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DISSERTATION

"An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

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"I would like to express my sincere gratitude to my supervisor, Dr. George Spais, for his professionalism, invaluable academic guidance, continuous support, and scholarly rigor in providing constructive feedback at all stages, from the conceptualization of the study, writing, and research, anytime I needed"

"To my daughters Katerina and Athina and my husband Kostas, for their continuous encouragement and support throughout this journey"

Abstract

The dissertation applies Expectation–Confirmation Theory and the IS/IT Continuance Model to explain how perceived performance, usefulness, and enjoyment influence continuance intention toward AI technologies in hospitality and tourism services, with satisfaction as a central mechanism. Using a deductive, quantitative design, the study administered an online Self- Administered Questionnaire comprising 17 established scale items to a convenience sample of 227 Greek AI users. Confirmatory Factor Analysis supported the measurement model, although one continuance item was removed because of poor fit. Direct hypotheses were tested using Spearman's rho and linear or quadratic equations, while indirect hypotheses were examined through bootstrapped mediation with 5,000 resamples. All direct hypotheses (H1–H9) were supported at $\alpha = .001$, and all indirect hypotheses (H10–H14) at $\alpha = .05$, with 95% bootstrap confidence intervals excluding zero. Confirmation predicts perceived performance and usefulness linearly, whereas perceived enjoyment is quadratic. Satisfaction responds nonlinearly to performance and usefulness, indicating diminishing returns, while increasing steadily with enjoyment. Perceived performance, usefulness, and enjoyment mediate the confirmation–satisfaction relationship; usefulness and enjoyment partially mediate the confirmation–continuance relationship. The study advances AI continuance research by integrating utilitarian and hedonic evaluations and identifying nonlinear, mediated mechanisms with practical implications for onboarding, feedback, and service design.

Keywords

Expectation–Confirmation Theory (ECT), IS/IT Continuance Model, AI continuance intention, satisfaction, perceived usefulness, perceived enjoyment, hospitality and tourism services

ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

«Μια εξερεύνηση των ρόλων της αντιληπτής απόδοσης, της αντιληπτής χρησιμότητας και της αντιληπτής απόλαυσης στην πρόθεση συνέχισης της χρήσης της τεχνολογίας τεχνητής νοημοσύνης για υπηρεσίες φιλοξενίας και τουρισμού»

Ευαγγελία Κυριακάκη

Περίληψη

Η διπλωματική εργασία εφαρμόζει τη Θεωρία Επιβεβαίωσης Προσδοκιών και το Μοντέλο Συνέχισης Χρήσης Πληροφοριακών Συστημάτων/Τεχνολογιών για να εξηγήσει πώς η αντιλαμβανόμενη απόδοση, η χρησιμότητα και η απόλαυση επηρεάζουν την πρόθεση συνέχισης χρήσης τεχνολογιών ΤΝ στις υπηρεσίες φιλοξενίας και τουρισμού, με την ικανοποίηση να λειτουργεί ως κεντρικός μηχανισμός. Υιοθετώντας έναν επαγωγικό, ποσοτικό ερευνητικό σχεδιασμό, η μελέτη χρησιμοποίησε ένα διαδικτυακό αυτοσυμπληρούμενο ερωτηματολόγιο, το οποίο περιλάμβανε 17 στοιχεία από καθιερωμένες κλίμακες μέτρησης, σε δείγμα ευκολίας 227 Ελλήνων χρηστών ΤΝ. Η Επιβεβαιωτική Παραγοντική Ανάλυση υποστήριξε το μοντέλο μέτρησης, αν και ένα στοιχείο της συνέχισης χρήσης αφαιρέθηκε λόγω ανεπαρκούς προσαρμογής. Οι άμεσες υποθέσεις ελέγχθηκαν με τον συντελεστή rho του Spearman και με γραμμικές ή τετραγωνικές εξισώσεις, ενώ οι έμμεσες υποθέσεις εξετάστηκαν μέσω διαμεσολάβησης με επαναδειγματοληψία bootstrap 5.000 επαναλήψεων. Όλες οι άμεσες υποθέσεις (H1–H9) επιβεβαιώθηκαν στο επίπεδο σημαντικότητας $\alpha = .001$ και όλες οι έμμεσες υποθέσεις (H10–H14) στο $\alpha = .05$, με τα διαστήματα εμπιστοσύνης bootstrap 95% να αποκλείουν το μηδέν. Η επιβεβαίωση προβλέπει γραμμικά την αντιλαμβανόμενη απόδοση και τη χρησιμότητα, ενώ η αντιλαμβανόμενη απόλαυση ακολουθεί τετραγωνική σχέση. Η ικανοποίηση ανταποκρίνεται μη γραμμικά στην απόδοση και τη χρησιμότητα, υποδηλώνοντας φθίνουσες αποδόσεις, ενώ αυξάνεται σταθερά με την απόλαυση. Η αντιλαμβανόμενη απόδοση, η χρησιμότητα και η απόλαυση διαμεσολαβούν στη σχέση μεταξύ επιβεβαίωσης και ικανοποίησης, ενώ η χρησιμότητα και η απόλαυση διαμεσολαβούν μερικώς στη σχέση μεταξύ επιβεβαίωσης και συνέχισης χρήσης. Η μελέτη προάγει την έρευνα για τη συνέχιση χρήσης της ΤΝ, ενσωματώνοντας ωφελιμιστικές και ηδονικές αξιολογήσεις και αναδεικνύοντας μη γραμμικούς, διαμεσολαβημένους μηχανισμούς με πρακτικές προεκτάσεις για την εισαγωγική εκπαίδευση, την ανατροφοδότηση και τον σχεδιασμό υπηρεσιών.

Λέξεις - Κλειδιά

Θεωρία Επιβεβαίωσης–Προσδοκιών, Μοντέλο Συνέχισης Χρήσης ΠΣ/ΤΟ, πρόθεση συνέχισης χρήσης ΤΝ, ικανοποίηση, αντιλαμβανόμενη χρησιμότητα, αντιλαμβανόμενη απόλαυση, υπηρεσίες φιλοξενίας και τουρισμού

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List of Abbreviations & Acronyms

AI: Artificial Intelligence

CAIC: Consistent Akaike Information Criterion

CFA: Confirmatory Factor Analysis

CFI: Comparative Fit Index

CI: Confidence Interval

CON: Confirmation of Expectations

ECT: Expectation-Confirmation Theory

EFA: Exploratory Factor Analysis

GDPR: General Data Protection Regulation

ICU: Intention to Continue Use

NFI: Normed Fit Index

PEN: Perceived Enjoyment

PPE: Perceived Performance

PUS: Perceived Usefulness

RMSEA: Root Mean Square of Approximation

SAQ: Self-Administered Questionnaire

SAT: Satisfaction

SD: Standard Deviation

SRMR: Standardized Root Mean Square Residual

TLI: Tucker-Lewis Index

VR: Virtual Reality

Chapter 1 - Introduction

1.1 Research aim and research problem

The hospitality and tourism industry is one of the fastest-growing industries worldwide. It is an industry based merely on the human factor. People who work in the hospitality and tourism industry play the most crucial role in its success and growth. Businesses in this sector rely on their financial performance, their capacity to adapt to changing conditions, and how they adapt their offerings to the demands and preferences of their customers to survive (Van Niekerk, 2016; Wikhamn, 2019).

Nevertheless, during the last few years, this situation has been affected by the ongoing rapid evolution of technology. New terms and technologies have entered our personal and work lives, promising to facilitate them. Virtual Assistants, chatbots, and ChatGPT are some of the new technologies firms in all industries invest in to improve customer experience and reduce the dependence on the human factor. All the technologies above are part of artificial intelligence (AI).

A collection of technologies that can identify, evaluate, act, learn, and exhibit sophisticated aspects of human intelligence in problem-solving is known as artificial intelligence (AI) (McCartney & McCartney, 2020). AI is particularly applicable in marketing (Davenport et al., 2020), as it processes large amounts of data to find patterns, behaviors, and opportunities (Mustak et al., 2021).

The hospitality and tourism industry can be significantly affected by different AI typologies in different stages by heightening operational efficiency and improving the customer experience. Recent research has tried to understand how consumers in the travel and hospitality sector view the application of AI and how it relates to their overall satisfaction and experience (Huang et al. 2024; Jamwal & Dhiman, 2023). They have concluded that customers' satisfaction depends on their social influence, hedonic motivation, anthropomorphism, performance and effort expectations, and emotional temperament towards AI (Lin et al., 2020). Li et al., (2021) distinguish four modes of AI-backed customer experiences: AI-supplemented, AI-generated, AI-mediated, and AI-facilitated encounters.

The dissertation aims to deepen how customers in the tourism and hospitality industry perceive performance, usefulness, and enjoyment in relation to their intention of continuing to use AI technology for hospitality and tourism services under the prism of expectation-confirmation theory and the IS/IT continuance model. Therefore, the study measures the tourism and hospitality industry customers' experiences, feelings, and intentions to continue using AI technologies.

1.2 Research objectives and initial assumptions

The beginning of the dissertation is the studies of Huang et al. (2024) and Dhiman and Jamwal (2023), and we investigate four research objectives to deepen our understanding of the impact and nature of relationships among the underlined key constructs.

First, we investigate the impact and the nature of the relationships (strength and direction) among confirmation, perceived performance, perceived usefulness, perceived enjoyment and customers' satisfaction using AI technology in hospitality and tourism industry.

Second, we investigate the impact and the nature of the relationship between customers' satisfaction and intention to continue use AI technology in the tourism and hospitality industry.

Third, we investigate the mediation effects of perceived performance, perceived usefulness and perceived enjoyment between confirmation and customers' satisfaction using AI technology in the hospitality and tourism industry.

Fourth, we investigate the mediating effects of perceived usefulness and perceived enjoyment between confirmation and customers' intention to continue use AI technology in the hospitality and tourism industry.

In continuance, we set forth some initial assumptions of the study to verify the truth in the reasoning realm and ensure that the initial assumptions allow the argumentation to set off.

(1) Initial expectations shape post-use confirmation. Customers in the hospitality and tourism industries use marketing, word-of-mouth, and past experiences to develop

pre-use expectations regarding AI technology. When these initial expectations are compared to actual performance, post-use confirmation or disconfirmation occurs, significantly impacting attitudes and perceptions later on. The underlying assumption of ECT is that expectations come before experience and are used as benchmarks to assess results.

(2) Confirmation directly influences satisfaction and indirectly affects continuance intention. Fulfilled expectations directly affect customer satisfaction. Continuance intention is indirectly influenced by perceived performance, perceived utility, and perceived enjoyment, aligning with the IS/IT Continuance Model's confirmation–satisfaction link.

(3) Post-adoption perceptions independently influence satisfaction and continuance intention. Perceived performance, usefulness, and enjoyment influence satisfaction, while utility, enjoyment, and satisfaction directly affect continuance intention (Huang et al., 2024). The IS/IT Continuance Model highlights both functional and hedonic drivers.

(4) Satisfaction determines continuance intention. Customer satisfaction drives continuance intention, with higher satisfaction leading to greater continued AI use in hospitality and tourism. Both ECT and the IS/IT Continuance Model position satisfaction as the link between experience and future behavior.

1.3 Research approach

In this study, propositions from Expectation–Confirmation Theory and the IS/IT Continuance Model were translated into hypotheses about confirmation, performance, usefulness, enjoyment, satisfaction, and continuance intention. Quantitative measures operationalized each construct, and statistical tests assessed direct and mediated effects. Findings are interpreted by confirming, refining, or rejecting theoretical expectations, strengthening explanatory validity and generalizability within hospitality and tourism contexts.

1.4 Importance of the topic, expected contributions and justification for the focus of the study

AI is transforming tourism and hospitality in the post-COVID-19 era. According to the projections, AI will add $15.7 trillion to global GDP by 2030 (PwC, 2017), while the AI market in travel and hospitality is expected to exceed $1.2 billion by 2026 (IndustryARC, 2021). In this sector, AI supports personalized recommendations, tailored communication, and customized services, thereby enhancing customer satisfaction and loyalty (Dilmegani, 2024).

To gain and sustain a competitive advantage, firms should integrate AI into traditional marketing strategies, as it can improve operational efficiency, customer service, and profitability (Buhalis, 2020; Samara et al., 2020). Traditional marketing functions such as market segmentation, pricing, distribution, and CRM can all benefit from AI applications. Hotels also use chatbots to answer questions about prices, availability, and payment methods, while customer data on prior experiences and preferences enable personalized offers via email and social media. Hotels are increasingly using voice-activated digital assistants to improve customer experience. Further, some handling companies use AI-based luggage systems to guarantee safe delivery without human intervention (Pagar et al., 2023).

To increase productivity, customer satisfaction, and profitability, AI should be incorporated into conventional marketing (Buhalis, 2020; Samara et al., 2020). Segmentation, pricing, distribution, CRM, chatbots for questions about price, availability, and payment, customized offers, voice assistants, and luggage systems for safer delivery are all supported by AI in the hospitality industry (Pagar et al. 2023). However, AI also creates privacy and security risks because personal data may be exposed (Patawari & Bairwa, 2022). Chatbots may misinterpret language and cannot replace complex human judgment (Folstad & Brandtzaeg, 2020). There is still little research on how consumers view AI in the hospitality industry, particularly about to enjoyment, feelings, expectations for service quality, and context-specific attitudes influenced by demographics, travel purpose, culture, and geography (Saini et al., 2025; Bulchand-Gidumal et al., 2024; Chen et al., 2024). Fouad et al., 2024; Huang et al., 2024). Further, since trust and privacy affect adoption, loyalty, and satisfaction, more research is necessary (Lee et al. 2024; Sivathanu and Pillai, 2020).

Despite these challenges, AI is now a major and rapidly evolving part of everyday life. Therefore, this study examines how customers in tourism and hospitality perceive AI performance, usefulness, and enjoyment, and how these perceptions shape their intention to continue using AI technologies in hospitality and tourism services. Specifically, it investigates customers' experiences, feelings, and intentions regarding continued use of AI.

1.5 Structure of the dissertation

The present dissertation consists of eight chapters. The structure of these eight chapters is the following:

In the first chapter, the research aim, research objectives, research approach are presented, along with the importance of the topic.

In the second chapter concepts such as Artificial Intelligence (AI), perceived enjoyment, perceived usefulness and perceived performance are analyzed.

In the third chapter the situation of the role of perceived performance, perceived usefulness and perceived enjoyment and the continue use AI technology in the hospitality and tourism industry is analyzed.

The fourth chapter presents the theoretical framework of Expectation-Confirmation Theory and the IS/IT Continuance Model, the theoretical models of Huang et al., (2024) and Dhiman and Jamwal (2023), the assumptions and hypotheses and the research model, research hypotheses and literature support.

The fifth chapter consists of the research methodology that was used for this dissertation. More analytically, the research motive, research approach and method are presented at the beginning of this chapter. Furthermore, the sampling strategy and data collection, the measurement of variables, the structure of the research instrument and the tools and statistical analyses are presented.

In the sixth chapter, the results of the research are stated. The questionnaire results will be interpreted, hypotheses will be tested and accepted or rejected depending on the results and a summary of the research results will be stated.

The seventh chapter is a discussion regarding antecedent similar studies and the contribution of the present study to future discussion regarding AI technology in the tourism and hospitality industry.

In the final eighth chapter, the conclusion of the dissertation is presented, along with a pithy summary of the main points.

Chapter 2 - Definition of the concepts

In this chapter we are providing some information about the basic concepts of this dissertation. These are considered vital for the comprehension of the rest of this work. The structure of the chapter is the following: 2.1 Artificial intelligence in hospitality and tourism,-2.2 Confirmation of customer's initial expectations and perceived performance of AI technology in hospitality and tourism, 2.3 Perceived usefulness of the AI technology in hospitality and tourism, and 2.4 Perceived enjoyment of the AI technology in hospitality and tourism.

2.1 Artificial intelligence in hospitality and tourism

The literature on artificial intelligence (AI) in the hospitality and tourism sectors reveals a variety of conceptual frameworks and applications. These variations are primarily categorized based on the type of AI technology, its application, and the interaction with human users, such as the anthropomorphism-based AI robots and AI technology-based service encounters (e.g., Saputra et al., 2024; Li et al., 2021).

AI significantly impacts the travel and hospitality industries because it allows machines to handle jobs historically done by people, like operational management and customer service (Koo et al., 2021; Ruel & Njoku, 2021). However, the implications of this technology must be considered in the scholarly discussion.

It is important to consider whether chatbots and virtual assistants driven by AI improve customer satisfaction or are only a cost-cutting strategy degrading the standard of interpersonal communication in services (Talukder & Das, 2024; Cheng & Jiang, 2020).

The key concept is that AI systems that examine client information to provide personalized suggestions have the potential to significantly improve the visitor experience (e.g., Bulchand-Gidumal et al., 2024). However, this presents moral questions about data privacy and how personalization might verge on invasion, which could drive away clients rather than win them over (e.g., Bulchand-Gidumal et al., 2024; Semwal et al., 2023). It is impressive how well AI can optimize pricing and inventory management (Zhang et al., 2021). Predictive analytics demand forecasting, however, introduces systematic biases in data interpretation that could result in resource misallocation and operational inefficiencies in the travel and hospitality industry.

AI's capacity to manage enormous datasets yields valuable insights into market trends and consumer behavior. However, depending on data-driven decision-making necessitates critically assessing the quality and representativeness of the data because erroneous data can lead to misguided strategies (Okeleke, 2024).

Artificial intelligence enhances automation by enabling machines to learn and adapt, which uses technology to streamline tasks. It is one way that similar but related concepts can be different from one another. Notwithstanding the importance of this distinction, it raises questions regarding industry job security and the possible replacement of human roles (Malik et al., 2021). Machine learning, a branch of artificial intelligence, involves algorithmic learning from data. Although this distinction is significant, it raises questions about the algorithms' transparency and the morality of using them to forecast consumer behavior (e.g., Azad et al., 2023). Data analytics can find patterns, but it does not have adaptive learning.

2.2 Confirmation of customer's initial expectations and perceived performance of AI technology in hospitality and tourism

Customer experiences and business outcomes in the hospitality and tourism industries are shaped by the confirmation of customers' initial expectations and perceived AI performance, two interrelated constructs (Roy et al., 2024; Lei et al., 2023; Chi et al.,2022). Peer recommendations, marketing, past experiences, and industry standards all influence customer expectations.

However, consumers frequently overestimate AI's potential, leading to irrational expectations and disappointment when performance is subpar (Prentice et al.; Xu et al., 2020; Gursoy et al., 2020; 2019). Concerns about the digital divide are also raised by innovation readiness, as tech-savvy consumers may have higher expectations, potentially excluding less tech-savvy clients (Shirazi & Hajli, 2021). Because the fundamental aspects of AI are subjective and differ among users, assessing perceived AI performance is difficult (Susanto & Khaq, 2024; Saeed & Omlin, 2023; Dwivedi et al., 2021). Comparing AI to competitors or traditional services may also distort its actual worth (Le et al., 2024). The digital divide can be illuminated by usability obstacles that reduce perceived effectiveness, particularly for clients with limited digital access or skills (e.g., Park et al., 2023; Cheng & Jiang, 2020).

Satisfaction depends on how expectations align with perceived performance, even though meeting expectations does not always guarantee high satisfaction (Tukiran et al., 2021; Habel et al., 2016). Even though the digital divide further affects retention and satisfaction, minor differences can still lead to dissatisfaction, especially when loyalty is low (Prentice et al., 2020). Trust is influenced by transparency, reliability, privacy, and ethics; less tech-savvy users are more likely to be dubious (Li et al., 2023; Ferdous & Aldboush, 2023; Liu et al., 2022). Many customers prefer a hybrid model that blends human empathy with AI efficiency, even though AI tools can enhance service delivery (Reis et al. 2020).

2.3 Perceived usefulness of the AI technology in hospitality and tourism

Since technology is anticipated to enhance worker performance, customer satisfaction, productivity, and service quality, perceived usefulness is a major factor in the adoption of AI in the hospitality and tourism industries (Singh et al., 2023; Tavitiyaman et al., 2022; Pillai & Sivathanu, 2020; Ma & Liu, 2005). Chatbots and automated check-ins are examples of AI tools that can improve operations, but their effectiveness depends on customer engagement and actual adoption (Samala et al. 2020).

Perceived ease of use, distinct from but closely linked to perceived usefulness, affects AI adoption: even beneficial tools may see lower uptake if difficult to use. Thus, adoption requires strong perceptions of utility and usability (Kashada et al., 2020). User satisfaction in AI-customer interactions is also linked to perceived usefulness. However, users may recognize functional value but still be unhappy with the experience, so usefulness does not always guarantee satisfaction (Salim et al., 2021).

The viewpoint is further expanded highlighting users' propensity to adopt technology based on social influence and enabling circumstances in addition to perceived utility and ease of use. Therefore, when organizational support is lacking or peer pressure discourages use, even very beneficial AI tools may encounter adoption barriers (Goel et al., 2022; Nuryyev, 2020). Lastly, innovation emphasizes how innovations spread within social structures. Research in healthcare and education shows that perceived usefulness can accelerate adoption, although diffusion also depends on contextual and cultural factors (He & Lee, 2020; Hubert et al., 2018). Differentiating perceived usefulness from related constructs helps hospitality and tourism professionals understand the challenges of integrating AI and promotes innovation, competitive advantage, and successful implementation.

2.4 Perceived enjoyment of the AI technology in hospitality and tourism

Perceived enjoyment is a key yet often overlooked factor in AI adoption in hospitality and tourism (e.g., Vorobeva et al., 2024). For managers, employees, and customers, this factor shapes emotional responses and influences their uptake of tools such as chatbots and automated services. Nevertheless, it is important to note that enjoyment and satisfaction do not always align; users from each group may be satisfied even if they do not enjoy the service (e.g., Liu et al., 2023).

Perceived ease of use is not the same as enjoyment. A system can be easy to navigate but still feel unengaging. Even if AI's usefulness encourages adoption, enjoyment is not guaranteed and may cause emotional detachment despite helpful outcomes (e.g., Jo, 2023; Pillai, 2020). This distinction is critical for AI design in travel and hospitality (Roy et al., 2024). Enjoyment can boost engagement, but it relies on multiple drivers, not just gamification or social sharing. This challenges the idea that enjoyment alone motivates interaction (Hajarian et al., 2019; Yang et al., 2017).

User perceptions of enjoyable AI are crucial in hospitality and tourism, driving adoption and satisfaction. Balance efficiency with humor, emotional intelligence, and personalization to emphasize experience over pure function. AI implementation is complex and needs careful planning.

Chapter 3 - Situation Analysis

Chapter 3 presents the situation analysis regarding AI technology for hospitality and tourism, focusing on AI implementation, the role of perceived performance, usefulness, and enjoyment in AI adoption, and the barriers to AI adoption. The chapter is structured as follows: 3.1 AI implementation in the hospitality and tourism industry in Greece and globally, 3.2 The role of perceived performance, usefulness, and enjoyment in AI adoption in hospitality and tourism in Greece and globally, and 3.3 Concluding remarks.

3.1 AI implementation in the hospitality and tourism industry in Greece and globally

By enhancing resource management, improving operational efficiency, and delivering personalized customer experiences, artificial intelligence is revolutionizing the travel and hospitality industry. Fifty-two percent (52%) of travel agencies globally have used AI tools like chatbots and predictive analytics to forecast demand (Statista, 2023a). AI-driven suggestions can increase client loyalty and engagement by using big data analysis to customize services to each user's preferences (Chen & Samiun, 2021).

Greece's competitive, seasonal tourism industry has great potential. However, only 30% of Greek lodging providers have implemented AI (Statista, 2023a), since chatbots offer round-the-clock assistance, reduce employee workload, and expedite responses. AI enhances peak-time resource allocation, according to Skandali et al. (2024). Further, 45% of destination management organizations use AI for marketing and visitor engagement (Statista, 2023b). AI facilitates more appealing destinations, customized offerings, and targeted advertising by evaluating traveler data (Pillai & Sivathanu, 2020). Travelers also increasingly accept AI-driven personalization when privacy is protected (Spanaki, 2024; Ho et al., 2022).

Greece faces obstacles such as poor infrastructure, a shortage of skilled workers, and high costs despite AI's potential (Vorobeva et al. 2024). Only 9 out of 81 companies in Greece, which was ranked 18th out of 27 in the EU in 2024, used AI; the most common uses were text mining (6.9%), natural language generation (5.4%), and voice recognition

(4.8%) (Naftemporiki, 2025). Seventy-five percent (75%) of SMEs in the travel and hospitality industry would invest with financial incentives, while 68% cite cost barriers (Ho et al. 2022).

3.2 The role of perceived performance, usefulness, and enjoyment in AI adoption in hospitality and tourism in Greece and globally

The use of AI in hospitality and tourism has significantly increased in Greece and around the world. According to recent studies, adoption is primarily influenced by perceived performance, utility, and enjoyment. The degree to which AI raises productivity and service quality is reflected in perceived performance. According to Pillai and Sivathanu (2020), AI chatbots have reduced customer service response times by up to 70%. Perceived performance and customer satisfaction are strongly correlated, as evidenced by 65% of Greek customers reporting that AI services improved their overall travel experience (Skandali et al., 2024). According to Pillai and Sivathanu (2020), businesses using AI reported a 30 percent increase in operational efficiency globally.

Perceived utility also has a major impact on adoption. Vorobeva et al. (2024) found that 78% of participants believed AI could personalize travel experiences, offering Greece's tourism sector a major competitive advantage. Similarly, 75% of hospitality companies globally had already implemented AI solutions to improve guest experiences and streamline operations, while 82% of travel and hospitality businesses planned to implement AI-powered services to improve customer interactions and operational efficiency (Ho et al., 2022).

Another important component is enjoyment, particularly in the hospitality industry, where experience adds value. Skandali et al. (2024) found that 58% of Greek customers reported that AI services improved their travel experiences. Similarly, 65% of users worldwide reported that AI tools such as recommendation engines and virtual assistants improved their travel experiences (Vorobeva et al. 2024). Customer satisfaction ratings have increased by 40% due to AI chatbots that inform and interact with consumers (Pillai & Sivathanu, 2020).

In general, the hospitality and tourism industries in Greece are adopting AI in line with global trends. Greece's 82% intention rate for future adoption is consistent with global trends (Ho et al., 2022), despite the global average for perceived performance improvement (70%) being marginally higher than Greece's 65% (Pillai & Sivathanu, 2020). According to these results, there is a good chance that AI will continue to grow as stakeholders improve perceptions of its effectiveness, utility, and enjoyment.

3.3 The barriers to AI adoption in hospitality and tourism in Greece and globally

For several reasons, the hospitality and tourism industries aren't using AI extensively. Because they frequently worry about losing their jobs and the human element that defines hospitality, service providers' resistance is a major barrier. According to Cho and Kwon (2025), 62% of hotel managers are concerned about how robots will affect employment, and 57% believe that greater automation will lead to lower customer satisfaction. Adoption is also hampered by low awareness. Anwar et al. (2025) found that 48% of small hospitality business owners are unaware of AI's potential applications, which reduces their willingness to invest and increases the likelihood they will misunderstand its benefits. High implementation costs, however, remain a significant barrier, especially for SMEs. According to Statista (2025), 45% of travel agencies cite cost as the main barrier to implementing generative AI because initial investment, maintenance, and training can be expensive.

The absence of a workforce with the necessary skills to effectively manage AI systems is another barrier. Bakir and associates. (2025) discovered that 53% of hotel managers have trouble finding workers with the requisite technological skills. This disparity also affects staff retention, as employees seek better training and career opportunities elsewhere. Complexity is increased by worries about privacy and data security. Pipyros and Liasidou (2025) report that 67% of stakeholders are concerned about data breaches and misuse of customer information, which is especially risky in a sector that heavily relies on personal data.

Cultural factors influence adoption: 55% of respondents prefer human interaction over automated services, and regional resistance varies, particularly in nations with strong hospitality industries, such as Greece (Pillai & Sivathanu, 2020). Further, according to Webster and Cain (2025), 60% of hospitality managers express concerns about the current regulations, suggesting that implementation is hampered by regulatory uncertainty. In general, resistance, low awareness, high costs, skill gaps, privacy concerns, cultural preferences, and regulatory ambiguity limit the adoption of AI in the hospitality and tourism industries.

