, and Information Quality.

4.1 Performance Expectancy

Performance Expectancy refers to "the degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2012, p. 159). This construct is conceptually rooted in Davis's (1989) earlier notion of perceived usefulness, which he defined as the degree to which a person believes that using a particular system would enhance his or her job performance. Venkatesh et al. (2003, 2012) acknowledged the conceptual overlap between Performance Expectancy and perceived usefulness. In the UTAUT2 model, which extends the original UTAUT to a consumer context, Performance

Expectancy was found to be the most significant predictor of Behavioural Intention. As they emphasized, “It has consistently been shown to be the strongest predictor of Behavioural Intention” (Venkatesh et al., 2012, p. 160). This reflects users’ expectations that adopting a certain technology will result in tangible benefits, such as time savings, greater convenience, or improved task efficiency.

Despite variations in settings and types of technologies examined, researchers have consistently validated the strong causal link between Performance Expectancy and Behavioural Intention to use the technology (Tam et al., 2020). Within the context of tourism, Performance Expectancy has been consistently shown to play a pivotal role in tourists’ adoption of mobile technologies (e.g. Tran & Vu, 2024). This construct captures tourists’ beliefs about the usefulness, ease of use, time-saving potential, and overall effectiveness of such technologies in enhancing their travel planning and decision-making processes (Gupta & Dogra, 2017; Tran & Vu, 2024). TMAs empower users by enabling them to compare airfare prices, make hotel or car rental reservations, and access real-time, accurate information- conveniently from their smartphones (Wu & Chen, 2014).

In the context of this study, Performance Expectancy is defined as the degree to which tourists believe that using TMAs during the pre-travel phase will enhance their trip planning experience by offering greater efficiency, utility, and convenience. The following hypothesis is proposed:

H1: Performance Expectancy has a positive effect on tourists’ intention to use TMAs during pre-travel phase.

4.2 Effort Expectancy

Effort Expectancy is defined as “the degree of ease associated with consumers’ use of technology” (Venkatesh et al., 2012, p. 159). This concept closely mirrors Davis’s (1989) notion of perceived ease of use, which he described as the degree to which a person believes that using a particular system would be free of effort. At its core, this construct is grounded in the notion that ease implies freedom from difficulty or great effort and thus contributes positively to an individual's willingness to adopt a technology. In other words, as Radner and Rothschild (1975) point out, effort is a finite resource that individuals must allocate across various responsibilities, meaning that technologies requiring minimal effort to use are more likely to be adopted.

Empirical studies have validated this perspective, showing that Effort Expectancy consistently predicts Behavioural Intention–users find a system intuitive and easy to operate, they are more inclined to adopt and integrate it into their routines (Wang & Liu, 2025).

In the context of tourism research, Effort Expectancy has emerged as a critical factor influencing technology adoption, as tourists often prefer digital platforms that are user-

friendly, easily accessible, and demand minimal technical effort. For example, Calderón-Fajardo et al. (2023) found that perceived ease of use played a central role in the adoption of augmented reality (AR) and virtual reality (VR) experiences in tourism settings. Likewise, Calderón-Fajardo et al. (2024) demonstrated that Effort Expectancy significantly influenced users' acceptance of metaverse applications for immersive tourism experiences as the platform incorporates norms and rules that mirror those of the real world, users are likely to perceive it as more intuitive, which in turn enhances their willingness to adopt and interact with it. Nathan et al. (2020) also showed that tourists' use of the Airbnb app during visits to historical cities was strongly linked to perceptions of ease of use. Gupta et al. (2018) also emphasized that ease of use was a key factor in tourists' adoption of mobile travel apps, reinforcing the idea that simplicity enhances engagement. Research shows that when tourists find apps simple and intuitive, their likelihood of adoption increases significantly (Gupta et al., 2018; Nathan et al., 2020). Conversely, when a system is overly complex or challenging to use, users often experience frustration and discouragement (Foroughi et al., 2025).

In this study, Effort Expectancy is defined as the degree to which tourists perceive that TMAs facilitate their experience to manage their activities during the pre-travel phase, by being simple, intuitive, and low-effort. Therefore, the following hypothesis is proposed:

H2: Effort Expectancy has a positive effect on tourists' intention to use TMAs during pre-travel phase.

4.3 Social Influence

Social Influence is defined as "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012, p. 159). Rooted in the Theory of Reasoned Action (TRA), the concept of subjective norm is defined as an individual's perception of whether important others believe they should perform a particular behavior (Fishbein & Ajzen, 1975). The use of technology is often driven not only by its functional value but also by the social image or status it may convey. Users may perceive that adopting a new or innovative digital tool enhances their reputation, self-image, or sense of modernity in the eyes of others (Williams et al., 2015).

Numerous studies have consistently validated the strong causal link between Social Influence and Behavioural Intention to use technology. For instance, Wang and Liu (2025) confirmed that Social Influence significantly and positively influenced intention to adopt Generative AI tools emphasizing the importance of peer and institutional encouragement in shaping technology acceptance.

In the context of tourism research, studies show that Social Influence has a significant positive effect on tourists' Behavioural Intention to use TMAs. For instance, Nathan et al. (2020) found that tourists were more inclined to adopt the Airbnb mobile app when

influenced by peers and social groups, affirming Social Influence as a key determinant within the UTAUT2 framework.

In this study, Social Influence is defined as the degree to which tourists perceive that important others (such as family, friends, or online communities) think they should use TMAs during the pre-travel phase. Therefore, the following hypothesis is proposed:

H3: Social Influence has a positive effect on tourists' intention to use TMAs during pre-travel phase.

4.4 Facilitating Conditions

Facilitating Conditions refer to "the degree to which consumers perceive that the resources and support available are sufficient to perform a behaviour" (Venkatesh et al., 2012, p. 159). Facilitating Conditions aligns closely with perceived behavioural control in TPB (Ajzen, 1991), emphasizing individuals' perceptions of having the necessary means-technological, financial, or organizational-to successfully adopt and use technology. This construct was primarily developed in UTAUT to capture both physical environmental features (such as access to infrastructure and technical devices) and intangible aspects, including user training, technical support, and organizational assistance (Venkatesh et al., 2003).

Empirical evidence indicates that Facilitating Conditions can significantly impact both Behavioural Intention and Actual Use. For example, Wang and Liu (2025) demonstrated that Facilitating Conditions–such as access, institutional support, and infrastructure–positively influenced user's intention to adopt and actual use of generative AI. In the context of tourism research, similar findings have emerged. For instance, Calderón-Fajardo et al. (2024) evaluated emerging platforms such as the Metaverse using the UTAUT2 model and found that Facilitating Conditions were key predictors of intention to use Metaverse-based tourism experiences. In their study, Facilitating Conditions were defined as the availability of technical infrastructure, support services, and device compatibility required to interact with immersive tourism platforms–highlighting the critical role of a stable and supportive technological environment in driving adoption (Calderón-Fajardo et al., 2025). Kamboj and Joshi (2021) also found that Facilitating Conditions, specifically mobile device compatibility, portability, and stable internet connectivity, significantly supported the use of smartphone apps at tourism destinations. Their findings highlight the broader influence of Facilitating Conditions on behavioural outcomes such as user satisfaction and loyalty across different stages of the tourism experience lifecycle.

Accordingly, this study defines Facilitating Conditions as the extent to which tourists perceive that the necessary technological infrastructure and support resources are available to assist them in using TMAs during the pre-travel phase. Therefore, the following hypothesis is proposed:

H4a: Facilitating Conditions have a positive effect on tourists' intention to use TMAs during pre-travel phase.

H4b: Facilitating Conditions have a positive effect on tourists' actual Use Behaviour of TMAs during pre-travel

4.5 Hedonic Motivation

Hedonic Motivation is defined as "the fun or pleasure derived from using a technology " (Venkatesh et al. 2012, p. 161). This concept originates from Hirschman and Holbrook's (1982) distinction between two types of consumption values: utilitarian (instrumental) and hedonic (emotional). While utilitarian motivations are associated with goal-oriented, efficient, and rational consumption- often tied to Performance Expectancy-Hedonic Motivations are rooted in the emotional satisfaction and intrinsic enjoyment individuals gain from the consumption experience itself (O'Brien, 2010).

In tourism, Hedonic Motivation is primarily associated with factors related to pleasure-seeking, relaxation, escapism, and entertainment (Dolnicar et al., 2023), all of which are core psychological needs that shape tourists' experiential expectations. It has emerged as a particularly salient driver of technology use in tourism contexts, especially where interactive and emotionally technologies are present. For instance, Foroughi et al. (2025) found that Hedonic Motivation significantly influenced tourists' intention to use ChatGPT for planning their trips, as tourists who experienced enjoyment and emotional satisfaction while interacting with AI tools were more inclined to engage with them during the pre-travel decision-making process. In the context of TMAs, Tran and Vu (2024) found that users are more likely to engage with digital platforms that offer fun, emotionally stimulating, and personally rewarding user experiences, rather than purely functional features.

In the context of this study, Hedonic Motivation is defined as the degree to which tourists perceive using TMAs during the pre-travel phase to be enjoyable, exciting, or emotionally satisfying. Therefore, the following hypothesis is proposed:

H5: Hedonic Motivation has a positive effect on tourists' intention to use TMAs during pre-travel phase.

4.6 Price Value

Price Value, a key construct within the UTAUT2 model, refers explicitly to the "consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost of using them" (Venkatesh et al., 2012, p. 161). In contexts where technologies are provided without direct monetary cost, the conceptualisation of price value shifts from a cost-based evaluation to a benefit-oriented perspective. Specifically, price value is interpreted as a price-saving orientation, reflecting the extent to which the use of technology contributes to

reducing overall expenditures on related products and services (Escobar-Rodríguez & Carvajal-Trujillo, 2014).

Empirical studies consistently demonstrate that digital platforms facilitate cost savings by allowing users to compare prices, access lower fares, identify better-value options, and supporting more cost-efficient decision-making (Jensen, 2012). This price-saving potential has been identified as a key driver of online consumer behaviour, particularly in tourism settings, where users actively seek to optimise travel-related expenses (Bigné et al., 2010; Wong & Law, 2005). For instance, consumers are more likely to book accommodation or transportation through digital platforms when they perceive that doing so enables them to obtain lower prices or superior value for a given price (Chang & Hung, 2013; Wen, 2012).

Despite its theoretical importance, the applicability and operationalization of Price Value have varied significantly across empirical UTAUT2 studies. A comprehensive meta-analysis of 79 UTAUT2-based studies by Tamilmani et al. (2020) highlighted this inconsistency: 47 studies (59%) omitted the construct entirely. The primary rationale provided was that the technologies under investigation–such as generic social networking platforms or educational tools–were largely cost-neutral for the end-user, rendering a direct 'monetary cost' trade-off irrelevant in those contexts.

This research addresses the existing literature gap by investigating how perceived price-saving influences the adoption of TMAs during pre-travel phase. Consequently, this study operationalizes Price Value as the perceived economic utility derived from the application's functional features. Therefore, the following hypothesis is proposed:

H6: Price Value, conceptualized as perceived cost-saving benefits, has a positive effect on tourists' Behavioural Intention to use TMAs during the pre-travel phase.

4.7 Habit

Habit is conceptualized as an "automatic response to contextual cues that have been associated with prior behaviour" (Venkatesh et al., 2012, p. 161). While often discussed in proximity to experience, the two constructs are conceptually distinct and require precise definition within technology adoption models. Experience refers primarily to the quantitative amount of exposure to a given technology over time, typically measured by duration since first use or frequency of interaction (Kim & Malhotra, 2005; Venkatesh et al., 2012).

In contrast, Habit captures the qualitative outcome of that repetition: the extent to which the use of the technology becomes automatic, routine, or instinctive as a result of repetition and learning (Limayem et al., 2007). This automaticity is a critical factor, recognizing that the intensity and frequency of interaction over time dictate whether behaviour becomes genuinely habitual. Researchers have operationalized habit either by measuring past

behaviour as a proxy or by directly assessing the user's perception of automaticity in their actions (Limayem et al., 2007). Repeated, positive experiences with a system reinforce automatic usage, making habit a potent predictor of future Behavioural Intention–sometimes surpassing more cognitive evaluations like perceived usefulness or ease of use (Lampo, 2023).

In the specific context of tourism and technology adoption, Habit has consistently been identified as a key determinant of tourists' Behavioral Intentions. Empirical evidence is robust across various studies. For example, Ali et al. (2022) found that Habit significantly influenced tourists' intention to use information and communication technology (ICT) and played a role in actual usage behaviour. Similarly, Sia et al. (2024) confirmed Habit was a significant predictor of intention to use a smart mobile tourism app integrating augmented reality and big data features. This finding is further supported by Gupta and Dogra (2017) in their study of mobile mapping apps, where Habit emerged as one of the strongest predictors of Behavioural Intention. Likewise, Palau-Saumell et al. (2019) reported Habit as the most influential factor in tourists' use of restaurant-related mobile apps. Herrero et al. (2017) further substantiated this in the context of social networking platforms, highlighting habit as one of the main drivers of tourists' intention to share travel experiences online.

In this study, Habit is defined as the degree to which tourists perceive their use of TMAs during the pre-travel phase to be automatic, routine, or instinctive, based on their prior experience with similar technologies. As tourists become more familiar with these apps across multiple trips, their reliance can become habitual, requiring less cognitive effort and leading to repeated use. Habit in this context thus serves as a crucial bridge between prior behavioural patterns and future intention or action. Therefore, the following hypotheses are proposed:

H7a: Habit has a positive effect on tourists' Behavioral Intention to use TMAs during the pre-travel phase.

H7b: Habit has a positive effect on tourists' actual Usage Behavior of TMAs during the pre-travel phase.

4.8 Behavioural Intention

Behavioural Intention is the cognitive representation of a person's readiness to perform a given behaviour (Ajzen, 2002) and it is widely recognized as a key predictor of actual behaviour (Venkatesh et al., 2012). A foundational premise of TPB is that Behavioural Intention represents the immediate antecedent of action, shaped by attitudes, subjective norms, and perceived behavioural control (Esfandiar & Hadinejad, 2025). The centrality of Behavioural Intention has been confirmed in recent literature. A meta-analysis by Jadil et al. (2021) concluded that Intention functions as the indispensable mechanism translating diverse influencing factors into actual mobile banking adoption behaviours.

Empirical studies within tourism domains have consistently validated the influence of Behavioural Intention on technology use. In particular, Palos-Sánchez et al. (2021) enhanced tourists' Behavioural Intention significantly increases their actual use of TMAs.

Building on the substantial body of evidence supporting the link Between Behavioural Intention and technology adoption, this study proposes that Behavioural Intention will positively influence tourists' use of TMAs during the pre-travel phase. Therefore, Behavioral Intention is expected to directly impact the likelihood of tourists utilizing such apps during their trip planning.

H8: Behavioural Intention has a positive effect on tourists' use of TMAs during pre-travel.

4.9 The extension of UTAUT2 with Perceived Trust

Trust is a multifaceted and deeply rooted psychological and sociological concept that has been extensively explored across disciplines, including philosophy, psychology, sociology, and economics (Uttenthal, 2024). Trust refers to an individual's willingness to be vulnerable to the actions of another party, based on the expectation that the other will act favourably or, at minimum, not harmfully (Mayer et al., 1995). This willingness is inherently shaped by uncertainty and risk; the two elements that make Trust both necessary and fragile (Mayer et al., 1995). Psychologically, Trust encompasses both cognitive and affective dimensions- where cognitive Trust arises from rational assessments of competence and reliability, and affective Trust emerges from emotional bonds and goodwill (McAllister, 1995).

In the domain of electronic commerce (e-commerce) and mobile commerce (m-commerce), Trust has consistently been identified as one of the most critical factors influencing both consumers' initial decisions to engage in online transactions and their continued interaction with digital platforms (Gefen, 2000; Zhang et al., 2012). Unlike conventional offline commerce- such as transactions in physical stores or through travel agents- where Trust is primarily built through face-to-face interactions (D.J. Kim et al., 2008), online environments often lack these interpersonal cues. Consequently, consumers may find it harder to judge the reliability of vendors due to the absence of physical presence, limited contextual information, and potential ambiguities in communication (Riegelsberger et al., 2005). Establishing Trust in m-commerce, particularly within the context of TMAs is even more complex than in traditional e-commerce environments, primarily due to the constraints associated with mobile devices. For instance, limited interface design (e.g., smaller screens) and variable network performance (e.g., unstable connections or reduced signal strength) add to user uncertainty and may hinder Trust formation (Lee & Benbasat, 2003). The small details are of major importance when discussing transitions such as the digital transformation, as users often make decisions based on subtle perceptions of reliability, security, and convenience (Tomej et al., 2022). Therefore, hen users have positive experiences, their Perceived Trust can grow into sustained Trust, which is important for keeping them engaged with mobile platforms. This finding is further supported by several

studies indicating that Trust positively influences customer satisfaction and strengthens purchase or usage intentions (Arumugam & Wing, 2020; Melović et al., 2021).

Trust in m-commerce is not static but rather a complex and gradually evolving construct (Lin et al., 2013). Building consumer Trust in this context is a gradual process that starts with creating initial Trust and continues by strengthening it over time. Although initial Trust serves as a critical catalyst- particularly in mobile banking and similar services- it does not automatically ensure long-term usage or favourable business outcomes unless actively maintained (Kim & Malhotra, 2005). Trust is shaped through repeated user interactions, and its development is influenced by experience which is often seen as a cycle that includes Trust, action, learning, and then renewed Trust (Song et al., 2009). Singh and Sinha (2020) found that such established Trust has a notable impact on consumers' willingness to repeatedly use m-commerce services. Since the present study does not employ a longitudinal design with data collection at multiple time points (e.g., T1 and T2), it does not empirically examine the evolution of Trust as shaped by repeated user interactions with TMAs over time. Instead, the focus of this research is on Perceived Trust which regards as the user's current, subjective evaluation of the Trustworthiness of TMAs during a specific phase of the pre-travel phase. In the context of cross-sectional studies like the present study, Perceived Trust serves as both a theoretically grounded and practically valuable proxy for assessing user initial attitudes, particularly during the early stages of adoption when longitudinal behavioural data may be unavailable or insufficient (Chandra et al., 2010).

Perceived Trust underpins every stage of the pre-travel phase and shapes the tourist experience. In Dreaming stage, Perceived Trust plays a foundational role in shaping whether users will continue engaging with app or abandon it in favour of another platform (Dang, 2024). Users are highly sensitive to visual credibility, the reliability of travel narratives, and the integrity of content sources such as destination overviews, travel blogs, or shared photos (Pop et al., 2022). Visually stimulating and emotionally Trustworthy content increases users' emotional receptivity and strengthens their early interest (Chatzigeorgiou & Christou, 2020). A strong sense of Perceived Trust can trigger emotional engagement, openness to unfamiliar destinations, and a willingness to continue exploring within the same platform, as Trust therefore acts as a psychological gatekeeper, mediating the transition from passive browsing to potential consideration (Chatzigeorgiou & Christou, 2020).

During the Planning and Decision-Making stage, Perceived Trust becomes crucial as users transition from casual browsing to actively comparing destinations, accommodations, transport options, and itineraries (Tan, 2017). This process heavily relies on the tools and content provided by tourism marketing agencies (TMAs)–including search filters, recommendations, and especially user-generated content (UGC) such as reviews, ratings, and testimonials–which have been shown to significantly shape destination choices and decision-making (Xu & Pratt, 2018). At this stage, Trust in the authenticity and transparency of both the platform and its content increases emotional engagement while lowering perceived risk (Pop et al., 2022). When users perceive the information as accurate, neutral,

and reliable, it enhances their sense of control, reduces decision-related stress, and leads to greater satisfaction with their chosen plans (Chatzigeorgiou & Christou, 2020). Conversely, a lack of Trust may prompt concerns about biased results or hidden costs, encouraging users to seek reassurance from external sources and introducing friction into the planning process (Djafarova & Trofimenko, 2019). Ultimately, a strong sense of Perceived Trust helps users manage uncertainty, boosts confidence, and supports more decisive, satisfying travel planning–serving as a stabilizing force in digital decision-making (Pourazad et al., 2025).

The Booking marks a shift from consideration to commitment (Vaz et al., 2024). Here, Perceived Trust takes on a more transaction-oriented character, but its influence extends beyond the payment itself. Users must be confident that the details of what they are booking (Berhanu & Raj, 2020)- including: flight times, hotel quality, refund policies, and additional fees- are presented clearly, accurately, and honestly. If Perceived Trust is lacking, users may hesitate, delay booking, or exit the process entirely (Chouykaew et al., 2024). Conversely, high Perceived Trust supports decisiveness, encourages the process within the same platform, and reduces the perceived need for further verification (Dang, 2024). All in all, the reservation systems in the hospitality sector, consumers' willingness to make room bookings is significantly influenced by the degree of Trust they place in the online booking platform (Wang et al., 2024). At this point, Trust is not just about the service offered but also about how it is communicated and operationalized within the TMAs.

During the transaction stage, users are required to share sensitive personal and financial information–such as names, contact details, credit card numbers, and, in some cases, passport data (Gupta et al., 2018). In this context, Perceived Trust becomes a critical enabler of user action, especially in online and app-based environments where the absence of physical interaction amplifies uncertainty (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Trust is built on a combination of factors, including the platform's competence (its technical reliability), benevolence (its intention to act in users' best interest), and integrity (its consistency and honesty) (Lacity et al., 2024). These dimensions influence users' confidence not only in how well the system functions but also in whether it will handle their data responsibly and ethically. Contributing to this perception are elements such as institutional reputation, past user experiences, and emotional responses like fear of fraud or exclusion (Kim et al., 2008). Therefore, in order to foster this Trust, platforms must demonstrate data protection and payment security, including compliance with regulations like General Data Protection Regulation GDPR (Fox et al., 2022). Despite the implementation of cybersecurity measures, risks such as data breaches or unauthorized access remain, underscoring the importance of rapid threat detection, transparency, and clear communication of safety features (Duan et al., 2024; Kaur et al., 2023). Trust-enhancing features–such as Secure Sockets Layer 8SSL9 encryption, secure checkout protocols, well-known payment gateways, and third-party certifications–visibly signal safety and accountability. Additionally, for users with limited technical literacy, user-friendly design and clear, accessible information are key to building reassurance and reducing vulnerability (Warsame

& Ireri, 2018). Failure to establish sufficient Trust at this stage can result in booking abandonment and long-term user disengagement. Therefore, cultivating Perceived Trust is not just a matter of compliance or security–it is essential for facilitating user participation and loyalty in digital transaction environments (Lacity et al., 2024).

In the Expectation Formation stage before departure, Perceived Trust continues to influence user behaviour and emotional readiness as follow. Having completed their bookings, users expect the mobile apps support (Sia et al., 2024)– including booking confirmations, reminders, updates, customer support access, and sometimes additional services (e.g., itinerary changes, add-on purchases, travel guides). Any inconsistency, delay, or lack of communication during this stage can erode Trust, leading to frustration or anxiety, whereas consistent and transparent post-booking communication reinforces Perceived Trust and fosters loyalty, increasing the likelihood of app reuse and positive word-of-mouth (Baki, 2020). A conventional app not only reassures users but also encourages them to explore value-added services such as upgrades or destination content, further deepening engagement (Haraty & Bitar, 2019). Moreover, Trust during the anticipation stage is strongly linked to expectation management- shaping whether users feel prepared and confident ahead of their travel experience.

Across all pre-travel phases, Perceived Trust supports users by shaping users' cognitive evaluations of the service provider's integrity, competence, and reliability. Especially in cross-sectional studies where behavioural data over time is unavailable, Perceived Trust serves as a practical and theoretically valid construct to assess user attitudes and intentions (Chandra et al., 2010). It influences both functional outcomes, such as decision satisfaction and booking completion (Gupta et al., 2018), and psychological outcomes, such as confidence and loyalty. Given these considerations, extending UTAUT2 with Perceived Trust allows for a more comprehensive understanding of TMA acceptance in the pre-travel phase, reflecting both functional perceptions of usefulness and ease of use, as well as risk-based evaluations driven by Trust. This extension aligns with prior research that successfully incorporated Trust into UTAUT2 in digital tourism and airline e-commerce contexts (Escobar-Rodríguez & Carvajal-Trujillo, 2014) and addresses a critical theoretical gap by capturing the socio-technical conditions shaping users' decisions in developing markets in TMAs context.

In this way, Perceived Trust is not merely a factor within the transaction (Escobar-Rodríguez & Carvajal-Trujillo, 2014)– it is a foundational element that underpins the entire user journey during the pre-travel phase of tourism mobile apps use. Building on this foundation, and in line with existing research emphasizing the significance of Trust in digital environments, this study employs the extended UTAUT2 model by incorporating Perceived Trust as an additional construct. Given the conceptual and empirical evidence supporting its influence on user behaviour, the following hypothesis is proposed:

H9: Perceived Trust positively affects tourists' intention to use TMAs during pre-travel.

4.10 Perceived Trust and the underlying key antecedents

This thesis adopts the perspective that Perceived Trust is shaped by three fundamental antecedents–Perceived Privacy, Perceived Security, and Perceived Information Quality–as identified by Escobar-Rodríguez and Carvajal-Trujillo (2014). Their study extended the UTAUT2 with Perceived Trust to examine online purchasing behaviour in the context of low-cost carrier (LCC) websites, focusing on how tourists adopt digital platforms to buy flight tickets. Their findings indicate that Perceived Trust, which is influenced by users' assessments of privacy, security, and information quality, constitutes a critical determinant of users' confidence in engaging with online transactions and completing purchases.

4.10.1 Perceived Privacy and Perceived Trust

Perceived Privacy refers to individuals' subjective evaluation of how their personal information is collected, stored, and utilized by digital platforms, particularly whether e-vendors recognize the sensitivity of such data and handle it responsibly (Al-Fedaghi, 2012). This construct is increasingly recognized as a critical factor influencing consumer behaviour in digital environments. Specifically, in e-commerce contexts, Perceived Privacy has been shown to significantly shape Trust and customer loyalty (Gong & Jin, 2008). When users perceive that their privacy is respected and safeguarded, they are more likely to Trust the platform and disclose personal information. However, this relationship is often moderated by the extent to which users inherently Trust the service provider (Joinson et al., 2010).

To understand how Perceived Privacy operates within consumer decision-making, Liu et al. (2005) developed and empirically tested the Privacy–Trust–Behavioural Intention (PTBI) model. Their study identified four core dimensions of privacy perception - notice, access, choice, and security- which collectively shape Perceived Privacy by addressing both informational transparency and control. Their study also found that each of these dimensions had a significant positive effect on Trust, and that Trust, in turn, significantly predicted Behavioural Intentions such as purchase, revisit, and recommendation. Thus, Perceived Privacy is not only a psychological comfort zone but also a measurable antecedent to Trust-based engagement in online settings (Liu et al., 2005).

The foundational role of privacy as an antecedent of Trust is consistently replicated in digital tourism contexts (Zhou & Li, 2014). Specifically, privacy concern–the degree to which individuals worry about how their personal data is accessed, used, and stored by service providers–plays a pivotal role in shaping tourists' Trust-related judgments (Ooi et al., 2018; Zhou & Li, 2014). When users doubt the service provider's commitment to safeguarding their privacy, their level of Trust diminishes, which in turn reduces their willingness to engage with digital tourism platforms (Bansal et al., 2015; Ngelambong et al., 2018). Therefore, when users perceive that TMAs handle their personal data responsibly, their Trust in the platform increases. This Trust, in turn, enhances their willingness to use and engage

with the application. Therefore, based on existing theoretical and empirical evidence, the following hypothesis is proposed:

H10: Perceived Privacy positively affects Perceived Trust in TMAs.

4.10.2 Perceived Security and Perceived Trust

Perceived security as the extent to which users believe their transactional information is safe from unauthorized access or modification (Hartono et al., 2014). Perceived Security has a significant and direct influences in formation of Trust, which in turn affects consumers' Behavioural Intentions (Siagian et al., 2022). Security perceptions significantly influence consumer willingness to engage in online transactions, primarily because such perceptions reduce concerns over potential misuse of personal information (Cheung & Lee, 2001).

In the context of tourism, perceived security has consistently emerged as a critical antecedent of consumer Trust in digital platforms. For instance, empirical evidence from Cui et al. (2018) demonstrates that in online travel shopping environments, higher levels of perceived security significantly enhance users' Trust by positively influencing their perception of the website's image, which subsequently contributes to e-loyalty. Similarly, Liu et al. (2025) provide further validation of this relationship in the realm of TMAs, where perceived security was found to have a direct and significant impact on tourists' Perceived Trust, which in turn influences their perceived value of co-creation and use intention. Collectively, these factors–confidentiality, availability, non-repudiation, and users' perceptions of data protection and system integrity–serve as core contributors to perceived security in TMAs (Cheung & Lee, 2001; Hartono et al., 2014; Kim et al., 2008).

These findings underscore the vital role of perceived security in shaping Trust- not only by offering users a sense of protection against potential risks, but also by fostering positive perceptions of the digital environment in which tourism services are delivered. Thus, enhancing perceived security is essential for tourism platforms aiming to build and sustain user Trust, engagement, and long-term loyalty.

H11: Perceived Security positively affects Perceived Trust in TMAs.

4.10.3 Perceived Security and Perceived Quality of Information

The concept of Information Quality has its roots in early research on information systems and data management (Wang & Strong ,1996). Information Quality is widely classified into four key dimensions: intrinsic (e.g., accuracy, credibility), contextual (e.g., relevance, timeliness, completeness), representational (e.g., clarity, interpretability), and accessibility (e.g., ease of access, security). In an online context Information Quality refers to users' perceptions of the quality and reliability of information presented for instance on a website (McKinney, 2002). These perceptions are shaped not only by traditional data attributes but

also by digital-specific factors, including website design, interactivity, and the overall user experience (Kim & Niehm, 2009). Poor Information Quality can result in user confusion, misinformation, and dissatisfaction, whereas High-Quality Information enhances user engagement, satisfaction, and ultimately fosters Perceived Trust in the online platform (Bliemel & Hassanein, 2007).

A growing body of literature has confirmed the central role of Information Quality in the formation of Perceived Trust and its influence on consumer decision-making in digital environments. For instance, Nilashi et al. (2023) emphasize that Information Quality, alongside system and service quality, significantly influences customer satisfaction, underlining its importance in consumer decision-making. Pertheban et al. (2020) highlight that unvalidated user-generated content shared through travel platforms can result in significant mismatches between users' pre-visit expectations and post-visit experiences. Similarly, Lucassen and Schraagen (2011) argue that in digital settings, the burden of evaluating the Trustworthiness of information increasingly falls on end users, amplifying the importance of perceived credibility. In context of TMAs, Grljević, et al. (2025), through their topic modeling of SalesForce mobile app reviews, found that users implicitly link the app's support for business organization with reliable and relevant information, suggesting that consumers associate structured digital experiences with high information quality. These studies collectively show that, for consumers, clear, accurate, and Trustworthy information is not only expected but essential for building confidence and reducing uncertainty throughout the travel planning process. Therefore, Perceived Information Quality plays a critical role in fostering users' Perceived Trust in TMAs. Therefore, the following hypothesis is proposed:

H12: Perceived Information Quality positively affects users' Perceived Trust in TMAs.

4.11 The moderating role of Experience

Although the UTAUT2 model recognises Habit as a key predictor of both Behavioural Intention and Use Behaviour (Venkatesh et al., 2012), the strength of this influence is not consistent across all users, as it can vary based on individual differences particularly users' experience with the technology (Venkatesh et al., 2012). As users become more familiar with a digital service, their interactions often shift from conscious decision-making to more automatic, Habitual behaviours (Limayem et al., 2007). Consequently, more experienced users tend to rely on established usage patterns, making Habit a stronger determinant of both intention and actual use (Venkatesh et al., 2012).

Prior research has specifically examined whether experience moderates the strength of Habit's influence. For example, Chang et al. (2019) employed the UTAUT2 model and confirmed the significant moderating role of experience in the context of online hotel reservation systems. Their findings demonstrate that the degree of a user's prior experience meaningfully shapes how certain antecedents influence their Behavioural Intentions and

actual Use Behaviours. Building on this evidence, the present study proposes that experience will moderate the relationship between Habit and both Behavioural Intention and Use Behaviour, such that Habit will exert a stronger influence among more experienced users. Therefore, the following hypotheses are proposed:

H13a. Experience moderates the relationship between Habit and Behavioural Intention to use TMAs during pre-travel phase.

H13b. Experience moderates the relationship between Habit and actual Use Behaviour of TMAs during pre-travel.

The proposed hypotheses are summarized in Table 1.

Table 1: Summary of Hypotheses

Hypotheses	**Relationship**	**Expected Effect**
H1	Performance Expectancy → Behavioural Intention	Positive
H2	Effort Expectancy → Behavioural Intention	Positive
H3	Social Influence → Behavioural Intention	Positive
H4a	Facilitating Conditions → Behavioural Intention	Positive
H4b	Facilitating Conditions → Use Behaviour	Positive
H5	Hedonic Motivation → Behavioural Intention	Positive
H6	Price Value → Behavioural Intention	Positive
H7a	Habit → Behavioural Intention	Positive
H7b	Habit → Use Behaviour	Positive
H8	Behavioural Intention → Use Behaviour	Positive
H9	Perceived Trust → Behavioural Intention	Positive
H10	Perceived Privacy → Perceived Trust	Positive
H11	Perceived Security → Perceived Trust	Positive
H12	Perceived Information Quality → Perceived Trust	Positive
H13a	Experience × Habit → Behavioural Intention	Positive
H13b	Experience × Habit → Use Behaviour	Positive

Source: Author's own work

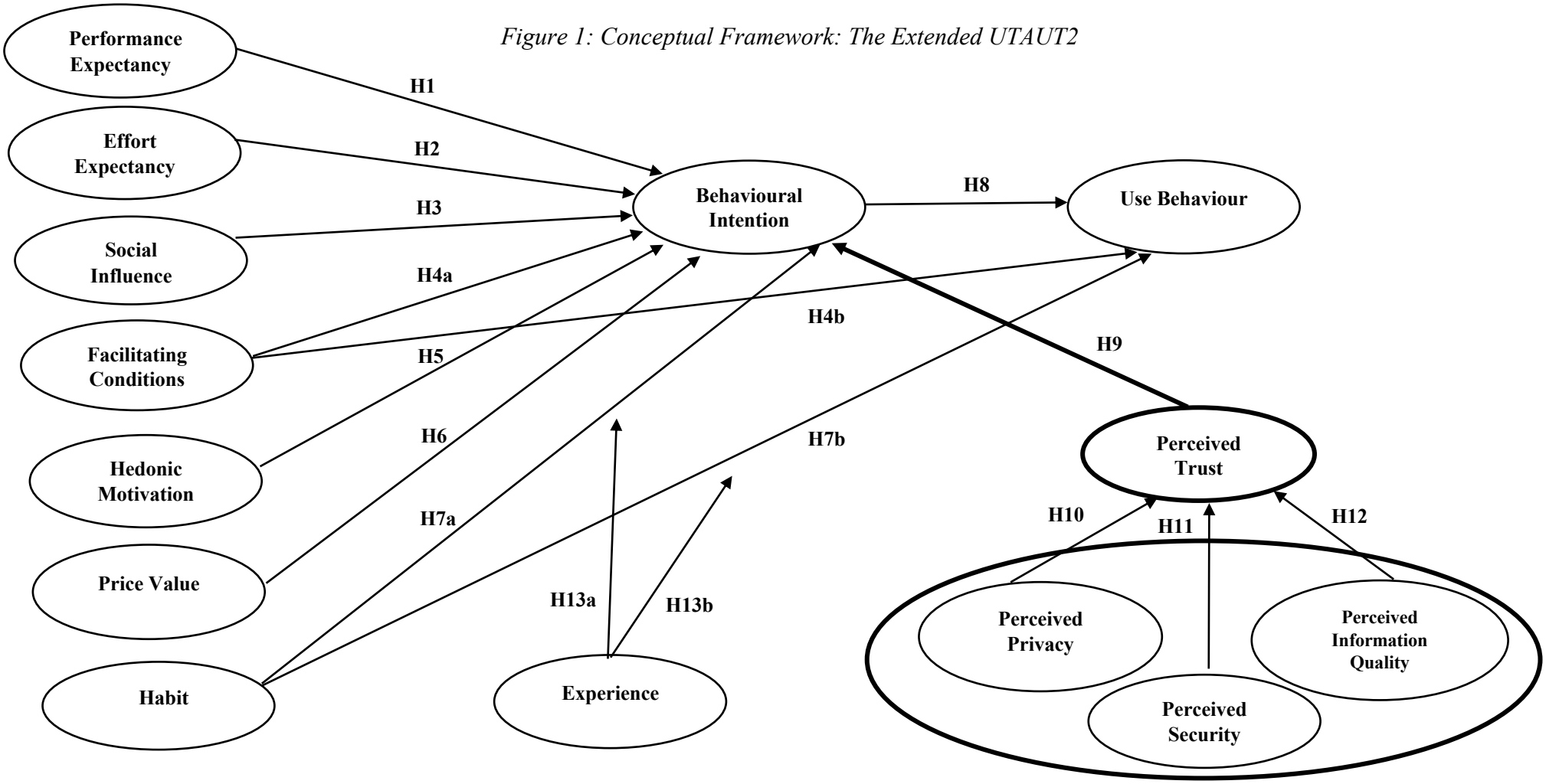
5 CONCEPTUAL MODEL

The conceptual model developed for this dissertation is grounded in the UTAUT2 framework (Venkatesh et al., 2012), which has been demonstrated to be suitable for analysing voluntary, consumer-driven technologies such as mobile applications (Gupta, 2017). As presented in the preceding chapter, UTAUT2 offers a comprehensive set of behavioural determinants relevant to TMA use in the pre-travel phase. Building on this foundation, the present study proposes an extended model tailored to the specific characteristics of mobile tourism environments and the contextual realities of a developing-country setting.