3.4 Concluding Remarks

The adoption of AI in Greece's tourism and hospitality sectors is primarily motivated by perceived utility, enjoyment, and performance. Even though Greece is not as advanced as other European nations, it can still enhance efficiency and customer experience. Greece may be able to take the lead in AI-driven travel by addressing infrastructure and skills gaps, and by attracting investment. Service provider resistance, low awareness, high costs, a lack of trained personnel, concerns about data privacy, cultural issues, and legal obstacles are among the factors that hinder adoption. These issues must be resolved to increase the industry's competitiveness and sustainability, as well as foster an environment that encourages AI integration.

Chapter 4 - Theoretical framework, research model and literature support

Chapter 4 is organized in 6 sections. Section 4.1 discusses the frame of reference, examining the misinterpretation of basic concepts and their interrelationships with other key theories and section 4.2 copes with Expectation-Confirmation Theory and IS/IT Continuance Model. Section 4.3 presents the theoretical models of Huang et al., (2024) and Dhiman and Jamwal (2023). Section 4.4 presents the assumptions and hypotheses for theory and the adopted model as well. Section 4.5 presents the dissertation's research model, hypotheses and literature support, whereas section 4.6 summarizes the conclusions of Chapter 4.

4.1 Frame of reference

Automated technology integration is revolutionizing the hospitality industry by improving operational efficiency and user experience. The Technology Acceptance Model (TAM) (Davis, 1989) remains essential (Surendran, 2012), rooted in the Theory of Reasoned Action and the Theory of Planned Behavior, asserts that attitude mediates the effects of perceived usefulness and perceived ease of use on adoption (Marangunic & Granic, 2015; Sharp, 2007).

TAM provides little information on post-adoption satisfaction and continuation, and focuses on pre-adoption behavior (Dugar, 2018; Liu and Yu, 2017; Jeyaraj et al., 2006; Venkatesh & Davis, 2000). Despite its ease of use and broad applicability, combining pre- and post-adoption assessments enhances ECT's effectiveness (Shiau et al., 2011). Similarly, UTAUT uses social influence, performance expectancy, effort expectancy, and facilitating conditions to explain adoption intentions (Papagiannidis & Marikyan, 2023; Venkatesh et al., 2003).

The Continuity Model for IS/IT connects system performance and perceived utility to expectations and satisfaction (Jia et al., 2023; Bhattacherjee, 2001). Therefore, taken together, these frameworks show that perceived performance, utility, and enjoyment significantly influence how long AI will remain in the hospitality and tourism industries.

4.2 Expectation- Confirmation Theory and IS/IT Continuance Model

Oliver (1980) developed the Expectation-Confirmation Theory (ECT), which expands upon previous military studies demonstrating that expectations met boost morale (Spector, 1956). Repurchase intention, post-purchase satisfaction, and consumer behavior are all explained by ECT, a widely used marketing concept. Prior experiences and social influences, such as social media, help customers develop pre-purchase expectations (Rogers, 1995; Zeithaml & Berry, 1990). They assess how well a product or service performs against these expectations after using it. This comparison leads to customer Satisfaction, and happy customers are more likely to make additional purchases (White & Yu, 2005).

ECT has also been applied in information systems (IS) to explain user expectations and continuance intentions. However, its application in IS has limitations. Because IS products and services are often complex, ECT does not fully explain how expectations are formed, nor does it adequately capture quality-related aspects that shape user satisfaction (Khalifa & Liu, 2004). To overcome these limitations, Bhattacherjee (2001) proposed the Expectation Confirmation Model (ECM) to explain continued use of IS products and services. ECM highlights three key determinants of continuance intention: user satisfaction, confirmation of expectations, and perceived usefulness after actual use (Hossain & Quaddus, 2012; Bhattacherjee, 2001). Unlike ECT, ECM assumes that perceived usefulness is formed only after users have sufficient experience with the system. In both models, however, confirmation directly affects satisfaction and continuance intention (Bhattacherjee et al., 2008).

Based on this logic, the IS/IT Continuance Model expands on ECT by emphasizing perceived utility and user satisfaction as important markers of continuance intention (Thong et al., 2006; Bhattacherjee, 2001). It adopts a post-adoption perspective, linking attitudes, experiences, and satisfaction to continued use and purchases, as users compare performance with prior expectations, confirming or disconfirming them (Huang et al., 2023).

Under the IS/IT Continuance Model, satisfaction and continuance depend on price advantage, reputation, critical mass, website quality, usability, and enjoyment (Islam et al., 2017; Zhang et al., 2015; Thong et al., 2006). Positive interactions with AI technologies can enhance long-term use and post-adoption behavior by increasing self-efficacy and self-esteem (Gupta et al., 2020).

4.3 Theoretical perspectives of hedonic dimensions (enjoyment) and integration of task-technology fit considerations

Huang et al., model (2024) investigates the factors that influence consumers' intentions to use AI-based services in the travel and hospitality sector in the future. They added elements like perceived performance and enjoyment to the Expectation-Confirmation Model (ECM). According to one of the main conclusions, confirmation of expectations was a significant predictor of satisfaction and intentions to use the product again. How pleasant AI services were viewed significantly impacted customer satisfaction and plans to use them again. The actual performance of AI services greatly impacted customer satisfaction and perceived performance. Huang et al., (2024) skilfully blend hedonic and utilitarian dimensions to emphasize the significance of functional and emotional factors in technology adoption. Furthermore, since social influence and trust are essential for adopting technology, the model may help consider other factors.

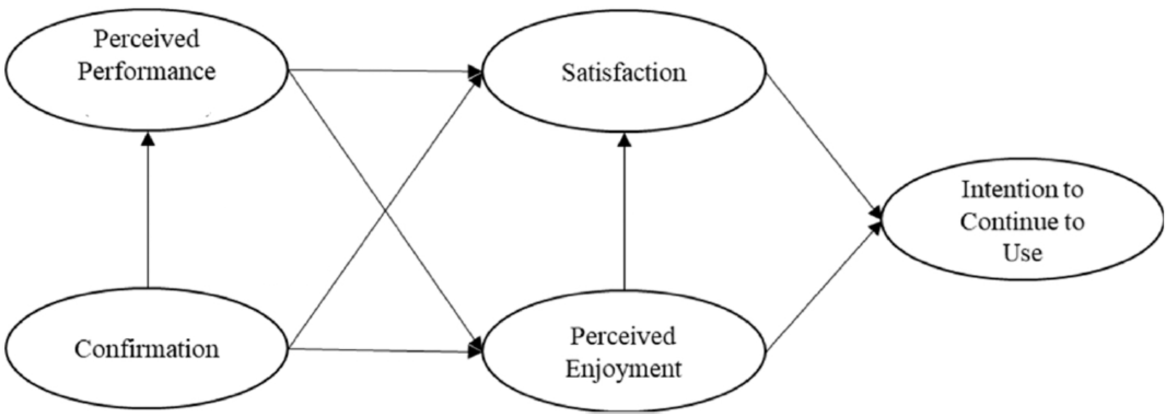

Figure 4.1: The model by Huang et al. "Model of utilizing AI technologies in tourism and hospitality experiences" (Huang et al., 2024, p.7).

The post-adoption continuance intentions of chatbots in the tourism industry are examined by Dhiman and Jamwal's (2023) model, which combines the Task-Technology Fit (TTF) Model and the Expectation-Confirmation Theory (ECT). The task-technology fit is one of the key findings, demonstrating that their technological attributes must align with the task's needs for chatbots to be helpful. The degree to which users' expectations were fulfilled also greatly influenced whether they kept using chatbots. This model thoroughly explains the factors influencing chatbot adoption and persistence. It emphasizes how important technological and task-related skills are. It could be improved by adding user experience and high-quality interaction, which are essential for sustained engagement.

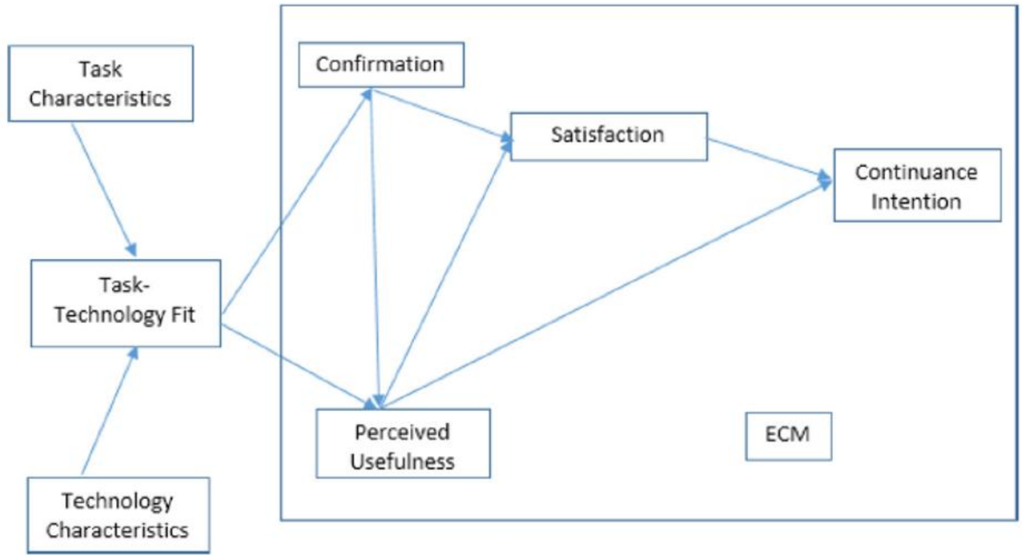

Figure 4.2: The model by Dhiman and Jamwal "Tourists' post-adoption continuance intentions of chatbots" (Dhiman & Jamwal, 2023, p.215)

Combining the models of Huang et al., (2024) and Dhiman and Jamwal (2023) provides a thorough understanding of the elements affecting the decision to keep using AI technology in hospitality and tourism services. The model by Huang et al., (2024) stresses the importance of perceived performance and enjoyment, showing how functional and emotional factors significantly impact customer satisfaction and plans to use the product again, whereas matching technological features to task requirements is the model's primary goal by Dhiman and Jamwal (2023). The combination of perceived performance, usefulness, and enjoyment allows us to see how users' intentions to continue using AI services are influenced. To increase trust and engagement, the combined approach emphasizes how AI technology must satisfy users' functional needs and offer a fulfilling and pleasurable experience to be adopted and maintained in the hospitality and tourism sectors.

4.4 Assumptions

Pre-purchase expectations are the first of the fundamental tenets of the Expectation-Confirmation Theory (ECT). Customers create expectations based on marketing, word-of-mouth, and past experiences before making a purchase. They compare those expectations with actual performance, quality, and satisfaction after purchase. When an experience meets or surpasses expectations, it's called confirmation; when it doesn't, it's called disconfirmation.

Disconfirmation occurs when experience falls short of expectations, causing negative evaluations. Satisfaction is directly linked to confirmation or disconfirmation, while confirmation increases satisfaction and positive perceptions.Future use may be discouraged by dissatisfaction resulting from disconfirmation. Finally, repurchase intentions are significantly influenced by satisfaction. Customer satisfaction increases the likelihood that they will use or repurchase a product or service. However, a decrease in repurchase intentions may result from dissatisfaction.

According to the IS/IT Continuity Model's underlying assumptions, perceived utility replaces post-consumption expectations in the context of information systems. This is a measure of how much customers think the IS/IT will improve their performance or satisfy their needs. Users contrast their initial expectations with the IS/IT's perceived usefulness. They experience pleasure when the system meets or surpasses their expectations, and they experience confirmation when the perceived utility is confirmed. Whether or not customers plan to keep using IS/IT depends on how satisfied they are with their experience. Satisfied users are more likely to remain loyal to the system, thereby ensuring its continued uptake and use.

In line with Huang et al., (2024), the mean-field approximation simplifies the study by averaging interactions across large populations. Learning these equilibria is like single-agent Reinforcement Learning, as it is possible to find Nash Equilibrium strategies in Mean-Field Games under the strategic exploration assumption. Model complexity is effectively characterized by the Partial Model-Based Eluder Dimension, which is often lower than conventional measures.

TPB can consider people's ongoing usage of chatbots (Dhiman & Jamwal, 2023). Several factors affect people's perceptions of chatbots (e.g., personal norms, their degree of concern for the environment, and their sense of behavioral control). These opinions then influence their actual behavior as well as their plans. Understanding what motivates consumers to keep using chatbots is the primary goal. Examining different situational and psychological elements that affect their continued use is part of it. The model incorporates psychological factors such as customer satisfaction and happiness. It leads to the final assumption. These factors significantly influence both overall consumer behavior and continuance intentions.

4.5 Research hypotheses development and research model

In the following paragraphs, we describe the research hypotheses derived from the literature review.

Cognitive consistency theory, which holds that people try to keep expectations and perceptions in balance, provides the basis for the positive impact of expectation confirmation on the perceived performance of AI technologies in the hospitality and tourism industries. When expectations are confirmed, users are psychologically motivated to perceive performance positively, reinforcing their initial decision to use the technology. Few empirical studies have investigated the direct relationship between confirmation and perceived performance in AI contexts, even though previous literature has looked at the relationship between confirmation and satisfaction or perceived performance and satisfaction.

This gap is especially pertinent in the hospitality and tourism industries, where AI performance is multifaceted and influenced by capabilities and interpretations. Different theoretical models (e.g., ECT, ECM, and TTF) provide a robust foundation for predicting this relationship. In a variety of AI applications, it has been demonstrated that perceived performance—users' post-use assessment of quality and value—positively influences user satisfaction (e.g., Meeprom & Suttikun, 2024. Lei et al., 2023; Chen et al., 2022). In hospitality, confirmed expectations enhance perceived usefulness and performance, shaping attitudes, engagement, and behavioral intentions (e.g., Wang & Hou, 2025; Roy et al., 2024). Therefore, we can state that:

H1: Confirmation of expectations positively influences perceived performance.

The relationship between perceived utility and expectation confirmation, which has been empirically validated in a range of contexts, is one of the fundamental ideas of technology continuance research. To show how confirmation directly affects users' perceptions of the usefulness of information systems, Bhattacherjee (2001) defined confirmation as the agreement between users' pre-adoption expectations and post-adoption perceptions of actual performance. Hossain and Quaddus (2012) empirically validated that confirmation significantly affects perceived usefulness, which subsequently enhances user satisfaction and continuance intentions. Li et al., (2021) present the mechanism of confirmation-usefulness in AI tourism applications by demonstrating how ChatGPT's information quality and accuracy, representing confirmed expectations, encourage continued use for tour route planning. This connection cuts across industry lines, as demonstrated by Lee and Kwon (2011) and Chou et al., (2010), who demonstrate how important expectation confirmation is in determining how beneficial e-learning environments are perceived. Likewise, this pathway was validated in e-commerce by Lee and Kwon (2011) and mobile commerce by Zhou (2011), while Chiu et al., (2020) added fitness applications to these findings, and Nong et al., (2022) added MOOC. Alshammari and Alshammari (2024) summarized the data and found that perceived utility and confirmation together drive satisfaction and intentions to adopt technology. There is still a great deal to learn about AI-specific applications in the hospitality industry, despite compelling evidence from other sectors (Huang et al., 2024). A more focused study is necessary because, despite Dhiman and Jamwal's (2023) examination of AI adoption generally, little research has identified

the confirmation-usefulness pathway for different AI typologies (mechanical, thinking, and feeling AI) in tourism services. Therefore, we can state that:
H2: Confirmation of expectations positively influences perceived usefulness.

In AI-enabled hospitality, expectation confirmation dramatically raises the perceived level of enjoyment (Huang et al., 2024), which increases intentions to reuse and satisfaction. Through the integration of task-technology fit and expectation-confirmation theory, Dhiman and Jamwal (2023) provided support for this using chatbots for tourism. These results are applied to AI service robots and show that intent to repurchase, enjoyment, and confirmation are related (e.g., Lei et al., 2023). Kim et al., (2019) claim that enjoyment acts as a mediator in the relationship between ongoing use of accommodation apps and confirmation. 2019). Additionally, Vorobeva et al., (2024) and Liu et al., (2023) discovered that hedonic responses rise when experience and expectations align. Yousaf et al., (2021) showed that the continued use of travel apps and over-the-top platforms depends on confirmation-driven satisfaction, with context affecting this relationship, according to recent data. Applying generative AI to applications greatly increases enjoyment by satisfying user demands for customization. According to research, AI-powered solutions raise customer satisfaction and engagement by validating experiential expectations (e.g., Rather, 2025; Folaud et al., 2024). There are still important gaps that need to be filled, such as whether enjoyment mechanisms vary among AI typologies (mechanical, thinking, and feeling AI) across different hospitality touchpoints and how repeated confirmation episodes compound enjoyment over time. Therefore, we can state that:
H3: Confirmation of expectations positively influences perceived enjoyment.

Research in hospitality and tourism has shown that perceived performance is a significant predictor of users' attitudes and intentions to continue using AI, according to Zhang and Qi (2019), bolstering the case for loyalty and repeat business (Gao et al., 2025; Leon et al., 2025). Further, the perceived intelligence of AI devices enhances user satisfaction and attitudes, underscoring the importance of intelligence and performance in shaping favorable perceptions.

It has been demonstrated that enhanced AI functionality significantly improves user experience and satisfaction. AI chatbots exhibit this pattern, with higher user satisfaction linked to higher performance (Chen et al., 2019), and this pattern is evident in high-end hotels, where AI systems improve guest satisfaction (Pelet et al., 2022).

Similar results hold across a variety of contexts, including messaging apps (Oghuma et al., 2016), food service (Basirat et al., 2025), and AI robots (Gao & Liang, 2025). Research on Human-Robot Interaction also highlights the importance of high performance in raising satisfaction because low performance tends to keep satisfaction levels constant (Schmidt et al., 2025). Therefore, we can state that:

H4: Perceived performance positively influences satisfaction.

Perceived usefulness is a key concept in satisfaction. It describes the users' perception that a new technology will improve their experience. Satisfaction is the extent to which a user is content with the technology and the experience he/she has used/received. Corne et al., (2023) assessed perceived usefulness in the tourism industry's adoption of Metaverse systems, demonstrating that perceived utility is crucial to user satisfaction and is positively affected when users believe chatbots are useful (Mejia et al., 2025). Further, Sousa et al., (2024) found that when guests perceive technology tools such as chatbots, QR codes, translation machines, etc., as accurate or helpful, their satisfaction increases.

In addition, a study by Borghi and Mariani (2024) showed that guests' PU of service robots positively influenced their satisfaction. Virtual platforms are found to offer unique experiences, both informative and interactive, that lead to increased customer satisfaction (Wu & Yu, 2024). On the contrary, we could cite the study by Goli et al., (2023), which examined the factors that affect the intention to use chatbots. The above study showed that when chatbots are overambitious, user satisfaction may be reduced. In addition, users who are not very familiar with new technologies may not realize their usefulness (Nisa et al., 2023). Therefore, we can state that:

H5: Perceived usefulness positively influences satisfaction.

The literature points to a positive link between perceived enjoyment and user satisfaction in AI contexts, though the strength and nature of this relationship warrant closer examination. Research consistently shows that perceived enjoyment—the pleasure or fun users derive from interacting with AI technologies—acts as a key psychological driver of both satisfaction and the intention to continue using these technologies in hospitality and tourism contexts. Enjoyment significantly boosts satisfaction and continued use through intrinsic motivation (Batouei et al., 2025; Khrouf et al., 2025). It is a key factor in chatbot satisfaction (e.g., Ashfaq et al., 2020; Rajaobelina et al., 2021; Mejia et al., 2025; Hsu & Lin, 2022), voice assistants (Hernandez-Ortega & Ferreira, 2021), and service robots (Caliskan & Sevim, 2023), and mediates effects of anthropomorphism and information quality on satisfaction (Magano et al., 2025). However, Pozo-Sanchez et al., (2021) caution that satisfaction requires both functional robustness and pleasurable interaction, not mere enjoyment. Therefore, we can state that:

H6: Perceived enjoyment positively influences satisfaction.

Traveler satisfaction is fundamentally linked to enjoyable and memorable experiences (Sthapit & Coudounaris, 2018), a requirement that drives the sustained adoption of AI. The hedonic motivation (Ashfaq et al., 2020; Zhang et al., 2023) is critical, as perceived enjoyment strongly predicts the continued use of both destination chatbots (Orden-Mejia et al., 2024) and AI-enhanced tour guide applications (Topsakal & Cuhadar, 2024). The positive correlation between enjoyment and continuance intention holds true even in the broader e-commerce context (Ding & Najaf, 2024).

Critically, however, this relationship is complicated by anthropomorphism. Studies reveal that high human resemblance in robots actually resulted in *decreased* perceived enjoyment, consequently diminishing user intention to engage (Huang et al., 2021). This crucial finding supports the assertion that the impact of anthropomorphism on positive user perception is non-linear and demands careful, nuanced design (Jia et al., 2021). Therefore, we can state that:

H7: Perceived enjoyment positively influences intention to continue to use AI technology.

Following the rapid advancements in AI technology, recent literature has attempted to examine and comprehend the reasons which drive users to continue using these technologies. Effort and performance Expectany, Social Influence and facilitating conditions are some of the users' drivers for continue use of AI technologies (Topsakal & Cuhadar, 2024). Perceived Usefulness has also been found to be a core driver regarding continue use of AI technologies. Nguyen et al., (2021) confirmed that perceived usefulness positively affects the continuance usage of banks' chatbot users. Furthermore, in the context of tourism and hospitality it was shown that the more the users perceived chatbots are useful, the more satisfied they were and subsequently more likely to continue using them (Orden-Mejia et al., 2024). Moreover, users were found to increase their shopping intention in AI-driven stores, in cases they found that AI was useful (Pillai, Sivathanu & Dwivedi, 2020). Furthermore, Jo, 2022 proved that perceived usefulness has a positive and significant effect on utilitarian value. The reason behind that is that when users think AI personal assistants as useful and easy to use, the possibility of them to continue using them increases.

Additionally, perceived usefulness of ChatGPT use in hospitality and tourism was found to significantly influence their continue use (Han et al., 2025). Alotaibi established the impact of Perceived Usefulness on the intention to use chatbots for airtickets (2024). In addition, Kaushik, Agrawal & Rahman (2015), found that perceived usefulness has a positive impact on self-service hotel technology. Moreover, it was shown that users tend to keep using AI painting applications when they consider them to be easy to use, accurate and helpful (Yu, Yang & Li, 2024). Therefore, we can state that:

H8: Perceived usefulness positively influences intention to continue to use AI technology.

Users' satisfaction with AI technologies is a crucial factor that determines their intention to continue using such technologies or not. Ku & Chen (2024), showed that tourist satisfaction positively influences their intention to continue use AI services. In another study concerning chatbots in the tourism industry it was also proved that users' satisfaction played a pivotal role in their continued use (Pereira et al., 2021). Likewise, in dialogue systems users' satisfaction with AI-based chatbots was found to positively affect their continued use (Li et al., 2021). Furthermore, Li et al., 2024 proved that tourists are more likely to use ChatGPT for planning tour routes when they perceive it as useful. Additionally, Jia et al., (2021) showed that satisfied users by hotels' robotic services were more likely to repurchase. Similarly, in an empirical study from hotels it was proved that consumer satisfaction via perceived warmth and competence was risen and led to continue use of robot services (Wu, Huo, 2023).

Moreover, in a study conducted in Thailand's smart hotels it was proved that guests' satisfaction from contactless technology positively influences their revisit intentions and the possibility of proposing these hotels to other guests (Soliman et al., 2025). In the context of medicine, it was found that citizens' satisfaction from mental health chatbots is positively linked to their intention to continue their use (Zhu, Wang & Pu, 2022). Enhancing the previous studies, Shi, Zhan & Lin, 2025, showed that hotel robots that are reliable, enjoyable and have human-like traits, increase users' satisfaction, leading to more loyal customers with revisit intentions. Regarding users' engagement in relation to AI chatbots, it was found that satisfaction is a dominant driver in the travel sector (Magano, Quintela & Banerjee, 2025). Therefore, we can state that:

H9: Satisfaction positively influences intention to continue to use AI technology.

Several studies highlight Perceived Performance as a mediator between users' confirmation of expectations and satisfaction with AI technologies. Oh et al. (2022), using a deep learning model based on ECT, showed that online hotel review comments can predict guests' satisfaction. In Thai chain hotels, Chotisarn and Phuthong (2025) found that AI reliability and efficiency significantly influence customer satisfaction and loyalty. Similarly, Ku and Chen (2024) showed that the perceived anthropomorphism of AI robots moderates the relationship between tourism products' functional benefits and user satisfaction. In historical theme parks, visitors' satisfaction was positively affected by perceived performance across staff, facilities, and resource conditions (Yuan & Marzuki, 2024). Borghi and Mariani (2024) found that human-robot interaction improves guest satisfaction in the hospitality industry, depending on how enjoyable, entertaining, and efficient the robots are. An analysis by Soliman et al. This mediating role in hotel AI technologies was also confirmed by (2023). Therefore, we can state that:

H10: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived performance.

Confirmation of expectations and satisfaction through the effect of perceived usefulness has been extensively studied in the last years. More specifically, Yap et al., review (2025) and show that guests' satisfaction is boosted when their expectations are met, across various smart tourism technologies.

A recent study by Hanji et al., (2023) showed that when users interact with AI technologies such as chatbots and smart applications and their expectations are met or exceeded, their satisfaction rises. Additionally, Oh et al., (2022), in their study where they applied the ECT in the hospitality services, discovered that guests' satisfaction was increased through the perceived usefulness of the services when their expectations were met. Moreover, in the context of religious tourism, it was found that regarding Hajj hospitality services, higher levels of guests' confirmation of expectations in pilgrims, resulted in greater perceived usefulness of those services, which in conclusion led to increased guest satisfaction (Albahar et al., 2023).

In addition, when it comes to customers' perceptions towards AI-hotels it was shown that perceived performance is a core factor that determines their intentions around new technologies (Ghazi et al., 2023). Furthermore, in the context of e-commerce, Perceived Usefulness was found to mediate the relationship between AI applications and users' satisfaction (Wang et al., 2023). Additionally, in other sectors it was shown that the more the users' expected Perceived Usefulness of the B2C banking AI chatbot, the greater the satisfaction they received (Proesch, 2025). Therefore, we can state that:

H11: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived usefulness.

According to research, people's perceptions of the usefulness of AI technologies rise when their expectations are fulfilled. The relationship between met expectations and the intention to keep using the technology is mediated by perceived utility (Khrouf et al., 2025; Li & Wang, 2025). Expected benefits increase perceived usefulness and encourage user participation in AI applications such as chatbots and hotel management systems (Li & Wang, 2025; Orden-Mejía et al., 2025).

Chatbot anthropomorphism and high-quality information increase perceived utility, and the increase in the intention to use these systems (Khrouf et al., 2025) has a beneficial impact on hotel employees' job performance and acceptance of technology, which promotes the long-term adoption of AI solutions (Yu et al., 2025; Wang & Hou, 2025). In VR tourism and the Metaverse, perceived utility is a strong predictor of future usage intentions (Zhang & Xiong, 2024; Liu & Park, 2024).

The latest empirical evidence indicates that satisfaction and future intentions to use hotel robots increase when they meet visitor expectations, with perceived usefulness acting as a significant mediating factor (Shi et al., 2025). Figueiredo et al., (2025) found that perceived utility, robotic servers, and AI personnel influence consumer loyalty and return rates, validating the usefulness of AI technology in the hotel industry. Thus, we can state that:

H12: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived usefulness.

Perceived enjoyment is a crucial mediator between expectation confirmation and satisfaction in AI-enabled hospitality and tourism services, according to numerous studies. Enjoyment increases when users' expectations are met or exceeded, thereby improving satisfaction and reuse intentions (Huang et al. 2024; Vorobeva et al., 2024). Consistent with previous research, recent data indicate that visitors' expectations and intentions for future visits are influenced by their satisfaction with service robots in smart hospitality (Liu et al., 2025; Huang et al., 2024; Go et al., 2020). Enjoyment has a major impact on satisfaction in smart hotel settings (Du et al. 2024). Similarly, Ku and Chen (2024) contend that the relationship between AI innovation and functional benefits is mediated by a positive user experience. Further evidence that enjoyment is a powerful predictor comes from deep learning and SEM-based research (Vorobeva et al., 2024; Shafique et al., 2023). Even though utilitarian value has a smaller impact, perceived enjoyment has a significant impact on perceived value, repurchase intentions, and experience quality across AI applications. Thus, we can state that:

H13: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived enjoyment.

The empirical evidence shows that consistent findings show that users' confirmation of expectations positively influences their intention to continue using AI technology, and this effect is significantly mediated by perceived enjoyment (e.g., Li et al., 2024). Huang et al., (2024) show that perceived enjoyment boosts users' emotional satisfaction, encouraging them to keep using AI when their expectations are met. Further, Orden-Mejía et al., (2024) discovered that satisfaction and enjoyment help turn users' positive expectations into intentions to visit and use AI-powered destination chatbots. In other studies, such as Rather's (2025), which show that factors related to AI foster user engagement and ongoing adoption mainly because they create a sense of enjoyment and perceived value.

The AI adoption mediated by the perception of enjoyment is stressed by Khrouf et al., (2025). Depending on the situation, social influences and immersive experiences can occasionally eclipse the perceived enjoyment (e.g., Yu et al., 2024). Despite these insights, there is still a need to understand how this enjoyment-mediated process varies across different types of AI and in different service environments. There is a lack of long-term studies to see if repeated positive experiences strengthen enjoyment over time, especially across different AI categories. Thus, we can state that:

H14: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived enjoyment.

The operational definitions of the key constructs are presented in Table 4.1.

Constructs	***Definitions***	***Sources***
Confirmation of Expectations	Confirmation denotes the alignment between users' initial expectations of the system's performance and their actual post-adoption experiences. It captures the post-adoption perception of how well the system fulfills or surpasses pre-adoption expectations. The extent of confirmation encapsulates the degree to which the system's actual performance resonates with users' expectations.	Huang et al., (2024); Hepola et al., (2020); Chang-Hu, (2015); Bhattacherjee (2001)
Perceived Performance	Perceived performance (sometimes referred to as usefulness) is defined as customers' judgments and evaluations of a product and service in terms of quality and how useful it is perceived after the purchase	Huang et al., (2024); Brill et al., (2019)
Perceived usefulness	The degree to which a person believes that using a particular system would enhance his or her job performance	Dhiman & Jamwal (2023); Davis (1989)
Perceived Enjoyment	Perceived Enjoyment is a measure of how enjoyable the user perceives the technology to be	Huang et al., (2024); Lee et al. (2019)

Satisfaction	The summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumer's prior feelings about the consumption experience	Dhiman & Jamwal (2023); Bhattacherjee (2001); Oliver (1980)
Intention to Continue Use	Is predicted by post-use satisfaction, which is influenced by prior expectations and perceived utility	Huang et al., (2024); Bhattacherjee (2001)

Table 4.1: Operational definitions of the key constructs

The hypotheses derived from the literature review that inform the research model are presented in Figure 4.3.

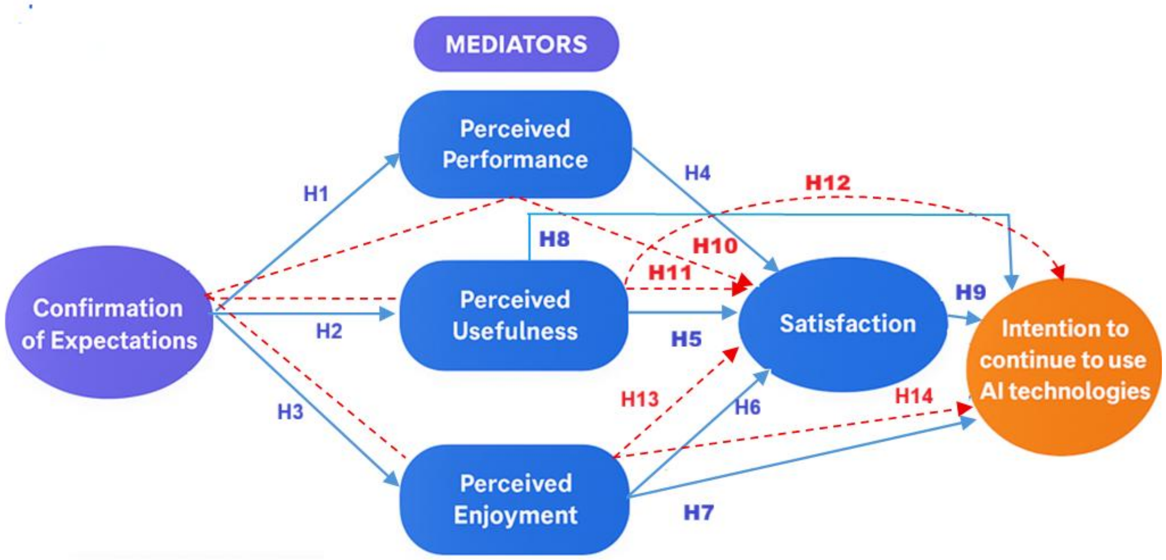

Figure 4.3: Research model. Source: Kyriakaki E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".

4.6 Concluding remarks

Chapter 4 outlined the theoretical foundations for an examination of the present applications of AI technology in the travel and hospitality sectors, the IS/IT Continuance Model, Expectation-Confirmation Theory, and the theoretical perspectives of hedonic dimensions (enjoyment) and integration of task-technology fit considerations. This led to the development of a comprehensive framework that considers both the utilitarian and hedonic aspects of adopting AI. Our proposed research model examines the relationships among perceived performance, perceived utility, and perceived enjoyment in relation to the confirmation of expectations. These factors, in turn, influence user satisfaction and retention intentions. We developed fourteen theories, all supported by extensive research highlighting the significance of emotional involvement and functional performance in sustaining the use of AI technology. This integrated approach addresses existing research gaps and provides a robust foundation for empirical analysis in subsequent chapters. It explores the direct, indirect, and mediating relationships between key constructs.

Chapter 5: Research Methodology

In this chapter the research methodology adopted for this study is presented. The chapter consists of five sections: the first section (5.1) describes the research motive, research approach and method. Section 5.2 analyses the sample, the sampling strategy, the process and the data collection, while Section 5.3 analyses the measures, measurement of variables and variables' level of measurement. Section 5.4 presents the structure of the research instrument and Section 5.5 describes the tools and statistical analyses that were used to analyze the primary data gathered for the purpose of this study.

5.1 Research motive, research approach and research method

Based on the survey method, the dissertation aims to provide helpful information on how (1) confirmation of expectations, (2) perceived usefulness, (3) perceived enjoyment, (4) perceived performance, and (5) satisfaction influence the continued use of AI technology in the hospitality and tourism industry. The completion of the dissertation is required for the Hellenic Open University's Master of Business Administration program.

In this study, we have chosen an online structured questionnaire for the primary data collection. After analyzing the data, we will test the 14 hypotheses under review.

The research approach we adopt is deductive. Building on established theories, we develop and test hypotheses about the relationships between perceived performance, usefulness, enjoyment, and intention to continue using AI technology, using quantitative data from a structured questionnaire (Saunders et al., 2023). Under the prism of Expectation-Confirmation Theory and the IS/IT continuance model, the dissertation will examine the interrelationships amongst the five key constructs that influence the intention to continue use AI technology to validate the proposed model (Figure 4.3) based on the survey of Greek users of AI technologies in the tourism and hospitality sector.

Based on the models of Huang et al., (2024) and Dhiman and Jamwal (2023), we aim to show that perceived usefulness, performance, and enjoyment are crucial for users' intention to continue using AI technologies in tourism and hospitality. The models will help us understand how these constructs relate to users' intention to use AI technology. This understanding will be critical to our conclusion at the end of our study.

5.2 Sample, Sampling Strategy, Process and Data Collection

In accordance with the study's research objectives, we investigate the relationships among confirmation, perceived performance, perceived enjoyment, perceived usefulness, and satisfaction with AI technology in the tourism and hospitality sector, as well as the link between satisfaction and intention to continue using AI technology. To collect data, we employ a self-administered questionnaire (SAQ) distributed online. The questionnaire was designed with attention to wording, formatting, and usability to ensure clarity and engagement.

Before full-scale data collection, we conduct a pilot test with 15 respondents who meet the inclusion criteria (users of AI technology in hospitality and tourism). The evaluation should focus on three key areas: first, assess the clarity and comprehension of the questions to ensure they are easily understood and interpreted as intended; second, identify any technical issues encountered with the online platform that may have affected user experience or functionality; and third, gather feedback on the completion time and overall ease of use to determine whether the process was efficient and user-friendly. Based on the pilot results, minor adjustments are made to improve the wording and layout of the questions. Pilot participants provided informed consent, and their data are excluded from the primary analysis.

The population includes all tourists and visitors who have used AI technology in hospitality and tourism services. The sample consists of Greek users of such technologies. Due to practical constraints, convenience sampling is employed, recruiting participants from the Hellenic Open University, workplace colleagues, and social media platforms (Facebook, Instagram). Efforts are made to include diverse generational cohorts and geographic areas of Greece.

The elements that defined the sample of the study are the following:

- Element: Tourists and visitors who have used AI technology in hospitality and tourism.
- Sampling Unit: Users from different generations (Baby Boomers, Generation X, Millennials, Generation Z).
- Sampling Area: Greece (Crete, Athens, Thessaloniki, Patras).
- Data Collection Period: December 2025-February 2026.

The study complies with ethical standards, including informed consent, voluntary participation, and GDPR compliance. Respondents are assured of anonymity and confidentiality, and no personally identifiable information was collected beyond what was necessary for research purposes.

5.3 Measures, measurement of variables and variables' level of measurement

We have created a structured questionnaire to meet the study's research requirements. It consists of 17 close-ended questions, 9 of which are measured on a 5-point Likert scale with response options ranging from "Strongly disagree" to "Strongly agree". Respondents are asked to indicate the extent of their agreement or disagreement with each question.

The scale employed in the studies that shape our research's theoretical foundations is the point scale and that is the reason we opted for it as well. Our questionnaire contains both nominal and ordinal variables. Nominal variables refer to the variables that can be classified to categories such as age groups, sex, education level etc. In contrast to nominal variables, ordinal variables imply a rank of the categories collected (Slater & Hasson, 2024).

In our study (1) *Confirmation of Expectations (CON)* refers to the alignment between users' initial expectations of the system's performance and their actual post-adoption experiences. It captures the post-adoption perception of how well the system fulfills or surpasses pre-adoption expectations. The extent of confirmation encapsulates the degree to which the system's actual performance resonates with users' expectations (Huang et al., 2024). The measurement level is ordinal.

(2) Perceived Performance (PPE) refers to the customers' judgments and evaluations of a product and service in terms of quality and how useful it is perceived after the purchase (Huang et al., 2024). The measurement level is ordinal.

(3) Perceived Usefulness (PUS) refers to the degree to which a person believes that using a particular system would enhance his or her job performance (Dhiman & Jamwal, 2023) The questionnaire items statements are adjusted using "AI technologies" instead of from "chatbots". The measurement level is ordinal.

(4) Perceived Enjoyment (PEN) refers to the extent to which using a technology is perceived to be enjoyable (Huang et al., 2024). The measurement level is ordinal.

(5) Satisfaction (SAT) refers to the summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumer's prior feelings about the consumption experience (e.g., Dhiman & Jamwal, 2023; Bhattacherjee, 2001; Oliver, 1980). We adopt the questionnaire items empirically tested by Huang et.al. (2024). The measurement level is ordinal.

(6) *Intention to continue use (ICU)* refers to the prediction of post-use satisfaction, which is influenced by prior expectations and perceived utility (Huang et al., 2024; Bhattacherjee, 2001). The measurement level is ordinal.

Constructs	***Variables***	***Questionnaire Items***	***Scale***	***Variables' level of measurement***	***References***
Confirmation of Expectations	CON	CON1: My experience with using AI technologies was better than what I expected.	1 = strongly disagree 2 = disagree 3 = neutral 4 = agree 5 = strongly agree	Ordinal	Huang et.al, 2024
		CON2: The level of service provided by AI technologies was better than I expected.			
		CON3: Overall, most of my expectations from using AI technologies were confirmed.			
Perceived Performance	PPE	PPE1: Using AI technologies enhances my effectiveness in managing hospitality and tourism services.			
		PPE2: My hospitality and tourism-related tasks were easier to complete with AI technologies.			
		PPE3: I can save time in managing my hospitality and tourism services when I use AI technologies.			
		PPE4: Overall, AI technologies are useful in managing hospitality and tourism services.			
Perceived Usefulness	PUS	PUS1: AI technologies helped me to enhance my performance in managing many tasks.			Dhiman & Jamwal, 2023
		PUS2: I find AI technologies very useful in my day-to-day work.			
		PUS3: Using AI technologies enhances my effectiveness in carrying out my intended task.			
		PUS4: Using AI technologies assists me to perform many tasks more conveniently.			
Perceived Enjoyment	PEN	PEN1: Using AI technologies in managing my hospitality and tourism services was fun.			Huang et.al., 2024
		PEN2: Using AI technologies in managing my hospitality and tourism services was enjoyable.			
		PEN3: Using AI technologies in managing my hospitality and tourism services was pleasant.			

Satisfaction	SAT	SAT1: I was satisfied with my overall experience with AI technologies.			
		SAT2: I was pleased with my overall experience with AI technologies.			
		SAT3: I was content with my overall experience with AI technologies.			
		SAT4: I was delighted with my overall experience with AI technologies.			
Intention to Continue Use	ICU	ICU1: I intend to continue using AI technologies rather than discontinue using them.			
		ICU2: My intentions are to continue using AI technologies rather than use other alternative means (e.g., call customer service, check websites, etc.).			
		ICU3: If I could, I would like to discontinue my use of AI technologies.			

5.4 Structure of the research instrument

Our survey was conducted using a structured questionnaire consisting of seventeen questions, organized in eight sections. The questionnaire was available in both English and Greek language as it is included in Appendix A.

The questionnaire is structured as follows:

Section A consists of seven questions (no. 1-7) relating to the use of AI technology for tourism and hospitality services.

Section B consists of four questions (no. 8-11) relating mainly to the responders' demographic profile.

Section C consists of one question (no. 12) that measures guests' confirmation of expectations of AI technologies in hospitality and tourism based on Huang et al., 2024.

Section D consists of one question (no. 13) that measures the perceived performance of AI technology in tourism and hospitality based on Huang et al., 2024.

Section E consists of one question (no. 14) that measures the perceived usefulness of AI technologies in hospitality and tourism based on Dhiman and Jamwal (2023).

Section F consists of one question (no. 15) that measures the perceived enjoyment of AI technology in tourism and hospitality based on Huang et al., 2024.

Section G consists of one question (no. 16) that measures the satisfaction of AI technology in tourism and hospitality based on Huang et al., 2024.

Section H consists of one question (no. 17) that measures the intention to use AI technology in tourism and hospitality based on Huang et al., 2024.

5.5 Tools and Statistical Analyses

Descriptive & Inferential Statistics

Descriptive Statistics summarize both categorical and numerical data numerically and graphically, providing readers with an overview of the variables investigated in a research/study (Zlokovich. Corts & Rogers, 2023). They are used to help describe main features of data, such as the middle value when the data is arranged in order (median), the average of the data (mean). Descriptive statics also include measures of variability such as the variance and standard deviation. In contrast, inferential statistics draw conclusions about a population by generalizing the data gathered (Allua & Thompson, 2009). Terms such as standard error and confidence interval are used in inferential statistics.

Spearman's Rank Correlation Coefficient

In statistics, correlation is a measure of the strength and direction of a relationship between two variables. Correlation value ranges from -1 to 1 with -1 meaning perfect negative correlation, 1 perfect positive correlation and 0 no correlation. Among the correlation methods, linear (Pearson) correlation and rank (Spearman) correlation are the most popular. Pearson correlation is more sensitive to outliers and suggests that changes in one variable are in proportion with changes to the other variable. On the other hand, Spearman correlation relies on the sequence of values in both variables, converting the data points into their corresponding ranks and is less sensitive to outliers since it is not based on the exact values of the data (Bocianowski et al., 2024).

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis is a statistical model used to assess latent variables (factors) by identifying a measurement model that defines the relationships between latent constructs and their corresponding observed indicators. Confirmatory Factor Analysis is based on prior theoretical knowledge to create a measurement model, which in continuance is assessed for how well it fits the means, variances and covariancies of the indicators. Exploratory Factor Analysis (EFA) on the contrary, imposes minimal assumptions concerning the latent variables (factors), or their relationships with observed indicators. This results to these structures be determined by the data. A set of goodness-of-fit-statistics is engaged to evaluate model performance. The set includes the root mean squared error of approximation (RMSEA), normed fit index (NFI), consistent Akaike information criterion (CAIC) and comparative fit index (CFI). A model is thought to be a good fit when the predicted patterns are in close alignment with the observed data.

There is a great number of statistical softwares that fit CFA models (R, Stata, SAS, LISREL, Mplus etc). For these softwares to function properly and provide the researchers with valid results, researchers have to configure the analysis and choose the variables. There are six main steps in the CFA process:

1. Definition of the latent variables (factors)
2. Determination of the measurement approach
3. Data collection
4. Specification of reliable parameters
5. Analysis and
6. Interpretation of the results (Roos & Bauldry, 2022).

Validity and Reliability analysis

Validity and Realiability analysis is extremely important for any research, as it ensures that the research will demonstrate a greater level of applicability and helps minimize the influence of cofounding variables on the measurement instrument (Karnia, 2024). Validity refers to the extent to which a tool measures what it intended to be measured (Chapelle & Voss, 2021). A test validity can be affected by several factors, such as ambiguity, improper question order, unclear instructions, lack of time etc (Chapelle & Voss, 2021). There are several types of validity: 1) content validity, 2) face validity, 3) criterion validity and 4) construct validity (Hidayana & Fuzi, 2025). For the content validity, the Content Validity Index (CVI) is the most common method used. It is used to organize data and provide a quantitative summary of classifications that are relevant with the items (McCoach, Bable & Madura, 2013). In case I-CVI $< .70$, the test or assessment question should be removed, if $.70 \leq$ I-CVI $\leq .90$ it should be revised and if I-CVI $\geq .90$ it should remain (Karnia, 2024).

The reliability of a survey instrument refers to its ability to produce consistent and repeatable results (Mellinger & Hanson, 2020). Researchers have to establish reliability in order to distinguish between variability due to measurement error and that of differences in the underlying constructs. There are four ways to assess reliability: 1) internal consistency, 2) inter-rater, 3) parallel or alternate forms and 4) instrument reliability. The most popular method for assessing reliability -which is the one we will use in our research- is the Cronbach's alpha coefficient. Cronbach's alpha coefficient values range from 0 to 1. A value of ≥ 0.70 is generally considered acceptable/satisfactory. A value 0.8 $\leq$ Cronbach's alpha coefficient ≤ 0.9 is considered very good, whereas a value of ≥ 0.9 is considered excellent.

Regression Analysis

Regression Analysis is a statistical method that is used to analyse the relationship between two or more variables. More specifically it analyses how a variable is formed (dependent variable) when the other variable(s) change(s) (independent variables). There are two types of regression analysis: 1) linear regression and 2) non-linear regression. In our study we will use the linear regression - which is the most popular and easiest to conduct. The coefficient of determination R^2 is used to evaluate the appropriateness of the regression equation. R^2 values range from 0 to 1. The closer to 1 the value of the R^2 , the more reasonable the equation.

Mediation Analysis

Mediation analysis investigates the relationship among variables in an attempt to reveal the way they affect each other. In the simple form of mediation a third variable (M) is added to the relationship between two variables (X, Y). It examines whether the mediator (M) affects X (independent variable) and at the same time has an impact on Y (dependent variable), so that X → M → Y (MacKinnon, Cheong & Pirlott, 2012).

There are three approaches regarding mediation analysis: 1) causal steps, 2) difference in coefficients and 3) product of coefficients (McKinnon et al., 2002). Regardless of the approach used, mediation analysis relies on a series of simple linear regressions to estimate the mediation pathways. First, variable Y is regressed on variable X to establish the total effect (path c). In continuance, M is regressed on Y to determine whether Y predicts M (path a), since this relationship is a prerequisite for mediation. In the third and last step, variable X is regressed both on Y and M. In case M significantly predicts Y (path b) and the effect of X on Y is considerably reduced compared to the initial result, there is evidence of mediation (McKinnon, Cheong & Pirlott, 2012).

Several methods are used to test mediation effects, some of which are the casual steps approach, the Sobel test, bootstrapping the indirect effect, Monte Carlo method for indirect effects etc. In our analysis, we will use the bootstrapping method. It is preferred to the other methods because it does not assume normality of the data and in addition it provides empirically derived confidence intervals by repeatedly resampling the dataset. Furthermore, it performs quite well even in smaller samples and is robust and flexible across a wide range of model specifications (Preacher & Hayes, 2004).

Moderation Analysis

Moderator variables influence the nature of the effect of a forerunner and often form the basis for meta-analyses in academic research (Logman, 2024). It examines whether the moderator variable Z influences the path relating X (independent variable) to Y (dependent variable) (Aguinis, Edwards & Bradley, 2016).

The moderation regression coefficients, p-values, confidence intervals and its standard error are evaluated to test the moderator's significance.

Chapter 6: Research results

Chapter 6 presents the research results based on the responses of the questionnaire's items. The chapter is structured as follows: Section 6.1 presents the sample characteristics and descriptive statistics, Section 6.2 discusses the interpretation of the questionnaire results, Section 6.3 presents the CFA, Section 6.4 presents the reliability analysis, 6.5 describes hypotheses testing, Section 6.6 summarizes our hypotheses testing results and Section 6.7 presents our empirical tested model.

6.1 Sample characteristics and descriptive statistics

The sample consisted of 227 responses, while all the participants had some kind of previous experience in using AI applications in hospitality and tourism sectors. As of the AI use, the majority of respondents mentioned that they rarely use AI, 55.5% (n=126), while 19% of the participants use AI monthly (n=45) and 12.3% use it weekly (n=28). Daily use of AI occupied 8.8% of the sample (n=20), and a small proportion seem to have used AI only once, reaching 3.5% of the sample (n=8). The above are presented in Figure B.1 in Appendix B.

Regarding the perceived ease of use, most of the participants, reaching 43.6% (n=99), characterized the AI systems as very easy to use, while 35.2% find it easy (n=80) and 18.1% have a neutral stance (n=41). There are participants who believe that using AI is somewhat difficult, reaching 2.6% of the sample (n=6), or even very difficult, as characterized by 0.4% (n=1). The above are presented in Figure B.2 in Appendix B.

Through Figure B.3 in Appendix B, it seems that 64.8% of the participants (n=147) are females, while males reach 35.2% (n=80).

Continuing, in Figure B.4 in Appendix B, the participants' age is analyzed. Specifically, 40.1% (n=91) are 35-44 years old, 23.3% (n=53) are 45-54 years old, and 21.1% (n=48) are 25-34 years old. Additionally, participants who are 55-64 years old occupy 7% (n=16), and those 18-24 years old occupy 5.3% (n=12), while only 3.1% of the participants are over 65 years old (n=7).

Participants' educational level is presented through Figure B.5 in Appendix B. It is evident that most of the participants, reaching 40.5% (n=92), have a postgraduate degree, 39.2% have higher education (n=89), while those who graduated from secondary education reach 16.3% (n=37). Participants who have a basic level of education reach 2.6% (n=6), those who have a doctoral degree occupy 0.9% of the sample (n=2), while participants with a vocational training institute education occupy 0.4% (n=1).

Continuing, in Figure B.6 in Appendix B, up to 20,000 euros occupy 44.9% of the sample (n=112), followed by the participants with 20,001 to 30,000 euros occupying 15% (n=37), and those who have up to 10,000 euros of annual income occupy 14.5% of the sample (n=33). Continuing, the participants with 30,001 to 40,000 euros of an income reach 12.8% (n=29), while those with an income above 40,000 euros reach 12.8% (n=29).

In the following Figure B.7 in Appendix B, the most popular AI application of the participants is the language translation applications, reaching 18.8% (n=117). Second place is the chatbots or virtual assistants, reaching 15.6% (n=97). Continuing, AI price comparison tools occupy 14.5% (n=90), AI documentation systems reach 14.3% (n=89), smart room controls reach 10.3% (n=64), and voice assistants 8.8% (n=55). Continuing, virtual simulations occupy 8.8% of the answers (n=55), facial recognition occupies 4.7% (n=29), dynamic pricing systems reach 2.1% (n=13), robotic concierge or service robots occupy 1.6% (n=10), while only 0.5% belongs to ChatGPT (n=3).

Also, the participants were asked regarding the most attractive AI features, and the results are presented in Figure B.8 in Appendix B. It seems that 24/7 availability was chosen, occupying 18.5% of the total answers (n=150). Ease of use is placed second with 17.3%, response speed occupies 16.6% (n=135), and personalized recommendations reach 11.3% (n=92). Multilingual support occupies 11.2% (n=91), real time information updates reach 9.6% (n=78), cost savings reach 8.8% (n=71), and contactless service occupies 6.5% (n=53). Lastly, large scale data search occupies only 0.1% (n=1).

In the following Figure B.9 in Appendix B, regarding the service categories, it seems that hotel accommodation booking and management represents 17.9% of the total answers (n=144). Second is trip planning and itinerary creation, occupying 16.6% (n=134). Local attraction recommendations reach 15.4% (n=124), and flight or transfer booking reaches 14.2% (n=114). Also, 10.1% refer to restaurant reservations or recommendations (n=81), check in and check out processes reach 8.9% (n=72), tour guide services reach 6.8% (n=55), and customer service support occupies 6.5% of the total answers (n=52). Lastly, in room service and controls reach 3.6% of the total answers (n=29).

Additionally, the reasons for when participants use AI were investigated through Figure B.10 in Appendix B. It seems that most often it is used in hotels or resorts, reaching 23% of the answers (n=133), or for tourist attractions or museums, reaching 18.3% of the answers (n=106). Continuing, travel booking websites or applications occupy 17.3% of the answers (n=100), airports reach 14% (n=81), restaurants or cafes occupy 11.4% (n=66), and transport services 7.3% (n=42). Continuing, the use of AI for tourist information centers occupies 7.1% of the answers (n=41), cruise ships reach 1.6% (n=9), and public event seat reservations reach 0.2% of the total answers (n=1).

6.2 Interpretation of questionnaire results

Continuing, the group of variables was investigated by calculating the average score of each respondent's answers to the statements referring to each construct that was investigated in the questionnaire. All the statements received answers on a 5 point scale, where 1 equals strongly disagree and 5 equals strongly agree, with the higher mean representing a higher level of agreement with each statement. A total of 227 participants were included, with the results being presented in both Table 1 and Table 2 in the same Appendix. The Appendix also presents the frequencies and percentages for each item respectively.

Based on the results, it is revealed that perceived usefulness has the highest mean (M=3.85), while slightly lower is the level of perceived performance of AI (M=3.84). Also, the intention to continue to use presented by the participants is quite high (M=3.84), followed by the confirmation of expectations (M=3.72) and the level of satisfaction (M=3.72), while last is placed the average level of the participants' perceived enjoyment (M=3.58). However, it should be mentioned that all of the variables are placed above the average level, so the participants of the sample present a positive attitude towards AI technologies in the tourism and hospitality sector.

Analytically, when it comes to the confirmation of expectations of the use of AI technologies, most of the participants, reaching 54.2%, 51.1%, and 58.6%, agree with the three items respectively. In general, it seems that the presentation level of confirmation of expectations is satisfactory (M=3.72, SD=0.69). As for the perceived performance, the level at which participants agreed was even higher, especially when it came to the time-saving ability that AI technologies offer, with 63.9% of the participants agreeing and 19.4% strongly agreeing. Additionally, 65.6% of the participants agreed, with the overall level of perceived performance being also quite high (M=3.84, SD=0.700).