In the proposed conceptual model, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, and Perceived Trust all function as predictors of Behavioural Intention. Behavioural Intention, Habit, and Facilitating Conditions in turn predict Use Behaviour, reflecting both intentional and Habitual pathways to actual usage. In the extended part of the model, Perceived Privacy, Perceived Security, and Perceived Information Quality predict Perceived Trust, which subsequently influences Behavioural Intention. Finally, Experience moderates the relationships between Habit and Behavioural Intention, as well as between Habit and Use Behaviour.

Overall, the proposed conceptual model integrates consumer-technology determinants from UTAUT2 with Trust-related factors that are especially salient in mobile tourism contexts. By combining these elements, the model provides a well-stablished structure for examining TMA acceptance and use during the pre-travel phase. Figure 1 presents the extended conceptual framework, which forms the basis for the hypotheses developed in the next section.

Figure 1: Conceptual Framework: The Extended UTAUT2



Note: Denoted with bold is the extended part of the model.

Source: Author's own work

In addition to the main constructs of the research model, several control variables are included due to their potential influence on users' Behavioural Intentions and technology adoption. Prior studies identify demographic, temporal and situational characteristics as relevant covariates. Age may influence perceptions of usefulness and ease of use, with older users often reporting greater challenges with mobile technologies (Venkatesh et al., 2003). Gender differences have been shown to affect perceived usefulness, Trust, or mobile-app usage (Gefen & Straub, 2004). Educational level is associated with digital literacy and may shape how users evaluate and Trust mobile platforms (Zhou, 2011). Finally, frequency of travel can influence behavioural patterns, as frequent users may exhibit different levels of Trust, intention, and perceived usefulness compared to occasional users (Amaro & Duarte, 2015). These variables are therefore controlled to isolate the effects of the main predictors in the structural model.

6 METHODOLOGY

This chapter presents the methodological approach employed to investigate users' acceptance and use of TMAs during the pre-travel phase. It outlines the procedures used to operationalise the constructs derived from the extended UTAUT2 framework, including the measurement of constructs and questionnaire development and structure. The chapter further describes the data collection methods, the sampling strategy, and the resulting sample characteristics. Finally, it explains the methods of data analysis, including the evaluation of the measurement and structural models. Together, these components establish the methodological foundation required to test the proposed conceptual model and hypotheses.

6.1 Measurement of constructs

Following Venkatesh et al. (2012), this study includes nine constructs of the UTAUT2 model: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioural Intention, and Use Behaviour, along with the extension through a construct of Perceived Trust and its three antecedents: Perceived Privacy, Perceived Security, and Perceived Information Quality. The model also incorporates Experience as a moderating variable, to examine the relationships between Habit and Behavioural Intention, as well as Habit and Use Behaviour. All constructs were measured using established multi-item scales adapted from prior literature. The full list of measurement items and their sources is presented in Table 2. Each construct in the model is operationalised using multiple items adapted from established measurement scales as illustrated in the following.

Performance Expectancy (PE) is measured by 3 items of usefulness, quick accomplishment of tasks, and productivity in completing pre-travel related activities by using TMAs–as it refers to the degree to which users believe that using technologies will enhance their effectiveness and efficiency (Venkatesh et al., 2012).

Effort Expectancy (EE) is measured by 4 items of ease of learning, clarity and understandability of interaction, ease of use, and ease of becoming skillful at using TMAs–as it refers to the degree of ease associated with learning and using technologies (Venkatesh et al., 2012).

Social Influence (SI) is measured by 3 items of the influence of important people, people who shape one's behavior, and valued opinions regarding the use of TMAs–as it refers to the extent to which individuals perceive that important others believe they should use technologies (Venkatesh et al., 2012).

Facilitating Conditions (FC) is measured by 5 items of availability of necessary resources, knowledge, technological compatibility, assistance from others, and guidance or instruction for using TMAs–as it refers to the degree to which individuals believe that the organizational and technical infrastructure supports the use of technologies (Park et al., 2011; Venkatesh et al., 2012).

Hedonic Motivation (HM) is measured by 3 items of the extent of fun, enjoyment, and entertainment experienced while using TMAs–as it refers to the enjoyment or pleasure derived from using technologies (Venkatesh et al., 2012).

Price Value (PV) is measured by 3 items of saving money, searching for reasonable travel deals, and perceived value for money–as it refers to users' evaluation of the trade-off between the benefits and the monetary costs of using technologies (Escobar-Rodríguez & Carvajal-Trujillo, 2014).

Habit (HT) is measured by 5 items of Habitual use, addiction, necessity, naturalness, and the perceived importance of TMAs in users' daily lives–as it refers to the extent to which individuals tend to perform behaviors automatically due to prior learning and repeated use of technologies (Chang et al., 2021; Venkatesh et al., 2012).

Behavioral Intention (BI) is measured by 3 items of intention to continue use, consistent effort to use, and planned frequency of future use–as it refers to a person's motivational readiness to engage in a specific behavior and is widely recognized as a key predictor of actual use of technologies (Venkatesh et al., 2012).

Use Behavior (UB) is measured by 5 items of the usage of TMAs for dreaming about future trips, decision-making and travel planning, booking, making transactions, and anticipating upcoming trips–as it refers to actual engagement with technologies (Venkatesh et al., 2012).

This study employs the extended UTAUT2 model and integrates Perceived Trust construct influenced by three key antecedents–Perceived Privacy (PP), Perceived Security (PS), and Perceived Information Quality (PIQ)–which together form the Trust-related extension of the model.

Perceived Trust (PT) is measured by 3 items of integrity, reliability, and Trustworthiness–as it refers to the extent to which individuals believe that the use of technologies will be reliable and credible, reflecting confidence in the system's integrity and performance (D. J. Kim et al., 2008).

Perceived Privacy (PP) is measured by 5 items of concerns about excessive data collection, unauthorized use, data sharing with other entities, unauthorized access by third parties, and privacy during transactions–as it refers to users' concerns about how technologies handle their personal information and data during use (D. J. Kim et al., 2008).

Perceived Security (PS) is measured by 5 items of security measures, protection of transactional information, confidence in electronic payment systems, willingness to use bank cards, and perceived safety of transactions–as it refers to the extent to which users believe that technologies provide a secure environment for transactions and protect their personal and financial information (Escobar-Rodríguez & Carvajal-Trujillo, 2014).

Perceived Information Quality (PIQ) is measured by 5 items of accuracy, sufficiency, helpfulness, clarity, and up-to-date information offered in the purchase process–as it refers to users' perceptions of the quality of information provided by technologies during the pre-travel phase (Kuan et al., 2008).

Experience (EXP) is measured by 3 items of frequency of use, duration of use, and the number of trips planned using TMAs within a given period–as it refers to users' prior familiarity and accumulated knowledge gained through the use of technologies (Venkatesh et al., 2012), moderating the relationships between Habit and Behavioural Intention as well as Habit and Use Behaviour within the UTAUT2 framework.

In this study, the endogenous variables are Behavioural Intention, Use Behaviour, and Perceived Trust. Behavioural Intention is modelled as a dependent construct explained by exogenous variables: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, and Perceived Trust. Perceived Trust is positioned as an intermediate endogenous variable, predicted by Perceived Privacy, Perceived Security, and Perceived Information Quality. Ultimately, Use Behaviour, as the final outcome variable, is predicted by Behavioural Intention, Habit, and Facilitating Conditions. These three constructs serve as the primary outcomes within the model and are central to the examination of the proposed causal pathways.

Table 2: *Measurement items*

Construct	**Item**	**Supporting literature**
Performance Expectancy (PE)	PE1. I find TMAs (Travel Mobile Apps) useful for my pre-travel activities. PE2. Using TMAs help me accomplish my pre- travel-related tasks more quickly. PE3. Using TMAs increase my productivity.	Venkatesh et al. (2012)
Effort Expectancy (EE)	EE1. Learning how to use TMAs is easy for me. EE2. My interaction with TMAs is clear and understandable EE3. I find TMAs easy to use. EE4. It is easy for me to become skilful at using TMAs.	Venkatesh et al. (2012)
Social Influence (SI)	SI1. People who are important to me think that I should use TMA. SI2. People who influence my behaviour think that I should use TMAs. SI3. People whose opinions that I value prefer that I use TMAs.	Venkatesh et al. (2012)
Facilitating Conditions (FC)	FC1. I have the necessary resources to use the system. FC2. I have the knowledge necessary to use TMAs. FC3. TMAs are compatible with other technologies I use. FC4. I can get help from others when I have difficulties using TMAs. FC5. Enough guidance and instruction were provided for the use of TMAs	Venkatesh et al. (2012) Park et al. (2011)
Hedonic Motivation (HM)	HM1. Using TMAs is fun. HM2. Using TMAs is enjoyable. HM3. Using TMAs is very entertaining.	Venkatesh et al. (2012)
Price Value (PV)	PV1. I can save money by examining the prices on TMAs. PV2. I like to search for cheap travel deals on TMAs. PV3. TMAs offer better value for my money.	Escobar-Rodríguez & Carvajal-Trujillo (2014)

To be continued

Table 2: Measurement items (cont.)

Constructs	**Item**	**Supporting Literature**
Habit (HT)	HT1. The use of TMAs has become a Habit for me. HT2. I am addicted to using TMAs. HT3. I must use TMAs. HT4. Using TMAs has become natural to me. HT5. I believe that TMAs have become important tools in my life,	Venkatesh et al. (2012) Chang et al. (2021)
Behavioral Intention (BI)	BI1. I intend to continue using TMAs for my pre-travel activities. BI2. I will always try to use TMAs for my pre-travel activities. BI3. I plan to continue to use TMAs frequently for my pre-travel activities.	Venkatesh et al. (2012)
Use Behaviour (UB)	UB1. I use TMAs to dream about future trips. UB2. I use TMAs for decision making and travel planning trips. UB3. I use TMAs to book a trip. UB4. I use TMAs to make transaction for my trips. UB5. I use TRMAs to anticipate my upcoming trips.	Gretzel (2021) Backhaus et al. (2022) Hamouda (2022) Putrevu & Mertzanis (2024) Xiang & Gretzel (2010)
Perceived Trust (PT)	PT1. TMAs have integrity. PT2. TMAs are reliable. PT3. TMAs are Trustworthy.	Escobar-Rodríguez & Carvajal-Trujillo (2014)
Perceived Information Quality (PIQ)	PIQ1. TMAs provide accurate information I need in the purchase process. PIQ2. TMAs provide sufficient information needed in the purchase process. PIQ3. The information provided by TMAs is helpful to me in the purchase process. PIQ4. The information in TMAs is clear. PIQ5. TMAs provide up-to-date information	Kuan et al. (2008)

To be continued

Table 2: Measurement items (cont.)

Constructs	**Item**	**Supporting Literature**
Perceived Security (PS)	PS1. TMAs implement security measures to protect users. PS2. TMAs usually ensure that transactional information is protected from accidentally being altered or destroyed during a transmission on the Internet. PS3. I feel secure about the electronic payment system at these TMAs. PS4. I am willing to use my bank card on these websites to make a purchase. PS5. I feel safe in making transactions on these TMAs.	Escobar-Rodríguez & Carvajal-Trujillo (2014)
Perceived Privacy (PP)	PP1. I am concerned that TMAs collect too much personal information from me. PP2. I am concerned that TMAs will use my personal information for other purposes without my authorization. PP3. I am concerned the TMAs will share my personal information with other entities without my authorization. PP4. I am concerned that unauthorized persons (i.e., hackers) have access to my personal information on TMAs. PP5. I am concerned about the privacy of my personal information during a transaction on TMAs.	D.J. Kim et al. (2008)
Experience (EXP)	EXP1. How frequently do you use TMAs? EXP2. For how long have you been using TMAs? EXP3. How many trips have you planned using TMAs the past year?	Venkatesh et al. (2012)

Note: The shaded background colours are used to differentiate construct categories (light grey - extensions and dark grey - moderation)

Source: Author's work

6.2 Questionnaire development and structure

The questionnaire, which served as the primary data collection instrument, was adopted from Venkatesh et al. (2012) and extended with items from Escobar-Rodríguez, & Carvajal-Trujillo (2014) to reflect the Trust-related constructs relevant to TMAs in the pre-travel context. The questionnaire composed of three sections. The first section provided an introduction outlining the purpose of the research, assurances of confidentiality, and instructions for completing the survey. The second section consisted of 7 demographic and background questions, including gender, age, education level, marital status, income, and travel behaviour measured through the number and duration of trips taken per year, to control for situational and socio-demographic factors that may influence TMA acceptance and use. The third section contained 55 measurement items assessing the study's constructs. To ensure contextual relevance, the wording of the items was carefully reviewed and refined to align with the technology-specific context of TMAs as well as phase of pre-travel. This adaptation process preserved the conceptual integrity of the original constructs while ensuring the measures accurately reflect users' perceptions and behavioural tendencies within the study context. The list of all measurement items and their sources is presented in Table 3, and the full English version of the questionnaire is provided Appendix A.

Since the target population is Iranian, the questionnaire is administered in Persian. The author translated the approved English version into Persian and refined the terminology to fit the tourism and mobile app context. A professional translator reviewed the draft for linguistic accuracy, after which an academic expert fluent in both languages verified conceptual equivalence. A back-translation was then conducted, and minor adjustments were made to ensure consistency between the two versions. The full Persian questionnaire is presented in Appendix B.

Prior to distribution, the questionnaire was subjected to a pilot test with a small group of 25 respondents, consisting of tourism students in the Faculty of Social Sciences at the University of Zanjan (ZNU), Iran, majoring in Geography and Tourism Planning. The online survey was administered via Google Forms, and the link was distributed with the assistance of a former professor who shared it with his students. Data collection for the pilot study was conducted throughout April 2024. Preliminary reliability analysis was performed, and the constructs demonstrated acceptable internal consistency, with values of Cronbach's alpha $\geq$ 0.70, indicating satisfactory reliability for proceeding with the main study. Moreover, the feedback obtained from respondents further indicated that the questionnaire was well-organized, the instructions were straightforward, and the language was easily understandable. The structure, layout, and wording were therefore retained in their original form, confirming the instrument's suitability for the main data collection phase.

The questionnaire utilized a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This scale is a widely accepted and validated method for capturing

attitudinal data in behavioral and social science research, as it offers an optimal balance between response precision and ease of use (Joshi et al., 2015). Its simplicity and clarity make it especially appropriate for mobile-based data collection, accommodating participants using smartphones with smaller screens or completing the survey while in transit. Furthermore, the use of Likert-type scales is consistent with the methodological approaches adopted in numerous studies applying the UTAUT2 model to examine technology adoption and usage in mobile contexts (e.g., Gharaibeh et al., 2018; Lock & Shihah, 2021), thereby supporting the validity and comparability of the present study's design.

6.3 Data collection and sampling

The study population consisted of Iranian TMA users such as Snapptrip, Alibaba, and similar platforms to manage their pre-travel activities.

In this study a non-probability sampling strategy was adopted, specifically combining elements of convenience sampling and snowball sampling. Despite the fact that non-probability sampling is often associated with limitations such as selection bias and limited generalizability, it is widely used when probability-based approaches are impractical, particularly in contexts where no comprehensive sampling frame exists or where access to the target population is constrained (Bryman & Bell, 2015). In the context of Iran, due to unique hurdles associated with the authoritarian environment and widespread surveillance, conducting research poses challenges to obtaining valid responses; therefore, researchers often prioritize response validity over strict sampling randomness, given evidence that measurement error in probability-based surveys in sensitive contexts may far exceed the sampling error inherent in non-probability designs (Maleki, 2025).

This approach was selected also due to the nature of the target population namely TMA users who are more readily accessible through online platforms. Convenience sampling allowed for the inclusion of individuals who were easily reachable (Emerson, 2015) via digital channels, while the snowball method enabled participants to refer others who met the eligibility criteria, thereby broadening the reach of the study (Ting et al., 2025).

This study applied Cochran's (1977) formulas to estimate the required sample size at a 95% confidence level with a ±5% margin of error, assuming maximum variability (p = 0.5).

$$\textit{Cochran Formula for Sample Size } (n) = \frac{(Z^2 p\ q)}{d^2} \quad (1)$$

$$n = \frac{(1.96^2 \times 0.5 \times 0.5)}{0.05^2} = 385$$

As shown in equation 1, n represents the sample size, z is the critical value from the standard normal distribution for the desired confidence level (1.96 for 95%), p is the estimated population proportion, q equals 1 − p, and d is the desired margin of error (0.05). These

values were substituted into the formula to calculate the minimum sample size. Accordingly, the minimum required sample size at a 95% confidence level and a 5% margin of error was approximately 385 respondents.

Data collection was carried out through an online questionnaire hosted on Google Forms. The data collection was conducted through an online survey administered via publicly accessible online platforms, including Telegram, WhatsApp, and Eitaa- (the national messaging application), Instagram, Twitter, and Facebook, all of which are actively used for tourism-related discussions in Iran. To encourage participation and improve the response rate, following Wilson et al. (2010) small financial incentives were offered in the form of Sim Card recharge vouchers and travel discount coupons, rewards that are both common and appealing in the Iranian context. Data collection was conducted over an eight-month period from July 2024 to February 2025, allowing sufficient time to gather responses from a broad and diverse participant base. In total, 510 responses were initially received. After removal of incomplete questionnaires, 424 valid responses were retained for the final analysis.

6.4 Sample description

The demographic profile of the respondents (N = 424) demonstrates a broad distribution across age, gender, education, marital status, income, and travel-related variables as shown in Table 3.

With respect to age, the largest proportion of respondents fell within the 25–34 age group (31.8%), followed by those aged 18–24 (27.4%). Together, these two groups accounted for nearly 60% of the sample, indicating a relatively young population. Participants aged 35–44 represented 18.6%, while smaller proportions were observed among the 45–54 (10.9%), 55–65 (7.8%), and 65 or older categories (3.5%). In terms of gender[1], the sample was relatively balanced, with males comprising 52.4% and females 47.6%. Regarding educational attainment, over half of the participants held at least a bachelor's degree. Specifically, 35.9% reported a bachelor's degree, 19.6% a master's degree, and 9.4% a doctoral degree or higher. Meanwhile, 20.5% had attended some college without completing a degree, and 14.6% reported a high school diploma or less. For marital status, 44.8% indicated being in a relationship, 30.7% were married, and 24.5% reported being single. Household income was concentrated in the lower to midrange categories. More than one-third (36.2%) reported earning between $200–$400 per month, and 28.4% between $400–$600. A further 21.9% reported income below $200, whereas only 13.5% reported earnings above $600.

Two control variables were included to capture respondents' travel behaviour: a temporal factor, represented by trip duration, and a situational factor, represented by travel frequency.

[1] In line with the conservative cultural context of the target population, the questionnaire did not include a response option for genders beyond the male–female binary. This design choice was made to facilitate participation and ensure a higher response rate, although it is acknowledged that this approach limits the inclusivity of the demographic data.

For the temporal factor, trip duration was most commonly reported as short stays of 1–3 days (42.7%), followed by trips lasting 4–7 days (38.6%), while longer trips of 8 days or more were less frequent (18.7%). For the situational factor, almost half of respondents (49.1%) reported traveling between 2 and 5 times per year, 29.7% traveled once per year, and 21.2% reported more than 5 trips annually. These temporal and situational indicators describe the travel activity patterns of the respondents and provide contextual information for understanding their use of TMAs.

Table 3: *Profile of the respondents*

Characteristic	**Categories**	**Frequency**	**Percentage**
Age	18-24	116	27.40%
	25-34	135	31.80%
	35-44	79	18.60%
	45-54	46	10.90%
	55-65	33	7.80%
	65 or more	15	3,5%
Gender	Female	202	47.6
	Male	222	52.4
Education	High school or less	62	14.60%
	Some college	87	20.50%
	Bachelor's degree	152	35.90%
	Master's degree	83	19.60%
	Doctoral degree or higher	40	9.40%
Marital Status	Single	104	24.50%
	Married	130	30.70%
	In relationship	190	44.80%
Income	<$200	93	21.90%
	$200–$400	154	36.20%
	$400–$600	120	28.40%
	$600-$800	41	9.70%
	> $800	16	3.80%
Trips per Year	Once per year	126	29.70%
	2-5 times per year	208	49.10%
	>5 trips per year	90	21.20%
Trip Duration	1-3 days	181	42.70%
	4-7 days	164	38.60%
	8 or longer	79	18.70%

Source: Author's own work

6.5 Methods

Data analysis began with descriptive statistics. In this step, the mean and standard deviation are calculated to understand central tendency and variability, while skewness and kurtosis are examined to assess data distribution and normality. This is followed by inferential statistics, employing the two-stage methodology recommended by Anderson and Gerbing (1988). In the first stage, the measurement (outer) model is evaluated, focusing on reliability and validity and the stage second is to develop the full structural equation model (i.e. hypotheses testing).

In detail, the first stage the inferential analysis focused on evaluating the measurement model to establish reliability and validity of all latent constructs through Confirmatory Factor Analysis (CFA) included reliability measures (Cronbach's alpha and Composite Reliability, CR), convergent validity (standardized loadings, Average Variance Extracted, AVE), and discriminant validity (Fornell–Larcker criterion, Heterotrait–Monotrait ratio, HTMT, and cross-loadings) (Fornell & Larcker, 1981; Hair et al., 2019; Henseler et al., 2015).

The second stage of the inferential analysis focused on evaluating the structural model, which is designed to test the hypothesized causal relationships among latent variables specified in the research model. To examine these relationships, path coefficients are estimated and evaluated to determine both the direction and magnitude of the hypothesized effects (Henseler et al., 2015). The coefficient of determination (R^2) is then used to assess the explanatory power of the endogenous constructs, indicating the proportion of variance explained by their respective predictors (Cohen, 1988). Additionally, effect sizes (f^2) are calculated to evaluate the relative impact of each exogenous variable on its associated endogenous construct, thereby supporting the interpretation of practical significance (Hair et al., 2019). In addition, Importance–Performance Matrix Analysis (IPMA) (Ringle et al., 2015), an advanced analytical tool in partial least squares structural equation modeling (PLS-SEM) that extends the traditional evaluation of structural relationships, is also employed in this study as a supplementary analysis.

The data analysis is conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM). This method is appropriate for this study due to the main following reasons: first, the proposed model in this study is complex, incorporating a higher number of variables and moderation effects and PLS-SEM is particularly suitable for estimating complex path models with latent variables and their interrelationships in social science research (Hair et al., 2022). Second, it estimates the model parameters that minimize the residual variance of the whole model dependent variables (Hsu, et al, 2006). Third, it performs effectively with medium/small sample sizes (e.g., 420) and focuses on maximizing the explained variance of the dependent constructs (Haji-Othman et al., 2024). Fourth, PLS-SEM is selected because despite Covariance-Based SEM (CB-SEM), it provides essential analytical capabilities important for this study, including cross-loadings for assessing indicator reliability, the Heterotrait Monotrait Ratio (HTMT) for evaluating discriminant validity, and the

Importance Performance Map Analysis (IPMA) for examining the relative importance and performance of constructs. Finally, PLS-SEM has been successfully applied to validate behavioral intentions and user behavior within the UTAUT2 in tourism and technology adoption research, with studies such as Escobar-Rodríguez and Carvajal-Trujillo (2014) analyzing online purchasing behavior in low-cost airline services and Foroughi et al. (2025) examining users' intentions to adopt ChatGPT for travel planning.

For the data analysis, SPSS version 22.0 for descriptive analysis (Rahman & Muktadir, 2021) and SmartPLS version 4 for variance-based structural equation modeling (PLS-SEM) (Ringle et al., 2015) were employed.

7 RESULTS

This chapter presents the results of the empirical analysis conducted to examine the factors affecting the acceptance and use of TMAs during the pre-travel phase. Building on the conceptual framework developed in Chapter 2, this chapter provides both descriptive and inferential analyses of the collected data in order to evaluate the proposed research model and test the formulated hypotheses. Descriptive statistics are used to provides an overview of the main research variables using frequency distributions, percentages, means, and standard deviations. This is followed by the inferential statistics which is complementary to descriptive statistics (Sand, 2022) and divided into two major parts.

The inferential analysis is divided into two parts: the measurement model and the structural model. The measurement model was evaluated through a two-level analysis using the Partial Least Squares (PLS) algorithm, functioning as Confirmatory Factor Analysis (CFA) in traditional Structural Equation Modeling (SEM), at (1) the indicator level and (2) the construct level. The indicator level focused on individual observed variables or survey items. Key indicator-level metrics include the outer/factor loadings (λ) and their statistical significance, assessed through t-values and p-values, as well as the Variance Inflation Factor (VIF) to evaluate multicollinearity. The construct-level analysis focused on key assessments to ensure both reliability and validity. Reliability was evaluated using Cronbach's alpha (α) and Composite Reliability (CR) measures, trough ρA and ρC. Convergent validity was assessed through the average variance extracted (AVE). Discriminant validity was examined using the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT), and indicator cross-loadings before advancing to the structural model analysis. The second part of inferential analysis evaluated the structural model, where the hypothesized causal relationships are tested through structural equation modelling. In addition, the effects of control variables are examined, and an importance–performance matrix analysis (IPMA) is conducted to provide further insights into the managerial implications of the findings.

7.1 Descriptive analysis of study variables

The descriptive results shown in Table, the mean values of the study variables fall predominantly within the mid-range (2.50–3.50), indicating generally moderate evaluations across constructs. Among all variables, Perceived Privacy recorded the highest mean (M = 3.874), suggesting that respondents held relatively positive perceptions regarding the protection of their personal information when using TMAs. Other constructs positioned at the upper end of the moderate range include Experience (M = 3.710), Perceived Information Quality (M = 3.609), and Habit (M = 3.516), reflecting favourable assessments in terms of familiarity, information accuracy, and routinised use.

Table 4: Descriptive Statistics

Variables	N	Mean	Std. Deviation	Skewness	Kurtosis
Use Behaviour	424	3.193	0.989	-0.156	-0.672
Facilitating Conditions	424	3.173	0.975	-0.202	-0.661
Effort Expectancy	424	3.446	0.965	-0.257	-0.639
Social Influence	424	3.241	0.985	0.020	-0.789
Habit	424	3.516	0.917	-0.320	-0.735
Hedonic Motivation	424	3.366	0.891	-0.269	-0.672
Prive Value	424	3.366	0.916	-0.368	-0.647
Performance Expectancy	424	2.891	1.022	0.023	-0.755
Perceived Trust	424	3.300	0.930	-0.300	-0.604
Perceived Privacy	424	3.874	0.793	-0.615	-0.287
Perceived Information Quality	424	3.609	0.893	-0.450	-0.612
Perceived Security	424	3.443	0.974	-0.306	-0.708
Behavioural Intention	424	3.132	1.066	-0.069	-0.856
Experience	424	3.710	0.902	-0.449	-0.340
Use Behaviour	424	3.193	0.989	-0.156	-0.672

Source: Author's own work

At the lower end of the spectrum, Performance Expectancy showed the lowest mean (M = 2.891), indicating more conservative expectations regarding the functional benefits of TMAs for enhancing efficiency and productivity during pre-travel planning. Variables such as Social Influence (M = 3.241), Behavioural Intention (M = 3.132), Use Behaviour (M = 3.193), and Facilitating Conditions (M = 3.173) also fall within the moderate range, reflecting neither strong agreement nor strong disagreement among participants. Overall, the patterns suggest a balanced distribution of perceptions, with stronger evaluations of privacy, information quality, and familiarity, and comparatively lower expectations regarding performance enhancements.

Before conducting inferential analyses, it is essential to assess normality, as parametric methods require data to be symmetrically distributed around the mean (Gupta et al., 2019),

In line with the recommendations of Hair et al. (2019), the skewness ranged from –0.615 to 0.023 and kurtosis ranged from –0.856 to –0.287, all within the acceptable range. This provided clear evidence that the distribution of all variables is approximately symmetric, with peaks and tails consistent with the characteristics of a normal distribution. The dataset satisfied the assumption of univariate normality, confirming its appropriateness for subsequent parametric analyses. Table 4 shows values of the sample size, mean, standard deviation, and the skewness and kurtosis values for each construct.

7.2 Measurement model assessment

7.2.1 Factor Loadings and Variance Inflation Factor (VIF)

At the indicator level, reliability is examined using standardized factor loadings (λ) and variance inflation factors (VIF). The results of factor loadings and the collinearity index showed that all standardized factor loadings (λ) were statistically significant at the 1% level ($p < 0.01$) and exceeded the recommended threshold of 0.70. The loadings ranged from 0.744 (PP1, Perceived Privacy) to 0.913 (BI1, Behavioral Intention), confirming that more than half of the variance in each indicator is explained by its underlying construct. Particularly high loadings were observed for constructs such as Behavioral Intention (0.896–0.913), Performance Expectancy (0.889–0.904), and Social Influence (0.887–0.903), reflecting strong relationships between items and their respective latent constructs.

According to Hair et al. (2022), loadings above 0.70 indicate that an item explains more than 50% of the variance in its corresponding latent construct and are therefore satisfactory. Items with loadings between 0.40 and 0.70 may be retained if the construct's overall reliability and validity are acceptable, whereas items below 0.40 are generally removed from the model (Hulland, 1999).

Multicollinearity was evaluated using the Variance Inflation Factor (VIF). In line with established guidelines (Hair et al., 2022), VIF values below 4 suggest that collinearity is unlikely to distort parameter estimates, whereas values greater than 10 indicate severe multicollinearity that may undermine model stability and necessitate respecification. The results indicated that all VIF values were comfortably below the threshold of 4, providing evidence for the absence of problematic multicollinearity and supporting the adequacy of the indicators.

Table 5 presents the results of the factor loadings and the collinearity index. The measurement model diagram, including standardized factor loadings and indicator contributions, is included in Appendix C.

Table 5: The results of factor loadings and the collinearity index

Construct	Item	Loading factor (λ)	t	P values	VIF	Mean	Sd
Behavioral Intention	BI1	0.910	109.591	0.001	2.624	3.18	1.138
	BI2	0.908	114.794	0.001	2.627	3.13	1.212
	BI3	0.896	84.094	0.001	2.507	3.08	1.186
Effort Expectancy	EE1	0.885	63.431	0.001	2.835	3.45	1.088
	EE2	0.888	77.180	0.001	2.685	3.86	1.024
	EE3	0.887	84.873	0.001	2.633	3.02	1.105
	EE4	0.888	77.786	0.001	2.798	3.46	1.133
Experience	EXP1	0.899	89.360	0.001	2.299	3.75	1.090
	EXP2	0.863	53.977	0.001	1.989	3.88	0.967
	EXP3	0.879	62.819	0.001	2.150	3.49	1.061
Facilitating Conditions	FC1	0.857	61.021	0.001	2.558	3.40	1.087
	FC2	0.861	62.392	0.001	2.557	3.13	1.133
	FC3	0.882	76.749	0.001	2.984	2.93	1.121
	FC4	0.884	84.421	0.001	3.013	3.05	1.121
	FC5	0.886	77.356	0.001	2.927	3.36	1.114
Habit	H1	0.860	59.108	0.001	2.760	3.65	1.061
	H2	0.866	69.614	0.001	2.745	3.83	1.046
	H3	0.860	66.305	0.001	2.531	2.74	1.113
	H4	0.867	71.587	0.001	2.606	3.38	1.093
	H5	0.868	70.553	0.001	2.670	3.98	0.991
Hedonic Motivation	HM1	0.860	56.972	0.001	1.930	4.28	0.899
	HM2	0.901	80.170	0.001	2.357	3.54	1.104
	HM3	0.844	50.674	0.001	1.833	2.27	1.072
Performance Expectancy	PE1	0.889	67.838	0.001	2.376	2.98	1.152
	PE2	0.897	70.562	0.001	2.532	2.77	1.132
	PE3	0.904	83.389	0.001	2.347	2.93	1.134
Perceived Quality Information	PQI1	0.858	62.772	0.001	2.469	3.57	1.083
	PQI2	0.846	54.805	0.001	2.294	2.90	1.124
	PQI3	0.839	47.991	0.001	2.349	3.92	1.025
	PQI4	0.822	47.370	0.001	2.109	4.18	0.927
	PQI5	0.869	63.368	0.001	2.600	3.49	1.104
Perceived Security	PS1	0.870	62.606	0.001	2.685	3.66	1.092
	PS2	0.867	61.236	0.001	2.700	3.40	1.146
	PS3	0.858	56.860	0.001	2.670	3.11	1.163
	PS4	0.855	50.118	0.001	2.473	3.69	1.083
	PS5	0.877	66.944	0.001	2.617	3.36	1.139
Perceived Trust	PT1	0.866	69.873	0.001	2.069	4.14	0.949
	PT2	0.902	93.569	0.001	2.451	3.00	1.098
	PT3	0.891	79.989	0.001	2.229	2.76	1.097

To be continued

Table 5: The results of factor loadings and the collinearity index (cont.)

Construct	Item	Loading factor (λ)	t	P values	VIF	Mean	Sd
Perceived Privacy	PP1	0.744	30.223	0.001	1.782	4.58	0.679
	PP2	0.865	69.124	0.001	2.480	4.08	0.973
	PP3	0.832	53.274	0.001	2.167	2.91	1.097
	PP4	0.877	68.340	0.001	2.788	3.84	0.993
	PP5	0.845	52.339	0.001	2.188	3.96	0.987
Price Value	PV1	0.882	65.179	0.001	2.263	2.49	1.034
	PV2	0.870	55.693	0.001	2.001	3.86	1.016
	PV3	0.894	77.962	0.001	2.239	3.75	1.065
Social Influence	SI1	0.895	77.375	0.001	2.400	3.41	1.059
	SI2	0.903	90.582	0.001	2.464	2.74	1.157
	SI3	0.887	70.912	0.001	2.259	3.58	1.086
Use Behavior	UB1	0.877	76.162	0.001	2.694	3.48	1.096
	UB2	0.878	78.804	0.001	2.816	3.11	1.157
	UB3	0.857	60.380	0.001	2.626	3.02	1.165

Source: Author's own work

7.2.2 Cronbach's Alpha (α)

At construct level, Cronbach's alpha values ranged from 0.837 to 0.923 with the lowest value observed for Hedonic Motivation (α = 0.837), while the highest for Facilitating Conditions (α = 0.923), followed closely by Use Behaviour (α = 0.922). These results indicate that all constructs achieved internal consistency and in line with recommended reliability thresholds: Cronbach's alpha values above 0.70 indicate satisfactory reliability for established scales, while values above 0.60 may be acceptable in exploratory research (Nunnally & Bernstein, 1994). As none of the constructs approached the redundancy threshold, the findings further suggest that the indicators for each construct consistently measure their intended latent variable without exhibiting excessive overlap.