Continuing with the perceived usefulness, it seems to also present participants' overall positive stance, since they seem to agree on the majority of all the items, with the percentages from 50.2% up to 56.8%, while many participants also selected strongly agree, reaching 22.5%. Overall, the perceived usefulness was also quite high regarding the participants' views (M=3.85, SD=0.84).

The perceived enjoyment presents a variety of neutral stances, even if the answer agreed was used by 50.1% of the participants to refer that they find the experience pleasant. However, 44.9% of them are neutral regarding finding the use of AI enjoyable. Overall, the mean is placed lower than the above (M=3.58, SD=0.718). However, the mean level of perceived enjoyment is also placed above average.

Regarding the participants' satisfaction, 63.9% of the participants agreed that they are overall satisfied, while 62.1% mentioned that they are pleased by the use of AI. So, the overall mean level of satisfaction was also high (M=3.72, SD=0.649). It is observed that statements related to the participants' emotions, like happiness and excitement when using AI methods, presented a high percentage of neutrality, reaching 45.5% and 39.2% respectively.

Continuing, the intention to continue the use of AI techniques presented a variety of answers. Analytically, when it comes to the participants' intention to continue using AI, 62.1% of the participants agree and 23.8% strongly agree, while 49.8% of the participants agree that they will continue using AI in the future and 12.5% strongly agree. However, when it came to negative phrase statements, like whether the participants would stop using

AI if they could, most of the participants, reaching 37.4%, disagree and 14.7% strongly disagree. The overall mean level of intention to continue use of the AI techniques is quite high (M=3.84, SD=0.653).

Regarding the standard deviations, most of the statements seem to range between 0.64 and 0.80, which highlights that there is consistency in the responses. However, there was a higher standard deviation (SD=1.159), which is presented in a negatively worded statement, which suggests that there is variability in the answers when it comes to the discontinuation of using AI techniques. The histograms and Q-Q plots for all of the above variables are presented in Figures 11-16 in the Appendix.

6.3 Measurement Model: Confirmatory Factor Analysis (CFA)

6.3.1 Measurement specification and estimation approach

The measurement model was evaluated using Confirmatory Factor Analysis (CFA) to test whether the observed indicators load on their theorized latent constructs (CON, PPE, PUS, PEN, SAT, ICU) as specified in the instrument operationalization.

All indicators were measured on a 5-point Likert scale (1–5) and were therefore treated as ordinal indicators in the interpretation of results.
Model estimation in JASP was carried out using Maximum Likelihood (ML), as reported in the CFA output.

Because Likert (1–5) indicators are ordinal, ML-based CFA can be sensitive to departures from multivariate normality and the discrete nature of the data; consequently, parameter estimates and fit indices were interpreted cautiously, and robustness checks using estimators appropriate for ordinal indicators are recommended where feasible.

6.3.2 Model fit assessment

(a) Initial measurement model (including Q32)

The initial CFA that included item Q32 (NEW Q32_ICU3) reported a statistically significant chi-square test, with $\chi^2 = 304.557$, df = 137, $p < .001$, indicating that exact-fit was not supported.

Although chi-square is well known to be sensitive to sample size and minor misspecifications, it provides a baseline indication that the model may not reproduce the observed covariance structure adequately. Table 7 (Appendix B) shows the results of the analysis.

(b) Respecified measurement model (excluding Q32)

Given the diagnostic evidence that Q32 performed poorly (see Section 6.4.3), the CFA was re-estimated excluding Q32.

For the respecified CFA measurement model, the output reported $\chi^2 = 309.466$, df = 137, $p < .001$, again rejecting exact-fit.

In the accompanying SEM output for the same specification, additional global fit indices were reported: CFI = 0.907, TLI = 0.890, RMSEA = 0.099 (90% CI: 0.089–0.108), and SRMR = 0.094. Table 8 (Appendix B) shows the results of the analysis. Taken together, these indices suggest borderline-to-poor global fit, particularly due to the elevated RMSEA and SRMR and the TLI below commonly used heuristic benchmarks.

Interpretation and implications

Overall, the removal of Q32 did not produce a clearly well-fitting measurement model at the global level, indicating that the source of misfit is not limited to a single problematic indicator.

Accordingly, the measurement model results are interpreted as providing partial support for the hypothesized structure, while also signaling remaining areas of misspecification that may require theoretically grounded refinement rather than purely data-driven adjustments.

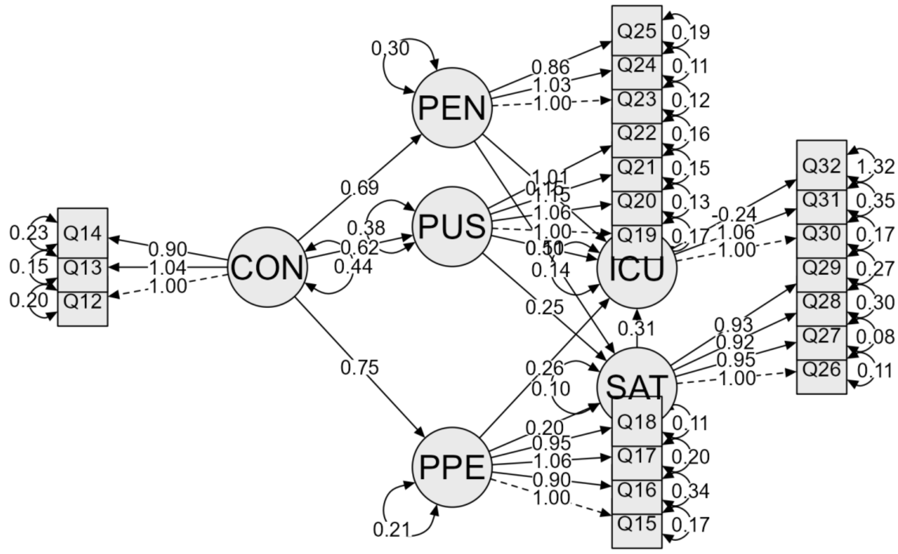

Figure 6.1: CFA Path diagram before the removal of item Q32_ICU3
Source: Kyriakaki, E. (2026) " An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

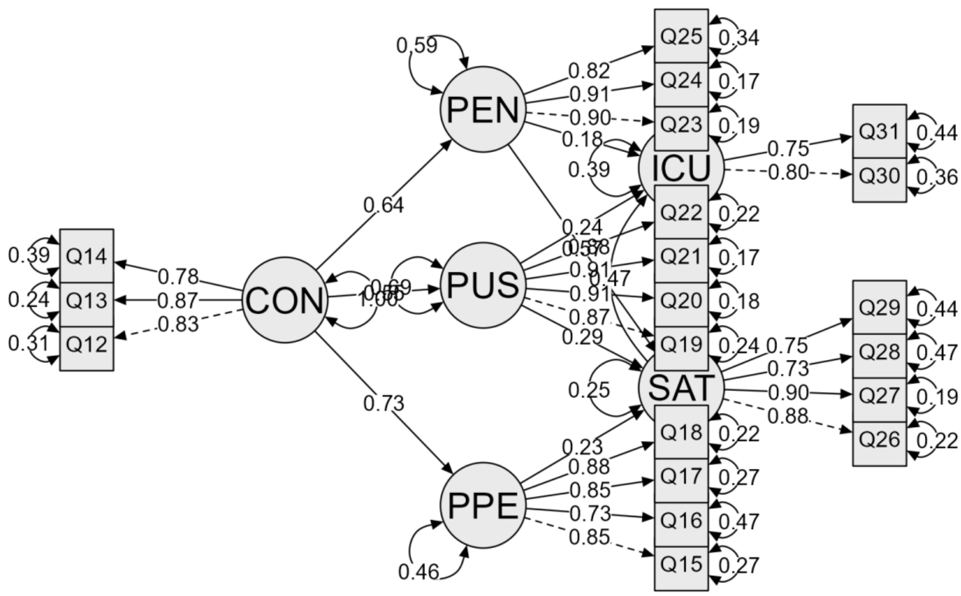

Figure 6.2: CFA Path diagram after the removal of item Q32_ICU3

Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

6.3.3 Factor loadings and statistical significance

Regarding the evidence from the initial CFA (including Q32), in the initial CFA, most items loaded significantly on their intended factors ($p<.001$), supporting the expected indicator–construct relationships for CON, PPE, PUS, PEN, SAT, and the ICU indicators Q30–Q31.

However, item Q32 (NEW Q32_ICU3) displayed a weak and non-significant loading on ICU (Estimate = 0.236, $z = 1.694$, $p = .090$, 95% CI includes 0), suggesting that Q32 does not function as a valid indicator of ICU in this sample.

In addition, modification indices indicated potential misspecification patterns involving Q32 (e.g., suggested cross-loading/correlated residual structures), which further supports treating Q32 as diagnostically problematic within the specified measurement structure.

Regarding the evidence from the respecified CFA (excluding Q32), after excluding Q32, ICU was measured only by Q30_ICU1 and Q31_ICU2, and both remaining ICU indicators showed statistically significant loadings (e.g., Q31: $z \approx 10.17$, $p<.001$).

Similarly, the remaining indicators for the other constructs continued to show statistically significant loadings on their respective factors ($p<.001$ across items in the reported output).

A key implication of dropping Q32 is that ICU becomes a two-indicator latent construct.

Two-indicator factors may require additional identification constraints and are generally more fragile than factors measured by three or more indicators, which can affect interpretability and stability of parameter estimates.

Therefore, while the remaining ICU loadings are statistically significant, the ICU factor should be interpreted cautiously and ideally strengthened in future measurement refinement (e.g., revise/replace Q32 or add an additional ICU indicator).

6.3.4 Reliability and internal consistency

Regarding the approach to reliability reporting, internal consistency reliability was assessed at the construct level using standard reliability indicators (e.g., Cronbach's α and, where available, model-based reliability such as composite reliability or ω), reported alongside CFA evidence to provide a broader evaluation of measurement quality.

Because single indices can be sensitive to assumptions and sampling variability, reliability and validity evidence should be interpreted collectively (loadings, residuals, and construct-level evidence), rather than relying on a single cutoff rule.

Regarding reliability implications of removing Q32, the poor performance of Q32 in the initial CFA (weak, non-significant loading) implies that retaining it could attenuate the measurement quality of ICU by increasing error variance and weakening convergent measurement of the construct.

Therefore, from a reliability perspective, excluding Q32 can be justified to remove a poorly functioning indicator; however, this comes at the cost of reducing ICU to two indicators, which typically weakens the robustness of reliability estimation for ICU.

For transparency and reproducibility, we report (for each construct) the internal consistency estimates computed on the final set of items used in the CFA/SEM model:

CON (Q12–Q14): $\alpha = 0.875$, ω/CR = 0.876

PPE (Q15–Q18): $\alpha = 0.895$, ω/CR = 0.900

PUS (Q19–Q22): $\alpha = 0.940$, ω/CR = 0.941

PEN (Q23–Q25): $\alpha = 0.908$, ω/CR = 0.909

SAT (Q26–Q29): $\alpha = 0.875$, ω/CR = 0.888 *(computed from the CFA measurement model; note the CFA section includes Q26–Q28)*

ICU (Q30–Q31): $\alpha = 0.747$ *(interpret cautiously due to 2 items)*, ω/CR = 0.756

Because ICU is measured by only two indicators (Q30–Q31) after excluding Q32, reliability estimates for ICU should be interpreted cautiously, as two-indicator constructs can yield less stable reliability estimates than constructs with three or more indicators.

6.3.5 Summary of CFA findings

In summary, the CFA provided evidence that most indicators load significantly on their intended constructs but identified Q32 as a problematic ICU indicator due to its weak and non-significant loading in the initial model. The respecified model excluding Q32 retained significant loadings for the remaining items, yet global fit indices remained suboptimal (notably RMSEA and SRMR), suggesting that additional sources of misspecification may exist beyond Q32.

Finally, removal of Q32 results in ICU being a two-indicator factor, which raises identification and stability concerns. Therefore, ICU should be interpreted cautiously and strengthened through measurement refinement (e.g., revising Q32 or adding a third ICU indicator) in subsequent work.

6.4 Hypothesis testing

6.4.1. Correlation analysis

To examine the direction, strength, and nature (shape) of the relationships among the study constructs, Spearman's rank-order correlation (Spearman's rho) was used, as the variables are measured on 5-point Likert-type (ordinal) scales and the focus is on monotonic associations rather than strictly linear ones. The full Spearman correlation matrix (coefficients and significance levels) is reported in Appendix B (Table 5), while the scatterplots with trendlines and their polynomial equations (used here as *descriptive visual aids* to depict linear vs. curvilinear monotonic patterns) are provided in Appendix B (Figures H1–H9).

Research Hypothesis 1 (H1): Confirmation of expectations (CON) positively influences perceived performance (PPE)

The relationship between confirmation of expectations (CON) and perceived performance of AI techniques (PPE) exhibits a clear and statistically meaningful positive association. Spearman's rho reveals a moderately strong positive correlation ($\rho = .593$, $p < .001$), indicating that higher levels of expectation confirmation are systematically linked to higher perceived performance and that this relationship is unlikely to be due to chance. This pattern is also evident in the scatterplot, where the data points follow an upward trend and the fitted linear regression line confirms the positive direction of the relationship. The equation (see 6.1) suggests that for every one-unit increase in confirmation of expectations, perceived performance increases by approximately 0.62 units, while the intercept of 1.53 represents the baseline level of perceived performance when confirmation is minimal. Taken together, the statistically significant correlation, the positive slope of the regression line, and the satisfactory explanatory power of the model shown in the Figure 6.3 provides strong empirical support for H1.

The equation explaining the relationship is:

$$\mathbf{Y = 1.53 + 0.62X \ (6.1)}$$

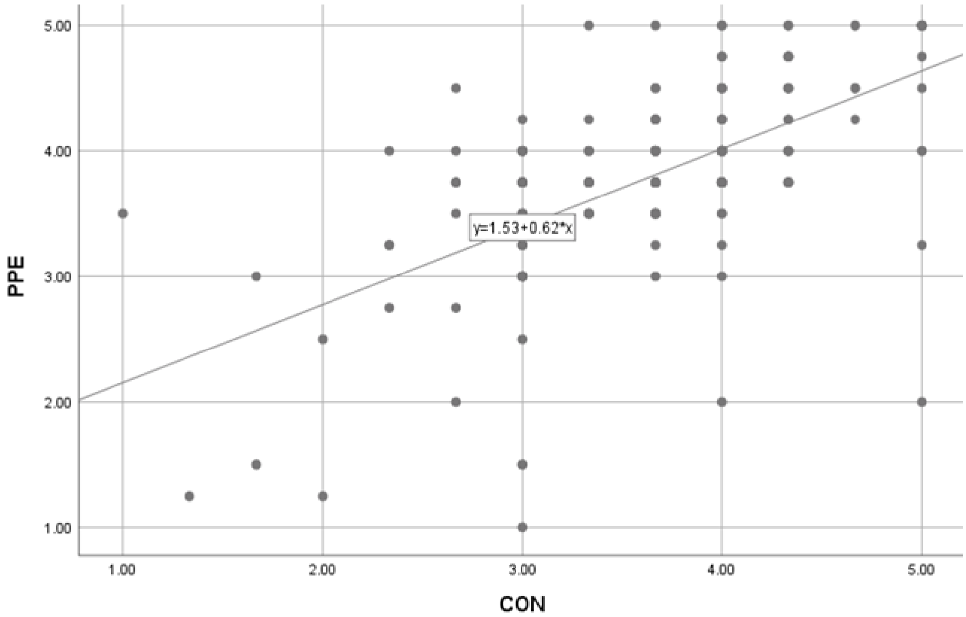

Figure 6.3: Linear positive monotonic relationship between CON and PPE

Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 2 (H2): Confirmation of expectations (CON) positively influences perceived performance (PUS)

The relationship between confirmation of expectations (CON) and perceived usefulness (PUS) shows a moderate positive monotonic trend, with Spearman's rho $\rho = .440$ ($p < .001$), indicating that higher confirmation is consistently associated with higher perceived usefulness and that this association is statistically significant rather than coincidental. This pattern is also evident in the attached scatterplot, where the points generally follow an upward direction and the fitted first-degree polynomial (linear) trendline reinforces the positive nature of the relationship. In polynomial form (as displayed in Figure 6.4), the relationship is described by the equation (see 6.2), meaning that for every one-unit increase in confirmation of expectations, perceived usefulness increases by approximately 0.50 units, while 2.01 represents the baseline level of perceived usefulness when confirmation is at its lowest observed. Overall, the significant positive Spearman correlation together with the upward polynomial trend shown in the shown in the Figure 6.4 provides empirical support for H2.

The equation explaining the relationship is:

$$\mathbf{Y=2.01+0.50x \quad (6.2)}$$

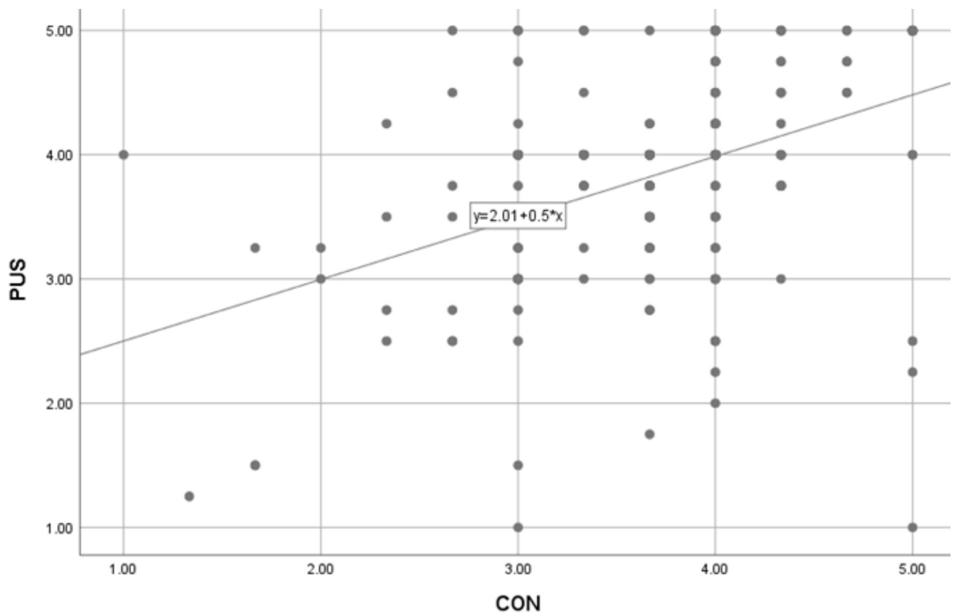

Figure 6.4: Linear positive monotonic relationship between CON and PUS
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 3 (H3): Confirmation of expectations (CON) positively influences perceived enjoyment (PEN)

The relationship between confirmation of expectations (CON) and perceived enjoyment (PEN) shows a moderately strong positive monotonic trend, with Spearman's rho $\rho = .567$ ($p < .001$, one-tailed), indicating that higher confirmation is consistently associated with higher perceived enjoyment and that this association is statistically significant rather than coincidental. This pattern is also evident in the attached scatterplot, where the points generally move upward as CON increases; however, the fitted trendline suggests that the association is nonlinear, following a second-degree (quadratic) polynomial rather than a strict linear form. In polynomial form (as displayed in Figure 6.3), the relationship is described by the equation (see 6.3), meaning the linear term (−0.55) and the quadratic term (+0.16) indicate how many PEN points are expected to change for a one-point increase in CON, with the positive quadratic component implying that the increase in PEN becomes stronger at higher levels of CON. Taken together, the significant positive Spearman association and the improved fit of the quadratic model shown in the Figure 6.5 provides empirical support H3.

The equation explaining the relationship is:

$$\mathbf{Y = 3.33 - 0.55x + 0.16x^2 \quad (6.3)}$$

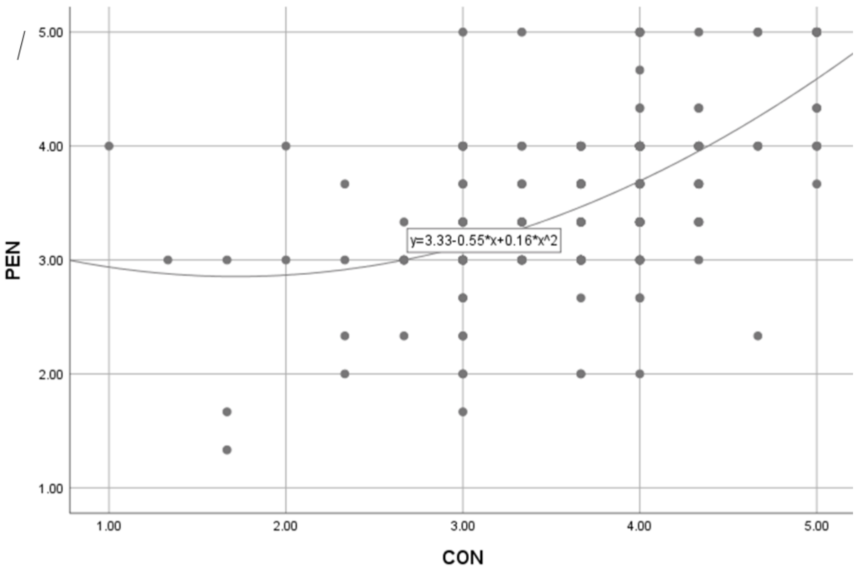

Figure 6.5: Nonlinear (quadratic) relationship between CON and PEN
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 4 (H4): Perceived Performance (PPE) positively influences Satisfaction (SAT)

The relationship between perceived performance (PPE; x) and satisfaction (SAT; y) shows a strong positive monotonic trend, with Spearman's rho ρ = .610 ($p < .001$, one-tailed), indicating that higher values of x are consistently associated with higher values of y and that this association is statistically significant rather than coincidental. This pattern is also evident in the attached scatterplot, where the points generally move upward as x increases; however, the fitted trendline suggests that the association is nonlinear, following a second-degree (quadratic) polynomial rather than a strict linear form. In polynomial form (as displayed in Figure 6.6), the relationship is described by the equation (see 6.4), meaning the linear term (−0.43) and the quadratic term (+0.15) indicate how many y points are expected to change for a one-point increase in x, with the positive quadratic component implying that the increase in y becomes stronger at higher levels of x. Taken together, the significant positive Spearman association and the improved fit of the quadratic model shown in the Figure 6.6 provides empirical support H4.

The equation explaining the relationship is:

$$\mathbf{y=3.1-0.43x+0.15x^2} \quad \textbf{(6.4)}$$

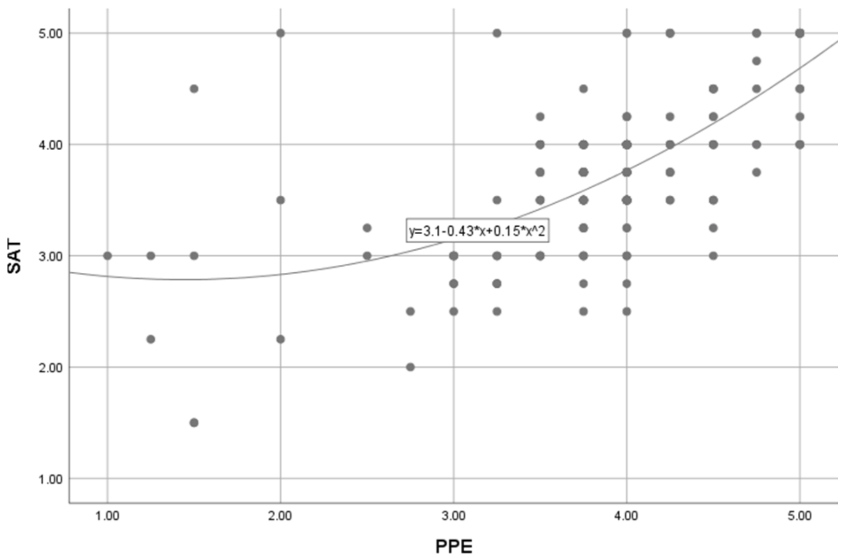

Figure 6.6: Nonlinear (quadratic) relationship between PPE and SAT
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 5 (H5): Perceived Usefulness (PUS) positively influences Satisfaction (SAT)

The relationship between perceived usefulness (PUS; x) and satisfaction (SAT; y) shows a strong positive monotonic association, with Spearman's rho $\rho = .597$ ($p < .001$, one-tailed), indicating that higher values of x are consistently associated with higher values of y and that this association is statistically significant rather than coincidental. This pattern is also evident in the attached scatterplot, where the points generally move upward as x increases; however, the fitted trendline suggests that the association is nonlinear, following a second-degree (quadratic) polynomial rather than a strict linear form. In polynomial form (as displayed in Figure 6.7), the relationship is described by the equation (see 6.5), meaning the linear term (−0.41) and the quadratic term (+0.13) indicate how many y points are expected to change for a one-point increase in x, with the positive quadratic component implying that the increase in y becomes stronger at higher levels of x. Taken together, the significant positive Spearman association and the improved fit of the quadratic model shown in the Figure 6.7 provides empirical support H5.

The equation explaining the relationship is:

$$\mathbf{y = 3.32 - 0.41x + 0.13x^2 \quad (6.5)}$$

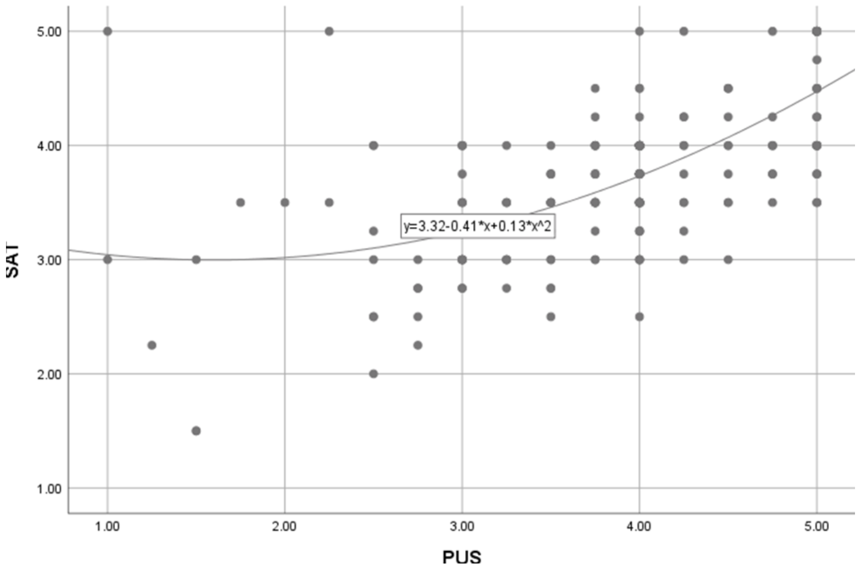

Figure 6.7: Nonlinear (quadratic) relationship between PUS and SAT
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 6 (H6): Perceived enjoyment (PEN) positively influences satisfaction (SAT)

The relationship between perceived enjoyment (PEN; x) and satisfaction (SAT; y) shows a moderate-to-strong positive monotonic association, with Spearman's rho $\rho = .702$ ($p < .001$), indicating that higher values of x are consistently associated with higher values of y and that this association is statistically significant rather than coincidental. This pattern is also evident in the attached scatterplot, where the points generally follow an upward direction and the fitted first-degree polynomial (linear) trendline reinforces the positive nature of the relationship. In polynomial form (as displayed in Figure 6.8), the relationship is described by the equation (see 6.6), meaning that for every one-unit increase in x, y is expected to increase by approximately 0.66 units. The constant term (1.36) represents the predicted level of y when x = 0 (i.e., the intercept), serving as the baseline of the fitted line at zero perceived enjoyment. Overall, the significant positive Spearman correlation together with the upward linear trend shown in the Figure 6.8 provides empirical support for H6.

The equation explaining the relationship is:

$$\mathbf{y = 1.36 + 0.66x \quad (6.6)}$$

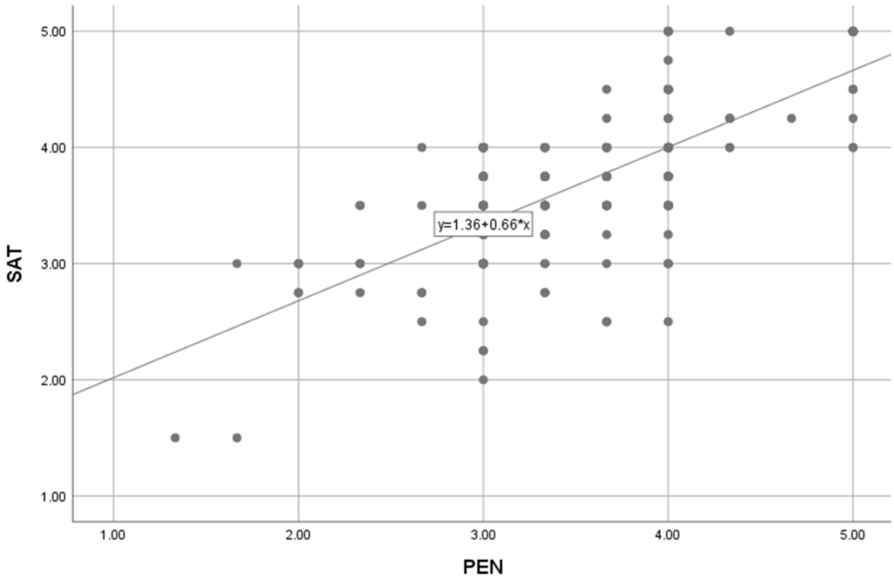

Figure 6.8: Linear positive monotonic relationship between PEN and SAT
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 7 (H7): Perceived enjoyment (PEN) positively influences intention to continue use AI technology (ICU)

The relationship between x and y shows a moderate positive monotonic trend, with Spearman's rho ρ = .308 (p < .001),–indicating that higher values of x are consistently associated with higher values of y, and that this association is statistically significant rather than coincidental. This pattern is also evident in the scatterplot, where the points generally follow an upward direction and the fitted first-degree polynomial (linear) trendline reinforces the positive nature of the relationship. In linear form, the relationship is described by the equation, meaning that for every one-unit increase in x, y increases by approximately 0.32 units. The constant term 2.69 represents the expected value of y when x=0. If x=0 is outside the observed range, the intercept should be interpreted as an extrapolated reference point that positions the fitted line rather than as a directly observed "baseline". Overall, the significant positive Spearman correlation together with the upward linear trend shown in the Figure 6.9 provides empirical support for H7.

The equation explaining the relationship is:

$$\mathbf{y = 2.69 + 0.32x \quad (6.7)}$$

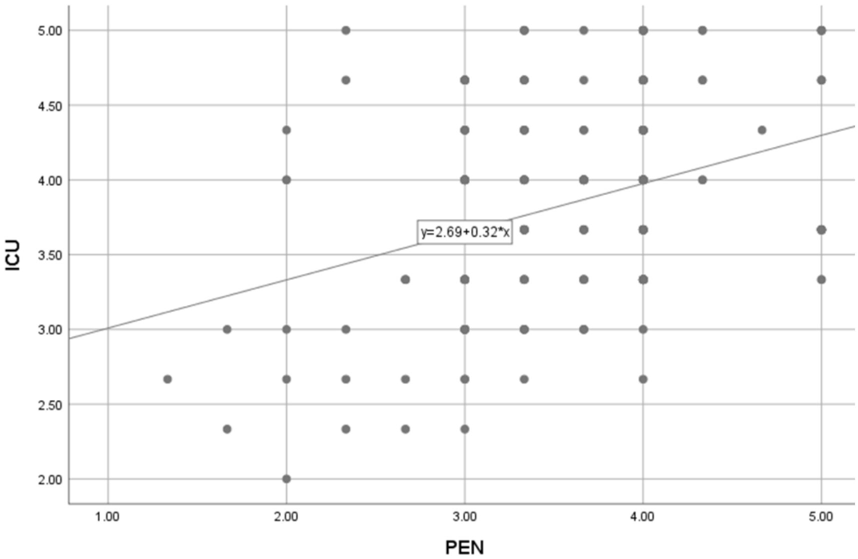

Figure 6.9: Linear positive monotonic relationship between PEN and ICU
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 8 (H8): Perceived usefulness (PUS) positively influences intention to continue use AI technology (ICU)

The relationship between x and y shows a moderate positive monotonic trend, with Spearman's rho $\rho = .382$ ($p < .001$), indicating that higher values of x are consistently associated with higher values of y and that this association is statistically significant rather than coincidental. This pattern is also evident in the scatterplot, where the points generally follow an upward direction and the fitted first-degree polynomial (linear) trendline reinforces the positive nature of the relationship. In linear (first-degree polynomial) form, the relationship is described by the equation (see 6.8), meaning that for every one-unit increase in x, y increases by approximately 0.35 units. The constant term 2.50 represents the expected value of y when x = 0 (i.e., the intercept). If x = 0 lies outside the observed range of x, this intercept should be interpreted as an extrapolated reference point that positions the fitted line rather than as an observed "baseline" at the lowest x. Overall, the significant positive Spearman correlation together with the upward linear trend shown in the figure 6.10 provides empirical support for H8.

The equation explaining the relationship is:

$$\mathbf{y = 2.50 + 0.35x} \quad \textbf{(6.8)}$$

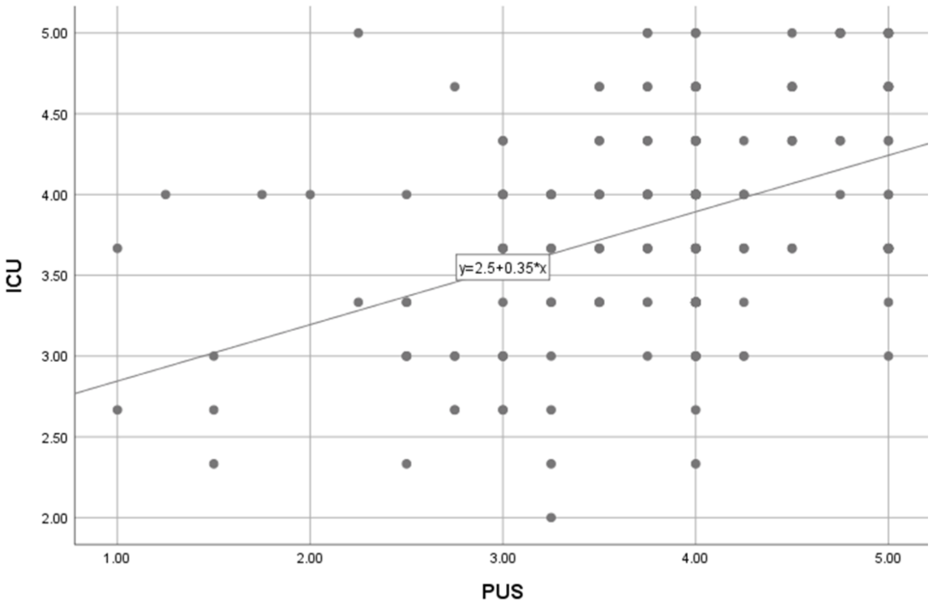

Figure 6.10: Linear positive monotonic relationship between PUS and ICU
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Research Hypothesis 9 (H9): Satisfaction (SAT) positively influences intention to continue use AI technology (ICU)

The relationship between x and y shows a moderate positive monotonic trend, with Spearman's rho ρ = .367 ($p < .001$), indicating that higher values of x are consistently associated with higher values of y and that this association is statistically significant rather than coincidental. This pattern is also evident in the scatterplot, where the points generally follow an upward direction and the fitted first-degree polynomial (linear) trendline reinforces the positive nature of the relationship. In linear (first-degree polynomial) form, the relationship is described by the equation (see 6.9) meaning that for every one-unit increase in x, y increases by approximately 0.44 units. The constant term 2.21 represents the expected value of y when x = 0 (i.e., the intercept). If x = 0 lies outside the observed range of x, this intercept should be interpreted as an extrapolated reference point that positions the fitted line rather than as an observed "baseline" at the lowest x. Overall, the significant positive Spearman correlation together with the upward linear trend shown in the figure 6.11 provides empirical support for H9.

The equation explaining the relationship is:

$$\mathbf{y = 2.21 + 0.44x \ (6.9)}$$

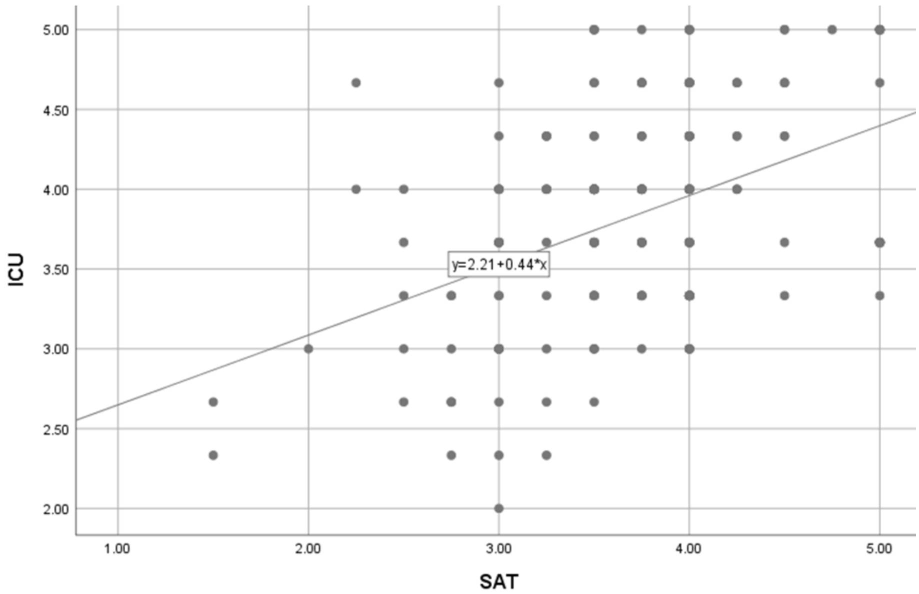

Figure 6.11: Linear positive monotonic relationship between SAT and ICU
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

6.4.2. Mediation analysis

H10: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived performance.

A mediation analysis was conducted via PROCESS (Version 4.2; Model 4) with 5,000 bootstrap samples. More specifically, it was investigated whether the perceived performance mediates the relationship between the level of confirmation of expectations and satisfaction of the participants. It was evident that the confirmation of expectations can statistically significantly predict the level of perceived performance ($b = 0.621$, $SE = 0.052$, $t(225) = 11.86$, $p < .001$, 95% CI [0.518, 0.724]). Additionally, when both confirmation of expectations and perceived performance were used as predictors, perceived performance was once again a statistically significant predictor of the level of satisfaction ($b = 0.305$, $SE = 0.055$, $t(224) = 5.58$, $p < .001$, 95% CI [0.197, 0.412]), while the direct effect that the confirmation of expectations had was also statistically significant ($b = 0.438$, $SE = 0.055$, $t(224) = 8.00$, $p < .001$, 95% CI [0.330, 0.545]), see Figure 6.12. Additionally, the bootstrapping indirect effect of confirmation of expectations on satisfaction through perceived performance was statistically significant as well ($ab = 0.189$, $BootSE = 0.065$, 95% bootstrap CI [0.076, 0.330]). Consequently, H10 is supported.

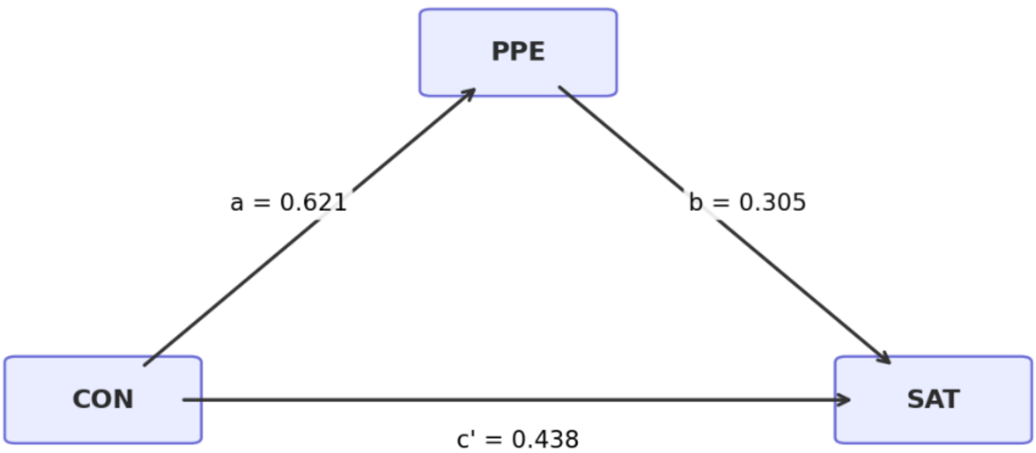

Figure 6.12: Mediation effect of perceived performance (PPE) on the relationship between confirmation of expectations (CON) and satisfaction (SAT)
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

H11: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived usefulness.

A mediation analysis was conducted once again. It is evident that the confirmation of expectations can statistically significantly predict the level of perceived usefulness ($b = 0.495$, $SE = 0.069$, $p < .001$). Also, it seems that the higher the level of expectation confirmation is, the higher the level of perceived usefulness that participants have. The overall model with both confirmation of expectations and perceived usefulness as predictors is also statistically significant ($R^2 = .571$, $p < .001$), while perceived usefulness seems to be a statistically significant predictor of satisfaction ($b = 0.304$, $SE = 0.039$, $p < .001$), with the direct effect of confirmation of expectations on satisfaction also being statistically significant ($b = 0.476$, $SE = 0.045$, $p < .001$), see Figure 6.13. Additionally, the bootstrapped indirect effect seems to present statistical significance ($ab = 0.150$, 95% CI [0.068, 0.251]), which indicates that there is partial mediation and confirms that expectations can directly and indirectly affect satisfaction through perceived usefulness. Consequently, H11 is supported.

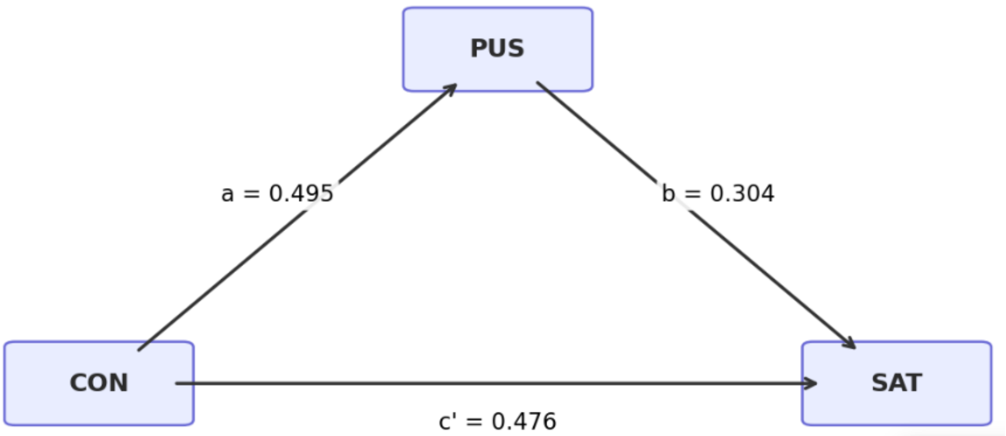

Figure 6.13: Mediation effect of perceived usefulness (PUS) on the relationship between confirmation of expectations (CON) and satisfaction (SAT)
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

H12: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived usefulness.

The third mediation analysis revealed that confirmation of expectations is positively associated with the level of perceived usefulness ($b = 0.495$, $SE = 0.069$, $p < .001$), which means that a higher level of expectation confirmation is linked to a higher level of perceived usefulness. When confirmation of expectations and perceived usefulness are used as predictors in the model of the intention to continue to use AI technology, the model presents statistically significant results ($R^2 = .262$, $F(2, 224) = 39.70$, $p < .001$). Also, perceived usefulness is a statistically significant predictor of the intention to continue to use AI methods ($b = 0.242$, $SE = 0.052$, $p < .001$), and the direct effect of confirmation of expectations on the intention to continue to use AI methods is also statistically significant ($b = 0.286$, $SE = 0.059$, $p < .001$), see Figure 6.14. Additionally, the bootstrapped indirect effect of confirmation of expectations on the intention to continue to use AI techniques through perceived usefulness is also statistically significant ($ab = 0.120$, 95% CI [0.059, 0.203]), since the confidence interval did not include the value zero. So, it seems that there is a partial mediation, which confirms that expectations affect the intention to continue using AI technology in a direct and indirect way through perceived usefulness. Consequently, H12 is supported.

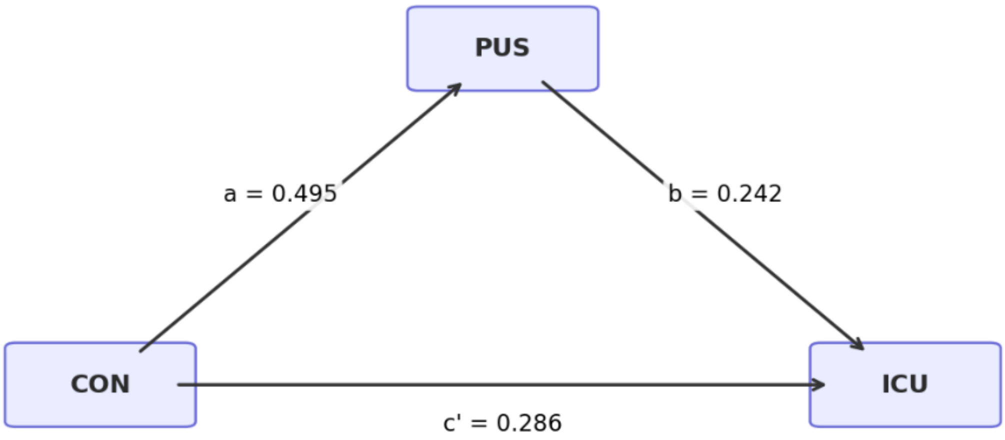

Figure 6.14: Mediation effect of perceived usefulness (PUS) on the relationship between confirmation of expectations (CON) and intention to continue to use AI technology (ICU)
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

H13: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived enjoyment.

Confirmation of expectations was found to significantly predict perceived enjoyment ($b = 0.559$, $SE = 0.057$, $p < .001$), indicating that higher levels of expectation confirmation are associated with increased perceived enjoyment. When both confirmation of expectations and perceived enjoyment were entered as predictors of satisfaction, the model was statistically significant ($R^2 = .644$, $F(2, 224) = 202.33$, $p < .001$). Perceived enjoyment emerged as a strong predictor of satisfaction ($b = 0.468$, $SE = 0.043$, $p < .001$), while the direct effect of confirmation of expectations on satisfaction remained statistically significant ($b = 0.365$, $SE = 0.044$, $p < .001$), see Figure 6.15.

The bootstrapped indirect effect was statistically significant ($ab = 0.261$, 95% CI [0.186, 0.340]), as the confidence interval did not include zero. The magnitude of the indirect effect suggests a substantial mediating role of perceived enjoyment in the relationship between confirmation of expectations and satisfaction. Overall, the findings indicate partial mediation, with confirmation influencing satisfaction both directly and indirectly through perceived enjoyment. Consequently, H13 is supported.

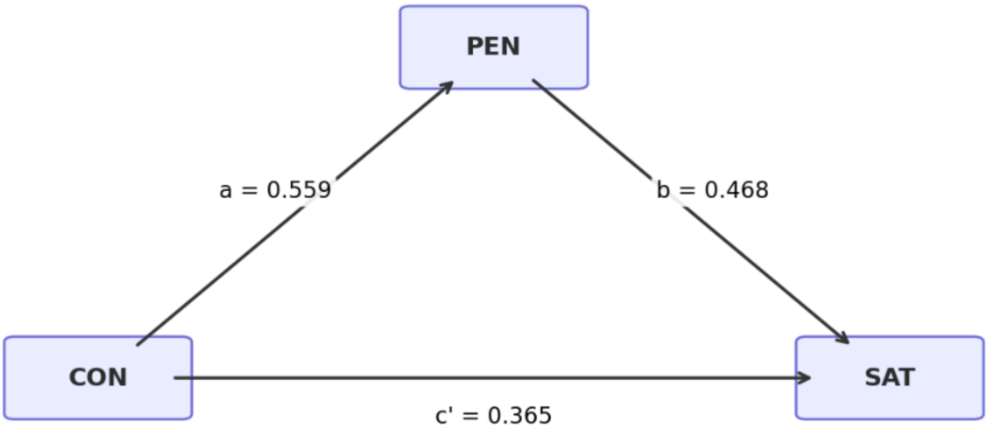

Figure 6.15: Mediation effect of perceived enjoyment (PEN) on the relationship between confirmation of expectations (CON) and satisfaction (SAT)
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

H14: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived enjoyment.

A mediation analysis was conducted. The results reveal that the confirmation of expectations can predict in a statistically significant way the perceived enjoyment (b = 0.559, SE = 0.057, p < .001), while a higher level of confirmation leads to a higher level of perceived enjoyment. Additionally, when confirmation of expectations and perceived enjoyment are both used as predictors of the intention to continue to use AI technology, the model also presents statistical significance (R^2 = .209, F(2, 224) = 29.54, p < .001). Further, it seems that perceived enjoyment can predict in a statistically significant way the level of intention to continue the use (b = 0.152, SE = 0.065, p = .020), while the direct effect of confirmation of expectations on the intention to continue to use AI technologies is also statistically significant (b = 0.322, SE = 0.066, p < .001), see Figure 6.16. Furthermore, the bootstrapped indirect effect also seems to be statistically significant (ab = 0.085, 95% CI [0.004, 0.175]), with the confidence interval not including the value zero. However, it should be noted that the indirect effect is smaller compared to the mediation observed regarding satisfaction, which indicates that there is a partial mediation. Consequently, H14 is supported.

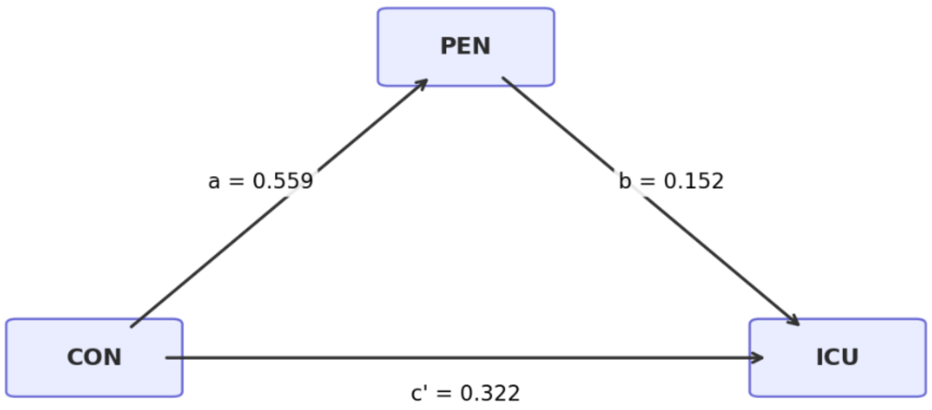

Figure 6.16: Mediation effect of perceived enjoyment (PEN) on the relationship between confirmation of expectations (CON) and intention to continue to use AI technology (ICU)
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

6.5 Summary of hypotheses testing

Figure 6.17 summarizes the research results.

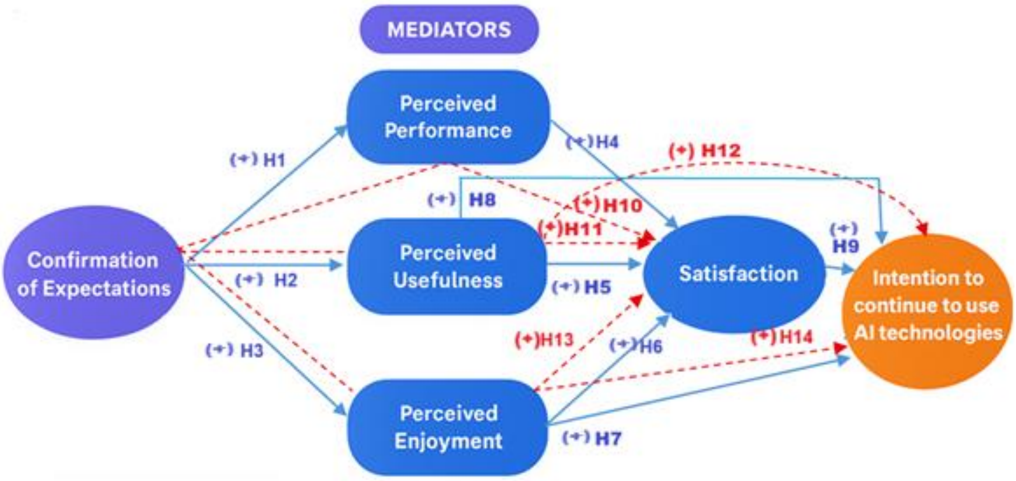

Figure 6.17: Research model including the research hypotheses' results.
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

In the following table (Table 6-1) we summarize the support of the research hypotheses and the significance level.

Hypothesis	Support	Significance level
H1: Confirmation of expectations positively influences perceived performance.	Supported	α = .001
H2: Confirmation of expectations positively influences perceived usefulness.	Supported	α = .001
H3: Confirmation of expectations positively influences perceived enjoyment.	Supported	α = .001
H4: Perceived performance positively influences satisfaction	Supported	α = .001
H5: Perceived usefulness positively influences satisfaction.	Supported	α = .001
H6: Perceived enjoyment positively influences satisfaction.	Supported	α = .001

H7: Perceived enjoyment positively influences intention to continue to use AI technology.	Supported	α = .001
H8: Perceived usefulness positively influences intention to continue to use AI technology.	Supported	α = .001
H9: Satisfaction positively influences intention to continue to use AI technology.	Supported	α = .001
H10: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived performance.	Supported	α = .05 (95% bootstrap CI excludes 0): [0.076, 0.330]
H11: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived usefulness.	Supported	α = .05 (95% bootstrap CI excludes 0): [0.068, 0.251]
H12: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived usefulness.	Supported	α = .05 (95% bootstrap CI excludes 0): [0.059, 0.203]
H13: Confirmation of expectations positively influences satisfaction through the intermediate effect of perceived enjoyment.	Supported	α = .05 (95% bootstrap CI excludes 0): [0.186, 0.340]
H14: Confirmation of expectations positively influences intention to continue to use AI technology through the intermediate effect of perceived enjoyment.	Supported	α = .05 (95% bootstrap CI excludes 0): [0.004, 0.175]
Note. H1–H9 were tested using Spearman's rho and statistical significance is reported using the α level. H10–H14 were tested using bootstrapped mediation analysis (PROCESS Model 4; 5,000 bootstrap resamples). Indirect effects are considered statistically significant at α = .05 when the 95% bootstrap confidence interval excludes zero.		