7.2.3 Composite Reliability (ρA and ρC)

Composite reliability is assessed using both ρA (Dijkstra–Henseler's reliability coefficient) and ρC (traditional composite reliability). The ρA values ranged from 0.838 to 0.925, while the ρC values ranged from 0.902 to 0.942. The lowest reliability was observed for Hedonic Motivation (ρA = 0.838; ρC = 0.902), whereas the highest values were found for Facilitating Conditions (ρA = 0.924; ρC = 0.942) and Use Behavior (ρA = 0.925; ρC = 0.941). Across all constructs, both coefficients exceeded the acceptable lower threshold and remained below the redundancy cutoff of 0.95, indicating strong internal consistency without signs of indicator overlap. These results are in line with the recommended threshold for composite

reliability values above 0.70 and below 0.95, which indicate satisfactory internal consistency, while values exceeding 0.95 may suggest redundancy due to overly homogeneous indicators (Diamantopoulos et al., 2012).

7.2.4 Average Variance Extracted (AVE)

Convergent validity was assessed using the average variance extracted (AVE). The AVE values ranged from 0.695 to 0.818. The lowest AVE was observed for Perceived Privacy (0.695), which still exceeds the recommended threshold, indicating that nearly 70% of the variance in its items is explained by the construct. The highest AVE was reported for Behavioural Intention (0.818), showing that more than 80% of the variance in its indicators is captured by the construct. Other constructs such as Performance Expectancy (0.804), Social Influence (0.800), and Effort Expectancy (0.787) also produced AVE values above 0.75, confirming strong convergent validity. All constructs exceeded the minimum requirement of 0.50, and most approached or surpassed 0.75 in line with Fornell and Larcker's (1981) criterion for adequate convergent validity. Table 6 presents the results of the reliability and convergent validity assessments.

Table 6: Reliabilty and Convergant validity

Constructs	Cronbach's alpha (α)	**Composite reliability (rhoa/ ρA)**	**Composite reliability (rhoc/ ρC)**	**Average variance xtracted (AVE)**
Behavioral Intention	0.889	0.891	0.931	0.818
Effort Expectancy	0.91	0.913	0.936	0.787
Experience	0.855	0.858	0.912	0.776
Facilitating Conditions	0.923	0.924	0.942	0.764
Habit	0.915	0.917	0.936	0.747
Hedonic Motivation	0.837	0.838	0.902	0.754
Perceived Information Quality	0.902	0.904	0.927	0.717
Perceived Security	0.916	0.924	0.937	0.749
Perceived Trust	0.864	0.867	0.917	0.786
Perceived Privacy	0.891	0.905	0.919	0.695
Performance Expectancy	0.878	0.885	0.925	0.804
Price Value	0.858	0.861	0.913	0.778
Social Influence	0.875	0.876	0.923	0.800
Use Behavior	0.922	0.925	0.941	0.761

Source: Author's own work

7.2.5 Fornell–Larcker Criterion

In order to assess discriminant validity, this study applied the Fornell–Larcker criterion. The square roots of AVE (diagonal values) spanned from the highest value, Behavioural Intention (√AVE = 0.905), to the lowest, Perceived Privacy (√AVE = 0.834). The inter-construct correlations (off-diagonal), conversely, were generally moderate to low, ranging from a minimum of (0.197) between Performance Expectancy and Facilitating Conditions to a maximum of (0.495) between Behavioural Intention and Use Behaviour. The results are in line with Fornell-Larcker criterion 1981), which demonstrates that the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlation with any other construct, thereby confirming adequate discriminant validity for the measurement model. Table 7 presents the results of the Fornell–Larcker Matrix.

Table 7: The Fornell–Larcker Matrix

	BI	EE	EXP	FC	HT	HM	PIQ	PS	PT	PP	PE	PV	SI	UB
Behavioral Intention	0.905													
Effort Expectancy	0.391	0.887												
Experience	0.325	0.455	0.881											
Facilitating Conditions	0.372	0.256	0.357	0.874										
Habit	0.437	0.324	0.374	0.268	0.864									
Hedonic Motivation	0.394	0.34	0.332	0.304	0.396	0.868								
Perceived information quality	0.302	0.349	0.29	0.272	0.376	0.437	0.847							
Perceived Security	0.354	0.406	0.315	0.351	0.369	0.38	0.296	0.865						
Perceived Trust	0.421	0.345	0.314	0.295	0.325	0.272	0.343	0.303	0.886					
Perceived Privacy	0.346	0.433	0.259	0.325	0.293	0.434	0.289	0.286	0.436	0.834				
Performance Expectancy	0.349	0.266	0.371	0.197	0.298	0.316	0.313	0.357	0.299	0.283	0.897			
Price Value	0.345	0.348	0.332	0.246	0.263	0.297	0.347	0.326	0.228	0.406	0.22	0.882		
Social Influence	0.4	0.259	0.365	0.238	0.253	0.338	0.38	0.343	0.227	0.385	0.311	0.281	0.895	
Use Behavior	0.495	0.425	0.409	0.337	0.372	0.321	0.365	0.493	0.33	0.388	0.248	0.369	0.316	0.872

Source: Author's own works

7.2.6 Heterotrait–Monotrait Ratio (HTMT)

The HTMT criterion, introduced by Henseler et al. (2015), is regarded as a more stringent and reliable approach to assessing discriminant validity compared to traditional methods such as the Fornell–Larcker criterion. HTMT is defined as the ratio of the average heterotrait–heteromethod correlations (i.e., correlations across constructs) to the average monotrait–heteromethod correlations (i.e., correlations within the same construct). In practice, HTMT values below 0.85 (conservative threshold) or 0.90 (liberal threshold) are considered adequate discriminant validity.

In this study, the conservative threshold of 0.85 is applied and the results confirm that all HTMT values ranged from 0.215 to 0.543, well below the cut-off point. The highest HTMT value was observed between Behavioural Intention and Use Behaviour (HTMT = 0.543), which is substantially lower than the 0.85 threshold, suggesting that while these two constructs are conceptually related, they remain empirically distinct. Conversely, the lowest HTMT value was found between Facilitating Conditions and Performance Expectancy (HTMT = 0.215), indicating minimal overlap and strong discriminant separation between these constructs.

The relatively narrow dispersion of HTMT values (0.215–0.543) further demonstrates that no construct pair exhibits problematic conceptual overlap. These findings affirm that the constructs included in the model capture distinct latent dimensions and that multicollinearity across constructs is not a concern. The results of HTMT are shown in Table 8.

Table 8: The Heterotrait-Monotrait Ratioo (HTMT)

	BI	EE	EXP	FC	HT	HM	PIQ	PS	PT	PP	PE	PV	SI	UB
Behavioral Intention														
Effort Expectancy	0.433													
Experience	0.371	0.515												
Facilitating Conditions	0.409	0.279	0.401											
Habit	0.482	0.351	0.421	0.289										
Hedonic Motivation	0.455	0.389	0.392	0.345	0.451									
Perceived Information Quality	0.337	0.386	0.331	0.297	0.414	0.503								
Perceived Security	0.390	0.446	0.356	0.381	0.400	0.434	0.324							
Perceived Trust	0.479	0.389	0.362	0.331	0.363	0.318	0.386	0.338						
Perceived Privacy	0.388	0.482	0.295	0.355	0.327	0.500	0.322	0.315	0.488					
Performance Expectancy	0.392	0.296	0.430	0.215	0.331	0.365	0.349	0.398	0.342	0.315				
Price Value	0.393	0.394	0.385	0.275	0.293	0.351	0.395	0.368	0.265	0.467	0.253			
Social Influence	0.453	0.292	0.423	0.265	0.281	0.395	0.428	0.382	0.258	0.437	0.352	0.324		
Use Behavior	0.543	0.461	0.459	0.364	0.402	0.363	0.398	0.535	0.367	0.431	0.275	0.415	0.351	

Source: Author's own work

7.2.7 Cross-Loadings

The cross-loading analysis evaluates discriminant validity at the indicator level by verifying that each indicator loads more strongly on its designated construct than on any other construct (Chin, 1998). A widely applied rule of thumb is that the loading on the intended construct should exceed the loading on any competing construct by at least 0.10–0.20 (Chin, 1998). If this condition is not met, it suggests that the indicator may not uniquely represent the intended latent construct and may contribute to cross-construct overlap. The results confirm that all indicators had their highest loadings on their intended constructs, with substantial differences compared to loadings on other constructs. For example, indicator BI1 loaded 0.910 on Behavioural Intention, while its highest cross-loading was 0.458 on Use Behaviour, resulting in a difference of 0.452, well above the acceptable threshold. Similarly, indicators such as EE2 (loading 0.888 on Effort Expectancy) and PIQ5 (loading 0.869 on Perceived information quality) also demonstrated clear separation from non-target constructs. In addition, all main loadings are above 0.70, which further confirms indicator reliability and the strength of item-construct associations. No indicator exhibited problematic cross-loadings that would challenge its assignment to a given construct.

Taken together, the cross-loading analysis confirms that each indicator is empirically aligned with its intended latent construct and does not display substantial overlap with competing constructs. This supports discriminant validity at the indicator level. The results of Factor Loadings are shown in Table 9.

In summary, the results obtained from all three approaches: the Fornell–Larcker criterion, the HTMT ratio, and the cross-loading analysis collectively confirm that discriminant validity is fully established for the constructs in the model. These findings show that each construct shares greater variance with its own indicators than with those of other constructs, that no substantial conceptual overlap exists among constructs, and that no indicators display problematic cross-loadings. Accordingly, the measurement model can be considered both robust and valid, offering a reliable foundation for advancing to the structural model analysis.

Table 9: Cross Loading

	Behavioural Intention	Effort Expectancy	Experience	Facilitating Conditions	Habit	Hedonic Motivation	Perceived Information	Perceived Security	Perceived Trust	Perceived_ Privacy	Performance Expectancy	Price Value	Social Influence	Use Behaviour	Experience x Habit
BI1	**0.910**	0.344	0.321	0.376	0.409	0.416	0.298	0.320	0.376	0.336	0.321	0.328	0.380	0.458	0.090
BI2	**0.908**	0.364	0.282	0.310	0.415	0.314	0.255	0.321	0.401	0.319	0.337	0.338	0.361	0.449	0.062
BI3	**0.896**	0.353	0.277	0.323	0.361	0.335	0.266	0.321	0.367	0.282	0.287	0.268	0.343	0.435	0.068
EE1	0.315	**0.885**	0.371	0.181	0.248	0.273	0.291	0.356	0.304	0.385	0.253	0.293	0.228	0.340	-0.068
EE2	0.360	**0.888**	0.396	0.235	0.308	0.297	0.293	0.319	0.324	0.424	0.179	0.287	0.212	0.389	-0.007
EE3	0.370	**0.887**	0.395	0.228	0.303	0.305	0.330	0.384	0.319	0.354	0.276	0.304	0.202	0.365	-0.040
EE4	0.336	**0.888**	0.451	0.261	0.284	0.329	0.321	0.383	0.274	0.375	0.234	0.351	0.282	0.411	-0.004
EXP1	0.326	0.409	**0.899**	0.342	0.356	0.294	0.283	0.295	0.299	0.251	0.331	0.348	0.327	0.364	-0.096
EXP2	0.264	0.357	**0.863**	0.322	0.257	0.251	0.229	0.257	0.246	0.190	0.326	0.256	0.327	0.353	-0.103
EXP3	0.266	0.435	**0.879**	0.277	0.373	0.332	0.252	0.280	0.283	0.241	0.323	0.270	0.311	0.365	-0.101
FC1	0.307	0.227	0.305	**0.857**	0.215	0.243	0.247	0.332	0.218	0.265	0.141	0.237	0.231	0.291	-0.006
FC2	0.355	0.228	0.349	**0.861**	0.267	0.325	0.205	0.292	0.280	0.336	0.216	0.202	0.220	0.281	-0.050
FC3	0.300	0.255	0.314	**0.882**	0.222	0.236	0.215	0.295	0.264	0.270	0.161	0.208	0.192	0.291	0.014
FC4	0.325	0.195	0.286	**0.884**	0.207	0.242	0.223	0.302	0.259	0.222	0.173	0.184	0.179	0.276	0.001
FC5	0.336	0.216	0.305	**0.886**	0.256	0.278	0.294	0.311	0.266	0.322	0.166	0.242	0.218	0.333	-0.023
H1	0.342	0.248	0.317	0.230	**0.86**	0.331	0.322	0.268	0.227	0.224	0.245	0.150	0.180	0.274	0.035
H2	0.357	0.276	0.314	0.188	**0.866**	0.369	0.357	0.331	0.285	0.24	0.319	0.192	0.204	0.331	-0.072
H3	0.409	0.296	0.340	0.258	**0.860**	0.331	0.327	0.307	0.302	0.289	0.229	0.271	0.262	0.319	0.017
H4	0.404	0.33	0.349	0.278	**0.867**	0.354	0.296	0.367	0.325	0.311	0.238	0.318	0.238	0.344	-0.064
H5	0.370	0.241	0.293	0.198	**0.868**	0.324	0.323	0.311	0.256	0.194	0.258	0.190	0.201	0.332	-0.083

To be continued

Table 9: Cross Loading (cont.)

	Behavioural Intention	Effort Expectancy	Experience	Facilitating Conditions	Habit	Hedonic Motivation	Perceived Information	Perceived Security	Perceived Trust	Perceived_ Privacy	Performance Expectancy	Price Value	Social Influence	Use Behaviour	Experience x Habit
HM1	0.344	0.287	0.246	0.284	0.370	**0.860**	0.376	0.333	0.285	0.362	0.235	0.232	0.289	0.326	-0.030
HM2	0.351	0.323	0.344	0.258	0.353	**0.901**	0.422	0.316	0.230	0.376	0.321	0.273	0.313	0.260	-0.032
HM3	0.330	0.275	0.274	0.250	0.307	**0.844**	0.337	0.342	0.192	0.393	0.268	0.27	0.278	0.250	-0.011
PE1	0.298	0.238	0.389	0.161	0.252	0.241	0.280	0.296	0.262	0.243	**0.889**	0.207	0.235	0.209	-0.017
PE2	0.294	0.220	0.316	0.148	0.254	0.266	0.217	0.311	0.278	0.213	**0.897**	0.187	0.257	0.202	-0.002
PE3	0.343	0.254	0.298	0.213	0.292	0.336	0.338	0.35	0.266	0.299	**0.904**	0.198	0.337	0.251	0.028
PP1	0.267	0.345	0.184	0.235	0.255	0.299	0.240	0.214	0.251	**0.744**	0.171	0.326	0.290	0.328	-0.050
PP2	0.264	0.339	0.193	0.291	0.203	0.380	0.261	0.224	0.413	**0.865**	0.201	0.361	0.316	0.291	0.012
PP3	0.273	0.301	0.230	0.286	0.277	0.340	0.223	0.275	0.355	**0.832**	0.310	0.327	0.361	0.335	-0.028
PP4	0.292	0.379	0.194	0.252	0.235	0.407	0.243	0.225	0.369	**0.877**	0.214	0.348	0.293	0.339	-0.018
PP5	0.348	0.445	0.275	0.287	0.269	0.369	0.242	0.256	0.396	**0.845**	0.275	0.334	0.348	0.341	-0.035
PIQ1	0.277	0.267	0.256	0.205	0.321	0.402	0.858	0.215	0.301	**0.301**	0.285	0.294	0.341	0.338	0.003
PIQ2	0.222	0.293	0.214	0.258	0.275	0.323	0.846	0.240	0.304	**0.252**	0.227	0.262	0.296	0.315	-0.069
PIQ3	0.258	0.356	0.267	0.252	0.311	0.398	0.839	0.251	0.261	**0.195**	0.274	0.321	0.305	0.291	-0.033
PIQ4	0.219	0.251	0.24	0.186	0.314	0.343	0.822	0.282	0.275	**0.245**	0.269	0.312	0.344	0.293	-0.037
PIQ5	0.302	0.316	0.256	0.249	0.368	0.386	0.869	0.268	0.306	**0.224**	0.275	0.288	0.322	0.305	0.007
PS1	0.287	0.335	0.254	0.352	0.315	0.348	0.297	0.870	0.269	**0.274**	0.290	0.297	0.317	0.418	0.073
PS2	0.353	0.384	0.308	0.310	0.329	0.336	0.213	0.867	0.249	**0.237**	0.391	0.340	0.252	0.419	-0.022
PS3	0.270	0.351	0.266	0.285	0.322	0.305	0.239	0.858	0.218	**0.209**	0.300	0.259	0.290	0.436	0.028
PS4	0.272	0.358	0.279	0.279	0.302	0.340	0.257	0.855	0.255	**0.256**	0.293	0.251	0.320	0.415	0.048
PS5	0.343	0.336	0.262	0.288	0.328	0.315	0.266	0.877	0.304	**0.254**	0.281	0.265	0.301	0.445	-0.004

To be continued

Table 9: Cross Loading (cont.)

	Behavioural Intention	Effort Expectancy	Experience	Facilitating Conditions	Habit	Hedonic Motivation	Perceived Information	Perceived Security	Perceived Trust	Perceived_ Privacy	Performance Expectancy	Price Value	Social Influence	Use Behaviour	Experience x Habit
PT1	0.327	0.326	0.222	0.275	0.285	0.221	0.272	0.292	**0.866**	0.377	0.216	0.218	0.134	0.255	0.003
PT2	0.387	0.277	0.284	0.278	0.284	0.231	0.300	0.270	**0.902**	0.389	0.260	0.185	0.197	0.323	0.042
PT3	0.402	0.317	0.325	0.233	0.296	0.269	0.336	0.247	**0.891**	0.393	0.315	0.205	0.265	0.297	0.034
PV1	0.284	0.297	0.269	0.215	0.231	0.247	0.281	0.282	0.215	0.385	0.193	**0.882**	0.244	0.354	-0.029
PV2	0.304	0.324	0.305	0.2	0.233	0.271	0.297	0.290	0.146	0.338	0.187	**0.870**	0.242	0.305	-0.031
PV3	0.323	0.299	0.303	0.234	0.233	0.268	0.337	0.291	0.241	0.353	0.202	**0.894**	0.257	0.32	-0.01
SI1	0.353	0.273	0.384	0.265	0.277	0.312	0.378	0.357	0.229	0.346	0.312	0.258	**0.895**	0.313	0.085
SI2	0.368	0.208	0.268	0.196	0.210	0.303	0.317	0.310	0.201	0.354	0.255	0.234	**0.903**	0.268	0.117
SI3	0.353	0.216	0.330	0.179	0.193	0.292	0.325	0.254	0.178	0.334	0.269	0.263	**0.887**	0.267	0.050
UB1	0.485	0.393	0.394	0.307	0.353	0.332	0.380	0.449	0.303	0.356	0.220	0.330	0.295	**0.877**	-0.003
UB2	0.443	0.376	0.370	0.281	0.320	0.293	0.291	0.461	0.298	0.363	0.212	0.351	0.303	**0.878**	0.034
UB3	0.376	0.326	0.309	0.281	0.315	0.265	0.298	0.418	0.230	0.297	0.251	0.284	0.281	**0.857**	-0.003
UB4	0.431	0.373	0.355	0.248	0.320	0.266	0.345	0.436	0.318	0.338	0.229	0.349	0.268	**0.877**	-0.006
UB5	0.412	0.377	0.349	0.354	0.311	0.238	0.270	0.383	0.285	0.334	0.174	0.290	0.228	**0.874**	-0.014

Source: Author's own work

According to results, Use Behaviour items show that users engage with TMAs across five pre-travel stages, with the mean values indicating different levels of use for each stage. Among these, the Expectation Formation stage shows the highest mean score (M = 3.59), representing the stage with the most frequent reported engagement. This is followed by the Dreaming stage (M = 3.48), which also demonstrates relatively high use. Planning and Decision-Making presents a moderate level of engagement (M = 3.11). Booking-related activities show a slightly lower mean value (M = 3.02), while the Transaction stage records the lowest engagement (M = 2.76) among the five stages. Together, these mean values provide an overview of how frequently respondents reported using TMAs across the different stages of the pre-travel process.

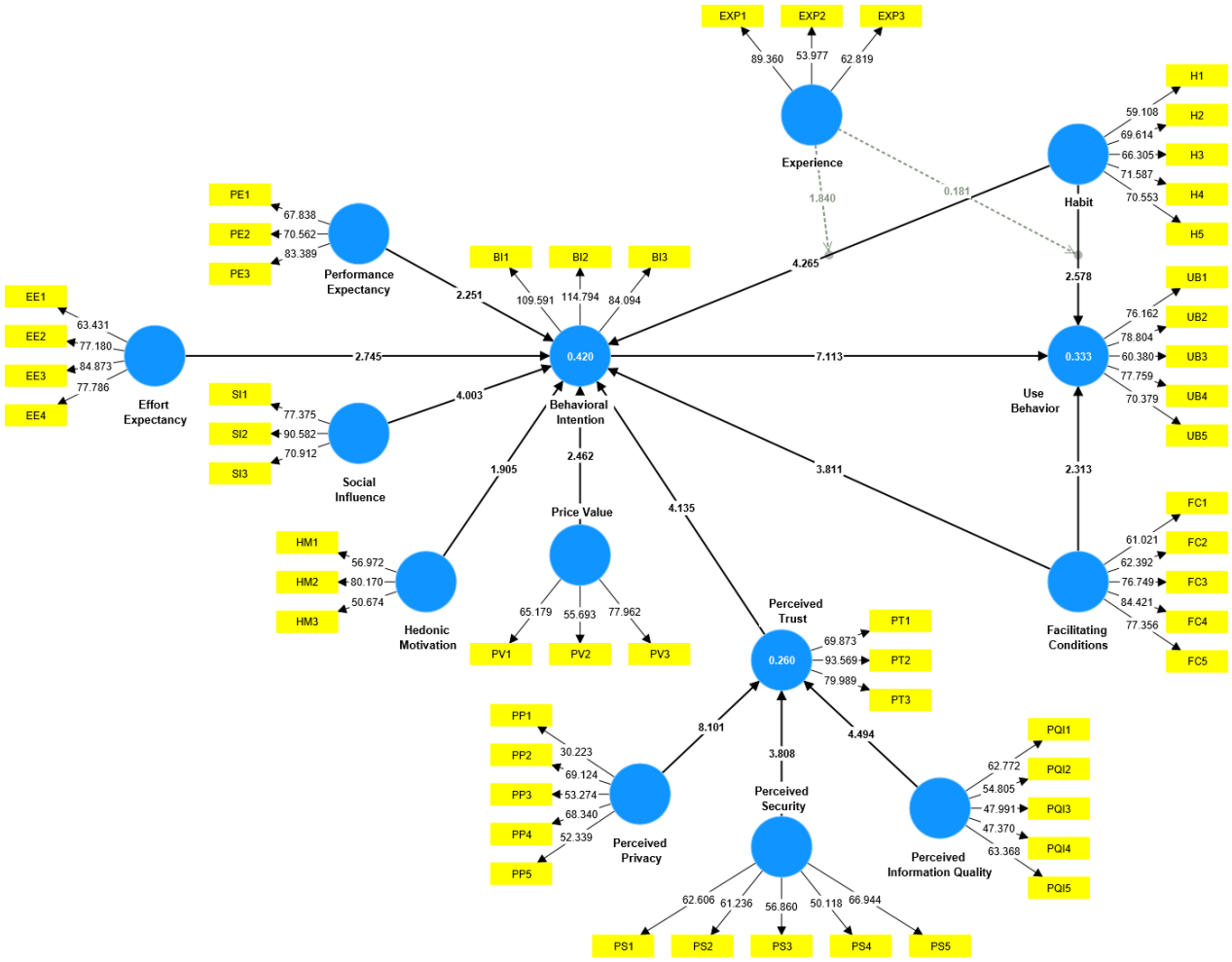
7.3 Structural model assessment

The structural model assessment is conducted to evaluate the hypothesized causal relationships among the latent constructs and to determine the predictive power of the model. Within the framework of partial least squares structural equation modeling (PLS-SEM), the structural model is primarily assessed through the magnitude and significance of the path coefficients (β), the explained variance of endogenous constructs (R^2 and adjusted R^2), effect sizes (f^2), and the examination of indirect (mediated) effects.

Bootstrapping with 5,000 resamples was employed in SmartPLS to estimate the significance of the path coefficients. This procedure generated t-values and p-values used to test the hypotheses and evaluate the statistical significance of the direct, indirect, and moderating effects in the structural model. To assess the model's explanatory power, the coefficient of determination (R^2) was calculated for each endogenous construct, indicating the proportion of variance explained by its predictors. Following Cohen's (1988) guidelines, R^2 values of 0.25, 0.50, and 0.75 were interpreted as representing weak, moderate, and substantial explanatory power. In addition, effect sizes (f^2) were computed to determine the contribution of each exogenous construct to its corresponding endogenous variable. These values were evaluated using the thresholds proposed by Cohen (1988), whereby $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ indicate small, medium, and large effects, respectively.

Figure 2 presents the structural model, illustrating the standardized path coefficients, R^2 values for endogenous constructs, and t-values obtained through bootstrapping with 5,000 resamples. The figure visually summarizes the strength and significance of hypothesized relationships between latent variables. R^2 values indicate the model's explanatory power, while the t-values assess the statistical significance of each path, providing support for hypothesis testing.

Figure 2: Structural Model with Standardized Path Coefficients (t-values) and R² Values.



Source: Author's own work

7.3.1 Hypotheses testing

The hypothesis testing results present the direct and indirect relationships specified in the proposed conceptual model. The direct effects correspond to the relationships linking the predictor constructs to the three endogenous variables–Perceived Trust, Behavioural Intention, and Use Behaviour–while the indirect effects reflect the mediated pathways operating through Perceived Trust and Behavioural Intention.

In regard to Behavioural Intention determinants, the structural model shows a positive and statistically significant path from Performance Expectancy to Behavioural Intention ($\beta = 0.097$, $t = 2.251$, $p = 0.024$). The effect size is small ($F^2 = 0.013$), but the relationship remains statistically significant within the model. Thus, H1, which states that Performance Expectancy positively influences tourists' intention to use TMAs during the pre-travel phase, is supported. In addition, there was a positive and statistically significant path from Effort

Expectancy to Behavioural Intention (β = 0.127, t = 2.745, p = 0.006). The effect size is small (F^2 = 0.019), but the relationship remains statistically significant, supporting H2, which proposes that Effort Expectancy positively influences tourists' intention to use TMAs during the pre-travel phase. Furthermore, the structural model indicates a positive and statistically significant effect of Social Influence on Behavioural Intention (β = 0.173, t = 4.003, p = 0.000), with a small effect size (F^2 = 0.039). Accordingly, H3, which states that Social Influence positively influences tourists' intention to use TMAs during the pre-travel phase, is supported. Likewise, Facilitating Conditions were found to have a positive and statistically significant impact on Behavioural Intention (β = 0.150, t = 3.811, p = 0.000), with a small effect size (F^2 = 0.031). Hence, H4a, which posits that Facilitating Conditions positively affect tourists' intention to use TMAs during the pre-travel phase, is supported.

The results also reveal that Hedonic Motivation has a positive, though marginally significant, effect on Behavioural Intention (β = 0.085, t = 1.905, p = 0.057). The effect size is small (F^2 = 0.009). Because the p-value falls slightly above the conventional 0.05 threshold but remains below the α = 0.10 level, the relationship is considered marginally supported. Thus, H5, which states that Hedonic Motivation positively influences tourists' intention to use TMAs during the pre-travel phase, is supported at the 10% significance level.

Moreover, Habit exhibits a positive and strongly significant influence on Behavioural Intention (β = 0.194, t = 4.265, p = 0.000), accompanied by a small-to-moderate effect size (F^2 = 0.047). Thus, H7a, which states that Habit positively influences tourists' intention to use TMAs during the pre-travel phase, is supported. Finally, Perceived Trust shows a positive and statistically significant path to Behavioural Intention (β = 0.175, t = 4.135, p = 0.000), with a small effect size (F^2 = 0.040). Consequently, H9, which states that Perceived Trust positively influences tourists' intention to use TMAs during the pre-travel stage, is supported.

In addition to the main determinants, the moderating effect of Experience × Habit on Behavioural Intention was examined. The interaction term shows a positive but marginally significant effect on Behavioural Intention (β = 0.073, t = 1.840, p = 0.066). Although the p-value exceeds the conventional 0.05 threshold, it falls within the acceptable range for marginal significance at the α = 0.10 level. The effect size is very small (F^2 = 0.008), indicating a limited influence. Nonetheless, the relationship meets the criteria for marginal support within the model. Therefore, H13a which states that Experience moderates the relationship between Habit and Behavioural Intention to use TMAs during pre-travel phase. is supported at the 10% significance level.

The coefficient of determination for the dependent variable Use Behavior shows values of R^2 = 0.333 and R^2adj = 0.325, indicating that about 33.3% of the variance in Use Behavior is explained by the variables Behavioral Intention, Facilitating Conditions, Habit, and the interaction effect of Experience × Habit. The closeness of the R^2 and R^2adj values demonstrates the stability of the model and the absence of overfitting.

For the dependent variable Behavioural Intention, the values of $R^2 = 0.420$ and $R^2adj = 0.405$ were obtained, indicating that about 42% of the variance in Behavioural Intention is explained by the variables Effort Expectancy, Facilitating Conditions, Habit, Hedonic Motivation, Perceived Trust, Performance Expectancy, Price Value, Social Influence, and the interaction effect of Experience × Habit. The closeness of the R^2 and R^2adj values demonstrates the stability of the model and the absence of overfitting.

Regarding the determinants of Perceived Trust, the structural model demonstrates a positive and statistically significant effect of Perceived Privacy on Perceived Trust ($\beta = 0.336$, $t = 8.101$, $p = 0.000$), with a moderate effect size ($F^2 = 0.133$). Thus, H10, which states that Perceived Privacy positively affects Perceived Trust in TMAs, is supported. In addition, Perceived Security shows a positive and statistically significant influence on Perceived Trust ($\beta = 0.147$, $t = 3.808$, $p = 0.000$), accompanied by a small effect size ($F^2 = 0.025$). Accordingly, H11, proposing that Perceived Security positively influences Perceived Trust in TMAs, is supported. Similarly, the structural model reveals a positive and statistically significant path from Perceived Information Quality to Perceived Trust ($\beta = 0.202$, $t = 4.494$, $p = 0.000$), with a small-to-moderate effect size ($F^2 = 0.048$). Therefore, H12, which states that Perceived Information Quality positively influences users' Perceived Trust in TMAs, is supported.

The coefficient of determination for the dependent variable Perceived Trust shows values of $R^2 = 0.260$ and $R^2adj = 0.255$, indicating that about 26% of the variance in Perceived Trust is explained by the variables Perceived Information Quality, Perceived Security, and Perceived Privacy. The closeness of the R^2 and R^2adj values demonstrates the stability of the model and the absence of overfitting.

Regarding the determinants of Use Behaviour, the structural model shows that Facilitating Conditions have a positive and statistically significant effect on Use Behaviour ($\beta = 0.104$, $t = 2.313$, $p = 0.000$), with a small effect size ($F^2 = 0.056$). Thus, H4b, which states that Facilitating Conditions have a positive effect on tourists' actual Use Behaviour of TMAs during the pre-travel phase, is supported. In addition, Habit has a positive and statistically significant effect on Use Behaviour ($\beta = 0.116$, $t = 2.578$, $p = 0.021$), accompanied by a small effect size ($F^2 = 0.020$). Therefore, H7b, which proposes that Habit positively affects tourists' actual usage behaviour of TMAs during the pre-travel phase, is supported. The structural model also shows a positive and statistically significant effect of Behavioural Intention on Use Behaviour ($\beta = 0.333$, $t = 7.113$, $p = 0.000$), with a small-to-moderate effect size ($F^2 = 0.119$). Accordingly, H8, which states that Behavioural Intention has a positive effect on tourists' use of TMAs during the pre-travel phase, is supported. Finally, the interaction term Experience × Habit shows no significant effect on Use Behaviour ($\beta = 0.007$, $t = 0.181$, $p = 0.856$), with a negligible effect size ($F^2 = 0.001$). Therefore, H13b, which posits that Experience moderates the relationship between Habit and actual Use Behaviour of TMAs during the pre-travel phase, is not supported.

The coefficient of determination for the dependent variable Use Behavior shows values of $R^2 = 0.333$ and $R^2adj = 0.325$, indicating that about 33.3% of the variance in Use Behavior is explained by the variables Behavioral Intention, Facilitating Conditions, Habit, and the interaction effect of Experience × Habit. The closeness of the R^2 and R^2adj values demonstrates the stability of the model and the absence of overfitting.

Regarding the indirect effects, the structural model shows that Facilitating Conditions have a positive and statistically significant indirect effect on Use Behaviour through Behavioural Intention ($\beta = 0.050$, $t = 3.229$, $p = 0.001$), and Effort Expectancy also demonstrates a significant indirect effect on Use Behaviour via Behavioural Intention ($\beta = 0.042$, $t = 2.487$, $p = 0.013$). Habit exhibits a positive and statistically significant indirect effect on Use Behaviour through Behavioural Intention ($\beta = 0.065$, $t = 3.809$, $p = 0.000$). In addition, Social Influence presents a significant indirect effect on Use Behaviour through Behavioural Intention ($\beta = 0.058$, $t = 3.452$, $p = 0.001$), while Perceived Trust similarly shows a positive and significant indirect effect on Use Behaviour through Behavioural Intention ($\beta = 0.058$, $t = 3.527$, $p = 0.000$). Hedonic Motivation has a positive but marginally significant indirect effect ($\beta = 0.028$, $t = 1.800$, $p = 0.072$), and Price Value demonstrates a positive and statistically significant indirect effect on Use Behaviour through Behavioural Intention ($\beta = 0.034$, $t = 2.259$, $p = 0.024$).

Furthermore, Perceived Security shows a positive and statistically significant sequential indirect effect on Use Behaviour through Perceived Trust and Behavioural Intention ($\beta = 0.009$, $t = 2.516$, $p = 0.012$). Performance Expectancy also shows a positive and significant indirect effect on Use Behaviour via Behavioural Intention ($\beta = 0.032$, $t = 2.130$, $p = 0.033$). In addition, Perceived Information Quality demonstrates a positive and statistically significant sequential indirect effect on Use Behaviour through Perceived Trust and Behavioural Intention ($\beta = 0.012$, $t = 2.638$, $p = 0.008$), and Perceived Privacy similarly presents a positive and statistically significant sequential indirect effect on Use Behaviour via Perceived Trust and Behavioural Intention ($\beta = 0.019$, $t = 3.168$, $p = 0.002$). All indirect paths in the model are supported.

In summary, the main predictors of Behavioural Intention, in order of importance, are Habit, Perceived Trust, and Social Influence, followed by Facilitating Conditions, Effort Expectancy, Price Value, and Performance Expectancy. Less influential predictors include Hedonic Motivation and the Experience × Habit interaction, both of which show only marginal support at the 10% significance level. For Perceived Trust, the three strongest antecedents are Perceived Privacy, Perceived Information Quality, and Perceived Security, all demonstrating significant effects. Regarding actual Use Behaviour, the most important predictors are Behavioural Intention, Habit, and Facilitating Conditions, while the moderating effect of Experience × Habit is not supported. The assessment of both the direct and indirect causal mechanisms within the proposed model shown in Table 10.