Table 6-1: Hypotheses' results
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Based on the assumptions of the adopted theoretical model we can interpret the above research results as follows:

- When users perceive that AI services meet or exceed their initial expectations, they also evaluate AI as performing better (higher perceived performance) (see H1). This directly corresponds to Expectation–Confirmation Theory, since confirmation is the post-use cognitive comparison that forms post-adoption evaluations of the service/technology. Therefore, based on our framework, confirmation functions as a basic "trigger" that improves performance-related beliefs about AI in hospitality/tourism.
- Confirmation also enhances perceived usefulness, consistent with the Expectation Confirmation Model (ECM) and the IS/IT Continuance Model, which claim that confirmation increases perceived usefulness after use (see H2). In other words, users interpret AI as more useful once it has proven to fulfill their expectations in real service interactions.
- Expectation confirmation also improves perceived enjoyment, strengthening the extended ECM perspective in which confirmation affects not only utilitarian (usefulness/performance) beliefs but also hedonic responses (see H3). This supports our model integration (e.g., Huang et al., 2024) and emphasizes enjoyment. When AI delivers what users expect, the experience is more pleasurable, not simply functional.
- Higher perceived performance increases satisfaction, which is consistent with ECT's assumption that satisfaction emerges after users evaluate post-use outcomes (see H4). Here, the "outcomes" include the degree to which AI performs effectively in the hospitality/tourism context; stronger performance evaluations translate into greater satisfaction.
- Perceived usefulness positively influences satisfaction, mirroring ECM/IS/IT Continuance logic (see H5). Usefulness is a central post-adoption belief that contributes to satisfaction once users experience the system. Thus, when AI is judged as beneficial and practically valuable, users indicate greater satisfaction with AI-enabled services.
- Perceived enjoyment also increases satisfaction, strengthening the hedonic extension of continuance models (see H6). Satisfaction is not only a function of "does it work?" (performance/usefulness) but also "did I enjoy it?" This supports

the assumption that emotional and experiential qualities are key determinants of favorable post-adoption outcomes in AI service encounters.

- Enjoyment positively influences the intention to continue use, indicating that continuance intention is partially driven by intrinsic/hedonic motivation rather than by rational utility (see H7). This result supports the integrated view that sustained AI usage in hospitality/tourism requires AI services to be engaging and pleasant, not just efficient.
- Perceived usefulness increases continuance intention, directly consistent with ECM: usefulness is one of the strongest drivers of continued IS/IT use (see H8). If AI demonstrably helps users accomplish tasks more conveniently/effectively (e.g., bookings, recommendations, information support), they become more willing to continue using it.
- Satisfaction positively influences continuance intention, exactly matching ECT/IS/IT continuance assumptions: satisfaction is the most immediate psychological driver of "repeat use" (continuance) (see H9). Thus, satisfied users demonstrate stronger intentions to keep using AI-enabled services in tourism and hospitality.
- Confirmation affects satisfaction indirectly through perceived performance, meaning that part of the reason confirmed expectations raise satisfaction is that confirmation improves users' judgments of AI performance (see H10). This is consistent with the proposed post-adoption evaluation chain "confirmation, performance beliefs and satisfaction".
- Confirmation also increases satisfaction through perceived usefulness, closely corresponding to ECM's core pathway: confirmation strengthens usefulness beliefs, which, in turn, raise satisfaction (see H11). This shows that confirmation contributes to satisfaction not only emotionally but also by validating AI's functional value.
- Confirmation increases continuance intention indirectly by increasing perceived usefulness (see H12). This is a classic ECM/IS continuance mechanism: when AI meets expectations, users perceive it as more useful, and usefulness then increases intention to continue using AI services.

- Confirmation increases satisfaction through enjoyment, providing strong support for the hedonic extension of continuance models (as emphasized in the Huang et al., integration, see H13). In other words, meeting expectations not only confirms functionality but also enhances positive affect and enjoyment, which, in turn, drives satisfaction. Notably, this indirect pathway has the largest CI bounds among the mediation tests, suggesting the strongest mediated satisfaction mechanism.
- Confirmation also increases continuance intention through enjoyment, meaning that confirmed expectations can promote continued AI use because users find the experience more pleasant (see H14). This supports the assumption that continuance is determined by both utilitarian and hedonic routes, even if the enjoyment-mediated effect is smaller and closer to the threshold (CI lower bound near zero), it remains statistically dependable under the bootstrap criterion.
- Taken together, the results support the adopted ECT/ECM/IS/IT Continuance logic; confirmation of expectations operates as the key post-adoption initiating mechanism that improves users' utilitarian beliefs (performance and usefulness) and hedonic evaluations (enjoyment). These perceptions then elevate satisfaction, and satisfaction, together with usefulness and enjoyment, strengthen continuance intention. Further, the significant indirect effects (H10–H14) indicate that confirmation translates into satisfaction and continuance through multiple pathways, thereby confirming the multidimensional structure of AI technology continuance in hospitality and tourism services.

6.6 Empirically Tested Model

Following validation of the individual hypotheses, sequential multiple linear regression analyses were conducted to empirically test the proposed framework and estimate the extent to which the key constructs jointly explain users' post-adoption perceptions and their intention to continue using AI technologies (ICU) in hospitality and tourism services. In this stage, each endogenous construct was examined as a dependent variable, while theoretically relevant predictors were entered and subsequently refined through a trimming process that progressively removed non-significant predictors. This approach allowed identification of parsimonious final models with the strongest explanatory power. The regression outputs are reported in Tables 9–13.

First, Perceived Performance (PPE) was regressed on Confirmation of Expectations (CON). The model was statistically significant and showed that higher expectation confirmation is associated with higher perceived performance of AI technologies. The model explained 38.5% of the variance in perceived performance ($R^2 = .385$; Adjusted $R^2 = .382$), indicating satisfactory predictive accuracy for PPE.

Next, Perceived Usefulness (PUS) was examined as a dependent variable with CON and PPE initially entered as predictors. After refinement, PPE remained the dominant significant predictor, indicating that usefulness perceptions are primarily driven by the extent to which AI technologies are perceived to enhance effectiveness and task performance. The final model explained 48.2% of the variance in PUS ($R^2 = .482$; Adjusted $R^2 = .480$), reflecting strong explanatory power.

Subsequently, Perceived Enjoyment (PEN) was treated as the dependent construct with CON, PPE, and PUS entered as predictors. The refinement procedure indicated that only CON remained significant, suggesting that enjoyment is chiefly determined by whether AI technologies meet or exceed users' initial expectations. The final model explained 32.1% of the variance in PEN ($R^2 = .321$; Adjusted $R^2 = .318$). Satisfaction (SAT) was then examined as a dependent variable with CON, PPE, PUS, and PEN entered as predictors. The final retained model showed that CON, PUS, and PEN significantly predict satisfaction, whereas PPE did not remain significant after controlling the other predictors and was therefore excluded. The resulting model demonstrated very strong explanatory power, explaining 71.9% of the variance in SAT ($R^2 = .719$; Adjusted $R^2 = .715$). This finding indicates that satisfaction reflects a combined evaluation of confirmation (benchmark comparison), practical value (usefulness), and affective experience (enjoyment).

Finally, Intention to Continue Use (ICU) was examined as the ultimate dependent variable of the framework. After sequentially removing non-significant predictors, the final parsimonious model retained CON, PPE, and PUS as significant predictors. This model explained 36.6% of the variance in ICU ($R^2 = .366$; Adjusted $R^2 = .358$), indicating satisfactory overall explanatory power. Substantively, continuance intention is strengthened when users' expectations are confirmed and when AI is perceived as both performance-enhancing and functionally useful.

Using the unstandardized coefficients (B) from the final ICU model (Table 13), the final regression equation is:

$$\mathbf{ICU = 1.214 + 0.214 \cdot CON + 0.268 \cdot PPE + 0.221 \cdot PUS \ (6.10)}$$

where ICU = Intention to Continue Use, CON = Confirmation of Expectations, PPE = Perceived Performance, and PUS = Perceived Usefulness.

Diagnostic checks indicated no multicollinearity concerns, as all VIF values remained below the commonly accepted threshold of 5.

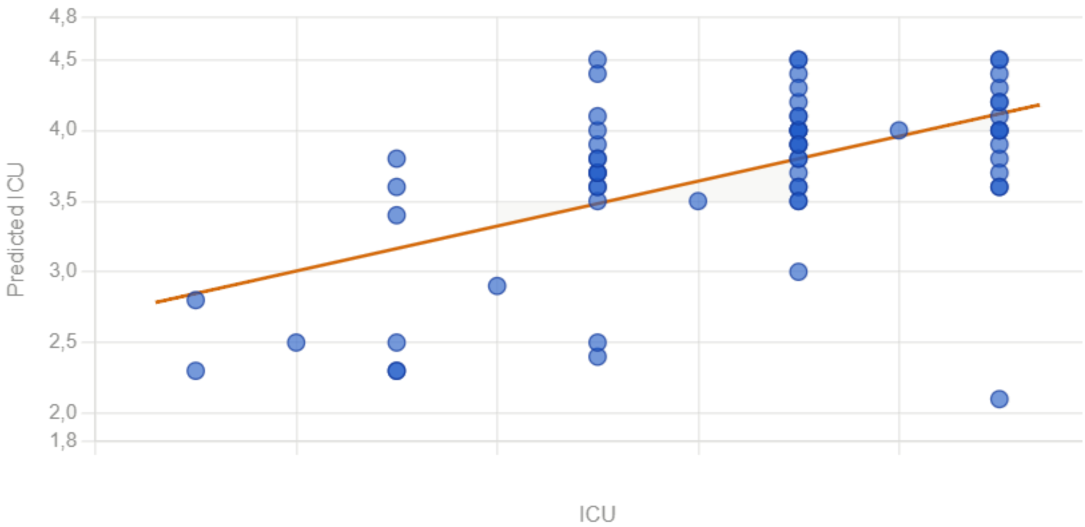

Figure 6.18: Regression fitted line plot.
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Therefore, based on the research results, the final model of our study is depicted in Figure 6.19.

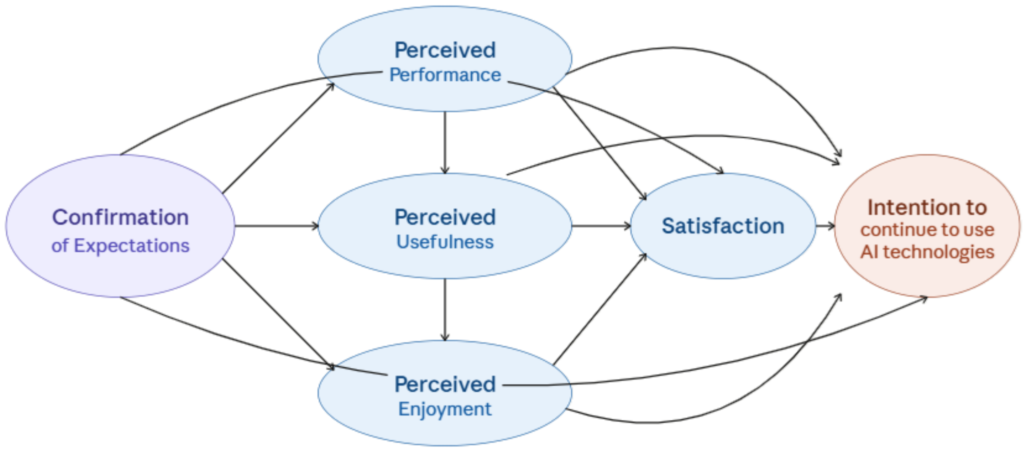

Figure 6.19: Empirical tested model
Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services"

Chapter 7: Discussion

Chapter 7 presents discussion points associated with our research results. The chapter is structured as follows: Section 7.1 discusses the degree of answering the research objectives and the support of the initial assumptions; Section 7.2 discusses relating our findings with those of previous studies; Section 7.3 examines theoretical and research implications; Section 7.4 discusses practical implications; and section 7.5 discusses proposed directions for further research and the study's limitations.

7.1 The degree of answering the research objectives and the support of the initial assumptions

Chapter 6's empirical data demonstrates that the study addresses each of the four research goals and substantially validates the four original hypotheses. The findings support strong positive correlations between the fundamental post-adoption constructs for Research Objective 1. Perceived performance, perceived utility, and perceived enjoyment are all positively correlated with confirmation. Stronger enjoyment gains at higher confirmation levels are indicated by the curvilinear (quadratic) pattern of the relationship between confirmation and enjoyment (CON and PEN).

There is an empirical connection between satisfaction and continuance intention for Research Objective 2. Satisfaction is closely related to perceived performance, enjoyment, and usefulness. Importantly, the regression-based model shows high explanatory power for satisfaction. Satisfaction is achieved by combining benchmark evaluation (confirmation) with utilitarian (usefulness) and hedonistic (enjoyment) assessments. Concerning Research Objective 3, mediation analyses show that confirmation affects satisfaction indirectly through perceived performance, usefulness, and enjoyment. There is partial mediation across all three pathways.

For Research Objective 4, confirmation affects continuance intention in part through perceived enjoyment and usefulness. Performance and usefulness are important predictors, according to the final ICU regression. This suggests that post-adoption assessments and expectation confirmation both influence continuance, mostly via a utilitarian indirect route with a smaller hedonic indirect route.

These results are consistent with and support the following initial hypotheses: (1) the centrality of confirmation reflects expectations or benchmarks; (2) confirmation influences satisfaction and continuance both directly and indirectly through mediators; (3) perceived performance, usefulness, and enjoyment all have an impact on satisfaction and continuance, either directly or indirectly; and (4) satisfaction is a major factor influencing continuance intention. It is necessary to exercise caution. ICU exhibits only acceptable internal consistency and is operationalized using two indicators. Measurement fragility should be considered when interpreting effects in the intensive care unit.

7.2 Relating the findings to earlier work

The observed relationships are consistent with the IS/IT continuance perspective and Expectation–Confirmation Theory, in which post-use confirmation influences beliefs and satisfaction, and influences continuance intentions (Bhattacherjee, 2001; Oliver, 1980). Perceived performance, usefulness, and enjoyment are positively correlated with confirmation, consistent with earlier studies that found higher utilitarian assessments when expectations are fulfilled or exceeded (Bhattacherjee, 2001; Oliver, 1980).

Further, the findings align with current studies on hospitality and tourism. Our study combines both functional and hedonic value to extend continuance models to AI-enabled services. The data reveal that satisfaction is significantly influenced by enjoyment. Both enjoyment and usefulness relate to the intention to continue. These findings are similar to those observed in AI service contexts, where users remain engaged because AI is effective and engaging (Huang et al., 2024; Dhiman & Jamwal, 2023), reinforcing the broader theory. A mix of instrumental benefits and experiential rewards, such as enjoyment, is necessary for persistence in experiential services. Utility is not the only factor to consider (Venkatesh et al., 2003; Davis, 1989).

Through various channels, confirmation leads to satisfaction and continued use. The relationship between confirmation and satisfaction is mediated by perceived performance, utility, and enjoyment. This agrees with continuance studies showing that confirmation strengthens post-adoption beliefs and increases satisfaction (Huang et al., 2024; Bhattacherjee, 2001). Usefulness and enjoyment partially mediate the relationship between confirmation and continuance intention. This fits with research on chatbots and AI in tourism. According to Huang et al., (2024) and Dhiman and Jamwal (2023), hedonic experience offers a smaller motivational pathway. Confirmed expectations promote continued use mainly through utility.

The findings are further explained by two recent works. Rubera et al., (2025) show that generative AI is changing the nature of marketing work. They stress that assets such as customer satisfaction and innovation deliver long-term value to marketing, supporting the current study's focus on satisfaction as the link between AI experience and sustained use. Leong et al., (2026) show that AI-chatbot service recovery quality indirectly affects continuance usage intention. Boundary conditions depend on how human-like the AI appears (Uncanny Valley effects), strengthening the idea of multiple pathways in the current study. It emphasizes that both experiential and evaluative factors affect persistence. The humanlike nature of AI could influence future hospitality and tourism research.

7.3 Theoretical and research implications

The ECM framework and Expectation–Confirmation Theory are supported by the findings. The primary evaluation method is post-use confirmation, which reinforces positive beliefs when user expectations are fulfilled. The intention to continue is then strengthened by the satisfaction that results from confirmation (Bhattacherjee, 2001; Oliver, 1980). Confirmation also influences users' reevaluation of the system's functionality, utility, and pleasure, eliciting both affective and cognitive reactions. As a result, utilitarian and hedonistic assessments complement one another and provide a thorough explanation of continuance behavior. The finding of the emphasis on the significance of experiential gratifications in service contexts, expands upon the conventional "belief–satisfaction–intention" logic (Venkatesh et al., 2003; Davis, 1989).

The results are consistent with the chosen position ontologically. Important post-adoption phenomena (e. The g. These latent constructs emerge as systematic covariation among measured indicators. According to Bhattacherjee (2001) and Oliver (1980), the mediation structure explains causal mechanisms as follows: (1) expectation alignment (confirmation) shapes (2) beliefs about usefulness/performance and affective responses (enjoyment), which together create (3) satisfaction as a composite state, leading to (4) intentional commitment to continued use. This sequence lends credence to a stratified understanding of post-adoption reality, according to which layered, interconnected mechanisms are responsible for users' continued use.

From an epistemological perspective, the findings are consistent with a deductive, post-positivist approach that regards theoretical hypotheses as verifiable claims. Correlational, regression, and mediation evidence are used to assess these. Because knowledge claims are supported not only by association but also by showing how confirmation affects satisfaction and intention through these mechanisms, the indirect pathways lend credence to a mechanism-based explanation.

The study supports a multipath continuation model for AI-enabled services from the standpoint of research implications. First, confirmation provides users with proof that their initial expectations were met, laying the groundwork for further interaction. Second, users' perceptions of value are shaped by hedonic (enjoyment) and utilitarian (usefulness/performance) appraisals, each of which makes a unique contribution to their overall assessment. Third, satisfaction connects post-adoption evaluation to continuance intention by integrating these evaluations and acting as a key mechanism (Yu et al., 2026; Venkatesh et al., 2003; Bhattacherjee, 2001; Davis, 1989).

7.4 Practical implications

According to the research results and findings, continuity is an "expectations-to-experience" management problem. When users' pre-use expectations are accurately set and then met or exceeded, confirmation increases, users become more satisfied, and they are more motivated to keep using AI-enabled services (Bhattacherjee, 2001; Oliver, 1980).

Therefore, marketers should align deliverables with their promises across touchpoints (advertising, app store descriptions, on-site signage, and staff scripts). Rather than exaggerated claims, communications should emphasize observable, verifiable benefits (e.g., faster check-in, fewer errors, more accurate recommendations), thereby safeguarding satisfaction by reducing expectation–experience gaps.

Second, the findings demonstrate that both hedonic experience (enjoyment) and utilitarian beliefs (performance, usefulness) are necessary for persistence and satisfaction, suggesting a dual marketing mandate to maximize both feel and function. Organizations should place a high priority on task completion, accuracy, speed, and dependability. These elements improve perceived performance and utility. AI interactions should be easy and enjoyable from an experiential standpoint. Calibrated personalization, a suitable tone of voice, and a clear conversational structure can all help achieve this. Ensuring pleasure increases contentment and promotes sustained involvement.

Nevertheless, trust must be taken seriously for the successful implementation of AI technologies in tourism and hospitality. Trust-related issues can reduce the intention to continue using AI technologies (Tran et al., 2024), especially because personalization relies on extensive personal data, raising ethical concerns about security and transparency in processing. Recent evidence in tourism and hospitality AI-chatbot contexts shows that privacy concerns can significantly dampen users' behavioral intentions, making transparency mechanisms essential for sustaining use (Yu et al., 2026). Therefore, firms should make data practices explicit to build trust alongside satisfaction. To ensure the service aligns with users' needs and expectations and maintains satisfaction and continuation intention, marketing managers should simultaneously record user feedback following AI interactions and act swiftly when technology falls short of usefulness or enjoyment.

7.5 Further research and limitations

Several limitations of this study should guide the interpretation of the results. First, it relies on self-reported perceptions, it may inflate relationships due to common method variance and limit causal inference. Second, generalizability across various tourism and hospitality contexts, cultures, and AI applications is limited by the sample characteristics and the single empirical setting (e.g., chatbots vs. robots-as-a-service systems of suggestions). Third, focusing only on post-adoption constructs might omit potentially significant contextual elements, such as operational quality and organizational service design, while some metrics, e.g., reliability and the accuracy of estimated effects, may be limited by continuance intention, which is captured by a limited number of indicators. Lastly, while the model does a good job of capturing utilitarian and hedonistic pathways, it falls short of accurately capturing the larger socio-technical context in which AI is embedded.

These findings can be strengthened and extended by testing temporal ordering (confirmation, beliefs, satisfaction, and continuance) and validating the observed nonlinear patterns using longitudinal or experimental designs. Further, studies could replicate the model across different AI touchpoints and traveler segments using behavioral data.

Chapter 8: Conclusion

The hospitality and tourism industry are going through a huge transformation due to the rapid technological advancements. Under this prism, this dissertation has focused on how AI technologies that are increasingly often used in hospitality and tourism, are perceived by users. Our goal has been to understand what influences users' intention to continue use of AI technologies. The dissertation adds to the comprehension of users' behaviour and acceptance toward the relatively new AI technologies that have emerged in the industry. It examines and interprets the relationships-direct and indirect- among six constructs that influence users' intention to continue the use of AI technologies in hospitality and tourism. We have set out our study based on the initial assumptions, all supported by our research results.

As for the first research objective, the findings indicate that verifying expectations is the main antecedent in the model and has a positive direct impact on perceived performance, perceived usefulness, and perceived enjoyment. Higher levels of confirmation strengthen these relationships, suggesting a stronger (nonlinear) positive correlation with satisfaction and enjoyment. Additionally, satisfaction is positively impacted by perceived performance, usefulness, and enjoyment, with enjoyment having the biggest impact.

Regarding the second research objective, satisfaction has a positive relationship with continuance intention; however, continuance is more strongly driven by perceived usefulness and perceived performance, suggesting a stronger direct utilitarian relationship than satisfaction.

In relation to the third research objective, satisfaction is positively impacted by confirmation of expectations through perceived performance, perceived usefulness, and perceived enjoyment. This confirms partial mediation across all pathways, with enjoyment serving as the strongest mediating link.

With respect to the fourth research goal, confirmation has a favorable indirect impact on continuance intention through perceived enjoyment and usefulness, with usefulness serving as the primary mediator. However, confirmation continues to have a direct positive impact on continuance, suggesting both a direct and a mediated relationship. In general, both hedonic and utilitarian relationships influence satisfaction, while direct and indirect utilitarian effects more strongly define continuance intention.

The Expectation-Confirmation Theory (ECT) and IS/IT Continuance model offer a framework for understanding users' continued use of AI technologies in hospitality and tourism. Further, the integration of the above-mentioned models offers significant opportunities for future research in AI-driven tourist ecosystems. Future research should investigate how factors such as anthropomorphism, trust, privacy concerns and personalization affect users' confirmation of expectations, satisfaction and intention to continue use AI technologies in hospitality and tourism. It is imperative to comprehend the degree of influence of the factors that drive users' continuance use of AI technologies. To increase growth and profitability and gain a competitive advantage in the modern technology-driven era, tourism and hospitality organizations should align their AI technology implementation with guests' expectations and satisfaction. It would be very intriguing for future research to see what such a project would reveal.

The dissertation contributes to consumer behavior research in hospitality and tourism by offering an integrated explanation of post-adoption continuance behavior toward AI-enabled services. It demonstrates that users' expectation confirmation is the primary trigger for both hedonic (perceived enjoyment) and utilitarian (perceived performance and usefulness) evaluations. These evaluations influence satisfaction and, eventually, the intention to keep using AI technologies. Building on a recent literature review of hospitality and tourism marketing (e.g., Aransyah et al., 2026) that highlights the importance of psychological, experiential, and technology-driven factors affecting consumer reactions to AI, this study adds to the growing research on AI-enabled consumer experience and persistence. Empirical evidence shows that sustainable AI use stems from the combined influence of enjoyment ("feel") and usefulness/performance ("function"). By offering a customer-focused framework, this study clarifies how AI experiences lead to long-term behavioral intentions and advances theory and managerial practice in AI-driven hospitality and tourism services.

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Appendix A: "Questionnaire"

COVER LETTER

Dear Madam/Sir,

For the research needs of the dissertation titled "*An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services",* we would like to invite you to participate in our study.

The dissertation is prerequisite for the successful completion of the Master in Business Administration (M.B.A.) Programme of the Hellenic Open University (H.O.U.). The study aims to deepen how customers in the tourism and hospitality industry perceive performance, usefulness, and enjoyment in relation to their intention of continuing to use AI technology for hospitality and tourism services under the prism of expectation-confirmation theory and the IS/IT continuance model.

Based on the survey method, the responses of adult Greek tourists and visitors who have used AI technology in hospitality and tourism services are investigated.

Your participation in this study is of great importance to us. It is completely voluntary, and you have the right to withdraw at any stage. It should only take you a few minutes to complete the survey.

The collected data will be used for the research needs of this dissertation.

Feel free to contact us.

Thank you in advance for your cooperation.

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QUESTIONNAIRE

Section A: Use of AI technology for hospitality and tourism services

1. Have you ever used AI technology for hospitality and tourism services? (mark (X) one answer).

☐ Yes ☐ No

If you chose «No», please do not continue to the following questions.

2. Which AI technology applications have you used? (mark (X) freely).

☐ Chatbots/Virtual Assistants (e.g., hotel booking assistants, customer service bots)
☐ AI-powered Recommendation Systems (e.g., personalized travel suggestions)
☐ Voice Assistants (e.g., Alexa, Google Assistant in hotel rooms)
☐ Facial Recognition (e.g., check-in/check-out systems)
☐ Robot Concierge/Service Robots
☐ Smart Room Controls (e.g., automated lighting, temperature)
☐ AI-based Price Comparison Tools
☐ Virtual Tours (e.g., AR/VR destination previews)
☐ Dynamic Pricing Systems
☐ Language Translation Apps
☐ Other (please specify) _______________________________

3. How frequently do you use AI technology for hospitality and tourism services? (mark (X) one answer).

☐ Daily
☐ Weekly
☐ Monthly
☐ Rarely
☐ Only once

4. What features do you find most appealing in AI technology for hospitality and tourism services? (mark (X) freely).

☐ 24/7 availability
☐ Personalized recommendations
☐ Fast response time
☐ Ease of use
☐ Cost savings
☐ Multilingual support
☐ Contactless service
☐ Real-time information updates
☐ Other (please specify) _______________________________

5. How easy was it to navigate and use AI technology for hospitality and tourism services? (mark (X) one answer).

☐ Very easy
☐ Somewhat easy
☐ Neutral
☐ Somewhat difficult
☐ Very difficult

6. What types of hospitality and tourism services would you be most interested in using AI technology for? (mark (X) freely).

☐ Hotel/accommodation booking and management
☐ Flight and transportation booking
☐ Restaurant reservations and recommendations
☐ Travel planning and itinerary creation
☐ Local attraction recommendations
☐ Customer service and support
☐ Check-in/check-out processes
☐ In-room services and controls
☐ Tour guide services
☐ Other (please specify) ________________________________

7. Where have you used AI technology for hospitality and tourism services in the past? (mark (X) freely).

☐ Hotels/Resorts
☐ Airports
☐ Restaurants/Cafes
☐ Tourist attractions/Museums
☐ Travel booking websites/apps
☐ Transportation services (e.g., ride-sharing, car rentals)
☐ Tourism information centers
☐ Cruise ships
☐ Other (please specify) ________________________________

Section B: Demographic profile of respondents and other information

8. Please select your gender (mark (X) one answer).

☐ Male
☐ Female
☐ I prefer not to say

9. Please select the age group you belong (mark (X) one answer).

☐ Under 18
☐ 18 - 24
☐ 25 - 34
☐ 35 - 44
☐ 45 - 54
☐ 55 - 64
☐ 65 or over

If you chose «Under 18», please do not answer the following questions.

10. Please select the highest level of education you have completed (mark (X) one answer).

☐ Basic Education
☐ Secondary Education
☐ Higher Education
☐ Postgraduate Studies
☐ Other

11. Please select your annual income (mark (X) one answer).

☐ 0 - 10.000 €
☐ 10.001 € - 20.000 €
☐ 20.001 € - 30.000 €
☐ 30.001 € - 40.000 €
☐ Over 40.000 €

Section C: Confirmation of Expectations

12. The following statements relate to *confirmation of expectations*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
My experience with using AI technologies was better than what I expected.	☐	☐	☐	☐	☐
The level of service provided by AI technologies was better than I expected.	☐	☐	☐	☐	☐
Overall, most of my expectations from using AI technologies were confirmed.	☐	☐	☐	☐	☐

Section D: Perceived Performance

13. The following statements relate to *perceived performance*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Using AI technologies enhances my effectiveness in managing hospitality and tourism services.	☐	☐	☐	☐	☐
My hospitality and tourism-related tasks were easier to complete with AI technologies.	☐	☐	☐	☐	☐
I can save time in managing my hospitality and tourism services when I use AI technologies.	☐	☐	☐	☐	☐
Overall, AI technologies are useful in managing hospitality and tourism services.	☐	☐	☐	☐	☐

Section E: Perceived Usefulness

14. The following statements relate to *perceived usefulness*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI technologies helped me to enhance my performance in managing many tasks.	☐	☐	☐	☐	☐
I find AI technologies very useful in my day-to-day work.	☐	☐	☐	☐	☐
Using AI technologies enhances my effectiveness in carrying out my intended task.	☐	☐	☐	☐	☐
Using AI technologies assists me to perform many tasks more conveniently.	☐	☐	☐	☐	☐

Section F: Perceived Enjoyment

15. The following statements relate to *perceived enjoyment*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Using AI technologies in managing my hospitality and tourism services was fun.	☐	☐	☐	☐	☐
Using AI technologies in managing my hospitality and tourism services was enjoyable.	☐	☐	☐	☐	☐
Using AI technologies in managing my hospitality and tourism services was pleasant.	☐	☐	☐	☐	☐

Section G: Satisfaction

16. The following statements relate to *satisfaction*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I was satisfied with my overall experience with AI technologies.	☐	☐	☐	☐	☐
I was pleased with my overall experience with AI technologies.	☐	☐	☐	☐	☐
I was content with my overall experience with AI technologies.	☐	☐	☐	☐	☐
I was delighted with my overall experience with AI technologies.	☐	☐	☐	☐	☐

Section H: Intention to Use

17. The following statements relate to *intention to use*. Please indicate to what extend you agree or disagree with the following statements. Please tick (x) one answer for each statement.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I intend to continue using AI technologies rather than discontinue using them.	☐	☐	☐	☐	☐
My intentions are to continue using AI technologies rather than use other alternative means (e.g., call customer service, check websites, etc.).	☐	☐	☐	☐	☐
If I could, I would like to discontinue my use of AI technologies.	☐	☐	☐	☐	☐

Thank you very much for your participation!

ΣΥΝΟΔΕΥΤΙΚΗ ΕΠΙΣΤΟΛΗ

Αξιότιμη κυρία/Αξιότιμε κύριε,

Για τις ερευνητικές ανάγκες της διπλωματικής εργασίας με τίτλο: «Μια εξερεύνηση των ρόλων της αντιληπτής απόδοσης, της αντιληπτής χρησιμότητας και της αντιληπτής απόλαυσης στην πρόθεση συνέχισης της χρήσης της τεχνολογίας τεχνητής νοημοσύνης για υπηρεσίες φιλοξενίας και τουρισμού».

Η εκπόνηση της Διπλωματικής Εργασίας αποτελεί βασική προϋπόθεση για την επιτυχή ολοκλήρωση του Μεταπτυχιακού Προγράμματος Σπουδών στη Διοίκηση Επιχειρήσεων (Μ.Β.Α.) του Ελληνικού Ανοικτού Πανεπιστημίου (Ε.Α.Π.).

Η διπλωματική εργασία αποτελεί προαπαιτούμενο για την επιτυχή ολοκλήρωση του Προγράμματος Μεταπτυχιακών Σπουδών στη Διοίκηση Επιχειρήσεων (Μ.Β.Α.) του Ελληνικού Ανοικτού Πανεπιστημίου (Ε.Α.Π.). Η μελέτη στοχεύει να εμβαθύνει στον τρόπο με τον οποίο οι πελάτες στη βιομηχανία του τουρισμού και της φιλοξενίας αντιλαμβάνονται την απόδοση, τη χρησιμότητα και την ευχαρίστηση σε σχέση με την πρόθεσή τους να συνεχίσουν να χρησιμοποιούν την τεχνολογία Τεχνητής Νοημοσύνης για υπηρεσίες φιλοξενίας και τουρισμού, υπό το πρίσμα της θεωρίας επιβεβαίωσης προσδοκιών και του μοντέλου συνέχισης χρήσης Πληροφοριακών Συστημάτων/Τεχνολογιών Πληροφορικής.

Με βάση τη μέθοδο της έρευνας, εξετάζονται οι απαντήσεις Ελλήνων ενήλικων τουριστών και επισκεπτών που έχουν χρησιμοποιήσει τεχνολογία Τεχνητής Νοημοσύνης σε υπηρεσίες φιλοξενίας και τουρισμού.

Η συμμετοχή σας στην παρούσα έρευνα έχει σπουδαία αξία για εμάς, είναι πλήρως εθελοντική και διατηρείτε το δικαίωμα να υπαναχωρήσετε οποιαδήποτε στιγμή. Θα χρειαστούν μόνο μερικά λεπτά για να ολοκληρώσετε την έρευνα.

Τα δεδομένα που θα συλλεχθούν θα χρησιμοποιηθούν για τις ερευνητικές ανάγκες της παρούσας διπλωματικής εργασίας.

Μη διστάσετε να επικοινωνήσετε μαζί μας.

Σας ευχαριστούμε εκ των προτέρων για τη συνεργασία σας.

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ΕΡΩΤΗΜΑΤΟΛΟΓΙΟ

ΕΝΟΤΗΤΑ Α: Τεχνολογίας τεχνητής νοημοσύνης για υπηρεσίες φιλοξενίας και τουρισμού

1. Έχετε χρησιμοποιήσει ποτέ τεχνολογία τεχνητής νοημοσύνης (ΤΝ) για υπηρεσίες φιλοξενίας και τουρισμού; (σημειώστε (Χ) μία απάντηση).

☐ Ναι ☐ Όχι

Εάν επιλέξατε «Όχι», παρακαλώ μην συνεχίσετε στις επόμενες ερωτήσεις.

2. Ποιες εφαρμογές τεχνολογίας τεχνητής νοημοσύνης έχετε χρησιμοποιήσει; (σημειώστε (Χ) ελεύθερα).

☐ Διαλογικά ρομπότ (chatbots)/Εικονικοί Βοηθοί (π.χ. βοηθοί κρατήσεων ξενοδοχείων, bots εξυπηρέτησης πελατών)
☐ Συστήματα Προτάσεων με Τεχνητή Νοημοσύνη (π.χ. εξατομικευμένες ταξιδιωτικές προτάσεις)
☐ Φωνητικοί Βοηθοί (π.χ. Alexa, Google Assistant σε δωμάτια ξενοδοχείων)
☐ Αναγνώριση Προσώπου (π.χ. συστήματα check-in/check-out)
☐ Ρομποτικός Θυρωρός/Ρομπότ Εξυπηρέτησης
☐ Έξυπνοι Έλεγχοι Δωματίου (π.χ. αυτοματοποιημένος φωτισμός, θερμοκρασία)
☐ Εργαλεία Σύγκρισης Τιμών με Τεχνητή Νοημοσύνη
☐ Εικονικές Περιηγήσεις (π.χ. προεπισκοπήσεις προορισμών με AR/VR)
☐ Συστήματα Δυναμικής Τιμολόγησης
☐ Εφαρμογές Μετάφρασης Γλωσσών
☐ Άλλο (παρακαλώ προσδιορίστε) ________________________________

3. Πόσο συχνά χρησιμοποιείτε τεχνολογία τεχνητής νοημοσύνης (ΤΝ) για υπηρεσίες φιλοξενίας και τουρισμού; (σημειώστε (Χ) μία απάντηση).

☐ Καθημερινά
☐ Εβδομαδιαία
☐ Μηνιαία
☐ Σπάνια
☐ Μόνο μία φορά

4. Ποια χαρακτηριστικά βρίσκετε πιο ελκυστικά στην τεχνολογία τεχνητής νοημοσύνης (ΤΝ) για υπηρεσίες φιλοξενίας και τουρισμού; (σημειώστε (Χ) ελεύθερα).

☐ Διαθεσιμότητα 24/7
☐ Εξατομικευμένες προτάσεις
☐ Ταχύτητα απόκρισης
☐ Ευκολία χρήσης
☐ Εξοικονόμηση κόστους
☐ Πολυγλωσσική υποστήριξη
☐ Υπηρεσία χωρίς επαφή
☐ Ενημερώσεις πληροφοριών σε πραγματικό χρόνο
☐ Άλλο (παρακαλώ προσδιορίστε) ________________________________

5. Πόσο εύκολο ήταν να πλοηγηθείτε και να χρησιμοποιήσετε την τεχνολογία τεχνητής νοημοσύνης (ΤΝ) για υπηρεσίες φιλοξενίας και τουρισμού; (σημειώστε (Χ) μία απάντηση).

☐ Πολύ εύκολο

☐ Κάπως εύκολο
☐ Ουδέτερο
☐ Κάπως δύσκολο
☐ Πολύ δύσκολο

6. Για ποιους τύπους υπηρεσιών φιλοξενίας και τουρισμού θα ενδιαφερόσασταν περισσότερο να χρησιμοποιήσετε τεχνολογία τεχνητής νοημοσύνης (ΤΝ); (σημειώστε (X) ελεύθερα).
☐ Κράτηση και διαχείριση ξενοδοχείου/καταλύματος
☐ Κράτηση πτήσεων και μεταφορών
☐ Κρατήσεις και προτάσεις εστιατορίων
☐ Σχεδιασμός ταξιδιού και δημιουργία δρομολογίου
☐ Προτάσεις τοπικών αξιοθέατων
☐ Εξυπηρέτηση και υποστήριξη πελατών
☐ Διαδικασίες check-in/check-out
☐ Υπηρεσίες και έλεγχοι εντός δωματίου
☐ Υπηρεσίες ξεναγού
☐ Άλλο (παρακαλώ προσδιορίστε) ________________________________

7. Πού έχετε χρησιμοποιήσει τεχνολογία τεχνητής νοημοσύνης (ΤΝ) για υπηρεσίες φιλοξενίας και τουρισμού στο παρελθόν; (σημειώστε (X) ελεύθερα).
☐ Ξενοδοχεία/Θέρετρα
☐ Αεροδρόμια
☐ Εστιατόρια/Καφετέριες
☐ Τουριστικά αξιοθέατα/Μουσεία
☐ Ιστοσελίδες/εφαρμογές κράτησης ταξιδιών
☐ Υπηρεσίες μεταφοράς (π.χ. ride-sharing, ενοικίαση αυτοκινήτων)
☐ Κέντρα τουριστικών πληροφοριών
☐ Κρουαζιερόπλοια
☐ Άλλο (παρακαλώ προσδιορίστε) ________________________________

Ενότητα Β: Δημογραφικό προφίλ ερωτώμενων και λοιπές πληροφορίες

8. Παρακαλούμε επιλέξτε το φύλο σας (σημειώστε (Χ) μια απάντηση).

- ☐ Άνδρας
- ☐ Γυναίκα
- ☐ Δεν επιθυμώ να δηλώσω

9. Παρακαλούμε επιλέξτε την ηλικιακή ομάδα στην οποία ανήκετε (σημειώστε (Χ) μια απάντηση).

- ☐ Κάτω από 18
- ☐ 18 - 24
- ☐ 25 - 34
- ☐ 35 - 44
- ☐ 45 - 54
- ☐ 55 - 64
- ☐ 65 ή άνω

Εάν επιλέξατε «Κάτω από 18», παρακαλώ μην συνεχίσετε στις επόμενες ερωτήσεις.

10. Παρακαλούμε επιλέξτε το υψηλότερο επίπεδο εκπαίδευσης που έχετε ολοκληρώσει. (Σημειώστε (x) μία απάντηση)

- ☐ Βασική εκπαίδευση
- ☐ Δευτεροβάθμια εκπαίδευση
- ☐ Ανώτατη εκπαίδευση
- ☐ Μεταπτυχιακές σπουδές
- ☐ Άλλο

11. Παρακαλούμε επιλέξτε το ετήσιο εισόδημα σας. (Σημειώστε (x) μία απάντηση)

- ☐ 0 - 10.000 €
- ☐ 10.001 € - 20.000 €
- ☐ 20.001 € - 30.000 €
- ☐ 30.001 € - 40.000 €
- ☐ Άνω των 40.000 €

Ενότητα Γ: Επιβεβαίωση των Προσδοκιών

12. Οι παρακάτω δηλώσεις αφορούν την *επιβεβαίωση των προσδοκιών*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Η εμπειρία μου από τη χρήση τεχνολογιών ΤΝ ήταν καλύτερη από ότι περίμενα.	☐	☐	☐	☐	☐
Το επίπεδο υπηρεσιών από τη χρήση τεχνολογιών ΤΝ, ήταν καλύτερο από ότι περίμενα.	☐	☐	☐	☐	☐
Συνολικά, οι περισσότερες από τις προσδοκίες μου από τη χρήση τεχνολογιών ΤΝ επιβεβαιώθηκαν.	☐	☐	☐	☐	☐

Ενότητα Δ: Αντιληπτή Απόδοση

13. Οι παρακάτω δηλώσεις αφορούν την *αντιληπτή απόδοση*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Η χρήση τεχνολογιών ΤΝ ενισχύει την αποτελεσματικότητά μου στη διαχείριση υπηρεσιών τουρισμού και φιλοξενίας.	☐	☐	☐	☐	☐
Τα καθήκοντά μου που σχετίζονται με τον τουρισμό και τη φιλοξενία ήταν πιο εύκολο να ολοκληρωθούν με τις τεχνολογίες ΤΝ.	☐	☐	☐	☐	☐
Μπορώ να εξοικονομήσω χρόνο στη διαχείριση των υπηρεσιών τουρισμού και φιλοξενίας με τη χρήση τεχνολογιών ΤΝ.	☐	☐	☐	☐	☐
Συνολικά, οι τεχνολογίες ΤΝ είναι χρήσιμες στη διαχείριση υπηρεσιών τουρισμού και φιλοξενίας.	☐	☐	☐	☐	☐

Ενότητα Ε: Αντιληπτή Χρησιμότητα

14. Οι παρακάτω δηλώσεις αφορούν την *αντιληπτή χρησιμότητα*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Οι τεχνολογίες ΤΝ με βοήθησαν να βελτιώσω την απόδοσή μου στη διαχείριση πολλών εργασιών.	☐	☐	☐	☐	☐
Βρίσκω τις τεχνολογίες ΤΝ πολύ χρήσιμες στην καθημερινή μου εργασία.	☐	☐	☐	☐	☐
Η χρήση τεχνολογιών ΤΝ ενισχύει την αποτελεσματικότητά μου στην εκτέλεση της προγραμματισμένης εργασίας μου.	☐	☐	☐	☐	☐
Η χρήση τεχνολογιών ΤΝ με βοηθά να εκτελώ πολλές εργασίες πιο εύκολα.	☐	☐	☐	☐	☐

Ενότητα ΣΤ: Αντιληπτή Απόλαυση

14. Οι παρακάτω δηλώσεις αφορούν την *αντιληπτή απόλαυση*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Η χρήση τεχνολογιών ΤΝ στη διαχείριση των υπηρεσιών τουρισμού και φιλοξενίας ήταν διασκεδαστική.	☐	☐	☐	☐	☐
Η χρήση τεχνολογιών ΤΝ στη διαχείριση των υπηρεσιών τουρισμού και φιλοξενίας ήταν απολαυστική.	☐	☐	☐	☐	☐
Η χρήση τεχνολογιών ΤΝ στη διαχείριση των υπηρεσιών τουρισμού και φιλοξενίας ήταν ευχάριστη.	☐	☐	☐	☐	☐

Ενότητα Ζ: Ικανοποίηση

16. Οι παρακάτω δηλώσεις αφορούν την *ικανοποίηση*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Έμεινα ικανοποιημένος(η) από τη συνολική μου εμπειρία με τις τεχνολογίες ΤΝ.	☐	☐	☐	☐	☐
Έμεινα ευχαριστημένος(η) από τη συνολική μου εμπειρία με τις τεχνολογίες ΤΝ.	☐	☐	☐	☐	☐
Ήμουν ευτυχισμένος(η) από τη συνολική μου εμπειρία με τις τεχνολογίες ΤΝ.	☐	☐	☐	☐	☐
Έμεινα ενθουσιασμένος(η) από τη συνολική μου εμπειρία με τις τεχνολογίες ΤΝ.	☐	☐	☐	☐	☐

Ενότητα Η: Πρόθεση χρήσης

17. Οι παρακάτω δηλώσεις αφορούν την *πρόθεση χρήσης*. Παρακαλούμε να υποδείξετε σε ποιο βαθμό συμφωνείτε ή διαφωνείτε με τις παρακάτω δηλώσεις. Παρακαλούμε επιλέξτε (x) μία απάντηση για κάθε δήλωση.

	Διαφωνώ Απόλυτα	Διαφωνώ	Ουδέτερο	Συμφωνώ	Συμφωνώ Απόλυτα
Προτίθεμαι να συνεχίσω να χρησιμοποιώ τις υπηρεσίες ΤΝ, από το να σταματήσω να τις χρησιμοποιώ.	☐	☐	☐	☐	☐
Προτίθεμαι να συνεχίσω να χρησιμοποιώ τις υπηρεσίες ΤΝ, αντί να χρησιμοποιώ εναλλακτικά μέσα (π.χ. κλήση σε εξυπηρέτηση πελατών, έλεγχο ιστοσελίδων)	☐	☐	☐	☐	☐
Αν μπορούσα, θα ήθελα να σταματήσω τη χρήση των τεχνολογιών ΤΝ	☐	☐	☐	☐	☐

Ευχαριστώ θερμά για τη συμμετοχή σας!

Appendix B: "Tables and Figures"

How often do you use AI for hospitality and tourism services?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Only once	8	3.5	3.5	3.5
	Rarely	126	55.5	55.5	59.0
	Monthly	45	19.8	19.8	78.9
	Weekly	28	12.3	12.3	91.2
	Daily	20	8.8	8.8	100.0
	Total	227	100.0	100.0	

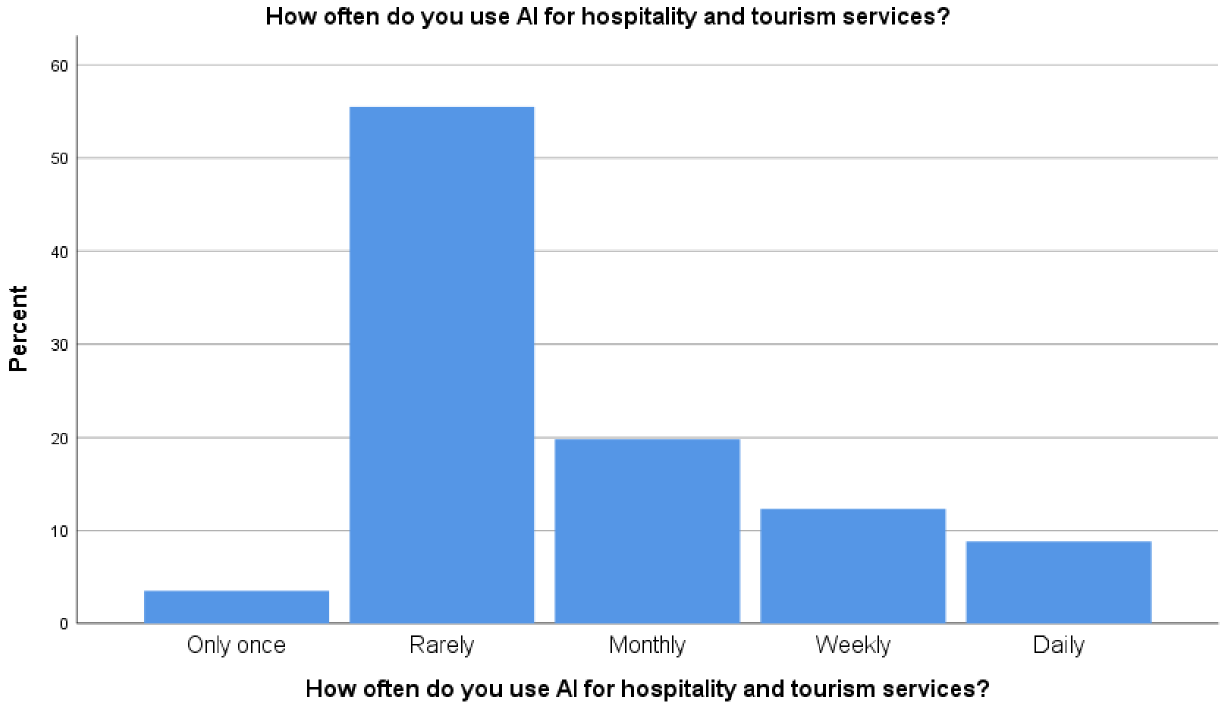


Figure B.1: Distribution of respondents according to how often they use AI for hospitality and tourism services. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

How easy was it to navigate and use AI for hospitality and tourism services?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very difficult	1	.4	.4	.4
	Somewhat difficult	6	2.6	2.6	3.1
	Neutral	41	18.1	18.1	21.1
	Somewhat easy	80	35.2	35.2	56.4
	Very easy	99	43.6	43.6	100.0
	Total	227	100.0	100.0	

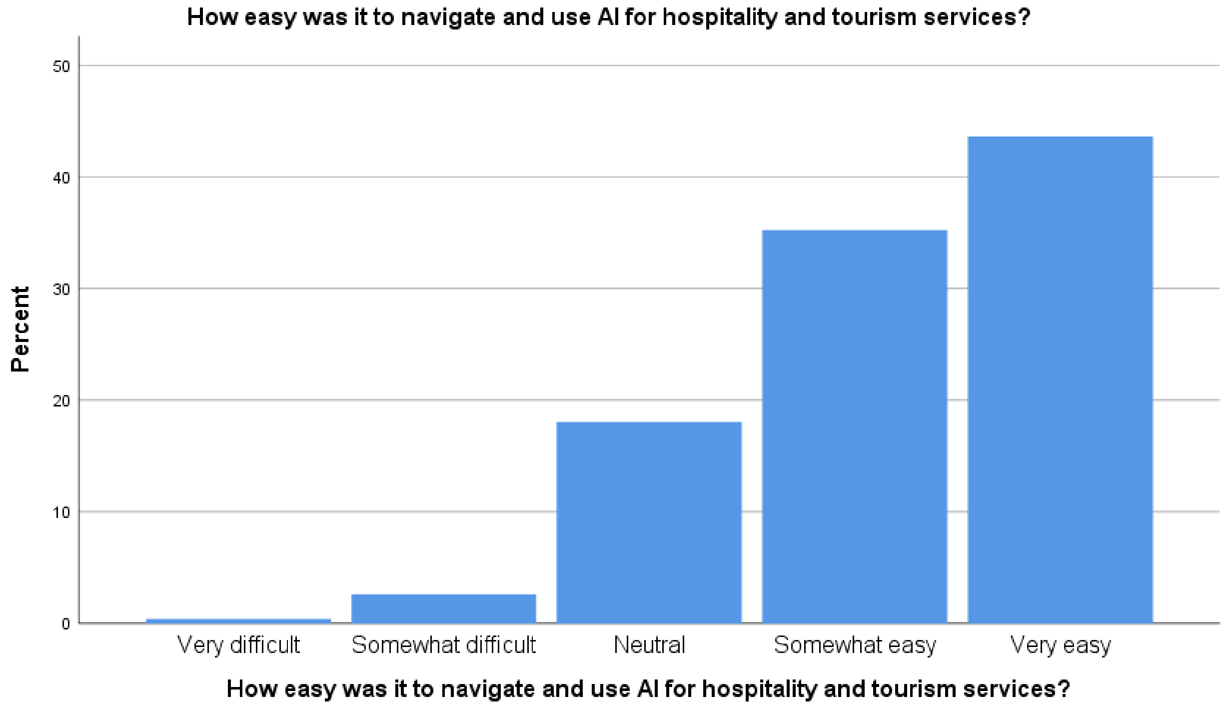


Figure B.2: Distribution of respondents according to perceived ease of navigating and using AI for hospitality and tourism services. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	80	35.2	35.2	35.2
	Female	147	64.8	64.8	100.0
	Total	227	100.0	100.0	

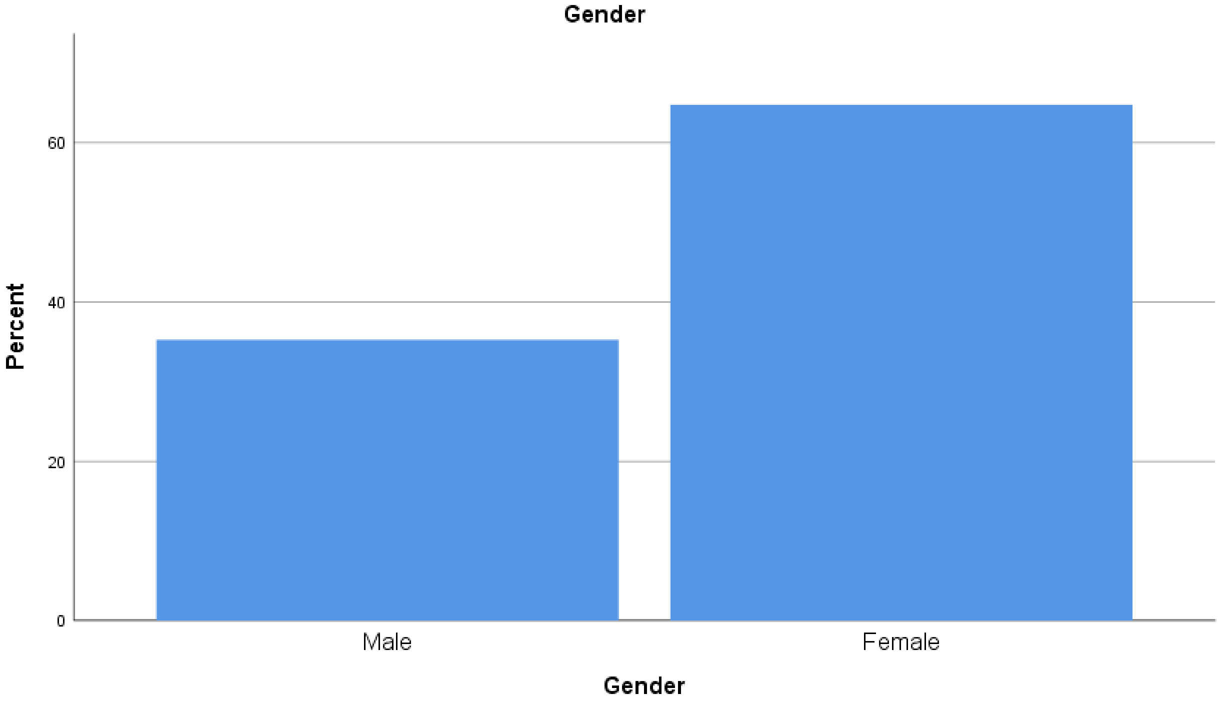


Figure B.3: Distribution of respondents by gender. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Age group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24	12	5.3	5.3	5.3
	25-34	48	21.1	21.1	26.4
	35-44	91	40.1	40.1	66.5
	45-54	53	23.3	23.3	89.9
	55-64	16	7.0	7.0	96.9
	65 or above	7	3.1	3.1	100.0
	Total	227	100.0	100.0	