Table 10: Structural Equation Modelling (Hypothesis Testing)

	Hypothesis	**beta**	**t**	**P**	**R2**	**R^2_{adj}**	**F^2**	**Results**
direct effect	Behavioural Intention → Use Behaviour	0.333	7.113	0.000			0.119	Supported
	Facilitating Conditions → Use Behaviour	0.104	2.313	0.000			0.056	Supported
	Habit → Use Behaviour	0.116	2.578	0.021			0.02	Supported
	Experience x Habit → Use Behaviour	0.007	0.181	0.856	0.333	0.325	0.001	Not Supported
	Performance Expectancy → Behavioural Intention	0.097	2.251	0.024			0.013	Supported
	Effort Expectancy → Behavioural Intention	0.127	2.745	0.006			0.019	Supported
	Social Influence → Behavioural Intention	0.173	4.003	0.000			0.039	Supported
	Facilitating Conditions → Behavioural Intention	0.150	3.811	0.000			0.031	Supported
	Hedonic Motivation → Behavioural Intention	0.085	1.905	0.057			0.009	Supported
	Price Value → Behavioural Intention	0.102	2.462	0.014			0.014	Supported
	Habit → Behavioural Intention	0.194	4.265	0.000			0.047	Supported
	Perceived Trust → Behavioural Intention	0.175	4.135	0.000			0.04	Supported
	Experience x Habit → Behavioural Intention	0.073	1.840	0.066	0.42	0.405	0.008	Supported (marginal, α = 0.10)
	Perceived Information Quality → Perceived Trust	0.202	4.494	0.000			0.048	Supported
	Perceived Security → Perceived Trust	0.147	3.808	0.000			0.025	Supported
	Perceived Privacy → Perceived Trust	0.336	8.101	0.000	0.26	0.255	0.133	Supported
Indirect effect	Facilitating Conditions → Behavioural Intention → Use Behaviour	0.05	3.229	0.001				Supported
	Effort Expectancy → Behavioural Intention → Use Behaviour	0.042	2.487	0.013				Supported
	Habit → Behavioural Intention → Use Behaviour	0.065	3.809	0.000				Supported
	Social Influence → Behavioural Intention → Use Behaviour	0.058	3.452	0.001				Supported
	Perceived Trust → Behavioural Intention → Use Behaviour	0.058	3.527	0.000				Supported
	Hedonic Motivation → Behavioural Intention → Use Behaviour	0.028	1.800	0.072				Supported
	Price Value → Behavioural Intention → Use Behaviour	0.034	2.259	0.024				Supported
	Perceived Security → Perceived Trust → Behavioural Intention → Use Behaviour	0.009	2.516	0.012				Supported
	Performance Expectancy→ Behavioural Intention → Use Behaviour	0.032	2.130	0.033				Supported
	Perceived Information Quality → Perceived Trust → Behavioural Intention → Use Behaviour	0.012	2.638	0.008				Supported
	Perceived Privacy → Perceived Trust → Behavioural Intention → Use Behaviour	0.019	3.168	0.002				Supported

Source: Authors's own work

7.4 Control variables

To examine the potential influence of background characteristics, a set of demographics, temporal and situational variables were included as controls in the model. The purpose of including these variables was to assess whether adoption and use of travel-related mobile apps are systematically shaped by users' personal attributes or travel behaviours, beyond the theoretical constructs of the model. The results as shown in Table 11 indicate that, age (β = 0.007, t = 0.058, p = 0.954), education (β = –0.047, t = 1.008, p = 0.314), gender (β = 0.142, t = 0.820, p = 0.412), income (β = 0.043, t = 0.538, p = 0.591), and marital status (β = 0.020, t = 0.166, p = 0.868) had non-significant effects. When examined against Use Behaviour, most demographic variables also did not demonstrate significant effects. Education (β = –0.047, p = 0.314), gender (β = 0.042, p = 0.822), income (β = 0.065, p = 0.506), and marital status (β = –0.089, p = 0.504) were statistically insignificant. Age, however, displayed a marginally significant positive effect on Use Behaviour (β = 0.227, t = 1.649, p = 0.099).

The temporal control variables capture dimensions of respondents' travel behaviour. Trip duration did not significantly influence Use Behaviour (β = –0.160, t = 1.320, p = 0.187), suggesting that the length of an individual trip does not determine whether respondents use mobile apps. By contrast, the situational control variable number of trips per year showed a marginally significant positive effect on Use Behaviour (β = 0.214, t = 1.905, p = 0.057).

Table 11: Control Variables

Path	**beta**	**t**	**P**	**Results**
Age → Behavioural Intention	0.007	0.058	0.954	NS
Education → Use Behaviour	-0.047	1.008	0.314	NS
Gender → Use Behaviour	0.042	0.225	0.822	NS
Income → Use Behaviour	0.065	0.665	0.506	NS
Marital Status → Use Behaviour	-0.089	0.668	0.504	NS
Trip Duration → Use Behaviour	-0.16	1.32	0.187	NS
Trips per Year → Use Behaviour	0.214	1.905	0.057	Supported at P<0.1
Age → Use Behaviour	0.227	1.649	0.099	Supported at P<0.1
Gender → Behavioural Intention	0.142	0.82	0.412	NS
Income → Behavioural Intention	0.043	0.538	0.591	NS
Marital Status → Behavioural Intention	0.02	0.166	0.868	NS

Source: Author's own work

Overall, the control variable analysis shows that most demographic variables (gender, education, income, marital status) and the temporal variable trip duration do not significantly influence either Behavioural Intention or Use Behaviour. The only exceptions were two

marginally significant results: the demographic factor age and the temporal factor trips per year, both of which were positively associated with Use Behaviour.

7.5 Importance–Performance Matrix Analysis (IPMA)

This study applies Importance–Performance Matrix Analysis (IPMA), which extends the PLS-SEM results by examining both the importance (total effects) and performance (average normalised scores) of the predictor constructs. Importance values indicate each construct's total effect on the selected target variable, while performance values reflect the construct's rescaled latent variable scores on a 0–100 scale. The rationale for rescaling is that the original latent variable scores in PLS-SEM are typically standardised (mean = 0, variance = 1), which makes them difficult to interpret in terms of absolute performance. By transforming these standardised scores into a 0–100 metric, the performance of each construct can be meaningfully compared and interpreted alongside its importance (Ringle et al., 2015).

The IPMA output positions constructs within a two-dimensional matrix comprising four quadrants: (1) high importance–low performance, (2) high importance–high performance, (3) low importance–low performance, and (4) low importance–high performance. In this study, 2 IPMAs were conducted for the dependent variables Behavioural Intention and Use Behaviour to identify predictor constructs that, beyond being statistically significant, also demonstrate relatively lower performance levels. These constructs represent priority areas for improvement and inform the managerial recommendations presented in the concluding section of this research.

7.5.1 Importance–Performance Matrix Analysis (IPMA)– Behavioural Intention

The constructs with the highest importance for Behavioural Intention are Habit (importance = 0.194), Perceived Trust (importance = 0.175), Social Influence (importance = 0.173), Facilitating Conditions (importance = 0.150), Effort Expectancy (importance = 0.127), Price Value (importance = 0.102), and Performance Expectancy (importance = 0.097). These factors can be categorized as high-importance constructs, indicating that both behavioral reinforcement (Habit), trust-related perceptions, social dynamics, and enabling conditions play a critical role in shaping users' intention to adopt travel-related mobile applications.

In contrast, Hedonic Motivation (importance = 0.085), Experience (importance = 0.067), Perceived Privacy (importance = 0.059), Perceived Information Quality (importance = 0.035), and Perceived Security (importance = 0.026) fall into the low-importance category. These results suggest that while experiential and informational factors contribute to the model, they exert a comparatively weaker influence on Behavioural Intention in this context. Overall, the findings emphasize that habitual behavior, trust, and social and infrastructural enablers are more decisive than purely cognitive or affective evaluations in driving user adoption.

The constructs with the highest performance for Behavioural Intention are Perceived Privacy (performance = 72.617), Experience (performance = 65.434), Perceived Information Quality (performance = 65.399), Habit (performance = 62.958), Perceived Security (performance = 61.437), Effort Expectancy (performance = 61.262), and Hedonic Motivation (performance = 60.884). These factors can be categorized as high-performance constructs (performance > 60), indicating that users evaluate these dimensions positively in the context of TMAs.

In contrast, Price Value (performance = 59.782), Perceived Trust (performance = 57.812), Social Influence (performance = 56.156), Facilitating Conditions (performance = 54.457), and Performance Expectancy (performance = 47.316) fall into the slightly lower performance category.

Together, these results provide a picture of the relative strengths and weaknesses in influencing Behavioural Intention. Table 12 presents the IPMA results, and Figure 3 illustrates the corresponding IPMA map for Behavioural Intention.

Table 12: Results of the Importance–Performance Matrix Analysis (IPMA)- Behavioural Intention

Constructs	**Importance**	**Performance**
Effort Expectancy	0.127	61.262
Experience	0.067	65.434
Facilitating Conditions	0.15	54.457
Habit	0.194	62.958
Hedonic Motivation	0.085	60.884
Perceived Information Quality	0.035	65.399
Perceived Security	0.026	61.437
Perceived Trust	0.175	57.812
Perceived Privacy	0.059	72.617
Performance Expectancy	0.097	47.316
Price Value	0.102	59.782
Social Influence	0.173	56.156

Source: Author's own work

Figure 3: Importance–Performance Map (IPMA) for Behavioural Intention



Source: Author's own work

7.5.2 Importance–Performance Matrix Analysis (IPMA)–Use Behaviour

The results combine the importance of each construct (total effects on Use Behaviour) with their performance (average rescaled construct scores from 0 to 100), offering a dual perspective on which factors most strongly drive Use Behaviour and how well they are currently performing.

The constructs with the highest importance for Use Behaviour are Behavioural Intention (importance = 0.333), Experience (importance = 0.199), and Habit (importance = 0.181). Together, these variables represent the most influential predictors of actual system use. Facilitating Conditions (importance = 0.153) also demonstrates high importance.

Constructs with moderate to low importance include Effort Expectancy (importance = 0.042), Performance Expectancy (importance = 0.032), Price Value (importance = 0.034), Perceived Trust (importance = 0.058), and Social Influence (importance = 0.058). Among these, Performance Expectancy is particularly notable: despite its relatively low importance, it records the lowest performance score across all constructs (47.32).

From performance perspective, Perceived Privacy (performance= 72.62), Perceived information quality (performance = 65.40) and Perceived Security (performance= 61.44),

Effort Expectancy (performance= 61.26), and Hedonic Motivation (performance= 61.00) record above-average performance. These results suggest that users perceive these aspects positively, but they do not substantially influence actual system use.

Overall, the IPMA results for Use Behaviour show that Behavioural Intention, Experience, Habit, and Facilitating Conditions have the highest importance values. Behavioural Intention records the strongest total effect but only moderate performance, while Experience combines high importance with comparatively strong performance. Facilitating Conditions and Habit also demonstrate high importance with moderate performance levels. Performance Expectancy shows relatively low importance and the lowest performance score among all constructs. Perceived Privacy, Perceived Information Quality, and Perceived Security exhibit high performance but low importance for Use Behaviour. Table 13 presents the IPMA results, and Figure 4 illustrates the corresponding IPMA map for Use Behaviour.

Table 13: *Results of the Importance–Performance Matrix Analysis (IPMA)- Use Behaviour*

Constructs	**Importance**	**Performance**
Behavioral Intention	0.333	53.354
Effort Expectancy	0.042	61.262
Experience	0.199	65.434
Facilitating Conditions	0.153	54.457
Habit	0.181	62.958
Hedonic Motivation	0.028	60.884
Perceived Information Quality	0.012	65.399
Perceived Security	0.009	61.437
Perceived Trust	0.058	57.812
Perceived Privacy	0.019	72.617
Performance Expectancy	0.032	47.316
Price Value	0.034	59.782
Social Influence	0.058	56.156

Source: Author's own work

Figure 4: Importance–Performance Map (IPMA) for Use Behaviour



Source: Author's own work

8 DISCUSSION

The purpose of this chapter is to synthesize and interpret the empirical findings presented in the previous chapter. This thesis investigated the acceptance and use of TMAs during the pre–travel phase, with a particular focus on developing–country context. Building on the UTAUT2, the study employs the extended model by incorporating Perceived Trust, grounded in its three antecedents: Perceived Privacy, Perceived Security, and Perceived Information Quality as well as the moderating role of prior user Experience. The following section, while addressing the research objectives and questions, connects the findings to the existing literature.

8.1 Direct effects on Behavioural Intention, Perceived Trust and Use Behaviour

8.1.1 Behavioural Intention

users' Behavioural Intention to use TMAs is affected by Habit emerged as the strongest determinant. This indicates that, repeated use fosters automatic behaviour, consistent with Venkatesh et al. (2012). These results align closely with prior research in tourism and technology contexts, which consistently identify Habit as a dominant predictor of technology adoption intentions. For instance, Sia et al. (2024) have empirically confirmed that Habit is a significant predictor of intention to use a smart mobile tourism app.

Perceived Trust was the next most influential factor on Behavioural Intention, revealing that users' confidence in data protection, security, and reliability strengthens their intention to use TMAs. It is consistent with the findings of Tran and Vu (2024), who emphasize that Trust is a central determinant of users' intention to use TMAs, where Trust emerges as one of the strongest predictors of Behavioural Intention, driven largely by users' perceptions of service reliability, secure transactions, and consistent quality. in this collectivist culture, where social norms and Trust heavily shape user decisions (Esfandiar et al., 2023)

Social Influence has the next significant positive effect on users' Behavioural Intention to use TMAs. This result aligns with prior research showing that Social Influence strongly affects tourists' intention to adopt tourism–related technologies and that normative pressures from one's social environment positively shape the intention to use smart tourism technologies, underscoring the importance of social context in technology acceptance within the tourism domain (Calderón–Fajardo et al., 202; Nathan et al., 2020). In tourism, where travel decisions are often socially driven and shaped by shared experiences (Oliveira et al., 2020), Social Influence plays a crucial role in shaping users' attitudes and their intention to use TMAs. Moreover, Social Influence is particularly important in collectivist cultures, where strong social norms and the emphasis on group harmony heavily influence user decision–making processes (Esfandiar et al., 2023)–within these contexts, individuals often rely heavily on the recommendations and feedback of Trusted peers or community members,

leading to a strong reliance on word–of–mouth dynamics in collectivist societies to build essential interpersonal Trust.

Facilitating Conditions statistically significant and positive relationship with Behavioural Intention suggests that when users perceive adequate technical resources, reliable internet access, and sufficient support whether through app design, device capability, or service infrastructure; they are more inclined to adopt TMAs. This result aligns with earlier evidence that Facilitating Conditions are a meaningful antecedent of intention to use tourism technologies (Kamboj & Joshi, 2021). It is also consistent with more specific research on tourists' acceptance of AI–enhanced tour–guide applications, where the availability of supportive technical infrastructure significantly strengthened usage intention (Foroughi et al., 2025).

Effort Expectancy showed a significant yet modest positive effect on Behavioural Intention, indicating that perceived ease of use contributes to adoption decisions. Similar patterns have been reported in tourism technology contexts: Calderón–Fajardo et al. (2023) identified perceived ease of use as a key determinant of adopting augmented–reality and virtual–reality experiences, while Nathan et al. (2020) likewise showed that tourists' use of the Airbnb app was strongly linked to perceptions of ease of use. These converging results suggest that streamlined interfaces, intuitive navigation, and clear instructions are critical for encouraging users to integrate mobile apps into their pre–travel.

Price Value had a positive and statistically significant impact on Behavioural Intention. This suggests that users who perceived greater economic benefits from using TMAs such as savings on bookings, access to exclusive deals, or reduced transaction costs are more likely to use them. Although many such apps are free to download, the construct remains relevant through the lens of perceived price–saving. Prior studies showed that perceived economic advantage can drive technology use even when no direct fee is involved (Khalilzadeh et al. 2017). Tak et al. (2016) identify price value a significant predictor of purchase intention in mobile apps. These findings support the notion that perceived economic benefit, rather than direct cost, plays a pivotal role in shaping users intentions to adopt mobile apps during the pre–travel stage.

Performance Expectancy exerted a statistically significant but modest influence on Behavioural Intention. This indicates that tourists are more likely to use TMAs when they perceive them as useful for enhancing efficiency and improving travel–related outcomes. Prior studies similarly emphasize the role of Performance Expectancy in shaping adoption across tourism technologies, including mobile payments in hotels (Morosan & DeFranco, 2016), online travel shopping platforms (Amaro & Duarte, 2013), and mobile tourism apps (Lai, 2015; Tan et al., 2017), identified as tourists' beliefs about the usefulness, ease of use, time–saving potential, and overall effectiveness of such technologies in enhancing their travel planning and decision–making processes (Gupta & Dogra, 2017; Tran & Vu, 2024). The current finding aligns with this literature, confirming that perceived usefulness remains

a central factor in driving Behavioural Intention, even if its effect is more modest compared to other predictors such as Social Influence or Habit.

Hedonic Motivation showed a positive, though statistically non–significant, effect on Behavioural Intention. This suggests that enjoyment and fun derived from using TMAs may still contribute to shaping users' adoption intentions, even if the influence was not strong in this context. Prior studies highlight Hedonic Motivation as an important driver of technology use in tourism, including travel apps (Tran & Vu, 2024; Palos–Sanchez et al., 2021), online hotel booking systems (Chang et al., 2019), and restaurant apps (Palau–Saumell et al., 2019), ChatGPT for travel planning (Foroughi et al., 2025). The positive trend observed here is consistent with these earlier findings; however, the weaker effect suggests that, for Iranian users, hedonic aspects may play a complementary rather than dominant role, with the functional and utilitarian benefits of TMAs carrying greater weight in shaping intention.

The study reveals a marginal interaction between Experience and Habit, suggesting that more experienced users may show a slightly stronger link between Habit and Behavioural Intention. Prior studies have also noted that the moderating role of Experience on intention is generally weak or non–significant (Chang et al., 2019), which is consistent with the limited effect observed here. While modest, this result still provides theoretical insight that Experience may subtly reinforce Habit by fostering familiarity and reducing cognitive effort.

8.1.2 Perceived Trust

Perceived Privacy demonstrated a strong and statistically significant positive effect on Perceived Trust. This finding suggests that when TMAs signalize acceptable data protection and adherence to privacy standards, users are more likely to develop Perceived Trust in the application. The prevailing role of privacy as an antecedent of Trust is consistently replicated in digital tourism contexts (Zhou & Li, 2014). Specifically, privacy concerns about how personal information is accessed, used, and stored by service providers play a crucial role in shaping tourists' Trust perceptions (Ooi et al., 2018; Zhou & Li, 2014).

Perceived Security has a positive and statistically significant effect on Perceived Trust. This finding indicates that users who feel confident in the technical safeguards and protection mechanisms of a TMA are more likely to Trust them. Well–stablished security perceptions such as confidence in encryption, secure payment processing, and protection against unauthorized access, reduce perceived risk and strengthen users' confidence in the app's reliability. This result aligns with prior research highlighting security as a key antecedent of Trust in digital contexts (Hartono et al., 2014). Liu et al. (2025) further validate this relationship in the context of TMAs, demonstrating that Perceived Security has a direct and significant influence on tourists' Trust perceptions.

Perceived Information Quality showed a positive and statistically significant effect on Perceived Trust. This finding indicates that when users view the content and the information

provided in TMAs as accurate, up–to–date, complete, and reliable, their Perceived Trust in the app increases accordingly. This result aligns with prior research in e–commerce and tourism technology, which consistently reports that Information Quality is a key antecedent of user Trust (e.g., Hartono et al., 2014; Kim et al., 2008).

8.1.3 Use Behaviour

Behavioural Intention has the strongest positive and statistically significant impact on Use Behaviour. This finding underscores a central premise of the UTAUT2 framework i.e. users who firmly intend to use TMAs are the most likely to engage in actual usage during the pre–travel phase. This result is fully consistent with prior UTAUT2 research across tourism and broader technology–adoption contexts, which repeatedly identifies Behavioural Intention as the primary determinant of technology use (e.g., Gupta, 2017; Venkatesh et al., 2012).

Habit has a positive and statistically significant impact on Use Behaviour. This indicates that when interacting with similar apps has become routine, users continue using them almost automatically, with little need for conscious deliberation during the pre–travel stage. The result underscores the power of behavioural automaticity in technology adoption and is consistent with prior tourism research showing that Habit is one of the most robust determinants of technology use (Gupta, 2017).

Moreover, the hypothesized moderating effect of experience on the relationship between Habit and Use Behaviour was not supported. This suggests that the positive impact of Habit on actual usage remains stable regardless of how much prior experience users have with TMAs. In other words, once use becomes Habitual, additional experience does not significantly strengthen or weaken the direct Habit–use link. The literature reports mixed evidence regarding the moderating role of experience in the relationship between Habit and actual technology use. Some studies confirm a significant moderating effect (e.g., Chang et al., 2019), whereas others find no significant effect (e.g., Nikolopoulou et al., 2021). The rejection of the moderation effects proposed in the original UTAUT model may be attributable to contextual and cultural differences (Nikolopoulou et al., 2021).

Facilitating Conditions showed a positive and statistically significant influence on users' Use Behaviour of TMAs. This indicates that when users perceive adequate technical resources, they are more likely to practically engage with these apps during the pre–travel stage. This finding is consistent with previous research highlighting that the availability of infrastructure and support is a critical enabler of actual technology use in tourism contexts (Foroughi et al., 2025).

8.2 Indirect effects on Use Behaviour

Habit exhibited a statistically significant indirect association with Use Behaviour also through its influence on Behavioural Intention. Similarly, Social Influence and Perceived Trust demonstrate indirect effects via Behavioural Intention. Constructs such as Facilitating Conditions, Effort Expectancy, and Performance Expectancy indicate that external support structures and system usability are meaningful predictors of intention formation. Price Value also appears as a relevant antecedent within this framework. Moreover, Perceived Trust serves as a mediating construct in more complex pathways, where Perceived Privacy, Perceived Information Quality, and Perceived Security first influence Perceived Trust, which subsequently impacts Behavioural Intention and Use Behaviour. The indirect effects revealed that these factors can exert meaningful influence on behavioural outcomes even when it does not have a direct path to the dependent variable. This supports the inclusion of mediating variables in models analysing user behaviour and aligns with the structural assumptions of frameworks such as UTAUT2 (e.g., Venkatesh et al., 2012).

Although the modelling of Use Behaviour as a single latent construct within the structural framework is acknowledged, this section provides an interpretive discussion of its indicators across the pre–travel stages to offer contextual insight.

Use Behaviour with its five indicators (UB1–UB5) were intentionally designed to reflect the interconnected stages of the pre–travel phase: dreaming, planning, booking, transaction, and expectation formation. The objective was to understand the level of interaction of users with TMAs during each stage of the pre–travel through the obtained Mean scores. While the identified positive and statistically significant factors apply to the overall pre–travel phase, the following stage–level interpretation, supported by existing literature, extends these factors to each individual stage for contextual understanding.

The Dreaming stage, as the potential travellers seek inspiration and begin to imagine possible destinations or travel experiences (Dai et al., 2025), TMAs play a central role in exposing users to ideas, images, and content that spark interest and shape early intentions. According to the findings of this study, Social Influence was confirmed to significantly predict Behavioural Intention (direct) and subsequently affect Use Behaviour (indirect) via Behavioural Intention. This finding aligns with prior studies that highlight the importance of peer recommendations, reviews, user–generated content (UGC) such as reviews, ratings and social networks in shaping tourists' early–stage decision–making (Sepehri & Gholinejad Pirbazari, 2021; Jalilvand & Samiei, 2012; Wang et al., 2012). In collectivist cultural settings, where social norms and community opinions carry significant weight (Esfandiar et al., 2023), this result is particularly relevant.

The study also revealed that Habit strongly influences behavioral intention and has a significant effect on actual Use Behavior. This underscores the Habitual nature of app use at the inspiration stage. Previous research has shown that repeated exposure to mobile apps

fosters automatic usage patterns, lowering cognitive effort in seeking travel–related content (Limayem et al., 2007). For many Iranian users, where digital engagement is already embedded in daily life (Koohikamali et al., 2024), Habitual browsing of travel–related apps may serve as a natural trigger for inspiration, reinforcing app reliance in the early stages of trip planning.

Perceived Trust has been shown to play an indispensable role in shaping Behavioural Intention and, subsequently, use behaviour during the pre–travel phase. In the dreaming stage, Perceived Trust significantly influences whether users continue to engage with the app or abandon it in favour of alternative platforms (Dang, 2024). Users are particularly sensitive to Quality of Information in terms of visual credibility, the reliability of travel narratives, and the integrity of content sources such as destination overviews, travel blogs, or shared photos (Pop et al., 2022).

The planning stage, as travellers engage in detailed decision–making, evaluate alternatives, and organize trip logistics and rely on TMAs (Backhaus et al., 2022), Effort Expectancy and Performance Expectancy play a crucial role in shaping Behavioural Intention and subsequently use behaviour. This finding is consistent with prior research indicating that perceived simplicity and low cognitive effort enhance adoption in information–intensive stages such as travel planning (Morosan & DeFranco, 2016; Venkatesh et al., 2012). Application design, service quality, and ease of use foster positive emotions and influence travellers' decisions (Rahardja et al., 2023)– particularly in context of Iranian users, digital literacy may vary, the ability to plan with minimal effort further strengthens intention to use TMAs during this stage.

In addition, Performance Expectancy indicates that when users believe TMAs will enhance their efficiency and help them achieve better travel outcomes, they are more likely to develop strong Behavioural Intentions to use TMAs during the planning stage. The role of Performance Expectancy at the planning stage aligns with studies that highlight the utilitarian value of digital tools in tourism contexts, where accurate, comprehensive, and timely information reduces uncertainty (Escobar–Rodríguez & Carvajal–Trujillo, 2014).

At this stage, Trust in the authenticity and transparency of both the platform and its content increases emotional engagement while lowering perceived risk (Pop et al., 2022). When users perceive the information as accurate, neutral, and reliable, it enhances their sense of control, reduces decision–related stress, and leads to greater satisfaction with their chosen plans (Chatzigeorgiou & Christou, 2020).

The booking stage, which is considered one of the most critical transitions from consideration to commitment (Vaz et al., 2024), Price Value plays an important role in shaping Behavioural Intention and subsequently Use Behaviour. At this stage, price sensitivity increases and perceptions of economic benefit become particularly influential (Hemantha, 2025; Zhu et al., 2024). Users who believe that for booking platforms such as a

mobile apps helps them secure lower prices, access exclusive deals, or reduce transaction costs are more inclined to finalize their reservations through the app rather than switch to competing platforms (Pérez–Ricardo & García–Mestanza, 2025). This aligns with the earlier finding that price value significantly enhances behavioral intention, demonstrating that perceived savings motivate not only initial planning but also the actual act of booking (Chen et al., 2022).

The analysis also revealed that Facilitating Conditions predict Behavioural Intention and Use Behaviour, suggesting that when users perceive sufficient resources, infrastructure, and technical support, they are more likely to rely on TMAs for planning activities. Hameed et al. (2025) identified barriers such as technological unfamiliarity and lack of perceived need, which restrict adoption in certain populations. In developing–country contexts, where barriers such as inconsistent internet connectivity may exist (Nirmani, 2025), Facilitating Conditions become especially relevant.

In regard to Perceived Trust in booking stage, according to different studies, when Perceived Trust is low at this stage, users may hesitate, postpone, or abandon bookings altogether (Chouykaew et al., 2024), whereas high perceived Trust encourages decisiveness, platform loyalty, and reduced verification behaviour (Dang, 2024). In the hospitality sector, consumers' willingness to make reservations is strongly influenced by the level of Trust they place in the platform (Wang et al., 2024), which is formed through the reliability and transparency of information as well as users' confidence in the platform's privacy and security mechanisms that together sustain engagement within TMAs.

The transaction stage represents the financial completion of booked services where users are required to share sensitive personal and financial information such as names, contact details, credit card numbers, and, in some cases, passport data (Gupta et al., 2018), and at this stage Perceived Trust becomes essential as users' willingness to proceed depends on their confidence in the platform's ability to protect their information and ensure a secure exchange. Descriptive statistics reveal that the Transaction stage records the lowest mean among the five pre–travel stages, indicating comparatively less user engagement in completing monetary exchanges through TMAs and significant Trust gaps specifically related to financial security. This reluctancy to finalize monetary exchanges can stem from perceived risks such as payment-security concerns, lack of Trust in vendors, or limited availability of preferred payment methods (Xu & Lu, 2019). This suggests that infrastructural or cultural barriers surrounding online payments may play a role. Users may prefer offline methods, bank transfers, or third–party payment channels due to concerns about fraud, lack of recourse mechanisms, or limited integration with local financial systems. Similar findings in the mobile commerce literature have shown that transaction reluctance is common in markets where institutional protections are perceived as weak (Slade et al., 2015).

The Expectation Formation stage, often associated with anticipatory feeling which involves a complex integration of cognitive, emotional, and physiological processes that prepare individuals for future events (Stefanova et al., 2020). The results suggest that enjoyment and excitement play a limited yet notable role in shaping users' intention to use TMAs. This partially aligns with prior research emphasizing that anticipation and emotional engagement are central to pre–travel experiences, with digital tools enhancing the affective dimension of travel planning (Kim & Fesenmaier, 2017; Wang et al., 2012). For users of this study, this may reflect a growing interest in TMAs not only as functional planning tools but also as spaces for emotional engagement and entertainment.

Results reveal a significant relationship between Perceived Information Quality and Perceived Trust, suggesting that high–quality, Trustworthy, and comprehensive information substantially increases users' confidence in the platform also at this stage. Digital mechanisms such as user–generated content, influencer narratives, and real–time updates heighten information quality, co–creating vivid destination images and enriching anticipatory feelings (Delone & McLean, 2003; Gretzel & Yoo, 2008; Lam et al., 2020; Wixom & Todd, 2005; Xiang & Gretzel, 2010;).

8.3 Role of demographic, temporal, and situational factors

In line with technology adoption literature (e.g. Jacob et al., 2022; Li et al., 2008) the analysis of control variables in this study confirms that demographic and basic travel characteristics play only a peripheral role in explaining travel–app adoption and use, reinforcing the primacy of the theoretical constructs in the model. Neither gender, education, income, nor marital status exerted meaningful influence on Behavioral Intention or Use Behavior, and trip duration was similarly irrelevant. Only two factors of age and travel frequency showed marginal, positive links to actual use, suggesting that more experienced or Habitual users may draw slightly greater utility from mobile apps. A plausible explanation could be that the distribution of participants had already attained a baseline level of digital literacy and app familiarity, thereby minimizing the variation typically associated with sociodemographic factors. In other words, the sample may reflect a digitally engaged population for whom travel–app usage is normalized, thus attenuating the predictive value of age, income, or education. This aligns with recent shifts in digital behavior, where technology use increasingly transcends traditional demographic boundaries (Venkatesh et al., 2012).

8.4 Importance–Performance Matrix Analysis (IPMA)

The IPMA findings can be meaningfully interpreted in light of the Iranian context, where structural, cultural, and technological conditions shape technology adoption behaviour. More specifically, the results suggest that, in a developing and infrastructurally constrained environment, adoption is not driven solely by individual perceptions of technology, but also by external conditions that influence the feasibility, reliability, and continuity of use.

For Behavioral Intention, the relatively weaker performance of facilitating conditions reflects persistent infrastructural and environmental constraints, such as unstable connectivity, limited technological resources, and broader systemic limitations observed in the Iranian context (Kazemi & Amini, 2024; Nafchi & Mohelska, 2018). These findings indicate that even when users are willing to adopt mobile applications, external barriers may still hinder effective engagement. This reinforces the argument that in developing-country contexts, adoption depends not only on users' internal evaluations, but also on the availability and reliability of the surrounding support infrastructure (Sepehri & Gholinejad Pirbazari, 2021). Therefore, reducing external friction remains a central area for improvement.

The comparatively lower performance of perceived trust can likewise be interpreted in relation to security concerns, institutional uncertainty, and the absence of standardised governance frameworks in the Iranian digital environment (Mollajafari, 2018). In this respect, trust appears to be especially salient in contexts where users must rely on digitally mediated transactions under conditions of greater uncertainty. Strengthening trust, therefore, requires not only technical safeguards, but also transparent communication, platform credibility, and visible assurances regarding reliability and security.

The strong importance of social influence is also consistent with the collectivistic nature of Iranian society, where individuals tend to rely on peer recommendations, shared experiences, and social norms in shaping their decisions (Hofstede, 2001; Tavakoli & Tavakoli, 2010). This suggests that adoption behaviour is socially embedded and can be reinforced through community-based mechanisms, interpersonal recommendations, and broader social validation.

At the same time, the relatively weaker perception of functional value suggests that Iranian users may not fully recognise the practical benefits of travel-related mobile applications. This aligns with prior research on perceived usefulness and system compatibility in Iranian context, which emphasises that adoption depends on the extent to which technologies are seen as relevant to users' needs, routines, and lifestyles (Mohammadi, 2015). Similarly, somewhat lower perceptions of price value indicate sensitivity to cost–benefit trade-offs in this context (Mollajafari, 2018), suggesting that users may still evaluate the applications in terms of economic benefit and perceived worth.

For Use Behavior, the findings reveal that actual usage is shaped by both behavioral reinforcement and contextual constraints. The continued importance of facilitating conditions indicates that infrastructural and environmental factors remain critical not only for intention but also for actual use, reinforcing the need to ensure reliable access, system support, and reduced technical barriers. This supports prior research emphasizing the role of external conditions in enabling sustained technology use in developing-country contexts (Nafchi & Mohelska, 2018).

At the same time, strong performance in experience and habitual usage suggests that once users engage with TMAs, they tend to report positive interactions and continued use. This indicates that retention mechanisms are relatively effective, and that users are capable of integrating these applications into their routines. This is consistent with prior UTAUT2-based research in the Iranian context, which demonstrates that habit exerts a significant positive effect on technology adoption intention, indicating that repeated use and accumulated experience reinforce behavioural engagement with digital platforms (Farzin et al., 2021).

Taken together, these findings indicate that improving Use Behavior requires reducing friction in the user journey and strengthening the link between intention and action, while maintaining positive user experience and reinforcing habitual engagement. At the same time, resources should remain focused on addressing key structural barriers, rather than overinvesting in already well-performing aspects.

This thesis addressed the six research questions posited in Chapter 1 on TMA acceptance and use in the specific pre–travel phase, while integrating the novel construct of perceived Trust into the UTAUT2 framework, examining the moderating role of prior experience, and considering the unique contextual factors inherent in a developing–country market. The key answers to these questions are summarized below.

Concerning RQ1, the study defined the pre–travel phase as comprising five none–linear but interconnected stages: dreaming, planning and decision–making, booking, transaction, and expectation formation. This stage–based framework was developed to capture the full spectrum of user engagement with TMAs prior to departure. Each stage reflects a different cognitive and behavioral process, ranging from initial inspiration and idea generation (dreaming), to evaluating and selecting travel options (planning and decision–making), followed by the execution of reservations (booking), the completion of sensitive and high–risk actions such as payment (transaction), and finally, the mental preparation and anticipation of the trip (expectation formation). This view acknowledges that users interact with TMAs not as a one–off decision but as part of a dynamic, multi–stage journey, with different psychological needs, risk perceptions, and decision drivers at each point.

Concerning RQ2, the findings revealed that Perceived Trust, Habit, And Social Influence emerged as the most significant predictors of Behavioral Intention to adopt TMAs. These results underscore the critical role of psychological assurance and social validation in encouraging users to engage with digital travel tools, particularly in a context such as Iran where collectivist cultural norms amplify the influence of peers, family, and social networks. Habit was shown to be especially powerful, indicating that once users develop routines around app usage, their intention to continue is reinforced automatically, even in the absence of additional incentives. This aligns with the broader behavioral literature, which suggests that technology usage often becomes embedded in daily life through repetition and familiarity. When examining Use Behavior, the findings showed that behavioral intention

itself was the strongest predictor of actual app usage, aligning with UTAUT2's core assumption that intention is a key antecedent to behavior. However, Habit, experience, and Facilitating Conditions also played important roles in determining whether users followed through with actual engagement.

Concerning RQ3, extending the UTAUT2 model with Perceived Trust significantly improved its ability to explain behavioral intention. Trust was defined through three key dimensions–perceived privacy, security, and information quality– each showing a significant positive effect on intention to use TMAs. These findings highlight that beyond usability and performance, users are deeply concerned with how their data is protected, the safety of transactions, and the reliability of app content. Notably, the importance of security was reinforced by the low performance in the transaction stage, where users are most sensitive to risk. Overall, the results confirm that Trust is a critical, multidimensional factor in technology adoption, especially in contexts involving sensitive information and financial exchanges.

Concerning RQ4, the Iranian context significantly shaped adoption patterns. Social Influence reflected the country's collectivist culture, where decisions are strongly guided by family, peers, and social networks. Meanwhile, Facilitating Conditions revealed ongoing infrastructural challenges, including unreliable internet, restricted payment systems, and gaps in digital literacy. These findings underscore that mobile app adoption is not just a matter of individual preference but is deeply influenced by cultural norms and structural limitations. As a result, even well–designed apps may struggle to gain traction if broader environmental barriers are not addressed. This highlights the need for context–sensitive strategies that combine technology design with policy interventions and infrastructure development.

Concerning RQ5, the moderating role of prior experience was not supported by the data. This suggests that Habitual use of TMAs is more likely to emerge through repeated interaction and positive reinforcement than from previous exposure alone. In other words, users do not necessarily need extensive past experience to develop strong behavioral intentions or usage patterns. This finding challenges the common assumption that experienced users are inherently more inclined to adopt or persist in using digital tools. It also underscores the importance of designing onboarding processes and early user experiences that can quickly foster familiarity and routine, even among first–time users.

Finally, regarding RQ6, the study emphasized that strengthening adoption requires TMAs that build Trust, promote usability, and embed social features, supported by policies that improve digital infrastructure and consumer protection mechanisms. This multi–layered approach highlights the interdependence between app design, user behavior, and the broader regulatory environment. Effective adoption strategies must therefore go beyond technical improvements to also address psychological Trust–building and systemic support structures.

Ensuring alignment across these levels can significantly enhance user engagement and long–term adoption, particularly in developing–country contexts.

8.5 Implications and limitations

This chapter discusses the implications and limitations of the study regarding TMAs acceptance and use. It outlines the theoretical, managerial, and policy insights derived from the findings, acknowledges the study's limitations, and proposes directions for future research.

8.5.1 Theoretical implications

The first theoretical contribution of this study lies in the application and structural extension of the UTAUT2 model with Perceived Trust as a core determinant of behavioral intention in the novel context of TMAs acceptanc and use. While the UTAUT2 model is widely applied across various technology adoption domains, its ability to explain behavioral intention has been repeatedly challenged in contexts where issues of privacy, security, and reliability are highly salient–particularly within digital tourism environments (Venkatesh et al., 2012). Although Escobar–Rodríguez and Carvajal–Trujillo (2014) previously extended the UTAUT2 model by incorporating Perceived Trust to explain online purchasing behavior on low–cost carrier (LCC) websites, their focus remained on transactional platforms for procurement. This study addresses a significant gap by investigating how Perceived Trust influences TMA acceptance and use during the pre-travel phase, which is multifaceted and shaped profoundly by exploratory, information-driven interactions.

The second theoretical contribution concerns the conceptualization of Perceived Trust as a multidimensional construct composed of Perceived Privacy, Perceived Security, and Perceived Information Quality. Existing research on Trust in tourism technologies often conceptualizes Trust narrowly, limiting the theoretical understanding of how Trust actually forms during digital interactions. By defining Trust through three theoretically grounded and empirically validated dimensions (Lee et al., 2025; Park, 2020), this study provides a clearer and more comprehensive understanding of the antecedents of Trust in TMAs environments. Each dimension demonstrated a significant positive effect on Behavioural Intention directly and Use Behaviour indirectly, indicating that users evaluate Trustworthiness not merely through the platform's reputation but through the perceived protection of their data, the security of transactions, and the quality and reliability of information presented. This multidimensional approach enriches the literature by offering an integrative and operationalizable conceptualization of Trust that future studies can adopt or refine. It also demonstrates that Trust is best interpreted as a layered psychological structure rather than a single evaluative judgment (Lee et al., 2025).

In this study, Experience was operationalised as a latent variable measured through multiple reflective indicators. This differs from the original UTAUT2, where Venkatesh et al. (2012) conceptualised Experience not as a directly measured construct but as a temporal condition that evolves with repeated technology use. Treating Experience as a measurable latent variable enables more precise empirical testing and enhances theoretical clarity in understanding its moderating role–particularly between Habit and Behavioural Intention, and between Habit and Use Behaviour. By adopting this operationalisation, the study not only extends the original UTAUT2 model but also provides a transferable and psychometrically well–stablished construct that future research can apply across diverse contexts and methodological designs.

A further theoretical contribution emerges from testing and validating the extended UTAUT2 model within the context of a developing country, specifically among Iranian users of TMAs. Much of the tourism technology adoption literature is dominated by studies conducted in technologically advanced or Western contexts (e.g., Sánchez–Torres et al., 2021), which often assume stable digital infrastructures, high levels of data protection, and strong institutional Trust.

By contrast, this study demonstrates that contextual factors such as infrastructural uncertainty, heightened sensitivity to privacy breaches, and culturally shaped expectations significantly influence technology perceptions and behavioral intentions in developing markets (Amiri & Sangar, 2023). The explanatory power of the extended model in this context reveals that UTAUT2 is not universally stable but interacts dynamically with local socio–technical conditions. The findings therefore broaden the theoretical boundary conditions of UTAUT2 and highlight the importance of conducting contextually grounded research in underrepresented regions. This contributes to a more global and equitable understanding of technology acceptance in tourism and encourages future research to further examine how national, cultural, and institutional differences shape model relationships.

Finally, this study makes a theoretical contribution by placing the pre–travel phase at the centre of analysis, recognising it as a critical yet underexamined part of the tourism literature (Eletxigerra et al., 2021). While much of the tourism technology literature focuses on the on–site or post–travel phases, the pre–travel stage strongly shapes tourists' perceptions, choices, and Behavioural Intentions. To capture its complexity, this study conceptualises the pre–travel phase as a structured, multi–stage process consisting of dreaming, decision–making and planning, booking, transaction, and expectation formation. Each stage involves distinct cognitive and behavioural tasks that influence how users engage with TMAs. This structured perspective provides a clearer theoretical lens for understanding early–stage interactions with TMAs and highlights why Perceived Trust plays a particularly influential role during these information–intensive stages (Tan, 2017). In particular, limited research has explicitly conceptualised the dreaming stage as a digitally mediated pre-planning phase that shapes early intention formation within technology adoption contexts. This limits

current understanding of how initial travel desires emerge and how TMAs influence users before active information search begins, which this study addresses.

8.5.2 Managerial implications

This study offers several practical insights for tourism organisations, TMA developers, and digital platform managers seeking to enhance user adoption and engagement during the pre–travel phase. A central practical implication stems from the critical role of Perceived Trust in shaping both Behavioural Intention and use behaviour. Since users rely heavily on TMAs for information search, trip planning, and expectation formation, developers must prioritise building Trustworthy environments by strengthening privacy protections, improving data security mechanisms, and delivering high–quality, accurate, and up–to–date content. The findings demonstrate that Trust is not merely a technical requirement but a strategic determinant of user acceptance; therefore, investment in transparent data practices, user–friendly privacy controls, and clear communication regarding data usage policies can meaningfully increase user confidence and platform loyalty.

The study's multidimensional conceptualisation of Trust also provides actionable guidance. Because perceived privacy, security, and information quality each exert a significant and positive effect on Behavioural Intention, managers should adopt an integrated Trust–building strategy rather than relying on isolated interventions. For example, implementing secure payment gateways or encryption alone is insufficient if information appears outdated or inconsistent. Similarly, high–quality content will not compensate for poor privacy assurances. A holistic approach that simultaneously addresses these three dimensions can create a more reliable and compelling user experience, thereby improving adoption rates among prospective users.

The study also has implications for tourism organisations operating in developing–country markets, where infrastructural limitations, digital literacy levels, and institutional Trust differ significantly from Western contexts. The findings reveal that users in such environments place heightened importance on data protection, transparency, and platform reliability. Tourism companies and TMA providers should therefore adapt their strategies to local expectations by strengthening security certifications, offering offline functionalities where connectivity is unstable, and ensuring compliance with local regulations regarding data handling. Given the elevated sensitivity toward risk in these markets, building Trust–oriented features–from visible privacy badges to secure login authentication–can significantly improve market penetration.

Finally, by emphasising the structured, multi–stage nature of the pre–travel phase, this study provides actionable insights for designing TMAs that align with users' evolving needs across the dreaming, planning, booking, transaction, and expectation–formation stages. Developers should tailor functionalities to support each stage–for example, inspirational content and destination imagery for the dreaming phase, decision–support tools for planning, streamlined

booking interfaces for the transaction stage, and personalised notifications or reminders during expectation formation. Understanding that users interact with TMAs differently across these stages enables tourism providers to design more intuitive, stage–specific user journeys that enhance both engagement and conversion. Importantly, because Trust plays a central role throughout the pre–travel journey, Trust–enhancing features should be embedded consistently at every stage to maximise user confidence and platform effectiveness.

8.6 Research limitations

Firstly, the research was conducted as a single–country case study focused on Iran. While this allowed for an in–depth exploration of cultural and infrastructural factors, it limits the generalizability of the results to other none–similar national contexts. Adoption patterns may differ significantly in countries with different socio–economic, technological, or regulatory environments.

Second, the study employed a cross–sectional quantitative design, capturing participants' responses at a single point in time. It relied solely on quantitative data and did not incorporate a mixed–methods approach, which constrains the ability to observe how users' perceptions and behaviors evolve as mobile technology and user familiarity continue to change. A longitudinal approach could provide deeper insights into the development of Trust, Habit, and continued use.

Third, while perceived Trust was successfully integrated into UTAUT2, Trust itself is a complex, multidimensional construct. The study operationalized it through privacy, security, and information quality, but additional dimensions such as reputation, institutional guarantees, or user experience design may also be relevant and were not captured.

Fourth, this study is subject to limitations arising from its sampling design. The use of a non-probability approach, based on convenience and snowball recruitment, enabled access to relevant respondents but limited the representativeness of the final sample. Since inclusion was shaped by availability, referral patterns, and voluntary participation, certain user profiles may be disproportionately reflected in the dataset, particularly those with stronger digital access or greater familiarity with TMAs. As a result, the empirical findings should not be interpreted as fully generalisable to the broader user population, but rather as evidence grounded in the characteristics of the sampled respondents.

In addition, the study focuses exclusively on individuals who currently use TMAs. This was a deliberate choice, as the research aims to examine actual usage behaviour and the factors influencing engagement with TMAs during the pre-travel phase. By concentrating on existing users, the study is able to capture more accurate evaluations of system-related constructs, such as perceived trust and performance-related perceptions, which require prior experience with the technology.

However, this focus also introduces a limitation. The exclusion of non-users restricts the ability to generalise the findings to the broader travelling population, particularly those who have not yet adopted TMAs. As a result, the study may not fully capture the barriers to initial adoption or the formation of behavioural intentions among potential users. Consequently, the explanatory power of the model is more applicable to current users rather than to predicting adoption behaviour across all traveller segments.

Moreover, while UTAUT2 is widely validated and known for its comprehensiveness, does not account for all possible determinants of TMA adoption, leaving out factors such individual innovativeness, technology readiness, or risk aversion that may shape user intentions and behavior (Dao, 2024). This limitation suggests that additional theoretical perspectives or context–specific constructs may be needed to capture the full range of influences on adoption.

Finally, the study proposed a five–stage framework for the pre–travel phase comprising dreaming, planning and decision–making, booking, transaction, and expectation formation but the structural model tested constructs across the entire pre–travel phase as a single unit. This means that stage–specific relationships were treated conceptually rather than statistically, limiting the ability to make precise inferences about how different adoption drivers operate at each stage.

8.7 Directions for future research

First, this study conceptualised the pre–travel phase as a five–stage process and examined technology acceptance at an aggregate level. Future research could isolate each stage–dreaming, decision making and planning, booking, transaction, and expectation formation–to understand how predictors of app use vary throughout the pre–travel phase. Stage–based models may reveal shifts in the relative importance of studies factors as users progress from inspiration to expectation formation.

Second, while the extended UTAUT2 model with Perceived Trust improved the explanatory power of Behavioural Intention and use behaviour, further studies could explore additional Trust–related antecedents–such as institutional Trust, platform reputation, or algorithmic transparency–to examine whether broader socio–technical dimensions also influence user adoption. Research might also explore whether specific components of Trust operate differently across various tourism technologies (e.g., AI–based assistants, virtual reality platforms,) compared with traditional TMAs.

Third, future research would benefit from employing longitudinal designs to capture how users' perceptions, attitudes, and behaviours toward TMAs evolve over time. This is particularly important because Perceived Trust is a complex, multi–dimensional construct that develops gradually rather than instantaneously; Trust is shaped through repeated

interactions, consistent information quality, and sustained perceptions of privacy and security.

In the present study, the unit of analysis is the individual user, which is appropriate for examining personal acceptance and use of mobile travel applications. However, as Turk et al. (2015) point out, technology adoption becomes considerably more complex when decisions are made at the household level, where multiple actors, shared roles, and negotiated preferences interact. Future research could therefore adopt a household-level perspective to explore how collective decision-making dynamics and intra-household interactions influence digital technology adoption in the pre-travel phase.

Future research could also explore additional moderating variables to provide a more nuanced understanding of the relationships within the extended UTAUT2 model. Although incorporating further moderators–such as, personal innovativeness, voluntariness, or situational factors–might reveal more detailed behavioural patterns, doing so in the present study would have substantially increased the complexity of the structural model and resulted in a much longer and more burdensome questionnaire.

With the rapid expansion of digital solutions in tourism–including travel apps, automated guest services, online reservation systems, and immersive technologies–the sector continues to face adoption barriers such as limited digital literacy, change resistance, technological incompatibility, and a general reliance on human interaction (Cirman et al., 2022). While the present study examines these issues from the perspective of users as the unit of analysis, future research should broaden this lens by integrating provider perspectives as well. Combining user-level and provider-level analyses would enable a more comprehensive understanding of how technological, organizational, and human factors interact during digital transformation, and could support the development of more realistic, ecosystem-wide models of mobile app adoption in tourism.

Future research may build upon the present study by extending the analytical scope beyond experienced users to include non-users and potential adopters of TMAs. While the current study provides insights into behavioural intention within an actual use context, incorporating a broader population would enable a more comprehensive examination of technology adoption across different stages of engagement. In this regard, future studies could complement the UTAUT2 framework with pre-adoption theories, such as Innovation Resistance Theory (Ram, 1987) in order to better capture resistance mechanisms and barriers to initial adoption. Additionally, the inclusion of constructs such as technology anxiety, digital literacy, personal innovativeness may further enhance the explanatory power of the model, particularly in understanding non-user behaviour. Adopting comparative or multi-group research designs that integrate both users and non-users would allow for the analysis of differences between pre-adoption and post-adoption dynamics, thereby contributing to a more holistic understanding of behavioural intention and technology acceptance within the broader travelling population.

Finally, methodological advancements could enrich future studies. Qualitative research–such as in–depth interviews, focus groups, or ethnographic approaches–may uncover additional psychological or contextual factors that influence Trust and adoption beyond what quantitative models capture. Future studies could also employ experimental designs to test how interface features, privacy cues, or content–quality signals influence Trust perceptions and behaviour in controlled settings. Combining quantitative and qualitative approaches would provide a more comprehensive understanding of user behaviour and further refine theoretical models in digital tourism research.

9 CONCLUSION

This dissertation aimed to examine the determinants of users' acceptance and use of Travel Mobile Apps (TMAs) during the pre-travel phase by integrating an extended UTAUT2 model with the construct of Perceived Trust and its antecedents of Perceived Privacy, Perceived Security, and Perceived Information Quality. The research addressed the need for a deeper understanding of TMA adoption among users, particularly within developing-country contexts where socio-cultural and infrastructural conditions differed from those in technologically advanced regions.

The study began by conceptualising the pre-travel phase as a multi-stage process comprising dreaming, planning and decision-making, booking, transaction, and expectation formation. Although the empirical model examined this phase holistically, the proposed framework offered a clearer understanding of the multidimensional mechanisms underlying the pre-travel stage and provided a basis for future stage-specific investigations. This conceptualisation highlighted that users engaged with TMAs across cognitive and emotional touchpoints, and that technology acceptance during pre-travel was shaped not only by functional perceptions but also by psychological evaluations such as perceived Trust.

In developing the extended model, Perceived Trust was incorporated as a key construct derived from Perceived Privacy, Perceived Security, and Perceived Information Quality, offering a more comprehensive perspective on Behavioural Intention and Actual Usage Behaviour of TMAs during the pre-travel phase. Experience was also included as a moderating variable to assess whether it influenced the relationships between Habit and Behavioural Intention, as well as Habit and Use Behaviour. To test the extended model, data were collected through a survey-based study involving 424 Iranian TMA users. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS, following a two-stage process that evaluated both the measurement model and the structural model to ensure reliability and validity. The analysis showed that Behavioural Intention was most strongly predicted by Habit, followed by Perceived Trust and Social Influence. Facilitating Conditions, Effort Expectancy, Price Value and Performance Expectancy also contributed to intention formation, while Hedonic Motivation showed a marginal and non-significant effect. Behavioural Intention emerged as the strongest

determinant of Use Behaviour, alongside direct influences from Habit and Facilitating Conditions. The moderating effect of Experience was only marginally supported for Behavioural Intention and was not supported for Use Behaviour.

Moreover, the demographic, temporal, and situational variables had only limited influence on users' acceptance and use of TMAs. Most control variables, including gender, education, income, marital status, and trip duration, did not significantly affect either Behavioural Intention or Use Behaviour. Only age and the number of trips per year showed marginally significant positive associations with Use Behaviour, indicating that slightly older individuals and more frequent users may use TMAs somewhat more regularly.

The Importance–Performance Matrix Analysis (IPMA) showed that Habit, Perceived Trust, Social Influence, and Facilitating Conditions were the most important yet moderately performing predictors of Behavioural Intention, suggesting room for improvement in these areas. For Use Behaviour, Behavioural Intention, Experience, Habit, and Facilitating Conditions had the highest importance, while several constructs such as Performance Expectancy and Facilitating Conditions showed relatively low performance. Overall, the IPMA highlighted that improving habitual engagement, trust-related factors, social support, and system facilitation could strengthen both intention and actual use of TMAs.

Beyond these empirical findings, the results contributed to a better understanding of how users behaved in digitally mediated environments during the pre-travel stage. The influence of Habit and Social Influence suggested that technology use was shaped by routine behaviours and social norms rather than solely by perceptions of usefulness or ease of use. The role of Perceived Trust indicated that Privacy, Security and Information reliability were meaningful considerations for users, particularly in environments where institutional protections were less established. The limited moderating effect of Experience implied that Habitual digital behaviour could form even among users with relatively little prior exposure. The contextual focus on Iranian TMA users offered insight into how cultural norms, infrastructural conditions and Trust environments shaped technology acceptance in a developing-country setting. This perspective helped broaden the scope of tourism-technology research, which had often concentrated on more technologically advanced contexts.

Overall, the findings of this dissertation suggested that users' engagement with TMAs during the pre-travel phase was shaped by a combination of behavioural, psychological and contextual factors. By extending the UTAUT2 model with Trust-related constructs and applying it in a developing-country setting, the study offered a broader view of how users approached digital travel tools in environments where institutional and infrastructural conditions were still evolving. While the results cannot be generalised to all contexts, they provided an initial step towards understanding the complexities of pre-travel technology use and highlighted areas where future research could build further. Taken together, the study concluded that fostering Trust, supporting routine use and addressing contextual constraints

may assist in improving the adoption and usability of TMAs, contributing to more effective and user-centred digital experiences in the tourism domain. As with any research, the study had limitations that may guide further investigation. While the conceptualisation of the pre-travel phase as a five-stage process was informative, future research could examine each stage separately to determine whether adoption drivers vary across them. Longitudinal approaches might also help capture how Trust, Habit and behavioural patterns developed over time. In addition, expanding the analysis to include household-level decision-making or provider perspectives may enhance understanding of TMA use within the broader tourism ecosystem.

REFERENCE LIST

1. Abashidze, I. (2024). The influence of online platforms on decision-making process and behavioural traits of international travellers. *European Scientific Journal, ESJ, 20*(37), 51. https://doi.org/10.19044/esj.2024.v20n37p51
2. Agag, G., & El-Masry, A. A. (2016). Understanding consumer intention to participate in online travel community and effects on consumer intention to purchase travel online and WOM: An Integration of Innovation Diffusion Theory and tam with Trust. *Computers in Human Behavior, 60*, 97–111. https://doi.org/10.1016/j.chb.2016.02.038
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T
4. Al-Fedaghi, S., & Al-Azmi, A. A. (2012). Experimentation with personal identifiable information. *Intelligent Information Management, 04*(04), 123–133. https://doi.org/10.4236/iim.2012.44019
5. Amaro, S., & Duarte, P. (2015). An integrative model of consumers' intentions to purchase travel online. Tourism Management, 46, 64–79. https://doi.org/10.1016/j.tourman.2014.06.006.
6. Amiri, E., & Sangar, A. B. (2023). Assessing the ICT development in Iranian cities: The strategy to Accelerate Digital Advancement. *Technological Forecasting and Social Change, 197*, 122904. https://doi.org/10.1016/j.techfore.2023.122904
7. Andersen, C., Nyhus, E. K., & Engeset, M. G. (2025). How pre-vacation factors influence post-vacation word-of-mouth. *Current Issues in Tourism, 1–9.* https://doi.org/10.1080/13683500.2025.2462160
8. Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411
9. Arumugam, S., & Wing, J. (2020). Antecedents of M-commerce user experience from a millennials perspective in a South African fashion retail context. *2020 Conference on Information Communications Technology and Society (ICTAS)*, 1–6. https://doi.org/10.1109/ictas47918.2020.233993

10. Asif, M., & Fazel, H. (2024). Digital Technology in tourism: A bibliometric analysis of transformative trends and emerging research patterns. *Journal of Hospitality and Tourism Insights, 7*(3), 1615–1635. https://doi.org/10.1108/jhti-11-2023-0847
11. Backhaus, C., Heussler, T., & Croce, V. (2022). Planning horizon in international travel decision-making: The role of individual and cultural determinants. *Journal of Travel Research, 62*(2), 432–447. https://doi.org/10.1177/00472875211066112
12. Baki, R. (2020). Analysis of factors affecting customer Trust in online hotel booking website usage. *European Journal of Tourism, Hospitality and Recreation, 10*(2), 106–117. https://doi.org/10.2478/ejthr-2020-0009
13. Bansal, G., Zahedi, F. M., & Gefen, D. (2015). The role of privacy assurance mechanisms in building Trust and the moderating role of privacy concern. *European Journal of Information Systems, 24*(6), 624–644. https://doi.org/https://doi.org/10.1057/ejis.2014.41
14. Baruah, P., & Sarma, B. (2024). Data Management, security challenges, and solutions in Blockchain Network. *Data Management and Security in Blockchain Systems*, 85–104. https://doi.org/10.2174/9789815305814124010006
15. Barzegari, S., Sharifi Kia, A., Bardus, M., Stoyanov, S. R., GhaziSaeedi, M., & Rafizadeh, M. (2022). The Persian Version of the Mobile Application Rating Scale (Mars-FA): Development and Validation Study. https://doi.org/10.2196/preprints.42225
16. Barzegari, S., Sharifi Kia, A., Bardus, M., Stoyanov, S. R., GhaziSaeedi, M., & Rafizadeh, M. (2022). The Persian Version of the Mobile Application Rating Scale (Mars-FA): Development and Validation Study. https://doi.org/10.2196/preprints.42225
17. Benckendorff, P. (2014). Attraction, tourism. In: Jafari, J., Xiao, H. (eds) Encyclopedia of Tourism. Springer, Cham. https://doi.org/10.1007/978-3-319-01669-6_12-1
18. Benslimane, A., & Semaoune, K. (2021). An analysis of Tourist's Behavioural Intention in the digital era: Using a modified model of the reasoned action theory. International Journal of Marketing, Communication and New Media. https://doi.org/10.54663/2182-9306.2021.v9n17.4-26
19. Berhanu, K., & Raj, S. (2020). The Trustworthiness of travel and tourism information sources of social media: Perspectives of international tourists visiting Ethiopia. Heliyon, 6(3). https://doi.org/10.1016/j.heliyon.2020.e03439
20. Bigné, E., Sanz, S., Ruiz, C., & Aldás, J. (2010). Why some internet users don't buy air tickets online. Information and Communication Technologies in Tourism 2010, 209–221. https://doi.org/10.1007/978-3-211-99407-8_18
21. Birenboim, A., Bulis, Y., & Omer, I. (2023). A typology of tourism mobility apps. Tourism Management Perspectives, 48, 101161. https://doi.org/10.1016/j.tmp.2023.101161
22. Björk, P., & Kauppinen-Räisänen, H. (2015). Contemporary insights to the dynamic pre-trip information sourcing behaviour. Tourism and Hospitality Research, 15(1), 39–53. https://doi.org/10.1177/1467358414553871

23. Bliemel, M., & Hassanein, K. (2007). Consumer satisfaction with online health information retrieval: A model and empirical study. E-Service Journal, 5(2), 53. https://doi.org/10.2979/esj.2007.5.2.53
24. Bretos, M. A., Ibáñez-Sánchez, S., & Orús, C. (2023). Applying virtual reality and augmented reality to the Tourism Experience: A Comparative Literature Review. Spanish Journal of Marketing - ESIC, 28(3), 287–309. https://doi.org/10.1108/sjme-03-2023-0052
25. Bryman, A., & Bell, E. (2015). Business research methods (4th ed.). Oxford University Press.
26. Calderón-Fajardo, V., Puig-Cabrera, M., & Rodríguez-Rodríguez, I. (2024). Beyond the real world: Metaverse adoption patterns in tourism among Gen Z and Millennials. Current Issues in Tourism, 28(8), 1261–1281. https://doi.org/10.1080/13683500.2024.2330675
27. Castagnoli, R., Büchi, G., Coeurderoy, R., & Cugno, M. (2022). Evolution of industry 4.0 and International Business: A Systematic Literature Review and a research agenda. European Management Journal, 40(4), 572–589. https://doi.org/10.1016/j.emj.2021.09.002
28. Chandra, S., Srivastava, S. C., & Theng, Y.-L. (2010). Evaluating the role of Trust in consumer adoption of Mobile Payment Systems: An empirical analysis. Communications of the Association for Information Systems, 27. https://doi.org/10.17705/1cais.02729
29. Chang, C.-M., Liu, L.-W., Huang, H.-C., & Hsieh, H.-H. (2019). Factors influencing online hotel booking: Extending UTAUT2 with age, gender, and experience as moderators. Information, 10(9), 281. https://doi.org/10.3390/info10090281
30. Chang, Y.-T., Chao, C.-M., Yu, C.-W., & Lin, F.-C. (2021). Extending the utility of UTAUT2 for hospital patients' adoption of medical apps: Moderating effects of e-health literacy. Mobile Information Systems, 2021, 1–10. https://doi.org/10.1155/2021/8882317
31. Chatzigeorgiou, C., & Christou, E. (2020). Destination Trust and user satisfaction: Digital content's psychological effect. Tourism Review, 75(2), 444–456.
32. Chen, L., Yang, Y., Wang, N., Yang, K., & Yuan, Q. (2019). How serendipity improves user satisfaction with recommendations? A large-scale user evaluation. The World Wide Web Conference, 240–250. https://doi.org/10.1145/3308558.3313469
33. Cheng, X., Fu, S., Sun, J., Bilgihan, A., & Okumus, F. (2019). An investigation on online reviews in Sharing Economy Driven Hospitality Platforms: A viewpoint of Trust. Tourism Management, 71, 366–377. https://doi.org/10.1016/j.tourman.2018.10.020
34. Cheung, C. M. K., & Lee, M. K. O. (2006). Understanding consumer Trust in internet shopping: A multidisciplinary approach. Journal of the American Society for Information Science and Technology, 57(4), 479–492. https://doi.org/10.1002/asi.20312
35. Cheung, C. M., & Lee, M. K. (2001). Trust in internet shopping. Journal of Global Information Management, 9(3), 23–35. https://doi.org/10.4018/jgim.2001070103

36. Chouykaew, T., Kim, L., & Issayeva, G. (2024). How perceived ease of use, Trust, and perceived usefulness influence tourists' decision to book Homestay Services Online. GeoJournal of Tourism and Geosites, 56(4), 1609–1616. https://doi.org/10.30892/gtg.56417-1331
37. Cirman, A., Farčnik, D., Dobnik, N., Šterpin, T., & Vrtačnik, I. (2022). Digital transformation in tourism. In Metaversing the corporate strategy: The opportunities and challenges of digital transformation (pp. 141–154). University of Ljubljana, School of Economics and Business. https://www.ef.uni-lj.si/assets/Studij/IMB/PKP-knjiga/PKP_22_Metaversing-the-Corporate-Strategy_The-Opportunities-and-Challenges-of-Digital-Transformation.pdf
38. Clawson, M., & Knetsch, J. L. (1966). Economics of outdoor recreation: Resources for the future. Baltimore: John Hopkins.
39. Cochran, W. G. (1977). Sampling techniques (3rd ed.). John Wiley & Sons.
40. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587
commerce: shopping online for tourism products and services in South Korea.
41. Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. MIS Quarterly, 19(2), 189–211. https://doi.org/10.2307/249688
42. Craig-Smith, S., & French, C. (1994). Learning to live with tourism. Melbourne: Pitman.
43. Cui F, Lin D, Qu H (2018) The impact of perceived security and consumer innovativeness on e-loyalty in online travel shopping. Journal of Travel & Tourism Marketing 35(6): 819–834. https://doi.org/10.1080/10548408.2017.1422452
44. Dadabayeva, G., Kovaleva, I., & Porter, D. (2025). *Iran in global trade and sanction research*. *Kazakhstan Oriental Studies, 16*(4). https://doi.org/10.63051/kos.2025.4.62
45. Dang, N. T. (2024). The roles of user adaptation and Trust in fostering continuance intention toward mobile banking: An extended decomposed theory of plan behavior. Multidisciplinary Science Journal, 7(6), 2025290. https://doi.org/10.31893/multiscience.2025290
46. Dao, N. T., & Anh, D. N. (2024). The impact of personal innovativeness on the behavioral intention to using tourism mobile applications of generation Z in Ho Chi Minh City, Vietnam. GeoJournal of Tourism and Geosites, 55(3), 1186–1197. https://doi.org/10.30892/gtg.55319-1291
47. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
48. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x
49. De Nisco, A., Mainolfi, G., Marino, V., & Napolitano, M. R. (2015). Tourism satisfaction effect on general country image, destination image, and post-visit intentions. Journal of Vacation Marketing, 21(4), 305–317. https://doi.org/10.1177/1356766715577502

50. Decrop, A., & Snelders, D. (2004). Planning the summer vacation: An adaptable process. Annals of Tourism Research, 31(4), 1008–1030. https://doi.org/10.1016/j.annals.2004.03.004
51. Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. Journal of the Academy of Marketing Science, 40(3), 434–449. https://doi.org/10.1007/s11747-011-0300-3
52. Dias, S., & Afonso, V. A. (2021). Impact of mobile applications in changing the tourist experience. European Journal of Tourism, Hospitality and Recreation, 11(1), 113–120. https://doi.org/10.2478/ejthr-2021-0011
53. Djafarova, E., & Trofimenko, O. (2018). 'instafamous' – credibility and self-presentation of micro-celebrities on social media. Information, Communication & Society, 22(10), 1432–1446. https://doi.org/10.1080/1369118x.2018.1438491
54. Dolnicar, S., Cvelbar, L. K., & Grün, B. (2023). A Sharing-Based Approach to Enticing Tourists to Behave More Environmentally Friendly. https://doi.org/10.31235/osf.io/yxuf6
55. Duan, W., Hu, N., & Xue, F. (2024). The information content of financial statement fraud risk: An ensemble learning approach. Decision Support Systems, 182, 114231. https://doi.org/https://doi.org/10.1016/j.dss.2024.114231
56. Dwivedi, Y.K., Rana, N.P., Jeyaraj, A. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. Information System Frontier, 21, 719–734 https://doi.org/10.1007/s10796-017-9774-y
57. Egger, R. (2022). Machine learning in tourism: A brief overview – Generation of knowledge from experience. In R. Egger (Ed.), Applied data science in tourism (pp. 85–104). Springer. https://doi.org/10.1007/978-3-030-88389-8_6
58. Eletxigerra, A., Barrutia, J. M., & Echebarria, C. (2021). Tourist expertise and pre-travel value co-creation: Task-related processes and beyond. Tourism Management Perspectives, 37, 100772. https://doi.org/10.1016/j.tmp.2020.100772
59. Emerson, R. W. (2015). Convenience sampling, random sampling, and snowball sampling: How does sampling affect the validity of research? Journal of Visual Impairment & Blindness, 109(2), 164–168. https://doi.org/10.1177/0145482X1510900215
60. Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (utaut) model. Tourism Management, 43, 70–88. https://doi.org/10.1016/j.tourman.2014.01.017
61. Esfandiar, K., Pearce, J., Dowling, R., & Goh, E. (2023). The extended theory of planned behaviour model and national parks visitors' pro-environmental binning behaviour: A cross-cultural perspective. Journal of Outdoor Recreation and Tourism, 42, 100602. https://doi.org/10.1016/j.jort.2022.100602
62. Farzin, M., Sadeghi, M., Yahyayi Kharkeshi, F., Ruholahpur, H., & Fattahi, M. (2021). Extending UTAUT2 in M-banking adoption and actual use behavior: Does WOM

communication matter? Asian Journal of Economics and Banking, 5(2), 136–157. https://doi.org/10.1108/ajeb-10-2020-0085
63. Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Addison-Wesley. https://people.umass.edu/aizen/f&a1975.html
64. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
65. Foroughi, B., Iranmanesh, M., Asadi, S., Al-Emran, M., Ghobakhloo, M., & Batouei, A. (2025). Extending UTAUT2 to explore intention to use chatgpt for Travel Planning: A hybrid PLS-ann approach. Journal of Tourism Futures. https://doi.org/10.1108/jtf-11-2023-0256
66. Fox, G., Lynn, T., & Rosati, P. (2022). Enhancing consumer perceptions of privacy and Trust: A GDPR label perspective. Information Technology & People, 35(8), 181–204. https://doi.org/10.1108/itp-09-2021-0706
67. Ganesan, V. (2022). Machine learning in Mobile applications. International Journal of Computer Science and Mobile Computing, 11(2), 110–118. https://doi.org/10.47760/ijcsmc.2022.v11i02.013
68. Gefen, D. (2000). E-commerce: The role of familiarity and Trust. Omega, 28(6), 725–737. https://doi.org/10.1016/s0305-0483(00)00021-9
69. 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
70. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly.
71. Gera, R., Menon, S. K., Chadha, P., & Bansal, S. (2025). Exploring the evolution of mobile tourism applications in business and Social Sciences: A bibliometric review spanning 2013-2022. International Journal of Internet Marketing and Advertising, 22(1/2). https://doi.org/10.1504/ijima.2025.10065755
72. Gharaibeh, M., Arshad, M. R. M., & Gharaibeh, N. (2018). Using the UTAUT2 model to determine factors affecting adoption of mobile banking services: A qualitative approach. International Journal of Interactive Mobile Technologies (iJIM), 12(4), 123–139. https://doi.org/10.3991/ijim.v12i4.8525
73. Gong, Z., & Jin, Y. (2008). The influence of perceived privacy upon the Trust in e-commerce. 2008 International Seminar on Future Information Technology and Management Engineering, 141–143. https://doi.org/10.1109/fitme.2008.13
74. Gretzel, U. (2021). Dreaming about travel: A Pinterest netnography. In Information and Communication Technologies in Tourism 2021 (pp. 256–268). https://doi.org/10.1007/978-3-030-65785-7_23
75. Gretzel, U., Sigala, M., Xiang, Z. and Koo, C. (2015). Smart tourism: foundations and developments. Electronic Markets, 25(3), 179-188.

76. Grljević, O., Marić, M., & Božić, R. (2025). Exploring mobile application user experience through topic modeling. Sustainability, 17(3), 1109. https://doi.org/10.3390/su17031109
77. Guerreiro, M., Pinto, P., deMatos, N., Bagheri, F., Sequeira, B. D., & Parra, A. (2025). Unveiling the impacts of tourist experiences on experiential image, satisfaction, and loyalty: A study in Algarve, a European premier beach destination. Journal of Vacation Marketing. https://doi.org/10.1177/13567667251335045
78. Gupta, A., & Dogra, N. (2017). Tourist adoption of mapping apps: A UTAUT2 perspective of Smart Travellers. Tourism and Hospitality Management, 23(2), 145–161. https://doi.org/10.20867/thm.23.2.6
79. Gupta, A., Dogra, N., & George, B. (2018). What determines tourist adoption of smartphone apps? Journal of Hospitality and Tourism Technology, 9 (1), 50-64 https://doi.org/10.1108/JHTT-02-2017-0013
80. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2022). Partial least squares structural equation modeling (PLS-SEM) using R. Springer. https://doi.org/10.1007/978-3-030-80519-7
81. Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. European Journal of Marketing, 53(4), 566–584. https://www.emerald.com/insight/content/doi/10.1108/EJM-10-2018-0665
82. Haji-Othman, Y., Sheh Yusuff, M. S., & Md Hussain, M. N. (2024). Data analysis using partial least squares structural equation modeling (PLS-SEM) in conducting quantitative research. International Journal of Academic Research in Business and Social Sciences, 14(10). https://doi.org/10.6007/ijarbss/v14-i10/23364
83. Hall, C. M., Scott, D., & Gössling, S. (2020). Pandemics, transformations and tourism: Be careful what you wish for. Tourism Geographies, 22(3), 577–598. https://doi.org/10.1080/14616688.2020.1759131
84. Hamouda, M. (2022). Mobile applications in tourism: Examining the determinants of intention to use. International Journal of Technology and Human Interaction (IJTHI). https://doi.org/10.4018/IJTHI.293198
85. Haraty, R. A., & Bitar, G. (2019). Associating learning technology to sustain the environment through Green Mobile Applications. Heliyon, 5(1). https://doi.org/10.1016/j.heliyon.2019.e01141
86. Hartono, E., Holsapple, C. W., Kim, K.-Y., Na, K.-S., & Simpson, J. T. (2014). Measuring perceived security in B2C electronic commerce website usage: A respecification and validation. Decision Support Systems, 62, 11–21. https://doi.org/10.1016/j.dss.2014.02.006
87. Heinonen, K., Strandvik, T., Mickelsson, J., Edvardsson, B., Sundström, E., & Andersson, P. (2010). A customer-dominant logic of service. Journal of Service Management, 21(4), 531–548. https://doi.org/10.1108/09564231011066088
88. 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

89. Herrero, Á., San Martín, H., & Garcia-De los Salmones, M. del. (2017). Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. Computers in Human Behavior, 71, 209–217. https://doi.org/10.1016/j.chb.2017.02.007
90. Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: Emerging concepts, methods and propositions. Journal of Marketing, 46(3), 92–101. https://doi.org/10.1177/002224298204600314
91. Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations (2nd ed.). SAGE Publications.
92. Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. Thousand Oaks, CA: Sage Publications.
93. Hsu, S.-H., & Chen, W.-H. (2006). Robustness testing of PLS, LISREL, EQS and ANN-based SEM for measuring customer satisfaction. Total Quality Management & Business Excellence, 17(3), 355–372. https://doi.org/10.1080/14783360500451465
94. Hua, C., Cole, S., & Xu, N. (2021). Rethinking Trust in tourism apps: The moderating effect of age. Journal of Hospitality and Tourism Technology, 12(3), 548–562. https://doi.org/10.1108/jhtt-01-2020-0013
95. Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic Management Journal, 20(2), 195–204. https://www.jstor.org/stable/3094025
96. Ioannou, A., Tussyadiah, I., & Miller, G. (2020). That's private! understanding travellers' privacy concerns and online data disclosure. Journal of Travel Research, 60(7), 1510–1526. https://doi.org/10.1177/0047287520951642
97. Ismail, R., & Jokonya, O. (2023). Factors affecting the adoption of emerging technologies in last-mile delivery in the retail industry. Procedia Computer Science, 219, 2084–2092. https://doi.org/10.1016/j.procs.2023.01.511
98. Jahani, A., Goshtasb, H., & Saffariha, M. (2020). Tourism impact assessment modeling of vegetation density for protected areas using data mining techniques. Land Degradation and Development, 31(12), 1502–1519. https://doi.org/10.1002/ldr.3549
99. Jamal, S., & Habib, M. A. (2020). Smartphone and daily travel: How the use of smartphone applications affect travel decisions. Sustainable Cities and Society, 53, 101939. https://doi.org/10.1016/j.scs.2019.101939
100. Jensen, J. M. (2012). Shopping orientation and online travel shopping: The Role of Travel experience. International Journal of Tourism Research, 14(1), 56–70. https://doi.org/10.1002/jtr.835
101. Jiao, H., Wang, T., Libaers, D., Yang, J., & Hu, L. (2025). The relationship between Digital Technologies and Innovation: A review, Critique, and research agenda. Journal of Innovation & Knowledge, 10(1), 100638. https://doi.org/10.1016/j.jik.2024.100638

102.Joinson, A. N., Reips, U. D., Buchanan, T., & Schofield, C. B. P. (2010). Privacy, Trust, and Self-Disclosure Online. Human–Computer Interaction, 25(1), 1–24. https://doi.org/10.1080/07370020903586662
103.Kamboj, S., & Joshi, R. (2020). Examining the factors influencing smartphone apps use at tourism destinations: A utaut model perspective. International Journal of Tourism Cities, 7(1), 135–157. https://doi.org/10.1108/ijtc-05-2020-0094
104.Kaur, P., Stoltzfus, J., & Yellapu, V. (2018). Descriptive statistics. International Journal of Academic Medicine, 4(1), 60. https://doi.org/10.4103/ijam.ijam_7_18
105. Kazemi, N., & Amini, J. (2024). Deprivation spatial concentration in a developing country: Evidence from Iran. Regional Science Policy & Practice, 16(2), 12560. https://doi.org/10.1111/rsp3.12560
106.Kebab, M. (2025). Travel app adoption intentions: Extending the Technology Acceptance Model With Trust. Marketing Science & Inspirations, 20(2), 45–58. https://doi.org/10.46286/msi.2025.20.2.4
107. Kemp, S. (2025). Digital 2025: Iran - DataReportal – *global digital insights. DataReportal*. https://datareportal.com/reports/digital-2025-iran
108.Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. Computers in Human Behavior, 70, 460-474. https://doi.org/10.1016/j.chb.2017.01.001
109.Killion, G. L. (1992). Understanding tourism. Rockhampton: Central Queensland University.
110.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
111.Kim, H., & Niehm, L. S. (2009). The impact of website quality on information quality, value, and loyalty intentions in apparel retailing. Journal of Interactive Marketing, 23(3), 221–233. https://doi.org/10.1016/j.intmar.2009.04.009
112.Kim, J., & Fesenmaier, D. R. (2017). Sharing tourism experiences: The posttrip experience. Journal of Travel Research, 56(1), 28–40. https://doi.org/10.1177/0047287515620491
113.Kim, M. J., Chung, N., & Lee, C. K. (2011). The effect of perceived trust on electronic
114.Kim, S. S., & Malhotra, N. K. (2005). A longitudinal model of continued is use: An integrative view of four mechanisms underlying postadoption phenomena. Management Science, 51(5), 741–755. https://doi.org/10.1287/mnsc.1040.0326
115.Kirilenko, A. P., Stepchenkova, S. O., & Dai, X. (2021). Automated topic modeling of tourist reviews: Does the Anna Karenina principle apply? Tourism Management, 83, 104241. https://doi.org/10.1016/j.tourman.2020.104241
116.Knani, M., Echchakoui, S., & Ladhari, R. (2022). Artificial Intelligence in tourism and hospitality: Bibliometric analysis and research agenda. International Journal of Hospitality Management, 107, 103317. https://doi.org/10.1016/j.ijhm.2022.103317
117.Krešić, D., & Prebežac, D. (2011). Index of destination attractiveness as a tool for destination attractiveness assessment. Tourism: An International Interdisciplinary

Journal, 59(4), 497–517. Retrieved from https://scispace.com/pdf/index-of-destination-attractiveness-as-a-tool-for-49o4c3jsha.pdf

118. Kuan, H. H., Bock, G. W., & Vathanophas, V. (2008). Comparing the effects of website quality on customer initial purchase and continued purchase at ecommerce websites. Behaviour & Information Technology, 27(1), 3–16. https://doi.org/10.1080/01449290600801959

119. Lacity, M. C., Schuetz, S. W., Kuai, L., & Steelman, Z. R. (2024). It's A matter of Trust: Literature reviews and analyses of Human Trust in Information Technology. Journal of Information Technology. https://doi.org/10.1177/02683962231226397

120. Lam, J. M. S., Ismail, H., & Lee, S. (2020). From desktop to destination: User-generated content platforms, co-created online experiences, Destination Image and satisfaction. Journal of Destination Marketing & Management, 18, 100490. https://doi.org/10.1016/j.jdmm.2020.100490

121. Lampo, A. (2023). The role of Habit in utaut-2 research: A Study of Bev Users. Proceedings of the 2023 9th International Conference on Industrial and Business Engineering, 449–453. https://doi.org/10.1145/3629378.3629384

122. Lamsfus, C., Xiang, Z., Alzua-Sorzabal, A., & Martín, D. (2013). Conceptualizing context in an intelligent mobile environment in Travel and tourism. Information and Communication Technologies in Tourism 2013, 1–11. https://doi.org/10.1007/978-3-642-36309-2_1

123. Lee, M., Lee, S. A., Shin, H. H., & Jeong, M. (2025). Revisiting and exploring trust in the digital era: scale development in tourism. Information Technology & Tourism. https://doi.org/10.1007/s40558-024-00310-2

124. Lee, Y. E., & Benbasat, I. (2003). Interface Design for Mobile Commerce. Communications of the ACM, 46(12), 48–52. https://doi.org/10.1145/953460.953487

125. Li, F. (Sam), Zhu, D., Lin, M.-T. (Brian), & Kim, P. B. (2024). The technology acceptance model and hospitality and tourism consumers' intention to use mobile technologies: Meta-analysis and Structural Equation Modeling. Cornell Hospitality Quarterly, 65(4), 461–477. https://doi.org/10.1177/19389655241226558

126. Li, T., Fan, Y., Li, Y., Tarkoma, S., & Hui, P. (2023). Understanding the long-term evolution of mobile app usage. IEEE Transactions on Mobile Computing, 22(2), 1213–1230. https://doi.org/10.1109/tmc.2021.3098664 Ganesan, V. (2022). Machine learning in Mobile applications. International Journal of Computer Science and Mobile Computing, 11(2), 110–118. https://doi.org/10.47760/ijcsmc.2022.v11i02.013

127. Li, Y., & Jiang, S. (2024). Modelling tourists' travel intention: Role of tourism destination image, perceived value and situational involvement. Journal of Infrastructure, Policy and Development, 8(11), 8069. https://doi.org/10.24294/jipd.v8i11.8069

128. Li, Y., Mahmoudzadeh, A., & Wang, X. B. (2022). Airlines seat pricing with seat upgrading. Multimodal Transportation, 1(4), 100054. https://doi.org/10.1016/j.multra.2022.100054

129.Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit limits the predictive power of intention: The case of information systems continuance. MIS Quarterly, 31(4), 705. https://doi.org/10.2307/25148817
130.Lin, J., Wang, B., Wang, N., & Lu, Y. (2013). Understanding the evolution of Consumer Trust in mobile commerce: A longitudinal study. Information Technology and Management, 15(1), 37–49. https://doi.org/10.1007/s10799-013-0172-y
131.Lin, P.-J., Jones, E., & Westwood, S. (2009). Perceived risk and risk-relievers in online travel purchase intentions. Journal of Hospitality Marketing & Management, 18(8), 782–810. https://doi.org/10.1080/19368620903235803
132.Lindberg, K., & Stemmer, K. (2022). Choice experiment selection of tourism destinations in a dual process theory framework: The role of decision style and potential to promote deliberation. PLOS ONE, 17(7). https://doi.org/10.1371/journal.pone.0270531
133.Liu, C., Marchewka, J. T., Lu, J., & Yu, C. S. (2005). Beyond concern- A privacy-Trust-Behavioural Intention model of electronic commerce. Information & Management, 42(2), 289–304. https://doi.org/https://doi.org/10.1016/j.im.2004.01.003
134.Liu, J., Cheng, V. T., Zhu, Z., & Wu, D. (2025). Antecedents and consequences of value co-creation in tourist behaviours: Empirical evidence from Smart Tourism Application. Current Issues in Tourism, 1–17. https://doi.org/10.1080/13683500.2025.2523543
135.Lock, M., & Mai Shihah. (2021). A review of UTAUT and extended model as a conceptual framework in education research. Jurnal Pendidikan Sains dan Matematik Malaysia, 1(Special Issues), 1–20. https://doi.org/10.37134/jpsmm.vol11.sp.1.2021
136.Lu, J., Mao, Z., Wang, M., & Hu, L. (2015). Goodbye maps, hello apps? exploring the influential determinants of travel app adoption. Current Issues in Tourism, 18(11), 1059–1079. https://doi.org/10.1080/13683500.2015.1043248
137.Lucassen, T., & Schraagen, J. M. (2011). Factual accuracy and Trust in information: The role of expertise. Journal of the American Society for Information Science & Technology, 62(7), 1232–1242. doi:10.1002/asi.21545
138.Madlmayr, G., Langer, J., Kantner, C., & Scharinger, J. (2008). NFC Devices: Security and privacy. 2008 Third International Conference on Availability, Reliability and Security. http://doi.org/10.1109/ares.2008.105
139.Maldonado-Canca, LA., Casado-Molina, AM., Cabrera-Sánchez, JP. et al. Beyond the post: an SLR of enterprise artificial intelligence in social media. Soc. Netw. Anal. Min. 14, 219 (2024). https://doi.org/10.1007/s13278-024-01382-y
140. Maleki, A. (2025). VPN sampling: A novel method for measuring sensitive topics in the authoritarian context of Iran. Paper presented at the WAPOR 78th Annual Conference, St. Louis, United States. https://hdl.handle.net/20.500.14602/105488
141.Mariano, A. M., Silva, M. C., Mello, T. M., & Santos, M. R. (2022). The importance of mobile applications for companies' brand image: A study using structural equations. Procedia Computer Science, 214, 1128–1135. https://doi.org/10.1016/j.procs.2022.11.287

142.Maric, A.-M., & Zoroja, J. (2019). Travel and accommodation web services: Usage in selected European countries. Interdisciplinary Description of Complex Systems, 17(2), 403–416. https://doi.org/10.7906/indecs.17.2.14
143.Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of Organizational Trust. The Academy of Management Review, 20(3), 709. https://doi.org/10.2307/258792
144.McAllister, D. J. (1995). Affect- and cognition-based Trust as foundations for interpersonal cooperation in organizations. Academy of Management Journal, 38(1), 24–59. https://doi.org/10.2307/256727
145.McCabe, S., Li, C. (Spring), & Chen, Z. (2015). Time for a radical reappraisal of tourist decision making? toward a new conceptual model. Journal of Travel Research, 55(1), 3–15. https://doi.org/10.1177/0047287515592973
146.McKinney, V., Yoon, K., & Zahedi, F. "Mariam." (2002). The measurement of web-customer satisfaction: An expectation and disconfirmation approach. Information Systems Research, 13(3), 296–315. https://doi.org/10.1287/isre.13.3.296.76
147.Melović, B., Šehović, D., Karadžić, V., Dabić, M., & Ćirović, D. (2021). Determinants of millennials' behavior in online shopping – implications on consumers' satisfaction and e-business development. Technology in Society, 65, 101561. https://doi.org/10.1016/j.techsoc.2021.101561
148.Merriam-Webster. (n.d.). Pretravel. In Merriam-Webster.com dictionary. Retrieved November 25, 2025, from https://www.merriam-webster.com/dictionary/pretravel
149. Metreau, E., Young, K. E., & Eapen, S. G. (2024, July 1). World Bank country classifications by income level for 2024-2025. World Bank Blogs. https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025
150. Mollajafari, S. (2018). Towards a more secure mobile banking system: The case of iran. International Journal of Scientific and Research Publications (IJSRP), 8(7). https://doi.org/10.29322/ijsrp.8.7.2018.p7960
151.Morabi Jouybari, H., Ghorbani, A., Mousazadeh, H., Golafshan, A., Akbarzadeh Almani, F., Dénes, D. L., & Krisztián, R. (2023). Smartphones as a platform for tourism management dynamics during pandemics: A case study of the shiraz metropolis, Iran. Sustainability, 15(5), 4051. https://doi.org/10.3390/su15054051
152.Nathan, R. J., Victor, V., Tan, M., & Fekete-Farkas, M. (2020). Tourists' use of Airbnb app for visiting a historical city. Information Technology & Tourism, 22(2), 217–242. https://doi.org/10.1007/s40558-020-00176-0
153.Navalón-García, R., & Mínguez, C. (2021). Tourist Guides and Free Tours: A controversial relationship. Tourist Studies, 21(3), 486–506. https://doi.org/10.1177/14687976211016073
154.Ngelambong, A., Nor, N. M., Abdullah, D., & Kamal, S. B. M. (2018). Perceived privacy concern, affective relationship Trust and relationship risk in airlines brand online community. International Journal of Academic Research in Business and Social Sciences, 8(15), 68–8

155.Nilashi, M., Abumalloh, R. A., Ahmadi, H., Samad, S., Alrizq, M., Abosaq, H., & Alghamdi, A. (2023). The nexus between quality of Customer Relationship Management Systems and customers' satisfaction: Evidence from online customers' reviews. Heliyon, 9(11). https://doi.org/10.1016/j.heliyon.2023.e21828
156.Nunnally, J.C. and Bernstein, I.H. (1994) The Assessment of Reliability. Psychometric Theory, 3, 248-292.
157.O'Brien, H. L. (2010). The influence of hedonic and utilitarian motivations on user engagement: The case of online shopping experiences. Interacting with Computers, 22(5), 344–352. https://doi.org/10.1016/j.intcom.2010.04.001
158.Oliveira, T., Araujo, B., & Tam, C. (2020). Why do people share their travel experiences on social media? Tourism Management, 78, 104041. https://doi.org/10.1016/j.tourman.2019.104041
159.Ooi, K. B., Hew, J. J., & Lin, B. (2018). Unfolding the privacy paradox among mobile social commerce users: A multi-mediation approach. Behaviour & Information Technology, 37(6), 575–595. https://doi.org/https://doi.org/10.1080/0144929X.2018.1465997
160.Ortaleza, M. S., & Mangali, G. R. (2021). Attributes of travel destinations that influence tourists' decisions: A systematic review. International Tourism and Hospitality Journal, 4(8), 1-17. https://doi.org/10.37227/ITHJ-2021-03-247
161.Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User acceptance of mobile apps for restaurants: An expanded and extended utaut-2. Sustainability, 11(4), 1210. https://doi.org/10.3390/su11041210
162.Palos-Sanchez, P., Saura, J. R., & Correia, M. B. (2021). Do tourism applications' quality and user experience influence its acceptance by tourists? Review of Managerial Science, 15(5), 1205–1241. https://doi.org/10.1007/s11846-020-00396-y
163.Park, S.-H. "Sunny," Lee, L., & Yi, M. Y. (2011). Group-level effects of Facilitating Conditions on individual acceptance of information systems. Information Technology and Management, 12(4), 315–334. https://doi.org/10.1007/s10799-011-0097-2
164.Parmar, K., Suman, O., & Sadariya, M. (2025). Geospatial Travel Companion: An Ai-Powered Personalized Travel Planning System. https://doi.org/10.2139/ssrn.5104109
165.Pertheban, S., Narayana Samy, G., & Shanmugam, B. (2019). A systematic literature review: Information accuracy practices in tourism. Journal of Quality Assurance in Hospitality & Tourism, 21(1), 1–30. https://doi.org/10.1080/1528008x.2018.1563016
166.Pine, B. J., & Gilmore, J. H. (1999). The Experience Economy: Work is Theatre & Every Business a Stage. Harvard Business School Press.
167.Pop, R.-A., Săplăcan, Z., Dabija, D.-C., & Alt, M.-A. (2021). The impact of social media influencers on travel decisions: The role of Trust in consumer decision journey. Current Issues in Tourism, 25(5), 823–843. https://doi.org/10.1080/13683500.2021.1895729
168.Pourazad, N., Stocchi, L., & Simmonds, L. (2025). Influencers and the choice of a travel destination: A customer journey and information processing perspective. Information Technology & Tourism. https://doi.org/10.1007/s40558-025-00330-6

169.Prebensen, N. K., Woo, E., & Uysal, M. S. (2013). Experience value: Antecedents and consequences. Current Issues in Tourism, 17(10), 910–928. https://doi.org/10.1080/13683500.2013.770451
170.Putrevu, J., & Mertzanis, C. (2024). The adoption of digital payments in emerging economies: Challenges and policy responses. Digital Policy, Regulation and Governance, 26(5), 476–500. https://doi.org/10.1108/DPRG-06-2023-0077
171.Radner, R., & Rothschild, M. (1975). On the allocation of effort. Journal of Economic Theory, 10, 358–376
172.Rahman, A., & Muktadir, Md. G. (2021). SPSS: An imperative quantitative data analysis tool for social science research. International Journal of Research and Innovation in Social Science, 05(10), 300–302. https://doi.org/10.47772/ijriss.2021.51012
173.Ranganathan, P., & Caduff, C. (2023). Designing and validating a research questionnaire – Part 1. Perspectives in Clinical Research, 14(3), 152–155. https://doi.org/10.4103/picr.picr_140_23
174.Rayun, S. M. N., Salam, M. A., Islam, W., Firmansyah, E. A., & Kalinaki, K. (2025). Unraveling the dynamics of Mobile Wallets in promoting cashless tourism in Bangladesh: Implementation of UTAUT2 model. Journal of Hospitality and Tourism Technology, 16(5), 1046–1065. https://doi.org/10.1108/jhtt-04-2024-0222
175.Rejali, S., Aghabayk, K., Esmaeli, S., & Shiwakoti, N. (2023). Comparison of technology acceptance model, theory of planned behavior, and unified theory of acceptance and use of technology to assess a priori acceptance of fully automated vehicles. Transportation Research Part A: Policy and Practice, 168, 103565. https://doi.org/10.1016/j.tra.2022.103565
176.Ridgway, N. M., & Kukar-Kinney, M. (2012). The role of price in the behavior and purchase decisions of compulsive buyers. Journal of Retailing, 88(1), 63–71. https://doi.org/10.1016/j.jretai.2011.02.004
177.Riegelsberger, J., Sasse, M. A., & Mccarthy, J. D. (2005). The mechanics of Trust: A framework for research and design. International Journal of Human-Computer Studies, 62(3), 381-422. https://doi.org/10.1016/j.ijhcs.2005.01.001
178.Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance–performance map analysis. Industrial Management & Data Systems, 116(9), 1865–1886. https://doi.org/10.1108/IMDS-10-2015-0449
179.Rogers, E. M. (1962). Diffusion of innovations (1st ed.). Free Press of Glencoe.
180.Sánchez-Torres, J. A., Arroyo-Cañada, F.-J., & Argila-Irurita, A. (2021). Adoption of tourist mobile applications. Journal of Telecommunications and the Digital Economy, 9(1), 1–18. https://doi.org/10.18080/jtde.v9n1.305
181.Sand, A. (2022). Inferential statistics is an unfit tool for interpreting data. Applied Sciences, 12(15), 7691. https://doi.org/10.3390/app12157691
182.Şeker, F., Kadirhan, G., & Erdem, A. (2023). The factors affecting tourism mobile apps usage. Tourism & Management Studies, 19(1), 7–14. https://doi.org/10.18089/tms.2023.190101

183. Sepehri, Y., & Gholinejad Pirbazari, A. (2021). Designing a mobile application for tourism in the Architectural Heritage of Tehran. Tourism and Heritage Journal, 3, 29–38. https://doi.org/10.1344/thj.2021.3.3

184. Sharma, A., Jain, S., & Yadav, R. L. (2023). Role of mobile apps in the Health Care Department. International Journal of Advanced Research in Science, Communication and Technology, 1–6. https://doi.org/10.48175/ijarsct-10711

185. Shen, S., Sotiriadis, M., & Zhang, Y. (2020). The influence of Smart Technologies on customer journey in tourist attractions within the Smart Tourism Management Framework. Sustainability, 12(10), 4157. https://doi.org/10.3390/su12104157

186. Sia, P. Y.-H., Saidin, S. S., & Iskandar, Y. H. (2023). Smart Mobile tourism app featuring Augmented Reality and Big Data Analytics: An empirical analysis using UTAUT2 and PCT models. Journal of Science and Technology Policy Management, 15(6), 1363–1386. https://doi.org/10.1108/jstpm-05-2022-0088

187. Siagian, H., Tarigan, Z. J., Basana, S. R., & Basuki, R. (2022). The effect of perceived security, perceived ease of use, and perceived usefulness on consumer behavioral intention through Trust in Digital Payment Platform. International Journal of Data and Network Science, 6(3), 861–874. https://doi.org/10.5267/j.ijdns.2022.2.010

188. Singh, N., & Sinha, N. (2020). How perceived Trust mediates merchant's intention to use a mobile wallet technology. Journal of Retailing and Consumer Services, 52, 101894. https://doi.org/10.1016/j.jretconser.2019.101894

189. Song, P., Zhang, C., Chen, W., & Huang, L. (2009). Understanding usage-transfer behavior between nonsubstitutable technologies: Evidence from instant messenger and portal. IEEE Transactions on Engineering Management, 56(3), 412–424. https://doi.org/10.1109/tem.2009.2023084

190. Statista. (2024). Mobile travel trends – statistics & facts. Retrieved October 30, 2025, from https://www.statista.com/topics/10685/mobile-travel-trends/#topicOverview

191. Stefanova, E., Dubljević, O., Herbert, C., Fairfield, B., Schroeter, M. L., Stern, E. R., Urben. (2020). Anticipatory feelings: Neural correlates and linguistic markers. Neuroscience & Biobehavioral Reviews, 113, 308–324. https://doi.org/10.1016/j.neubiorev.2020.02.015

192. Stylos, N. (2022). An integrated duality theory framework (IDTF): Marking pathways for consumer decision-making researchers in the hospitality and Tourism Industry. International Journal of Contemporary Hospitality Management, 34(7), 2597–2619. https://doi.org/10.1108/ijchm-10-2021-1256

193. Tak, P., & Panwar, S. (2016). Using UTAUT 2 model to predict mobile app based shopping: Evidences from India. Journal of Indian Business Research, 9(3), 248-264. https://doi.org/10.1108/jibr-11-2016-0132

194. Tam, C., Santos, D., & Oliveira, T. (2020). Exploring the influential factors of continuance intention to use mobile apps: Extending the expectation confirmation model. Information Systems Frontiers, 22, 243–257. https://doi.org/10.1007/s10796-018-9874-4

195. Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2020). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. Information Systems Frontiers, 23(4), 987–1005. https://doi.org/10.1007/s10796-020-10007-6
196. Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended unified theory of acceptance and use of Technology (UTAUT2): A systematic literature review and theory evaluation. International Journal of Information Management, 57, 102269. https://doi.org/10.1016/j.ijinfomgt.2020.102269
197. Tan, W.-K. (2017). From fantasy to reality: A study of pre-trip planning from the perspective of destination image attributes and temporal psychological distance. Service Business, 12(1), 65–84. https://doi.org/10.1007/s11628-017-0337-6
198. Tavakoli, M., & Tavakoli, A. (2010). A cross-cultural study of advice and social pressure. Procedia - Social and Behavioral Sciences, 5, 1533–1539. https://doi.org/10.1016/j.sbspro.2010.07.321
199. Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176. https://doi.org/10.1287/isre.6.2.144
200. Tekin, Y. (2025). Augmented reality in tourism: Enhancing traveller experiences through Digital Innovation. International Journal of Engineering and Innovative Research, 7(1), 24–28. https://doi.org/10.47933/ijeir.1615406
201. Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS Quarterly, 15(1), 125–143. https://doi.org/10.2307/249443
202. Tian, Z., Lu, M., & Cheng, Q. (2021). The relationships among mobile travel application attributes, customer engagement, and brand equity. Social Behavior and Personality: An International Journal, 49(7), 1–10. https://doi.org/10.2224/sbp.10353
203. Ting, H., Memon, M. A., Thurasamy, R., & Cheah, J.-H. (2025). Snowball sampling: A review and guidelines for survey research. Asian Journal of Business Research, 15(1), 1–15. https://doi.org/10.14707/ajbr.250186
204. Tomej, K., Liburd, J., Blichfeldt, B. S., & Hjalager, A.-M. (2022). Blended and (not so) splendid teaching and learning: Higher education insights from university teachers during the Covid-19 pandemic. *International Journal of Educational Research Open, 3*, 100144. https://doi.org/10.1016/j.ijedro.2022.100144
Tourism Management, 32(2), 256e265.
205. Tran, B. D., & Vu, D. H. (2024). Gen-y behavioral intention to adopt mobile tourism apps: Extending utaut2 with Trust and security. International Journal of Data and Network Science, 8(4), 2173–2184. https://doi.org/10.5267/j.ijdns.2024.6.014
206. Triandis, H. C. (1980). Values, attitudes, and interpersonal behavior. In H. E. Howe & M. M. Page (Eds.), Nebraska Symposium on Motivation (Vol. 27, pp. 195–259). University of Nebraska Press.
207. Tung, V. W. S., & Ritchie, J. R. B. (2011). *Exploring the essence of memorable tourism experiences*. *Annals of Tourism Research, 38*(4), 1367–1386. https://doi.org/10.1016/j.annals.2011.03.009

208.Turk, T., Cornacchia, M., Livi, S., Papa, F., & Sapio, B. (2015).Households technology adoption and use patterns: The case of digital terrestrial television in six Italian regions. Technology Analysis & Strategic Management. Advance online publication. https://doi.org/10.1080/09537325.2015.1071788

209.Tussyadiah, I. P. (2016). The influence of innovativeness on on-site smartphone use among American travellers: Implications for context-based push marketing. *Journal of Travel & Tourism Marketing, 33*(6), 806–823. https://doi.org/10.1080/10548408.2015.1068263

210.Urry, J., & Larsen, J. (2011). *The Tourist Gaze 3.0*. https://doi.org/10.4135/9781446251904

211.Uttenthal, M. (2024). A conceptual analysis of Trust. Social Science Information, 63(3), 392–410. https://doi.org/10.1177/05390184241270835

212.Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

213.Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412

214.Venkatesh, V., Thong, J., & Xu, X. (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

215.Vlahović, O., Rađenović, Ž., Perović, Đ., & Vujačić, V. (2024). Digital transformation in tourism: The role of e-booking systems. Croatian Regional Development Journal, 5(2), 129–145. https://doi.org/10.2478/crdj-2024-0012

216.Wang, H., & Liu, T. (2025). Psychological determinants of GenAI adoption for foreign language education: An extended UTAUT2 model and sentiment analysis approach. Frontiers in Psychology. https://www.frontiersin.org/articles/10.3389/fpsyg.2025.1622926

217.Wang, H., Liang, C., Zhu, Y., & Zhou, M. (2024). Congruence in Communication and Customer Booking Decision: A Cognitive Heuristic Perspective. International Journal of Business Communication, 61(3), 703-721. https://doi.org/10.1177/23294884231157561

218.Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Destination image: A review from 2012 to 2023. Cogent Social Sciences, 9(1). https://doi.org/10.1080/23311886.2023.2240569

219.Warsame, M. H., & Ireri, E. M. (2018). Moderation effect on mobile microfinance services in Kenya:An extended utaut model. Journal of Behavioral and Experimental Finance, 18, 67–75. https://doi.org/10.1016/j.jbef.2018.01.008

220.Wen, I. (2012). An empirical study of an online travel purchase intention model. Journal of Travel & Tourism Marketing, 29(1), 18–39. https://doi.org/10.1080/10548408.2012.638558

221. Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. Journal of Enterprise Information Management, 28(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088
222. Wilson, P. M., Petticrew, M., Calnan, M., & Nazareth, I. (2010). Effects of a financial incentive on health researchers' response to an online survey: A randomized controlled trial. Journal of Medical Internet Research, 12(2). https://doi.org/10.2196/jmir.1251
223. Wong, J., & Law, R. (2005). Analysing the intention to purchase on hotel websites: A study of travellers to Hong Kong. International Journal of Hospitality Management, 24(3), 311–329. https://doi.org/10.1016/j.ijhm.2004.08.002
224. Wu, I. L., & Chen, J. L. (2014). A stage-based diffusion of IT innovation and the BSC performance impact: A moderator of technology-organization-environment. Technological Forecasting and Social Change, 88, 76–90. https://doi.org/10.1016/j.techfore.2014.06.015
225. Xiang, Z., & Gretzel, U. (2010). Role of social media in Online Travel Information Search. Tourism Management, 31(2), 179–188. https://doi.org/10.1016/j.tourman.2009.02.016
226. Xu (Rinka), X., & Pratt, S. (2018). Social Media influencers as endorsers to promote travel destinations: An application of self-congruence theory to the Chinese Generation Y. Journal of Travel & Tourism Marketing, 35(7), 958–972. https://doi.org/10.1080/10548408.2018.1468851
227. Xu, L., & Lu, X. (2020). Influencing factors in online tourism service quality: A Fuzzy cognitive map based on customers' perceptions. Journal of Systems and
228. Yoon, Y., & Uysal, M. (2005). An examination of the effects of motivation and satisfaction on Destination Loyalty: A structural model. Tourism Management, 26(1), 45–56. https://doi.org/10.1016/j.tourman.2003.08.016
229. Zarezadeh, Z. Z., Benckendorff, P., & Gretzel, U. (2023). Online tourist information search strategies. Tourism Management Perspectives, 48, 101140. https://doi.org/10.1016/j.tmp.2023.101140
230. Zhang, L., Zhu, J., & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. Computers in Human Behavior, 28(5), 1902–1911. https://doi.org/10.1016/j.chb.2012.05.008
231. Zhou, T. (2011). The effect of initial Trust on user adoption of mobile payment. Information Development, 27(4), 290–300. http://doi.org/10.1177/0266666911424075
232. Zhou, T., & Li, H. (2014). Understanding mobile SNS continuance usage in China from the perspectives of Social Influence and privacy concern. Computers in Human Behavior, 37, 283–289. https://doi.org/https://doi.org/10.1016/j.chb.2014.05.00
233. Ziaei Nafchi, M., & Mohelská, H. (2018). Industry 4.0 and labor market in Iran as a developing country. Hradec Economic Days, 8, 550–561. https://doi.org/10.36689/uhk/hed/2018-02-053

APPENDICES

Appendix 1: Questionnaire in English

You are invited to participate in a research study examining travellers' use of Travel Mobile Applications (TMAs) during the pre-travel phase. Your responses will contribute to a better understanding of how users interact with these applications and which factors influence their adoption. Participation is completely voluntary, and all information you provide will remain strictly confidential and used solely for academic purposes. No identifying information will be collected, and your responses will be analysed in aggregate form only. Please read each question carefully and answer as honestly as possible. The survey will take approximately 20 minutes to complete. If you agree to participate, please proceed to the next section. Thank you in advance for your contribution.
Please choose your age category: 18-24 25-34 35-44 45-54 55-65 65 or more
Please indicate your gender: Male Female
Please indicate your level of education: High school or less High school Bachelor's degree Master's degree Doctoral degree or higher
Please indicate your marital status: Single Married In relation
Please indicate your monthly income: <$200 $200–$400 $400–$600 $600-$800 >$800

Please indicate the number of your trips per year: Once per year 2-5 times per year >5 trips per year
Please indicate the duration of your trip: 1-3 days 4-7 days 8 or longer
Please indicate the extent to which you agree with each of the following statements:
I use TRMAs (travel-related mobile applications) to dream about future trips. Never Rarely Sometimes Often Always
I use TRMAs for decision making and travel planning trips. Never Rarely Sometimes Often Always
I use TRMAs to book a trip. Never Rarely Sometimes Often Always
I pay and conduct transactions for my trips through TMAs. Never Rarely Sometimes Often Always

I use TRMAs to anticipate my upcoming trip. Never Rarely Sometimes Often Always
I find TMAs useful for my pre-travel activities. Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs help me accomplish my pre- travel-related tasks more quickly. Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs increase my productivity. Strongly Disagree Disagree Neutral Agree Strongly Agree
Learning how to use TMAs is easy for me. Strongly Disagree Disagree Neutral Agree Strongly Agree
My interaction with TMAs is clear and understandable. Strongly Disagree Disagree Neutral Agree Strongly Agree
I find TMAs easy to use. Strongly Disagree Disagree Neutral Agree Strongly Agree
It is easy for me to become skilful at using TMAs.

Strongly Disagree Disagree Neutral Agree Strongly Agree
People who are important to me think that I should use TMA. Strongly Disagree Disagree Neutral Agree Strongly Agree
People who influence my behaviour think that I should use TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
People whose opinions that I value prefer that I use TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
I have the resources necessary to use TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
I have the knowledge necessary to use TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs are compatible with other technologies I use. Strongly Disagree Disagree Neutral Agree Strongly Agree
I can get help from others when I have difficulties using TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree

Enough guidance and instruction were provided for the use of TMAs Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs is fun. Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs is enjoyable. Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs is very entertaining. Strongly Disagree Disagree Neutral Agree Strongly Agree
I can save money by examining the prices on TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
I like to search for cheap travel deals on TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs offer better travel deals and more value for my money. Strongly Disagree Disagree Neutral Agree Strongly Agree
The use of TMAs has become a Habit for me.

Strongly Disagree Disagree Neutral Agree Strongly Agree
I am addicted to using TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
I must use TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
Using TMAs has become natural to me. Strongly Disagree Disagree Neutral Agree Strongly Agree
I believe that TMAs have become important tools in my life. Strongly Disagree Disagree Neutral Agree Strongly Agree
I intend to continue using TMAs for my pre-travel activities. Strongly Disagree Disagree Neutral Agree Strongly Agree
I will always try to use TMAs for my pre-travel activities. Strongly Disagree Disagree Neutral Agree Strongly Agree
I plan to continue to use TMAs frequently for my pre-travel activities. Strongly Disagree Disagree Neutral Agree Strongly Agree

TMAs have integrity. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs are reliable. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs are Trustworthy. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs implement security measures to protect users.
Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs usually ensure that transactional information is protected from accidentally being altered or destroyed during a transmission on the Internet.
Strongly Disagree Disagree Neutral Agree Strongly Agree
I feel secure about the electronic payment system at these TMAs.
Strongly Disagree Disagree Neutral Agree Strongly Agree
I am willing to use my bank card on these websites to make a purchase.
Strongly Disagree Disagree Neutral Agree Strongly Agree

I feel safe in making transactions on these TMAs.
Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs provide accurate information I need in the purchase process. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs provide sufficient information needed in the purchase process. Strongly Disagree Disagree Neutral Agree Strongly Agree
The information provided by TMAs is helpful to me in the purchase process. Strongly Disagree Disagree Neutral Agree Strongly Agree
The information in TMAs is clear. Strongly Disagree Disagree Neutral Agree Strongly Agree
TMAs provide up-to-date information. Strongly Disagree Disagree Neutral Agree Strongly Agree
I am concerned that TMAs collect too much personal information from me. Strongly Disagree Disagree Neutral Agree Strongly Agree
I am concerned that TMAs will use my personal information for other purposes without my authorization.

Strongly Disagree Disagree Neutral Agree Strongly Agree
I am concerned that TMAs will share my personal information with other entities without my authorization. Strongly Disagree Disagree Neutral Agree Strongly Agree
I am concerned that unauthorized persons (i.e., hackers) have access to my personal information on TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
I am concerned about the privacy of my personal information during a transaction on TMAs. Strongly Disagree Disagree Neutral Agree Strongly Agree
For how long have you been using travel-related mobile apps (e.g., for booking, planning, searching)? Just started Less than 3 months 3–6 months 6–12 months More than a year
How frequently do you use travel-related mobile apps to plan your travel activities? Rarely Occasionally Sometimes Often Very frequently
How many trips have you planned using travel-related mobile apps in total so far? 1-2 trips 3–5 trips 6–10 trips 11–15 trips More than 15 trips

Appendix 2: Questionnaire in Persian

شما به شرکت در یک پژوهش دعوت شده‌اید که به بررسی نحوهٔ استفادهٔ مسافران از اپلیکیشن‌های سفر در مرحلهٔ پیش از سفر می‌پردازد .پاسخ‌های شما به درک بهتر از شیوهٔ تعامل کاربران با این اپلیکیشن‌ها و عوامل مؤثر بر پذیرش و استفاده از آن‌ها کمک خواهد کرد .شرکت در این پژوهش کاملاً داوطلبانه است و تمامی اطلاعاتی که ارائه می‌کنید به‌طور محرمانه نگهداری شده و فقط برای اهداف علمی مورد استفاده قرار می‌گیرد .هیچ اطلاعات هویتی از شما جمع‌آوری نخواهد شد و پاسخ‌های شما فقط به‌صورت کلی و تجمیعی تحلیل می‌شود .لطفاً هر سؤال را با دقت مطالعه کرده و با صداقت کامل به آن پاسخ دهید .پاسخگویی به پرسشنامه حدود ۲۰ دقیقه زمان خواهد برد .در صورت موافقت با شرکت در پژوهش، لطفاً به بخش بعدی بروید پیشاپیش از شما سپاسگزارم
لطفاً گروه سنی خود را مشخص کنید سال یا بیشتر ۶۵ ۵۵–۶۵ ۴۵–۵۴ ۳۵–۴۴ ۲۵–۳۴ ۱۸–۲۴
جنسیت خود را مشخص کنید مرد زن
میزان تحصیلات خود را مشخص کنید دیپلم یا کمتر دیپلم کارشناسی کارشناسی‌ارشد دکتری یا بالاتر
وضعیت تأهل خود را مشخص کنید مجرد متأهل در رابطه
درآمد ماهیانهٔ خود را مشخص کنید بیش از ۸۰۰ دلار دلار ۶۰۰–۸۰۰ دلار ۴۰۰–۶۰۰ دلار ۲۰۰–۴۰۰ کمتر از ۲۰۰ دلار
تعداد سفرهای سالانهٔ خود را مشخص کنید یک بار در سال ۲ تا ۵ بار در سال بیش از ۵ بار در سال

مدت زمان معمول سفرهای شما تا ۳ روز ۴ تا ۷ روز ۸ روز یا بیشتر ۱
لطفاً میزان موافقت خود را با هر یک از جملات زیر مشخص کنید
من از اپلیکیشن‌های سفر برای خیال‌پردازی دربارهٔ سفرهای آینده استفاده می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من از اپلیکیشن‌های سفر برای تصمیم‌گیری و برنامه‌ریزی سفر استفاده می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من از اپلیکیشن‌های سفر برای رزرو سفر استفاده می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من از اپلیکیشن‌های سفر برای پرداخت و انجام تراکنش‌های مربوط به سفر استفاده می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من از اپلیکیشن‌های سفر برای پیش‌بینی و آمادگی برای سفر پیش‌رو استفاده می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
اپلیکیشن‌های سفر برای فعالیت‌های پیش از سفر من مفید هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم

استفاده از این اپلیکیشن‌ها به من کمک می‌کند کارهای پیش از سفر را سریع‌تر انجام دهم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از این اپلیکیشن‌ها بهره‌وری مرا افزایش می‌دهد کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
یادگیری نحوهٔ استفاده از اپلیکیشن‌های سفر برای من آسان استی کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
تعامل من با این اپلیکیشن‌ها واضح و قابل‌فهم است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از این اپلیکیشن‌ها برای من آسان است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
کسب مهارت در استفاده از این اپلیکیشن‌ها برای من ساده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
افراد مهم زندگی‌ام فکر می‌کنند باید از اپلیکیشن‌های سفر استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
افرادی که بر رفتار من تأثیر می‌گذارند معتقدند باید از این اپلیکیشن‌ها استفاده کنم

کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
کسانی که نظرشان برای من ارزشمند است ترجیح می‌دهند از این اپلیکیشن‌ها استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من منابع لازم برای استفاده از اپلیکیشن‌های سفر را دارم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من دانش لازم برای استفاده از این اپلیکیشن‌ها را دارم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها با سایر فناوری‌هایی که استفاده می‌کنم سازگار هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
در صورت بروز مشکل، می‌توانم از دیگران کمک بگیرم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
راهنمایی‌ها و دستورالعمل‌های کافی برای استفاده از این اپلیکیشن‌ها ارائه شده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از اپلیکیشن‌های سفر برای من سرگرم‌کننده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم

استفاده از این اپلیکیشن‌ها برای من لذت‌بخش است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از این اپلیکیشن‌ها برای من بسیار سرگرم‌کننده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
با بررسی قیمت‌ها در اپلیکیشن‌های سفر می‌توانم در هزینه‌ها صرفه‌جویی کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
دوست دارم در این اپلیکیشن‌ها به دنبال قیمت‌های ارزان سفر باشم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌های سفر ارزش بیشتری نسبت به هزینهٔ پرداختی ارائه می‌کنند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از اپلیکیشن‌های سفر برای من تبدیل به عادت شده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
من به استفاده از این اپلیکیشن‌ها اعتیاد پیدا کرده‌ام کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
احساس می‌کنم باید از این اپلیکیشن‌ها استفاده کنم

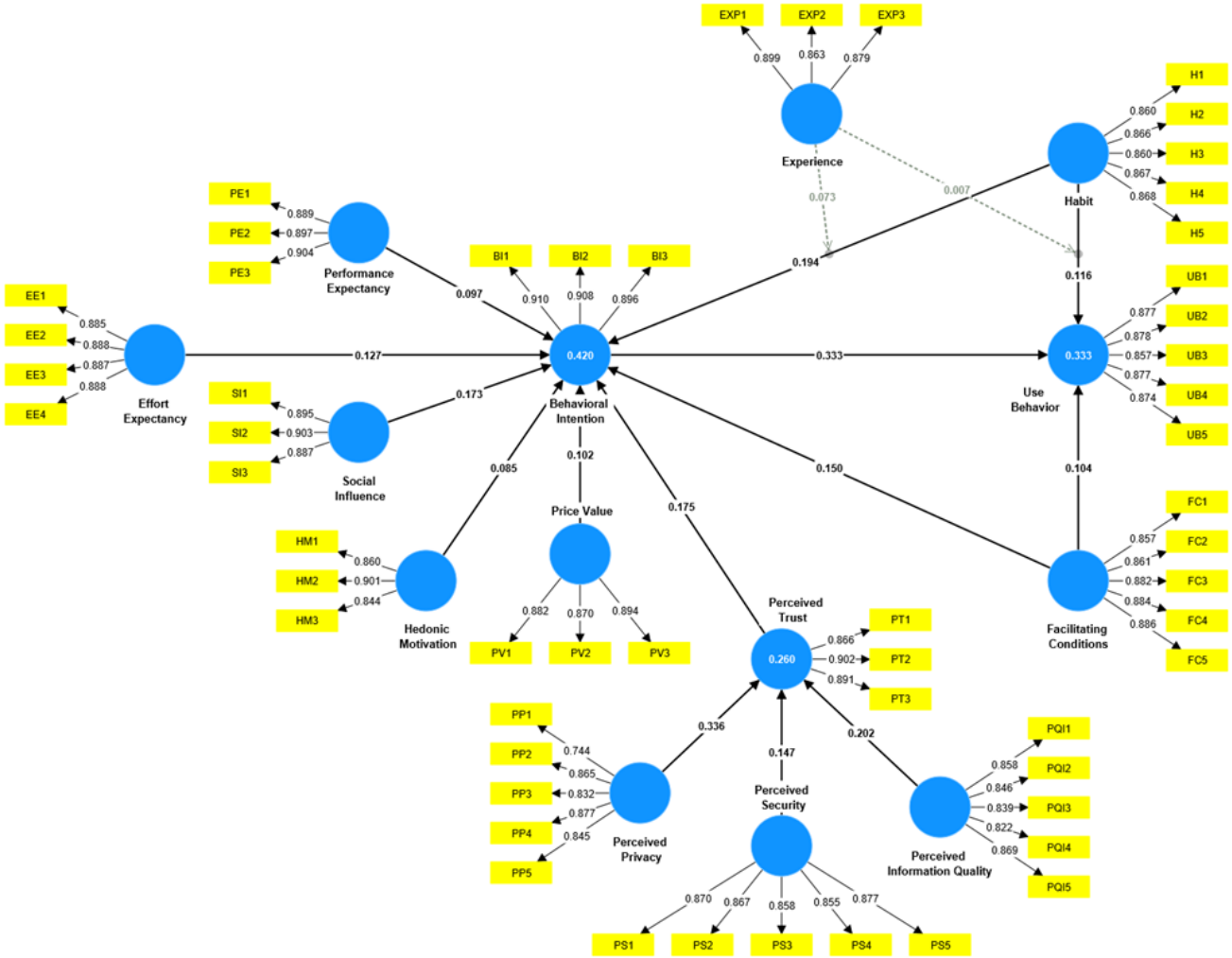
کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
استفاده از این اپلیکیشن‌ها برای من طبیعی و همیشگی شده است کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها به ابزارهای مهمی در زندگی من تبدیل شده‌اند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
قصد دارم از این اپلیکیشن‌ها برای فعالیت‌های پیش از سفر استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
همیشه تلاش خواهم کرد از این اپلیکیشن‌ها برای فعالیت‌های پیش از سفر استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
قصد دارم از این اپلیکیشن‌ها به‌طور مداوم برای فعالیت‌های پیش از سفر استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها دارای یکپارچگی و صداقت هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها قابل اعتماد هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم

این اپلیکیشن‌ها قابل اطمینان و درستکار هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
اپلیکیشن‌های سفر تدابیر امنیتی لازم را برای حفاظت از کاربران اجرا می‌کنند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها تضمین می‌کنند اطلاعات تراکنش هنگام انتقال آسیب نبیند یا تغییر نکند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
نسبت به سیستم پرداخت الکترونیکی این اپلیکیشن‌ها احساس امنیت می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
مایلم از کارت بانکی خود برای پرداخت در این اپلیکیشن‌ها استفاده کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
هنگام انجام تراکنش در این اپلیکیشن‌ها احساس امنیت می‌کنم کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها اطلاعات دقیق ارائه می‌دهند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها اطلاعات کافی ارائه می‌دهند

کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
اطلاعات ارائه‌شده در این اپلیکیشن‌ها برای من مفید هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
اطلاعات ارائه‌شده در این اپلیکیشن‌ها واضح هستند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
این اپلیکیشن‌ها اطلاعات به‌روز ارائه می‌دهند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
نگرانم که این اپلیکیشن‌ها اطلاعات شخصی زیادی از من جمع‌آوری کنند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
نگرانم این اپلیکیشن‌ها اطلاعات من را بدون اجازه برای اهداف دیگری استفاده کنند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
نگرانم این اپلیکیشن‌ها اطلاعات من را بدون اجازه با دیگران به اشتراک بگذارند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
نگرانم افراد غیرمجاز مانند هکرها به اطلاعات من دسترسی پیدا کنند کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم

نگرانم هنگام انجام تراکنش، حریم خصوصی اطلاعات شخصی من حفظ نشود کاملاً مخالفم مخالفم نظری ندارم موافقم کاملاً موافقم
از چه مدت پیش شروع به استفاده از اپلیکیشن‌های سفر کرده‌اید؟ کمتر از ۳ ماه ۳ تا ۶ ماه ۶ تا ۱۲ ماه بیش از یک سال
هر چند وقت یک‌بار از این اپلیکیشن‌ها استفاده می‌کنید؟ به‌ندرت گاهی گاهی‌اوقات اغلب بسیار زیاد /تقریباً همیشه
تاکنون چند سفر را با استفاده از اپلیکیشن‌های سفر برنامه‌ریزی کرده‌اید؟ تا ۲ سفر ۳ تا ۵ سفر ۶ تا ۱۰ سفر ۱۱ تا ۱۵ سفر بیش از ۱۵ سفر ۱

Appendix 3: Measurement model with standardized factor loadings



Source: Author's own work

Appendix 4: Daljši povzetek

Razširitev enotne teorije sprejemanja in uporabe tehnologij na primeru turističnih mobilnih aplikacij

Namen doktorske disertacije je preučiti dejavnike, ki vplivajo na sprejemanje in uporabo mobilnih aplikacij za potovanja (angl. Travel Mobile Applications – TMAs) v fazi pred potovanjem, ter pojasniti, kako tehnološki, motivacijski, socialni in na zaupanju temelječi dejavniki oblikujejo vedenjski namen in dejansko vedenje uporabnikov v digitalnem turističnem okolju. V zadnjih letih so mobilne tehnologije postale osrednja infrastruktura turistične potrošnje, saj uporabnikom omogočajo iskanje informacij, primerjanje ponudb, načrtovanje itinerarjev, izvajanje rezervacij ter finančnih transakcij prek enotnega digitalnega vmesnika (Gretzel et al., 2015; Xiang & Gretzel, 2010). Mobilne aplikacije za potovanja so se iz dopolnilnih orodij razvile v ključne podporne mehanizme odločanja, zlasti v fazi pred potovanjem, ko turisti oblikujejo namene, ocenjujejo tveganja in razvijajo pričakovanja glede potovalne izkušnje (Tung & Ritchie, 2011; Gretzel, 2021).

Kljub vse večjemu pomenu TMAs akademsko razumevanje dejavnikov, ki vplivajo na njihovo sprejemanje in stalno uporabo, ostaja nepopolno iz več razlogov. Prvič, večina raziskav sprejemanja tehnologije v turizmu obravnava uporabo mobilnih aplikacij celostno skozi celotni potovalni proces, pri čemer pogosto zanemarja fazno specifičnost turističnega odločanja (Eletxigerra et al., 2021). Faza pred potovanjem ne predstavlja zgolj začetnega koraka potovalnega cikla, temveč ključno obdobje, v katerem turisti intenzivno iščejo informacije, vrednotijo alternative, ocenjujejo tveganja in sprejemajo temeljne odločitve, ki bistveno vplivajo na potek in kakovost celotne potovalne izkušnje (Tung & Ritchie, 2011; Gretzel et al., 2020). Ta faza zato zahteva samostojno teoretično in empirično obravnavo.

Drugič, velik delež empiričnih raziskav izhaja iz tehnološko naprednih okolij, za katera so značilni visoko razviti institucionalni mehanizmi, regulativni okviri in digitalna infrastruktura. Takšna geografska in institucionalna pristranskost omejuje prenosljivost ugotovitev na razvijajoča se okolja, kjer so zaščita potrošnikov, regulacija digitalnih trgov ter raven zaupanja v spletne transakcije pogosto šibkejši, kulturni dejavniki pa pomembneje vplivajo na zaznavanje tveganja in sprejemanje tehnologije (Sánchez-Torres et al., 2021; Hanafizadeh et al., 2014).

Za obravnavo teh vrzeli disertacija uporablja in razširja teoretični okvir Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), ki predstavlja enega najvplivnejših modelov za razlago potrošniškega sprejemanja tehnologije (Venkatesh et al., 2012). UTAUT2 vključuje konstrukte, kot so pričakovana učinkovitost, pričakovani napor, socialni vpliv, omogočitveni pogoji, hedonistična motivacija, vrednost cene in navada, ter zagotavlja visoko pojasnjevalno moč pri razlagi vedenjskega namena in dejanske uporabe. Vendar v izvirni obliki model ne vključuje konstrukta zaupanja, ki ima v kontekstu TMAs posebno

vlogo, saj uporabniki razkrivajo osebne podatke, se zanašajo na verodostojnost informacij ter pogosto izvajajo finančne transakcije (Kim et al., 2008; Hartono et al., 2014).

Osrednji namen disertacije je zato razviti in empirično preveriti razširjeni model UTAUT2, v katerem je zaznano zaupanje vključeno kot dodatni osrednji dejavnik vedenjskega namena uporabe TMAs. Zaupanje je konceptualizirano kot večdimenzionalni konstrukt, ki ga oblikujejo trije ključni predhodniki: zaznana zasebnost, zaznana varnost in zaznana kakovost informacij (Kim et al., 2008; Hartono et al., 2014). Poleg tega disertacija preučuje moderirajočo vlogo predhodnih uporabniških izkušenj, zlasti v razmerjih med navado, vedenjskim namenom in dejansko uporabo, skladno z izhodišči modela UTAUT2 (Venkatesh et al., 2012).

Empirična validacija razširjenega modela temelji na podatkih, zbranih med uporabniki mobilnih aplikacij za potovanja v Iranu, ki predstavlja razvijajoče se okolje, v katerem so vprašanja zaupanja, institucionalne negotovosti in digitalne pismenosti še posebej izrazita. Raziskava uporablja metodo modeliranja strukturnih enačb z delnimi najmanjšimi kvadrati (PLS-SEM) ter vključuje analizo neposrednih, posrednih in moderirajočih učinkov na podlagi vzorca 424 veljavnih odgovorov.

Z vključitvijo zaznanega zaupanja in njegovih predhodnikov v model UTAUT2 ter z osredotočenostjo na fazo pred potovanjem disertacija prispeva k (1) poglobljenemu teoretičnemu razumevanju sprejemanja mobilnih turističnih aplikacij, (2) razširitvi empiričnih dokazov iz razvijajočih se gospodarstev ter (3) oblikovanju praktičnih priporočil za razvijalce aplikacij, turistične ponudnike in oblikovalce politik, usmerjenih v krepitev zaupanja, spodbujanje navade in dolgoročno uporabo TMAs v digitalnem turizmu.

Raziskovalna vrzel in raziskovalni problem

Kljub vse večjemu zanimanju raziskovalcev za sprejemanje mobilnih tehnologij v turizmu ostaja več pomembnih teoretičnih in empiričnih vrzeli še nerešenih. Obstoječe raziskave o mobilnih aplikacijah za potovanja večinoma obravnavajo njihovo uporabo kot splošno orodje skozi celotni potovalni proces, brez natančne razmejitve posameznih faz turistične izkušnje (Asif & Fazel, 2024; Tung & Ritchie, 2011). Doslej je bila največja pozornost namenjena fazi potovanja na destinaciji, ki je predmet skoraj petkrat več študij kot faza pred potovanjem (Eletxigerra et al., 2021). Posledično faza pred potovanjem, ki predstavlja ključno obdobje za iskanje informacij, vrednotenje alternativ, oblikovanje potovalnih namenov ter sprejemanje odločitev o rezervacijah in transakcijah, ostaja razmeroma slabo konceptualizirana in empirično raziskana kot samostojen kontekst odločanja.

Čeprav je faza pred potovanjem prepoznana kot temeljni del potovalnega cikla (Tung & Ritchie, 2011; Gretzel, 2021), obstoječe študije redko analizirajo njeno notranjo strukturo in vlogo mobilnih aplikacij v posameznih podfazah, kot so navdihovanje, načrtovanje, rezervacija, transakcija in oblikovanje pričakovanj (Eletxigerra et al., 2021). Ta raziskovalna vrzel omejuje razumevanje, kako turisti dejansko uporabljajo mobilne aplikacije v zgodnjih

fazah odločanja, kjer se oblikujejo ključne preference, zaznave tveganja in pričakovanja glede potovalne izkušnje.

Druga pomembna vrzel izhaja iz prevladujoče uporabe klasičnih modelov sprejemanja tehnologije, kot so TAM, TPB ter izvirni modeli UTAUT in UTAUT2. Čeprav model UTAUT2 predstavlja enega najvplivnejših in najbolj razširjenih okvirov za razlago potrošniškega sprejemanja tehnologije (Venkatesh et al., 2012; Venkatesh et al., 2016), v svoji osnovni obliki ne vključuje konstrukta zaznanega zaupanja. To predstavlja pomembno omejitev, saj imajo v kontekstu mobilnih aplikacij za potovanja uporabniki opravka z razkrivanjem osebnih podatkov, zanašanjem na verodostojnost informacij ter izvajanjem finančnih transakcij, kar povečuje zaznano tveganje in negotovost (Ioannou et al., 2020; Tran & Vu, 2024).

Predhodne raziskave so že pokazale, da ima zaznano zaupanje ključno vlogo pri sprejemanju digitalnih platform. Escobar-Rodríguez in Carvajal-Trujillo (2014) sta z vključitvijo zaupanja v model UTAUT2 bistveno izboljšala njegovo pojasnjevalno moč pri spletnem nakupu letalskih vozovnic. Kljub temu je zaupanje v raziskavah mobilnih aplikacij za potovanja še vedno razmeroma zapostavljeno, zlasti v fazi pred potovanjem, kjer uporabniki intenzivno vrednotijo varnost, zasebnost in kakovost informacij (Hartono et al., 2014; Kim et al., 2008; Baruah & Sarma, 2024).

Tretja pomembna raziskovalna vrzel se nanaša na izrazito geografsko in institucionalno pristranskost obstoječe literature. Večina empiričnih študij je bila izvedena v tehnološko naprednih okoljih z visoko digitalno pismenostjo in razvitimi institucionalnimi mehanizmi (Sánchez-Torres et al., 2021). Razmeroma malo pa je znanega o vedenju uporabnikov v razvijajočih se državah, kjer so digitalna infrastruktura, regulativni okviri in zaščita potrošnikov pogosto omejeni, kulturni dejavniki pa pomembneje vplivajo na zaznavanje tveganja in oblikovanje zaupanja (Gretzel, 2015; Amiri & Sangar, 2023; Esfandiar et al., 2023).

Na podlagi navedenega disertacija naslavlja tri ključne raziskovalne vrzeli: (1) pomanjkanje fazno specifičnih analiz sprejemanja mobilnih aplikacij v fazi pred potovanjem, (2) nezadostno vključevanje zaznanega zaupanja v okvir modela UTAUT2 v kontekstu mobilnih aplikacij za potovanja ter (3) omejeno število empiričnih študij iz razvijajočih se okolij.

RAZISKOVALNI CILJI

Za obravnavo opredeljenih raziskovalnih vrzeli in raziskovalnega problema si disertacija zastavlja naslednje glavne cilje:

Konceptualizirati fazo pred potovanjem kot samostojno stopnjo turističnega odločanja in analizirati vlogo mobilnih aplikacij za potovanja v tej fazi.

Razviti razširjeni model UTAUT2 z vključitvijo zaznanega zaupanja kot dodatnega pojasnjevalnega konstrukta ter z opredelitvijo njegovih predhodnikov v obliki zaznane zasebnosti, zaznane varnosti in zaznane kakovosti informacij.

Empirično preveriti neposredna in posredna razmerja med konstrukti UTAUT2, spremenljivkami zaupanja, vedenjskim namenom in dejansko uporabo.

Preučiti moderirajočo vlogo predhodnih uporabniških izkušenj, zlasti v razmerjih med navado, vedenjskim namenom in uporabo.

Oblikovati teoretične in upravljavske implikacije za razvoj, oblikovanje in upravljanje zaupanja vrednih mobilnih turističnih aplikacij v razvijajočih se digitalnih trgih.

RAZISKOVALNA VPRAŠANJA

Na podlagi navedenih ciljev disertacija obravnava naslednja raziskovalna vprašanja:

RV1: Kako je mogoče konceptualno strukturirati fazo pred potovanjem kot večstopenjski proces in kako turisti uporabljajo mobilne aplikacije za potovanja v posameznih podfazah te faze?

RV2: Kateri tehnološki, motivacijski in socialni dejavniki pozitivno ali negativno vplivajo na sprejemanje in uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem?

RV3: V kolikšni meri vključitev zaznanega zaupanja ter njegovih predhodnikov (zaznane zasebnosti, zaznane varnosti in zaznane kakovosti informacij) izboljša pojasnjevalno moč razširjenega modela UTAUT2 v kontekstu mobilnih aplikacij za potovanja v fazi pred potovanjem?

RV4: Kako kulturni in kontekstualni dejavniki, značilni za iranske uporabnike v razvijajočem se okolju, oblikujejo njihove zaznave in vedenje pri uporabi mobilnih aplikacij za potovanja?

RV5: V kolikšni meri predhodne uporabniške izkušnje moderirajo razmerja med navado, vedenjskim namenom in dejansko uporabo mobilnih aplikacij za potovanja v okviru razširjenega modela UTAUT2?

RV6: Katere praktične oblikovalske in politične smernice je mogoče izpeljati za izboljšanje zaupanja vrednosti, uporabnosti in kontekstualne ustreznosti mobilnih aplikacij za potovanja v razvijajočih se državah?

KONCEPTUALNI OKVIR IN RAZVOJ HIPOTEZ

Konceptualni okvir disertacije temelji na razširjenem modelu Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), ki predstavlja enega najcelovitejših in empirično najbolje podprtih teoretičnih modelov za razlago potrošniškega sprejemanja tehnologije.

Model UTAUT2 izhaja iz integracije več klasičnih teorij sprejemanja tehnologije, vključno z Modelom sprejemanja tehnologije (TAM), Teorijo načrtovanega vedenja (TPB) in izvirnim modelom UTAUT, ter vključuje sedem osrednjih konstruk-tov: pričakovano učinkovitost, pričakovani napor, socialni vpliv, omogočitvene pogoje, hedonistično motivacijo, vrednost cene in navado. Ti konstrukti pojasnjujejo vedenjski namen uporabe tehnologije in dejansko uporabo ter zagotavljajo visoko pojasnjevalno moč v različnih potrošniških in tehnoloških kontekstih.

V kontekstu mobilnih aplikacij za potovanja v fazi pred potovanjem ima model UTAUT2 posebno uporabno vrednost, saj zajema tako instrumentalne kot tudi hedonične in socialne vidike digitalnega vedenja. Pričakovana učinkovitost odraža stopnjo, do katere uporabniki zaznavajo, da jim uporaba aplikacije pomaga učinkoviteje načrtovati potovanje, pridobiti ustrezne informacije in sprejemati boljše odločitve. Pričakovani napor opisuje zaznano enostavnost uporabe aplikacije, ki lahko vpliva na začetno sprejemanje, zlasti pri manj izkušenih uporabnikih. Socialni vpliv zajema zaznano mnenje pomembnih drugih, kot so prijatelji, družina ali spletne skupnosti, glede uporabe mobilnih aplikacij. Omogočitveni pogoji odražajo razpoložljivost tehničnih virov, podpore in infrastrukture, ki omogočajo dejansko uporabo aplikacije. Hedonistična motivacija opisuje stopnjo užitka in zadovoljstva pri uporabi aplikacije, vrednost cene pa zaznano razmerje med koristmi in stroški uporabe. Navada predstavlja avtomatizirano vedenje, ki nastane kot posledica ponavljajoče se uporabe tehnologije in ima pogosto neposreden vpliv tako na vedenjski namen kot tudi na dejansko uporabo.

Čeprav model UTAUT2 zagotavlja visoko pojasnjevalno moč, v izvirni obliki ne vključuje konstrukta zaupanja, ki ima v digitalnih okoljih, zlasti v kontekstu mobilnih aplikacij za potovanja, ključno vlogo. V fazi pred potovanjem uporabniki intenzivno iščejo informacije, razkrivajo osebne podatke in pogosto izvajajo finančne transakcije, kar povečuje zaznano tveganje in negotovost. Številne raziskave na področju e-poslovanja, elektronskega bančništva in digitalnega turizma dokazujejo, da je zaupanje eden najpomembnejših dejavnikov sprejemanja tehnologije, saj zmanjšuje zaznano tveganje, povečuje pripravljenost na uporabo in spodbuja dolgoročno zvestobo platformam.

Na tej podlagi disertacija razširja model UTAUT2 z vključitvijo konstrukta zaznanega zaupanja kot dodatnega osrednjega pojasnjevalnega dejavnika vedenjskega namena uporabe mobilnih aplikacij za potovanja. Zaupanje je opredeljeno kot stopnja, do katere uporabniki verjamejo, da je aplikacija zanesljiva, poštena, tehnično kompetentna in sposobna varno obdelovati njihove osebne in finančne podatke. Poleg neposrednega vpliva na vedenjski namen disertacija predvideva, da zaupanje deluje tudi kot posredni mehanizem, preko katerega različni zaznavni dejavniki vplivajo na sprejemanje tehnologije.

V skladu z obstoječo literaturo je zaznano zaupanje v disertaciji konceptualizirano kot večdimenzionalni konstrukt, ki ga oblikujejo trije ključni predhodniki. Zaznana zasebnost odraža stopnjo, do katere uporabniki verjamejo, da aplikacija ustrezno varuje njihove osebne

podatke in jih ne uporablja na neprimeren način. Zaznana varnost opisuje zaznano stopnjo zaščite pred tehničnimi tveganji, kot so zlorabe podatkov, vdori ali goljufije, zlasti v povezavi s spletnimi plačili in rezervacijami. Zaznana kakovost informacij zajema zaznano natančnost, popolnost, aktualnost in uporabnost informacij, ki jih aplikacija zagotavlja v fazi načrtovanja potovanja. Skupaj ti trije dejavniki oblikujejo osnovo zaupanja uporabnikov v mobilne turistične aplikacije.

Poleg neposrednih in posrednih učinkov disertacija vključuje tudi moderirajočo vlogo predhodnih uporabniških izkušenj. Na podlagi teorije navade in empiričnih ugotovitev predhodnih raziskav se predvideva, da stopnja izkušenosti z uporabo mobilnih aplikacij vpliva na moč razmerij med navado, vedenjskim namenom in dejansko uporabo. Pri bolj izkušenih uporabnikih naj bi imela navada močnejši vpliv na vedenjski namen in uporabo, medtem ko naj bi bili pri manj izkušenih uporabnikih pomembnejši drugi dejavniki, kot so zaznana učinkovitost, napor in zaupanje.

Na podlagi predstavljenega konceptualnega okvira so bile oblikovane raziskovalne hipoteze, ki povezujejo osnovne konstrukte modela UTAUT2, zaznano zaupanje in njegove predhodnike z vedenjskim namenom in dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

Raziskovalne hipoteze

Na podlagi predstavljenega konceptualnega okvira in izhodišč modela UTAUT2 ter literature s področja digitalnega zaupanja so bile oblikovane raziskovalne hipoteze, ki povezujejo osnovne konstrukte sprejemanja tehnologije, zaznano zaupanje in njegove predhodnike z vedenjskim namenom in dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem. Poleg neposrednih učinkov disertacija preverja tudi moderirajočo vlogo predhodnih uporabniških izkušenj.

Hipoteze, povezane z osnovnimi konstrukti modela UTAUT2, so naslednje:

H1: Pričakovana učinkovitost pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H2: Pričakovani napor pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H3: Socialni vpliv pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H4a: Omogočitveni pogoji pozitivno vplivajo na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H4b: Omogočitveni pogoji pozitivno vplivajo na dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H5: Hedonistična motivacija pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H6: Vrednost cene v obliki prihranka stroškov pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H7a: Navada pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H7b: Navada pozitivno vpliva na dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H8: Vedenjski namen pozitivno vpliva na dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

V nadaljevanju so oblikovane hipoteze, ki se nanašajo na razširitev modela UTAUT2 z vključitvijo zaznanega zaupanja:

H9: Zaznano zaupanje pozitivno vpliva na vedenjski namen turistov za uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

H10: Zaznana zasebnost pozitivno vpliva na zaznano zaupanje v mobilne aplikacije za potovanja.

H11: Zaznana varnost pozitivno vpliva na zaznano zaupanje v mobilne aplikacije za potovanja.

H12: Zaznana kakovost informacij pozitivno vpliva na zaznano zaupanje v mobilne aplikacije za potovanja.

Na koncu so bile oblikovane hipoteze, ki preverjajo moderirajočo vlogo predhodnih uporabniških izkušenj:

H13a: Predhodne uporabniške izkušnje moderirajo razmerje med navado in vedenjskim namenom uporabe mobilnih aplikacij za potovanja v fazi pred potovanjem.

H13b: Predhodne uporabniške izkušnje moderirajo razmerje med navado in dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

Metodologija raziskave

Raziskava temelji na kvantitativnem raziskovalnem pristopu s presečno zasnovo, katerega cilj je empirično preveriti predlagani razširjeni konceptualni model sprejemanja mobilnih aplikacij za potovanja v fazi pred potovanjem. Izbrani metodološki pristop omogoča sistematično testiranje neposrednih, posrednih in moderirajočih učinkov med konstrukti

modela UTAUT2, zaznanim zaupanjem in njegovimi predhodniki ter vedenjskim namenom in dejansko uporabo.

Raziskovalni dizajn in zbiranje podatkov

Podatki so bili zbrani s pomočjo strukturiranega anketnega vprašalnika, namenjenega uporabnikom mobilnih aplikacij za potovanja, ki so imeli predhodne izkušnje z uporabo tovrstnih aplikacij v fazi pred potovanjem. Raziskava je bila izvedena v Iranu, ki predstavlja razvijajoče se okolje z naraščajočo uporabo digitalnih turističnih storitev, vendar z relativno omejenimi institucionalnimi mehanizmi zaščite potrošnikov in nižjo ravnijo zaupanja v spletne transakcije. Izbira tega konteksta omogoča poglobljen vpogled v vlogo zaupanja pri sprejemanju tehnologije v okoljih z višjo zaznano negotovostjo.

Anketiranje je potekalo v spletni obliki, pri čemer so bili anketiranci povabljeni k sodelovanju prek univerzitetnih in družbenih omrežij ter specializiranih spletnih skupnosti, povezanih s turizmom in potovanji. V raziskavo so bili vključeni le tisti respondenti, ki so izpolnjevali pogoj predhodne uporabe mobilnih aplikacij za potovanja v fazi pred potovanjem. Po čiščenju podatkov in izločitvi nepopolnih oziroma nekonsistentnih odgovorov je končni vzorec obsegal 424 veljavnih vprašalnikov, kar presega minimalne zahteve za analizo s pomočjo modeliranja strukturnih enačb z metodo delnih najmanjših kvadratov (PLS-SEM).

Vzorec

Struktura vzorca odraža raznoliko populacijo uporabnikov mobilnih turističnih aplikacij glede na spol, starost, stopnjo izobrazbe in pogostost uporabe digitalnih tehnologij. Večina anketirancev je pripadala mlajšim in srednjim starostnim skupinam, ki predstavljajo najaktivnejše uporabnike mobilnih aplikacij. Udeleženci so imeli različno raven izkušenj z uporabo TMAs, kar je omogočilo preverjanje moderirajoče vloge predhodnih uporabniških izkušenj v predlaganem modelu.

Merilni instrument

Merilni instrument je bil razvit na podlagi uveljavljenih in validiranih merskih lestvic iz literature o sprejemanju tehnologije in digitalnem zaupanju. Postavke za konstrukte modela UTAUT2 (pričakovana učinkovitost, pričakovani napor, socialni vpliv, omogočitveni pogoji, hedonistična motivacija, vrednost cene in navada) so bile prilagojene iz izvirnih lestvic Venkatesha in sodelavcev. Konstrukti zaznanega zaupanja ter njegovih predhodnikov – zaznane zasebnosti, zaznane varnosti in zaznane kakovosti informacij– so bili operacionalizirani na podlagi merilnih instrumentov iz literature s področja e-poslovanja in digitalnega turizma.

Vsi konstrukti so bili merjeni z več postavkami na sedemstopenjskih Likertovih lestvicah, ki so zajemale stopnjo strinjanja z danimi trditvami. Pred glavno raziskavo je bil vprašalnik

pilotno testiran na manjšem vzorcu, da bi zagotovili razumljivost vprašanj, ustreznost prevodov in vsebinsko veljavnost meritev.

Analiza podatkov in ocenjevanje merilnega modela

Empirična analiza je bila izvedena s pomočjo metode PLS-SEM v programskem paketu SmartPLS, ki je posebej primerna za kompleksne modele z več konstrukti, mediacijami in moderacijami ter za raziskave z raziskovalno-razlagalnim ciljem. Analiza je potekala v dveh glavnih korakih: najprej je bil ocenjen merilni model, nato strukturni model.

Pri ocenjevanju merilnega modela so bili preverjeni kazalniki zanesljivosti in veljavnosti. Notranja konsistentnost konstruk-tov je bila ocenjena s Cronbachovim alfa koeficientom in sestavljeno zanesljivostjo (Composite Reliability). Konvergentna veljavnost je bila preverjena na podlagi povprečne izvzete variance (Average Variance Extracted – AVE), diskriminantna veljavnost pa s pomočjo Fornell-Larckerjevega kriterija in razmerij heterotrait-monotrait (HTMT). Rezultati so potrdili ustrezno zanesljivost in veljavnost vseh konstruk-tov.

Ocenjevanje strukturnega modela

V drugem koraku je bil ocenjen strukturni model z analizo poti med konstrukti, preverjanjem statistične značilnosti hipotez ter izračunom pojasnjene variance (R^2) za vedenjski namen in dejansko uporabo. Za oceno stabilnosti in statistične značilnosti parametrov je bila uporabljena metoda neparametričnega bootstrapiranja z velikim številom ponovitev.

Poleg neposrednih učinkov so bili analizirani tudi posredni učinki zaznanega zaupanja kot mediacijskega mehanizma med njegovimi predhodniki in vedenjskim namenom. Moderirajoča vloga predhodnih uporabniških izkušenj je bila preverjena z vključitvijo interakcijskih spremenljivk v strukturni model.

Za dodatno interpretacijo praktične pomembnosti posameznih konstruk-tov je bila izvedena tudi analiza pomembnosti–učinkovitosti (Importance-Performance Map Analysis – IPMA), ki omogoča identifikacijo ključnih dejavnikov z največjim potencialom za izboljšanje uporabe mobilnih aplikacij za potovanja.

Glavni rezultati raziskave

Empirični rezultati potrjujejo ustreznost in visoko pojasnjevalno moč razširjenega konceptualnega modela sprejemanja mobilnih aplikacij za potovanja v fazi pred potovanjem. Vrednosti pojasnjene variance (R^2) za vedenjski namen in dejansko uporabo kažejo, da predlagani model uspešno pojasnjuje pomemben delež variance obeh odvisnih spremenljivk, kar potrjuje primernost razširitve modela UTAUT2 z vključitvijo zaznanega zaupanja v kontekstu digitalnega turizma v razvijajočem se okolju.

Rezultati ocenjevanja merilnega modela

Rezultati ocenjevanja merilnega modela potrjujejo ustrezno psihometrično kakovost uporabljenih merskih lestvic. Vsi konstrukti izkazujejo visoko notranjo konsistentnost, saj vrednosti Cronbachovega alfa koeficienta in sestavljene zanesljivosti presegajo priporočene mejne vrednosti. Konvergentna veljavnost je bila potrjena z vrednostmi povprečne izvzete variance (AVE), ki presegajo prag 0,50 pri vseh konstruk-tih, kar kaže, da postavke ustrezno pojasnjujejo pripadajoče latentne spremenljivke.

Diskriminantna veljavnost je bila potrjena tako s Fornell-Larckerjevim kriterijem kot tudi z razmerji heterotrait-monotrait (HTMT), pri čemer nobena od vrednosti ni presegla priporočenih mej. Ti rezultati potrjujejo, da so posamezni konstrukti med seboj empirično razločljivi in da merilni instrument zanesljivo meri teoretično opredeljene koncepte.

Rezultati strukturnega modela in preverjanje hipotez

Rezultati strukturnega modela razkrivajo več pomembnih ugotovitev glede dejavnikov, ki vplivajo na vedenjski namen in dejansko uporabo mobilnih aplikacij za potovanja v fazi pred potovanjem.

Med osnovnimi konstrukti modela UTAUT2 se je kot najmočnejši napovednik vedenjskega namena izkazala navada, kar potrjuje ključno vlogo avtomatiziranega in rutinskega vedenja pri sprejemanju digitalnih tehnologij. Pomemben in statistično značilen vpliv ima tudi zaznano zaupanje, kar potrjuje osrednjo vlogo zaupanja pri sprejemanju mobilnih turističnih aplikacij. Med socialnimi dejavniki se je socialni vpliv izkazal kot pomemben dejavnik vedenjskega namena.

Rezultati nadalje kažejo, da imajo tudi klasični konstrukti modela UTAUT2 pomembno, vendar relativno šibkejšo vlogo. Pričakovana učinkovitost, pričakovani napor in omogočitveni pogoji imajo pozitiven in statistično značilen vpliv na vedenjski namen, vendar z majhnimi velikostmi učinkov. Vrednost cene nima izrazitega neposrednega vpliva na vedenjski namen, vendar pomembno posredno vpliva na dejansko uporabo preko vedenjskega namena. Hedonistična motivacija izkazuje le mejno statistično značilen vpliv na ravni 10 %.

Pri razlagi dejanske uporabe se kot najpomembnejši napovedniki izkažejo vedenjski namen, navada in omogočitveni pogoji, ki imajo vsi pozitiven in statistično značilen vpliv.

Na področju zaznanega zaupanja rezultati potrjujejo, da so vsi trije predhodniki statistično značilni. Najmočnejši vpliv ima zaznana zasebnost, sledita ji zaznana kakovost informacij in zaznana varnost. Zaupanje deluje tudi kot pomemben posredni mehanizem, preko katerega ti dejavniki vplivajo na vedenjski namen in dejansko uporabo.

Rezultati moderirajoče analize kažejo, da imajo predhodne uporabniške izkušnje omejen moderirajoč učinek. Moderacija je bila mejno statistično potrjena pri razmerju med navado

in vedenjskim namenom, medtem ko moderirajoči vpliv izkušenj na razmerje med navado in dejansko uporabo ni statistično značilen.

Vloga zaznanega zaupanja in njegovih predhodnikov

Rezultati potrjujejo osrednjo vlogo zaznanega zaupanja v razširjenem modelu. Zaupanje ima pomemben neposredni vpliv na vedenjski namen ter deluje tudi kot posredni mehanizem, preko katerega njegovi predhodniki vplivajo na sprejemanje tehnologije.

Vsi trije predhodniki zaupanja – zaznana zasebnost, zaznana varnost in zaznana kakovost informacij – izkazujejo statistično značilen pozitiven vpliv na zaznano zaupanje. Med njimi ima zaznana kakovost informacij najmočnejši učinek, kar kaže, da uporabniki v fazi pred potovanjem posebno pozornost namenjajo točnosti, popolnosti in aktualnosti informacij. Sledita zaznana varnost in zaznana zasebnost, ki potrjujeta pomen zaščite osebnih podatkov in varnosti transakcij pri oblikovanju zaupanja.

Analiza posrednih učinkov potrjuje, da zaznano zaupanje delno mediira razmerja med njegovimi predhodniki in vedenjskim namenom, kar dodatno potrjuje njegovo vlogo osrednjega povezovalnega mehanizma v razširjenem modelu.

Moderirajoči učinki predhodnih uporabniških izkušenj

Rezultati moderirajoče analize kažejo, da imajo predhodne uporabniške izkušnje omejen moderirajoč učinek. Moderacija je bila potrjena pri razmerju med navado in vedenjskim namenom, kar pomeni, da ima navada pri bolj izkušenih uporabnikih nekoliko močnejši vpliv na oblikovanje vedenjskega namena. Nasprotno pa moderacija pri razmerju med navado in dejansko uporabo ni bila potrjena, kar kaže, da stopnja izkušenosti ne vpliva bistveno na neposredno izvajanje dejanske uporabe aplikacij. Pri manj izkušenih uporabnikih imajo pomembnejšo vlogo drugi dejavniki, zlasti zaupanje in zaznana učinkovitost. Ti rezultati potrjujejo, da proces sprejemanja tehnologije ni homogen, temveč je delno pogojen s stopnjo izkušenosti uporabnikov.

Analiza pomembnosti–učinkovitosti (IPMA)

Rezultati analize IPMA potrjujejo, da imajo navada, zaznano zaupanje, socialni vpliv in omogočitveni pogoji ključno vlogo pri spodbujanju sprejemanja in uporabe mobilnih aplikacij za potovanja. Ti dejavniki izkazujejo visoko pomembnost, vendar le zmerno učinkovitost, kar kaže na pomemben potencial za ciljno usmerjene upravljavske ukrepe.

Pri dejanski uporabi se kot najpomembnejši dejavniki izkažejo vedenjski namen, predhodne uporabniške izkušnje in navada, pri čemer njihove ravni učinkovitosti ostajajo zmerne. Nasprotno pa zaznana zasebnost, zaznana kakovost informacij in zaznana varnost dosegajo visoko učinkovitost, vendar nizko pomembnost, kar pomeni, da predstavljajo obstoječe prednosti, ki jih je predvsem smiselno ohranjati.

Skupaj rezultati IPMA kažejo, da bi morali upravljavci prednostno izboljševati dejavnike z visoko pomembnostjo in zmerno učinkovitostjo, zlasti navado, zaznano zaupanje in omogočitvene pogoje, saj ti predstavljajo ključne vzvode za povečanje dolgoročne uporabe mobilnih aplikacij za potovanja.

Razprava in interpretacija rezultatov

Rezultati empirične analize ponujajo pomembne teoretične in praktične vpoglede v procese sprejemanja mobilnih aplikacij za potovanja v fazi pred potovanjem ter potrjujejo ustreznost razširjenega konceptualnega okvira, ki temelji na modelu UTAUT2 in vključuje zaznano zaupanje kot osrednji dodatni konstrukt (Venkatesh et al., 2012). Ugotovitve razkrivajo, da sprejemanje tehnologije v digitalnem turističnem okolju ni zgolj rezultat instrumentalnih ocen uporabnosti in enostavnosti uporabe, temveč kompleksen proces, v katerem imajo ključno vlogo navada, zaupanje, socialni vplivi in kontekstualni dejavniki (Venkatesh et al., 2012; Esfandiar et al., 2023).

Ena najpomembnejših ugotovitev raziskave je osrednja vloga navade kot najmočnejšega napovednika vedenjskega namena in pomembnega neposrednega dejavnika dejanske uporabe. Ta rezultat potrjuje ugotovitve prejšnjih študij, ki poudarjajo, da se z naraščajočo stopnjo izkušenosti uporaba tehnologije postopoma avtomatizira in postane manj odvisna od zavestnega odločanja (Limayem et al., 2007; Venkatesh et al., 2012). V kontekstu mobilnih aplikacij za potovanja to pomeni, da uporabniki, ki so že razvili rutinske vzorce uporabe, nadaljujejo z uporabo predvsem na podlagi preteklih izkušenj in ponavljajočih se vedenjskih vzorcev, kar je skladno z ugotovitvami novejših študij na področju pametnih turističnih aplikacij (Sia et al., 2024).

Pomembna vloga navade ima tudi širše teoretične implikacije. Rezultati potrjujejo, da modeli sprejemanja tehnologije, ki ne vključujejo konstrukta navade, podcenjujejo dolgoročne mehanizme oblikovanja vedenja, zlasti v okoljih, kjer tehnologije postanejo del vsakodnevnih praks (Limayem et al., 2007; Venkatesh et al., 2012). S tem disertacija dodatno potrjuje ustreznost uporabe razširjenega modela UTAUT2 v raziskavah digitalnega turizma.

Druga ključna ugotovitev raziskave je izrazit vpliv zaznanega zaupanja na vedenjski namen uporabe mobilnih aplikacij za potovanja. Ta rezultat potrjuje teoretično predpostavko, da je zaupanje osrednji mehanizem sprejemanja tehnologije v okoljih, za katera so značilni visoka zaznana tveganja, obdelava osebnih podatkov in izvajanje finančnih transakcij (Kim et al., 2008; Hartono et al., 2014; Tran & Vu, 2024). V fazi pred potovanjem uporabniki pogosto sprejemajo odločitve z dolgoročnimi posledicami, kar še povečuje pomen zaupanja v digitalne platforme, zlasti v kolektivističnih okoljih, kjer socialne norme in zaupanje pomembno oblikujejo uporabniške odločitve (Esfandiar et al., 2023).

Rezultati dodatno kažejo, da zaznano zaupanje ne deluje zgolj kot neposreden dejavnik vedenjskega namena, temveč tudi kot posredni povezovalni mehanizem, preko katerega

zaznana zasebnost, zaznana varnost in zaznana kakovost informacij vplivajo na sprejemanje tehnologije (Kim et al., 2008; Hartono et al., 2014). Ta ugotovitev potrjuje večdimenzionalno naravo zaupanja ter poudarja pomen celostnega pristopa k njegovemu oblikovanju.

Med predhodniki zaupanja ima najmočnejši vpliv zaznana zasebnost, kar poudarja osrednji pomen varovanja osebnih podatkov pri oblikovanju zaupanja (Zhou & Li, 2014; Ooi et al., 2018). Pomembno vlogo imata tudi zaznana kakovost informacij in zaznana varnost, kar kaže, da uporabniki v fazi pred potovanjem zaupanje dodatno gradijo na podlagi točnosti, popolnosti in aktualnosti informacij ter na podlagi občutka varnosti pri uporabi aplikacije, zlasti pri deljenju občutljivih podatkov in pri izvajanju transakcij (Kim et al., 2008; Hartono et al., 2014; Liu et al., 2025). Slabša kakovost informacij ali dvomi glede varnosti lahko zato pomembno zmanjšajo pripravljenost za uporabo aplikacij.

Rezultati glede drugih konstruktov modela UTAUT2 ponujajo dodatne vpoglede v posebnosti digitalnega turističnega konteksta. Socialni vpliv se je izkazal kot pomemben dejavnik vedenjskega namena, kar kaže, da priporočila pomembnih drugih in mnenja spletnih skupnosti močno vplivajo na odločanje uporabnikov (Nathan et al., 2020; Calderón-Fajardo et al., 2023). Ta rezultat je skladen z značilnostmi turističnih storitev, ki so izkustvene narave in pogosto povezane z visoko stopnjo negotovosti, zato uporabniki iščejo potrditev v socialnem okolju, zlasti v kolektivističnih kulturah (Esfandiar et al., 2023).

V primerjavi z navado, zaupanjem in socialnim vplivom imajo preostali dejavniki bolj sekundarno vlogo. Pričakovana učinkovitost, pričakovani napor in omogočitveni pogoji statistično značilno prispevajo k vedenjskemu namenu, vendar z relativno šibkejšimi učinki (Venkatesh et al., 2012; Kamboj & Joshi, 2021; Foroughi et al., 2025). Hedonistična motivacija izkazuje pozitiven, vendar šibek oziroma mejno potrjen vpliv (Chang et al., 2019; Tran & Vu, 2024), medtem ko vrednost cene deluje predvsem prek posrednih mehanizmov, saj zaznane ekonomske koristi krepijo oblikovanje vedenjskega namena (Tak et al., 2016; Khalilzadeh et al., 2017).

Rezultati glede dejanske uporabe potrjujejo ključno vlogo vedenjskega namena kot neposrednega predhodnika vedenja, kar je skladno s temeljnimi predpostavkami teorij sprejemanja tehnologije (Venkatesh et al., 2012; Gupta, 2017). Pomemben neposreden vpliv navade in omogočitvenih pogojev dodatno poudarja pomen tehnične infrastrukture in podpornih mehanizmov pri prehodu od namere k dejanskemu vedenju (Foroughi et al., 2025).

Pomemben prispevek disertacije predstavlja tudi analiza moderirajoče vloge predhodnih uporabniških izkušenj. Rezultati kažejo, da je moderirajoči učinek izkušenj omejen: pri bolj izkušenih uporabnikih se povezava med navado in vedenjskim namenom nekoliko okrepi, medtem ko moderirajoči vpliv izkušenj na razmerje med navado in dejansko uporabo ni potrjen (Chang et al., 2019; Nikolopoulou et al., 2021). To pomeni, da izkušnje vplivajo

predvsem na fazo oblikovanja namena, medtem ko se pri dejanski uporabi učinek navade ohranja stabilen.

Skupaj rezultati potrjujejo, da razširjeni model UTAUT2 z vključitvijo zaznanega zaupanja ponuja celovitejšo in kontekstualno primernejšo razlago sprejemanja mobilnih aplikacij za potovanja v fazi pred potovanjem (Venkatesh et al., 2012; Tran & Vu, 2024). Disertacija tako prispeva k poglobljenemu razumevanju mehanizmov digitalnega vedenja turistov ter potrjuje, da so v sodobnih digitalnih okoljih poleg klasičnih tehnoloških dejavnikov ključni tudi psihološki, socialni in institucionalni vidiki (Esfandiar et al., 2023).

Znanstveni prispevki

Doktorska disertacija prispeva k razvoju znanstvenega znanja na področju digitalnega turizma in sprejemanja tehnologije na več medsebojno povezanih teoretičnih, metodoloških in empiričnih ravneh.

Prvi in temeljni teoretični prispevek disertacije je razširitev modela UTAUT2 z vključitvijo zaznanega zaupanja kot osrednjega dodatnega konstrukta pri razlagi sprejemanja mobilnih aplikacij za potovanja. Medtem ko izvirni model UTAUT2 zagotavlja visoko pojasnjevalno moč za razlago vedenjskega namena in uporabe tehnologije, v svoji osnovni obliki ne zajema mehanizmov, povezanih s tveganjem, negotovostjo in obdelavo osebnih podatkov, ki so značilni za sodobna digitalna okolja. Z integracijo zaznanega zaupanja disertacija ponuja konceptualno razširjen in kontekstualno ustreznejši okvir za razlago sprejemanja digitalnih turističnih platform.

Drugi pomemben teoretični prispevek predstavlja konceptualizacija zaupanja kot večdimenzionalnega konstrukta, ki ga oblikujejo zaznana zasebnost, zaznana varnost in zaznana kakovost informacij. Disertacija empirično potrjuje, da zaupanje ne nastaja kot enodimenzionalna zaznava, temveč kot rezultat sočasnega delovanja več zaznavnih dejavnikov, povezanih z zaščito podatkov, varnostjo transakcij in informacijsko vrednostjo vsebin. S tem disertacija prispeva k poglobljenemu razumevanju procesov oblikovanja zaupanja v digitalnih turističnih okoljih ter razširja obstoječe modele digitalnega zaupanja v kontekstu mobilnih aplikacij.

Tretji teoretični prispevek je fazno specifična obravnava sprejemanja tehnologije, osredotočena izključno na fazo pred potovanjem. Večina dosedanjih raziskav mobilnih tehnologij v turizmu obravnava uporabo aplikacij celostno skozi celotni potovalni proces ali se osredotoča na fazo potovanja in popotovalno fazo. Disertacija pa fazo pred potovanjem konceptualizira kot samostojen in teoretično relevanten kontekst odločanja, v katerem imajo informacijski procesi, zaznano tveganje in zaupanje posebno vlogo. S tem prispeva k razvoju fazno orientiranih pristopov v raziskavah turističnega vedenja.

Četrti pomemben prispevek disertacije predstavlja vključitev moderirajoče vloge predhodnih uporabniških izkušenj v razširjeni model UTAUT2. Rezultati empirične analize

potrjujejo, da stopnja izkušenosti pomembno vpliva na moč razmerij med navado, vedenjskim namenom in dejansko uporabo. Ta ugotovitev prispeva k boljšemu razumevanju heterogenosti uporabnikov in potrjuje, da proces sprejemanja tehnologije ni linearen niti homogen, temveč dinamičen in pogojen z individualnimi značilnostmi uporabnikov.

Na empirični ravni disertacija prispeva z zagotavljanjem kontekstualno občutljivih dokazov iz razvijajočega se gospodarstva. Večina obstoječih raziskav sprejemanja mobilnih tehnologij v turizmu temelji na podatkih iz tehnološko naprednih držav z razvitimi institucionalnimi mehanizmi zaščite potrošnikov. S preučevanjem vedenja uporabnikov v Iranu disertacija širi geografski in institucionalni domet raziskav ter ponuja nove vpoglede v vlogo zaupanja v okoljih z višjo zaznano negotovostjo in šibkejšimi regulativnimi okviri.

Metodološki prispevek disertacije se kaže v uporabi kompleksnega strukturnega modela, ki vključuje neposredne, posredne in moderirajoče učinke ter v uporabi metode PLS-SEM za analizo razmerij med konstrukti. Disertacija združuje klasične konstrukte sprejemanja tehnologije z zaupanjem in njegovimi predhodniki ter tako ponuja celovit analitični okvir, ki ga je mogoče uporabiti tudi v drugih kontekstih digitalnih platform in storitev.

Skupaj ti prispevki potrjujejo, da disertacija pomembno razširja obstoječe teorije sprejemanja tehnologije in digitalnega zaupanja ter ponuja nov, kontekstualno prilagojen okvir za razumevanje digitalnega vedenja turistov v fazi pred potovanjem.

Upravljavske implikacije

Ugotovitve disertacije ponujajo pomembne upravljavske in praktične implikacije za razvijalce mobilnih aplikacij za potovanja, turistične ponudnike, digitalne platforme ter oblikovalce politik, ki želijo spodbujati sprejemanje in dolgoročno uporabo mobilnih turističnih aplikacij v fazi pred potovanjem, zlasti v razvijajočih se digitalnih trgih.

Ena najpomembnejših implikacij izhaja iz osrednje vloge navade kot najmočnejšega napovednika vedenjskega namena in pomembnega dejavnika dejanske uporabe. Ta ugotovitev nakazuje, da morajo upravljavci aplikacij in turistične platforme posebno pozornost nameniti spodbujanju ponavljajoče se uporabe in oblikovanju uporabniških rutin. Praktično to pomeni razvoj funkcionalnosti, ki uporabnike redno vključujejo v uporabo aplikacije, kot so personalizirana obvestila, opomniki, priporočilni sistemi, programi zvestobe in integracija več storitev v enotno platformo. S spodbujanjem navade lahko ponudniki dolgoročno povečajo zvestobo uporabnikov in zmanjšajo odvisnost od kratkoročnih promocijskih strategij.

Pomembna vloga zaznanega zaupanja ima neposredne implikacije za oblikovanje in upravljanje digitalnih turističnih platform. Rezultati kažejo, da je zaupanje ključen pogoj za sprejemanje aplikacij v fazi pred potovanjem, ko uporabniki sprejemajo odločitve z dolgoročnimi posledicami in pogosto izvajajo finančne transakcije. Razvijalci aplikacij

morajo zato sistematično vlagati v gradnjo in komunikacijo zaupanja, tako na tehnični kot tudi na komunikacijski ravni.

Na področju zasebnosti je priporočljivo jasno in pregledno komunicirati politike varovanja osebnih podatkov, uporabnikom omogočiti nadzor nad obsegom in načinom uporabe njihovih podatkov ter zagotoviti skladnost z mednarodnimi standardi varstva podatkov. Transparentnost pri obdelavi podatkov lahko bistveno prispeva k povečanju zaznanega zaupanja in zmanjšanju zaznanega tveganja.

Na področju varnosti rezultati poudarjajo pomen robustnih tehničnih rešitev za zaščito transakcij in preprečevanje zlorab. Uporaba varnih plačilnih sistemov, šifriranje podatkov, večstopenjska avtentikacija in redne varnostne posodobitve niso zgolj tehnični ukrepi, temveč ključni elementi strategije upravljanja zaupanja. Pomembno je tudi, da ponudniki varnostne mehanizme jasno in razumljivo predstavijo uporabnikom, saj zaznana varnost temelji tako na dejanski zaščiti kot tudi na komunikaciji o njej.

Posebno pomembna implikacija izhaja iz vloge zaznane kakovosti informacij kot najmočnejšega predhodnika zaupanja. Razvijalci in upravljavci platform morajo zagotoviti visoko raven točnosti, popolnosti, aktualnosti in uporabnosti informacij, ki jih aplikacije ponujajo. To vključuje redno posodabljanje podatkov o destinacijah, cenah, razpoložljivosti in pogojih storitev ter uporabo preverjenih virov in partnerskih omrežij. Kakovostne informacije ne povečujejo zgolj zaupanja, temveč tudi zmanjšujejo negotovost uporabnikov in izboljšujejo celotno uporabniško izkušnjo.

Rezultati glede socialnega vpliva kažejo, da imajo priporočila pomembnih drugih in mnenja spletnih skupnosti pomembno vlogo pri oblikovanju vedenjskega namena. To ponuja priložnosti za uporabo strategij digitalnega trženja, ki temeljijo na družbenih omrežjih, ocenah uporabnikov, priporočilih vplivnežev in sistemih ocen ter komentarjev. Spodbujanje pozitivnih uporabniških izkušenj in aktivno upravljanje spletnega ugleda lahko pomembno prispevata k povečanju sprejemanja aplikacij.

Implikacije se nanašajo tudi na segmentacijo uporabnikov glede na stopnjo izkušenosti. Rezultati moderirajoče analize kažejo, da imajo pri manj izkušenih uporabnikih pomembnejšo vlogo zaupanje, zaznana učinkovitost in podpora, medtem ko je pri bolj izkušenih uporabnikih ključna navada. To pomeni, da morajo ponudniki razvijati diferencirane strategije: za nove uporabnike je priporočljivo zagotoviti enostavne uvodne vodiče, podporne storitve in jasna pojasnila varnostnih mehanizmov, za izkušene uporabnike pa napredne funkcionalnosti, personalizacijo in mehanizme za krepitev dolgoročne zvestobe.

Na ravni oblikovalcev politik in regulatorjev rezultati poudarjajo pomen vzpostavitve stabilnih institucionalnih mehanizmov za zaščito potrošnikov v digitalnem turizmu. Jasni pravni okviri glede varstva podatkov, varnosti spletnih plačil in odgovornosti platform lahko

bistveno prispevajo k povečanju zaupanja uporabnikov in pospešitvi digitalne transformacije turističnega sektorja v razvijajočih se gospodarstvih.

Skupaj te implikacije kažejo, da uspešno upravljanje mobilnih aplikacij za potovanja zahteva celostni pristop, ki združuje tehnične rešitve, kakovostne informacije, učinkovito komunikacijo in uporabniško usmerjene strategije za krepitev zaupanja, oblikovanje navad in spodbujanje dolgoročne uporabe v digitalnem turističnem okolju.

Omejitve in prihodnje raziskave

Kljub pomembnim teoretičnim in praktičnim prispevkom ima disertacija tudi nekatere omejitve, ki jih je treba upoštevati pri interpretaciji rezultatov in posploševanju ugotovitev ter ki hkrati odpirajo priložnosti za nadaljnje raziskave.

Prva pomembna omejitev se nanaša na geografski in kulturni kontekst raziskave. Podatki so bili zbrani izključno v Iranu, ki predstavlja specifično razvijajoče se okolje z lastnimi institucionalnimi, kulturnimi in regulativnimi značilnostmi. Čeprav ta izbira omogoča pomemben vpogled v sprejemanje mobilnih turističnih aplikacij v okoljih z višjo zaznano negotovostjo in šibkejšimi institucionalnimi mehanizmi, hkrati omejuje posplošljivost rezultatov na druga kulturna in gospodarska okolja. Prihodnje raziskave bi morale preveriti veljavnost predlaganega razširjenega modela v drugih razvijajočih se državah ter v tehnološko naprednejših gospodarstvih, kar bi omogočilo primerjalne analize in poglobljeno razumevanje vpliva institucionalnega konteksta na vlogo zaupanja.

Druga omejitev izhaja iz presečne narave raziskovalnega dizajna. Podatki so bili zbrani v enem časovnem trenutku, kar onemogoča analizo sprememb v vedenju uporabnikov skozi čas ter ne omogoča neposrednega sklepanja o vzročnih razmerjih med konstrukti. Sprejemanje tehnologije in oblikovanje navade sta dinamična procesa, ki se razvijata postopoma. Prihodnje raziskave bi morale uporabiti longitudinalne raziskovalne pristope, ki bi omogočili spremljanje sprememb v zaznavah zaupanja, navadah in dejanski uporabi mobilnih aplikacij skozi daljše časovno obdobje.

Tretja omejitev se nanaša na uporabo samoocenjevalnih merskih instrumentov. Vsi podatki temeljijo na subjektivnih zaznavah anketirancev, kar lahko vodi v pristranskosti, povezane z družbeno zaželenimi odgovori, selektivnim spominom ali skupno metodo merjenja (common method bias). Čeprav so bili uporabljeni uveljavljeni postopki za zmanjšanje tovrstnih pristranskosti, prihodnje raziskave lahko izboljšajo veljavnost rezultatov z vključitvijo objektivnih vedenjskih podatkov, kot so dejanski zapisi uporabe aplikacij ali podatki o transakcijah.

Četrta omejitev se nanaša na izbor konstruk-tov in strukturo predlaganega modela. Čeprav razširjeni model UTAUT2 vključuje ključne dejavnike sprejemanja tehnologije in zaupanja, obstajajo tudi drugi potencialno pomembni konstrukti, ki niso bili vključeni, kot so zaznana

transparentnost, institucionalno zaupanje, zaznana pravičnost algoritmov, kulturne vrednote ali osebnostne značilnosti uporabnikov. Prihodnje raziskave bi lahko razširile predlagani okvir z vključitvijo dodatnih psiholoških, socialnih in institucionalnih dejavnikov ter preverile njihove neposredne in posredne učinke.

Peta omejitev se nanaša na osredotočenost izključno na fazo pred potovanjem. Čeprav je ta faza teoretično in praktično izjemno pomembna, se vedenje uporabnikov in vloga zaupanja lahko bistveno razlikujeta v fazi potovanja in popotovalni fazi. Prihodnje raziskave bi morale razširiti analizo na celoten potovalni cikel ter preveriti, kako se pomen posameznih dejavnikov spreminja skozi različne faze potovanja.

Nazadnje velja omeniti tudi omejitve, povezane z izborom vzorca. Čeprav velikost vzorca omogoča zanesljivo uporabo metode PLS-SEM, vzorec ne zajema vseh segmentov populacije enakomerno. Prihodnje raziskave bi morale vključiti bolj raznolike vzorce glede na starost, izobrazbo, digitalno pismenost in potovalne navade ter preveriti morebitne razlike med posameznimi segmenti uporabnikov.

Na podlagi navedenih omejitev disertacija odpira več pomembnih smeri za prihodnje raziskave. Nadaljnje študije bi morale (1) preveriti razširjeni model v različnih kulturnih in institucionalnih okoljih, (2) uporabiti longitudinalne in eksperimentalne pristope, (3) vključiti objektivne vedenjske podatke, (4) razširiti nabor konstruk-tov, povezanih z zaupanjem in tveganjem, ter (5) analizirati sprejemanje mobilnih aplikacij skozi celoten potovalni cikel. Takšni pristopi bi pomembno prispevali k nadaljnjemu razvoju teorije sprejemanja tehnologije in poglobljenemu razumevanju digitalnega vedenja turistov.

Zaključek

Doktorska disertacija celovito obravnava problematiko sprejemanja in uporabe mobilnih aplikacij za potovanja v fazi pred potovanjem ter pomembno prispeva k razumevanju digitalnega vedenja turistov v sodobnem turističnem okolju. Z osredotočenostjo na fazo pred potovanjem disertacija zapolnjuje pomembno raziskovalno vrzel in poudarja pomen fazno specifičnih pristopov pri analizi turističnega odločanja, kjer imajo informacijski procesi, zaznano tveganje in zaupanje osrednjo vlogo.

Temeljni cilj disertacije je bil razviti in empirično preveriti razširjeni model UTAUT2, ki vključuje zaznano zaupanje kot osrednji dodatni konstrukt ter njegove ključne predhodnike – zaznano zasebnost, zaznano varnost in zaznano kakovost informacij – ter preveriti moderirajočo vlogo predhodnih uporabniških izkušenj. Rezultati empirične analize potrjujejo ustreznost in visoko pojasnjevalno moč predlaganega modela ter jasno kažejo, da sprejemanje mobilnih turističnih aplikacij ni zgolj rezultat tehnoloških ocen uporabnosti in enostavnosti uporabe, temveč kompleksen proces, v katerem imajo ključno vlogo navada, zaupanje, socialni vplivi in kontekstualni dejavniki.

Disertacija empirično potrjuje osrednjo vlogo navade kot najmočnejšega napovednika vedenjskega namena in pomembnega dejavnika dejanske uporabe ter s tem poudarja pomen dolgoročnih vedenjskih mehanizmov pri sprejemanju digitalnih tehnologij. Prav tako potrjuje ključno vlogo zaznanega zaupanja, ki deluje kot neposredni dejavnik vedenjskega namena in kot posredni mehanizem, preko katerega zaznana zasebnost, zaznana varnost in zaznana kakovost informacij vplivajo na sprejemanje tehnologije. Ti rezultati potrjujejo, da je zaupanje temeljni pogoj za uspešno digitalno transformacijo turističnega sektorja, zlasti v okoljih z višjo zaznano negotovostjo.

Pomemben prispevek disertacije predstavlja tudi analiza moderirajoče vloge predhodnih uporabniških izkušenj, ki potrjuje, da proces sprejemanja tehnologije ni homogen, temveč dinamičen in pogojen z individualnimi značilnostmi uporabnikov. S tem disertacija dodatno prispeva k razvoju bolj diferenciranih in kontekstualno prilagojenih modelov sprejemanja tehnologije.

Na teoretični ravni disertacija razširja obstoječe modele sprejemanja tehnologije in digitalnega zaupanja ter ponuja nov, celovit konceptualni okvir za razlago sprejemanja mobilnih turističnih aplikacij v fazi pred potovanjem. Na empirični ravni prispeva z zagotavljanjem redkih in dragocenih dokazov iz razvijajočega se gospodarstva ter s tem širi geografski in institucionalni obseg raziskav na področju digitalnega turizma. Na praktični ravni pa ponuja konkretne smernice za razvijalce aplikacij, turistične ponudnike in oblikovalce politik pri oblikovanju zaupanja vrednih, uporabniku prijaznih in dolgoročno uspešnih digitalnih turističnih platform.

Skupaj disertacija potrjuje, da uspešno sprejemanje mobilnih aplikacij za potovanja zahteva celostni pristop, ki presega zgolj tehnične vidike in vključuje psihološke, socialne in institucionalne razsežnosti digitalnega vedenja. S tem prispeva k poglobljenemu razumevanju digitalne transformacije turizma ter ponuja trdne teoretične in empirične temelje za nadaljnje raziskave in razvoj inovativnih digitalnih rešitev v turistični industriji.