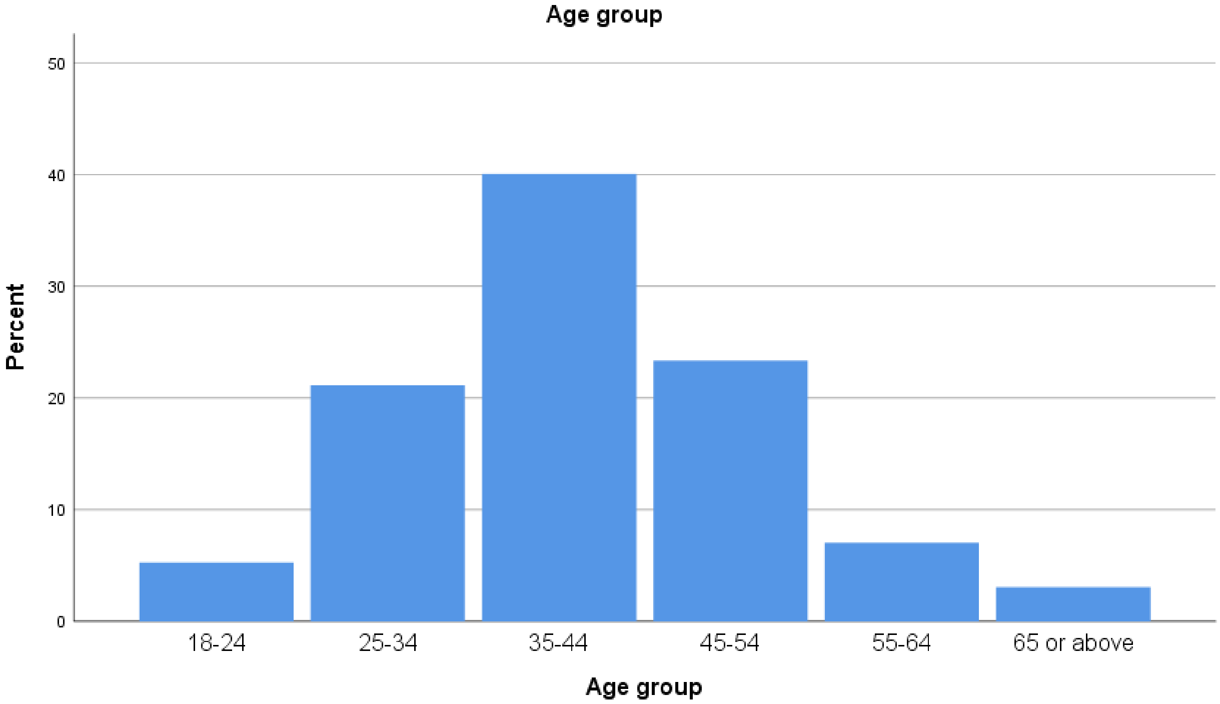


Figure B.4: Distribution of respondents by age group. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Education level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Basic education	6	2.6	2.6	2.6
	Secondary education	37	16.3	16.3	18.9
	Vocational training institute (IIEK)	1	.4	.4	19.4
	Higher education	89	39.2	39.2	58.6
	Postgraduate studies	92	40.5	40.5	99.1
	Doctoral degree	2	.9	.9	100.0
	Total	227	100.0	100.0	

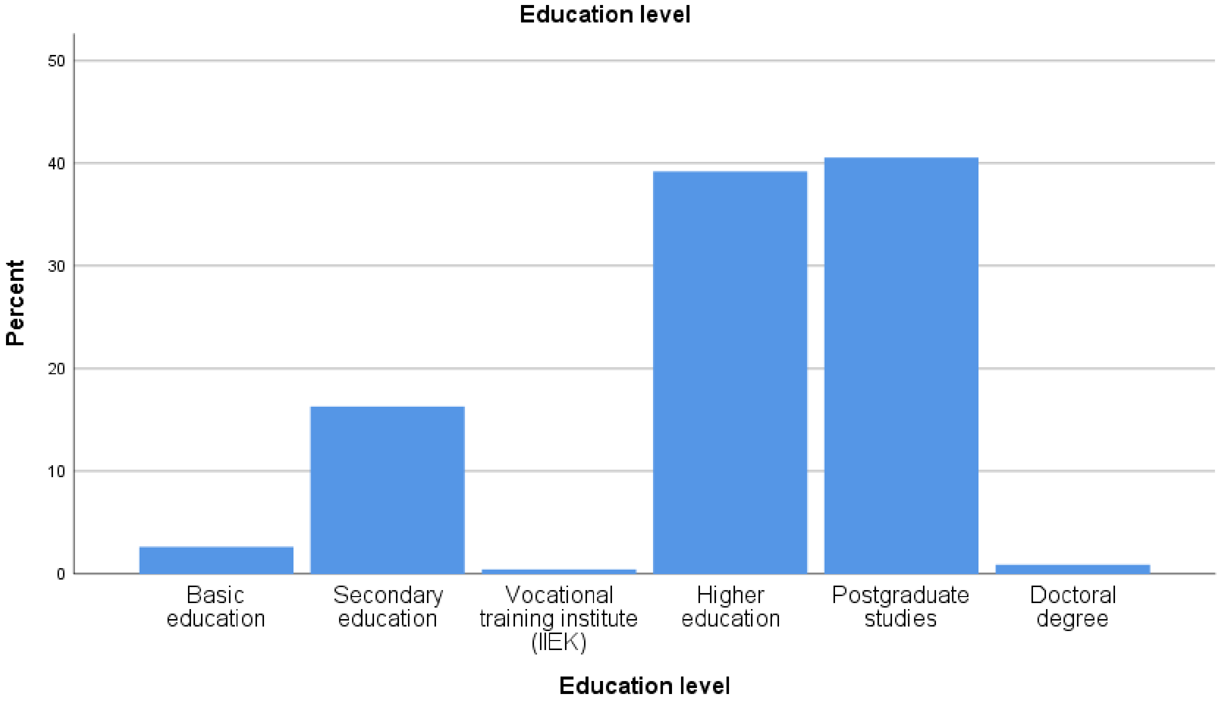


Figure B.5: Distribution of respondents according to education level. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Annual income

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-10000€	33	14.5	14.5	14.5
	10001-20000€	102	44.9	44.9	59.5
	20001-30000€	34	15.0	15.0	74.4
	30001-40000€	29	12.8	12.8	87.2
	Above 40000€	29	12.8	12.8	100.0
	Total	227	100.0	100.0	

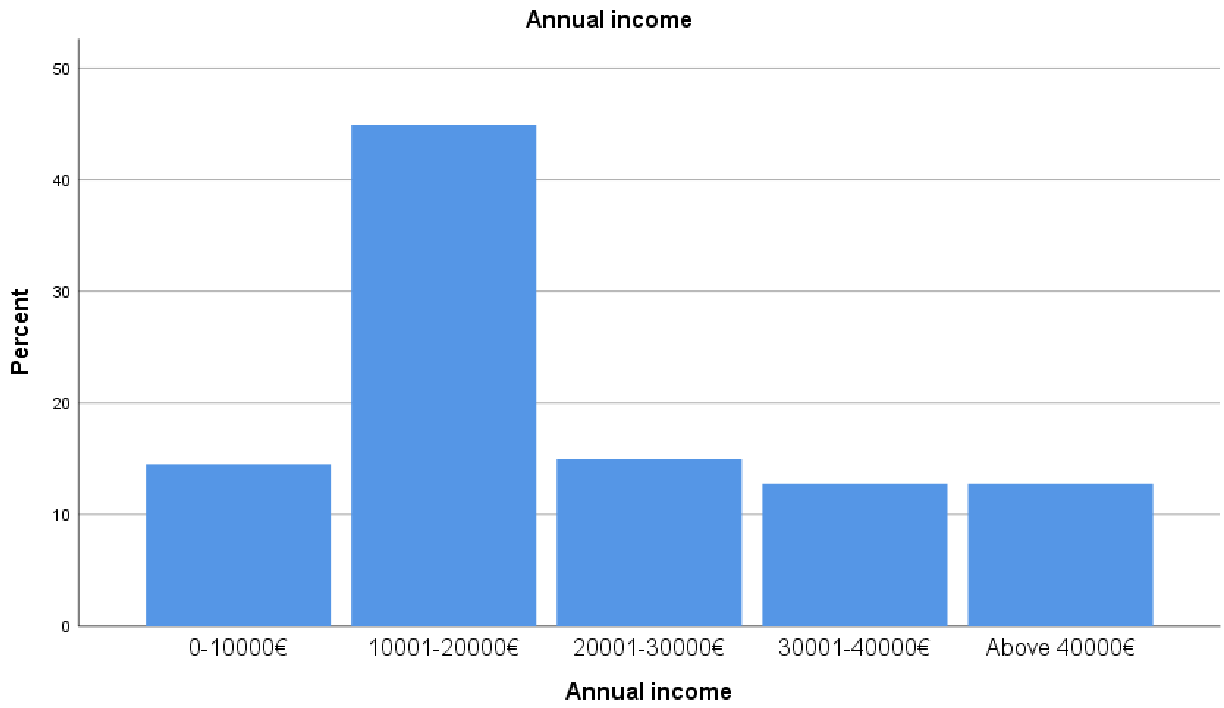


Figure B.6: Distribution of respondents according to annual income. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Which AI applications have you used?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	AI Price Comparison Tools	90	11.1	14.5	14.5
	Chatbots / Virtual Assistants	97	12.0	15.6	30.1
	AI Recommendation Systems	89	11.0	14.3	44.4
	Smart Room Controls	64	7.9	10.3	54.7
	Voice Assistants	55	6.8	8.8	63.5
	Facial Recognition	29	3.6	4.7	68.2
	Virtual Tours	55	6.8	8.8	77.0
	Language Translation Applications	117	14.4	18.8	95.8
	ChatGPT	3	.4	.5	96.3
	Robotic Concierge / Service Robot	10	1.2	1.6	97.9
	Dynamic Pricing Systems	13	1.6	2.1	100.0

	Total	622	76.7	100.0

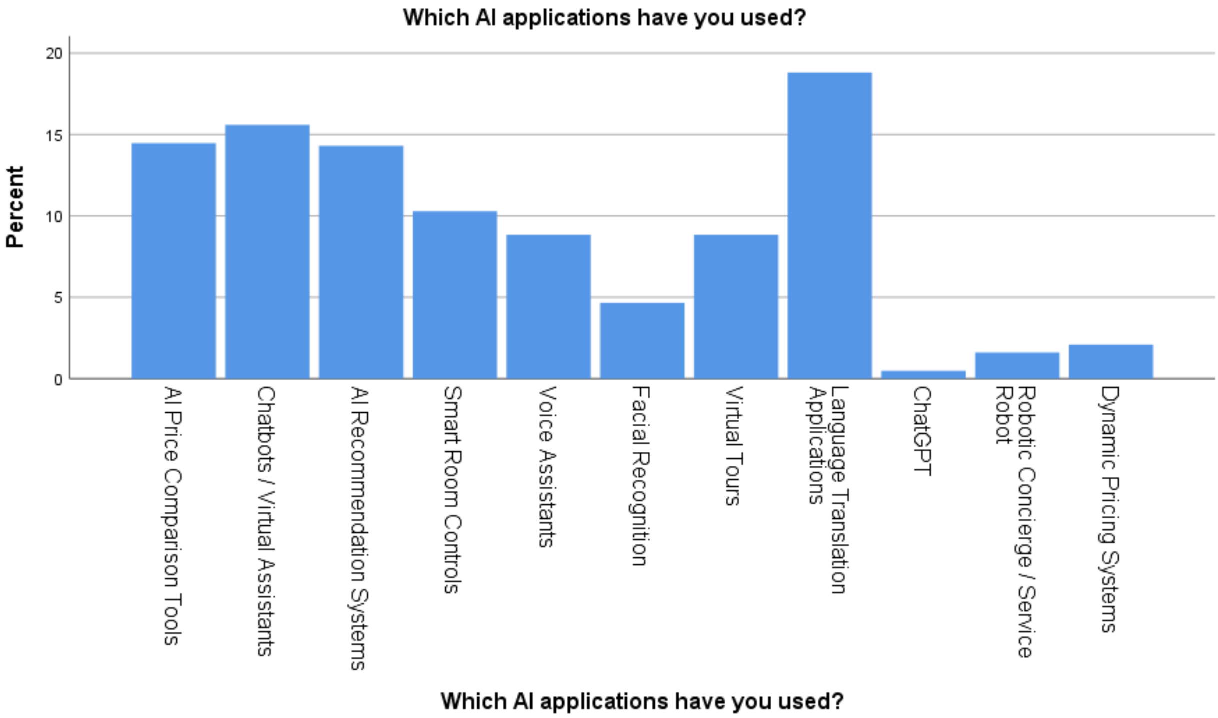


Figure B.7: Distribution of AI applications that respondents have used in hospitality and tourism services. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Which features do you find most attractive in AI for hospitality and tourism services?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	24/7 Availability	150	18.5	18.5	18.5
	Response Speed	135	16.6	16.6	35.1
	Ease of Use	140	17.3	17.3	52.4
	Personalized Recommendations	92	11.3	11.3	63.7
	Multilingual Support	91	11.2	11.2	75.0
	Real-Time Information Updates	78	9.6	9.6	84.6
	Contactless Service	53	6.5	6.5	91.1
	Cost Savings	71	8.8	8.8	99.9
	Large-Scale Data Search in Minimal Time	1	.1	.1	100.0

	Total	811	100.0	100.0

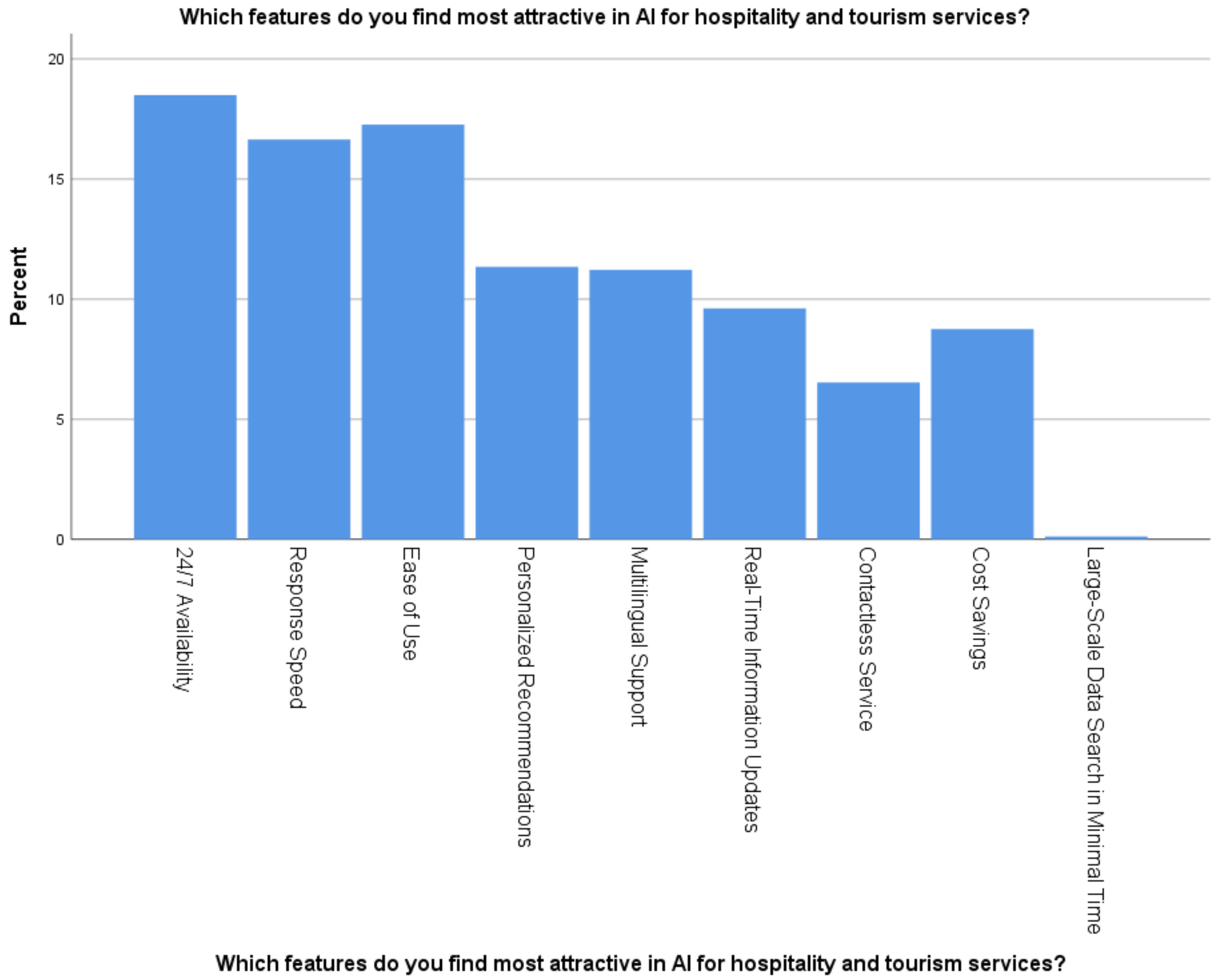


Figure B.8: Distribution of features considered most attractive in AI for hospitality and tourism services. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

For which types of hospitality and tourism services would you be most interested in using AI?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Flight and Transportation Booking	114	14.1	14.2	14.2
	Hotel/Accommodation Booking and Management	144	17.8	17.9	32.0
	Restaurant Reservations and Recommendations	81	10.0	10.1	42.1

Trip Planning and Itinerary Creation	134	16.5	16.6	58.8
Customer Service and Support	52	6.4	6.5	65.2
Local Attractions Recommendations	124	15.3	15.4	80.6
Check-in/Check-out Procedures	72	8.9	8.9	89.6
Tour Guide Services	55	6.8	6.8	96.4
In-Room Services and Controls	29	3.6	3.6	100.0
Total	805	99.3	100.0	

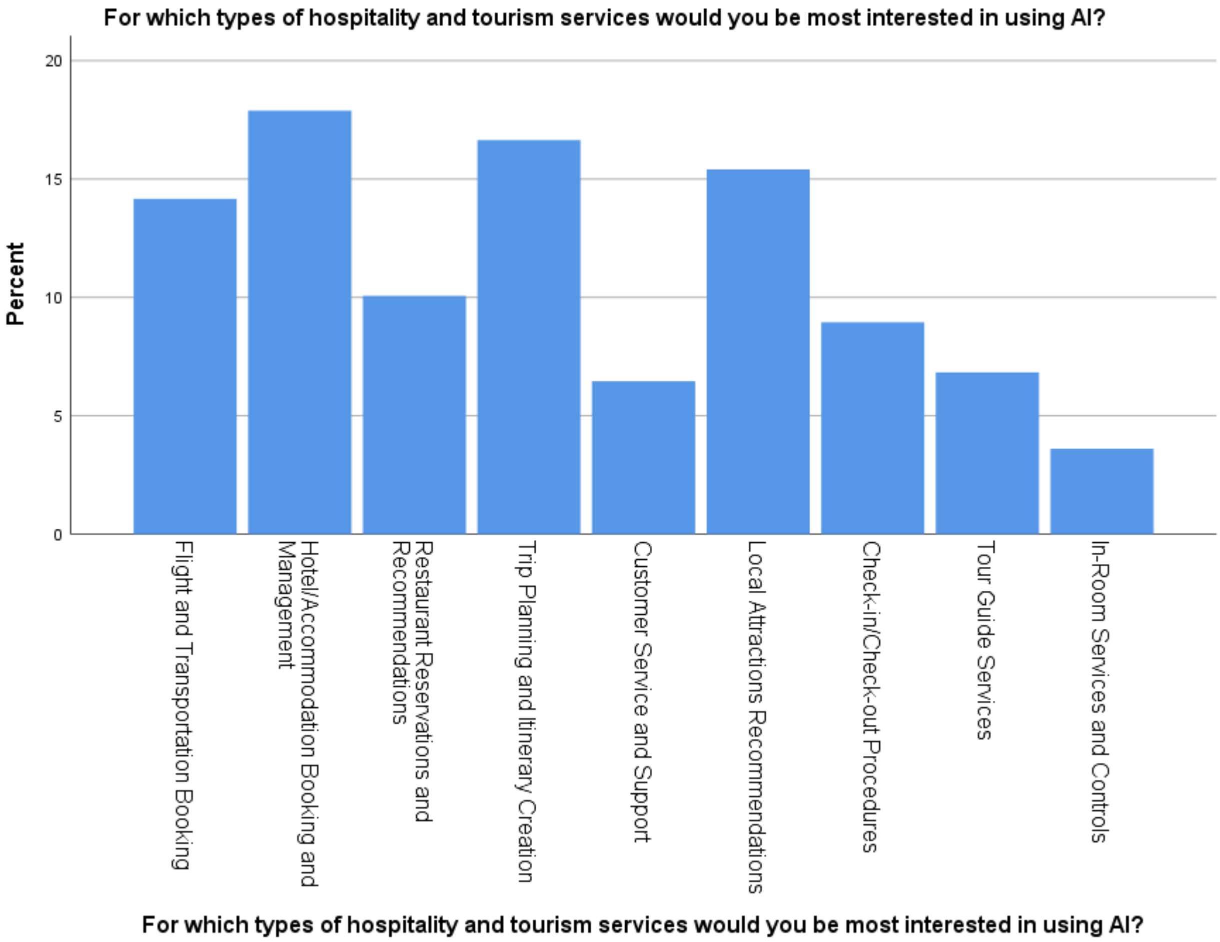


Figure B.9: Distribution of hospitality and tourism service types in which respondents are most interested in using AI. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

Where have you used AI for hospitality and tourism services in the past?

		Frequency	Percent	Valid Percent	Cumulative Percen
Valid	Airports	81	10.0	14.0	14.0
	Hotels/Resorts	133	16.4	23.0	37.0
	Restaurants/Cafes	66	8.1	11.4	48.4
	Tourist Attractions/Museums	106	13.1	18.3	66.7
	Tourist Information Centers	41	5.1	7.1	73.7
	Travel Booking Websites/Applications	100	12.3	17.3	91.0
	Transportation Services	42	5.2	7.3	98.3
	Cruise Ships	9	1.1	1.6	99.8
	Public Event Seat Reservations	1	.1	.2	100.0
	Total	579	71.4	100.0	

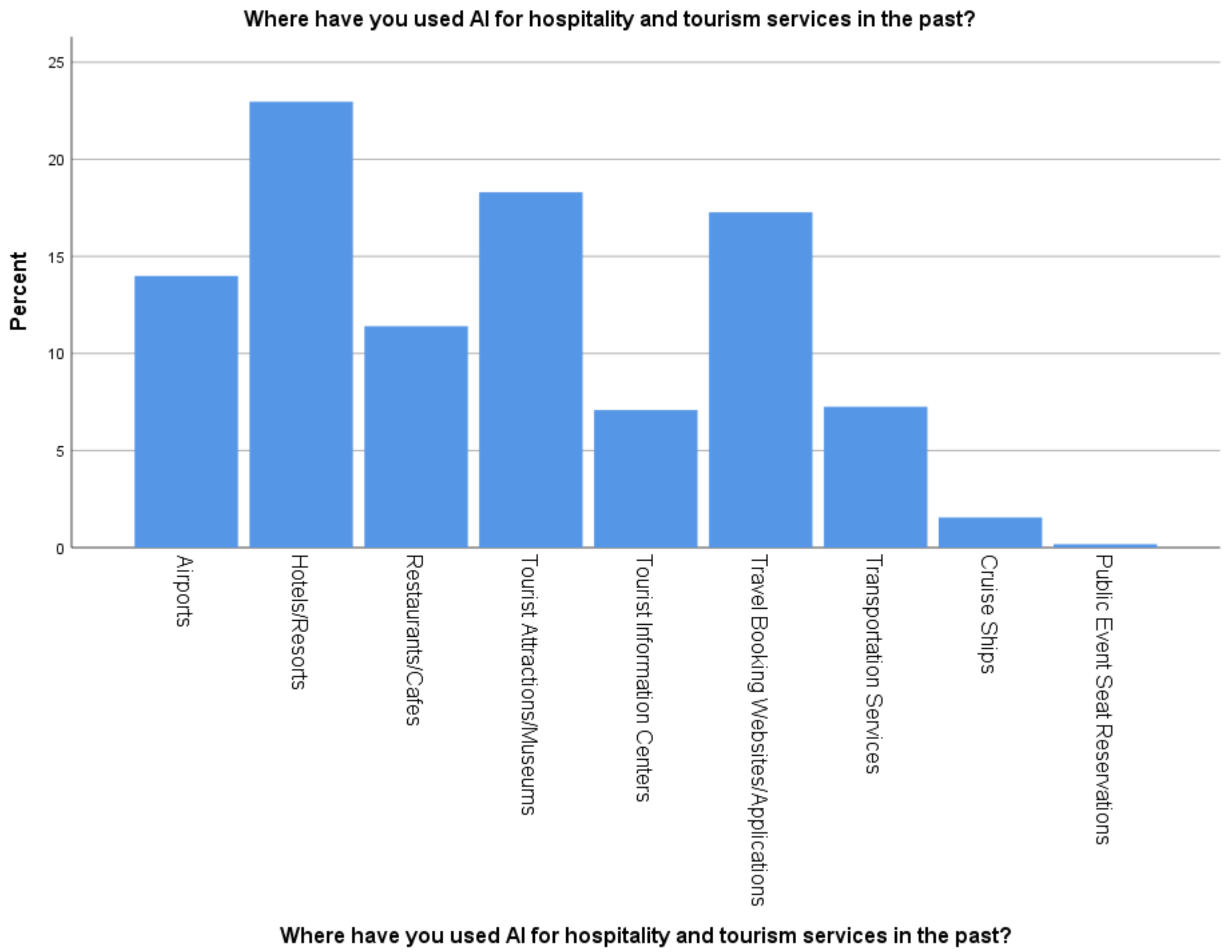


Figure B.10: Distribution of locations and service environments where respondents have previously used AI for hospitality and tourism services. Source: Kyriakaki, E. (2026). An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.

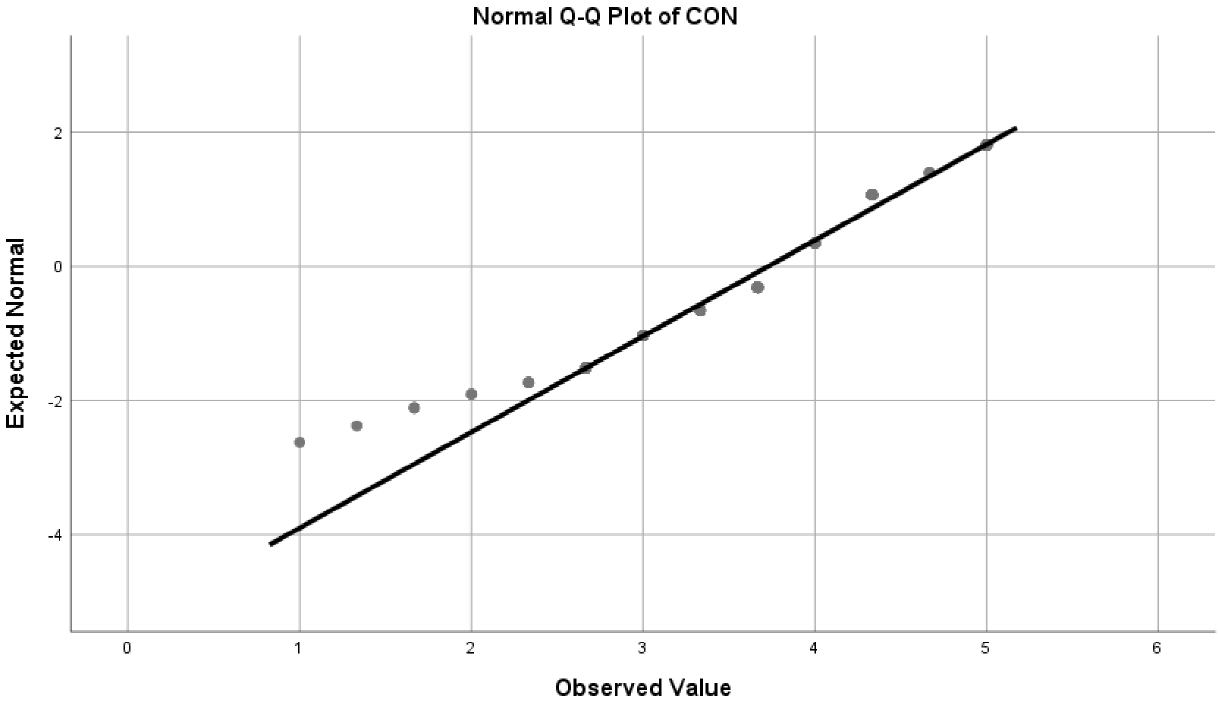
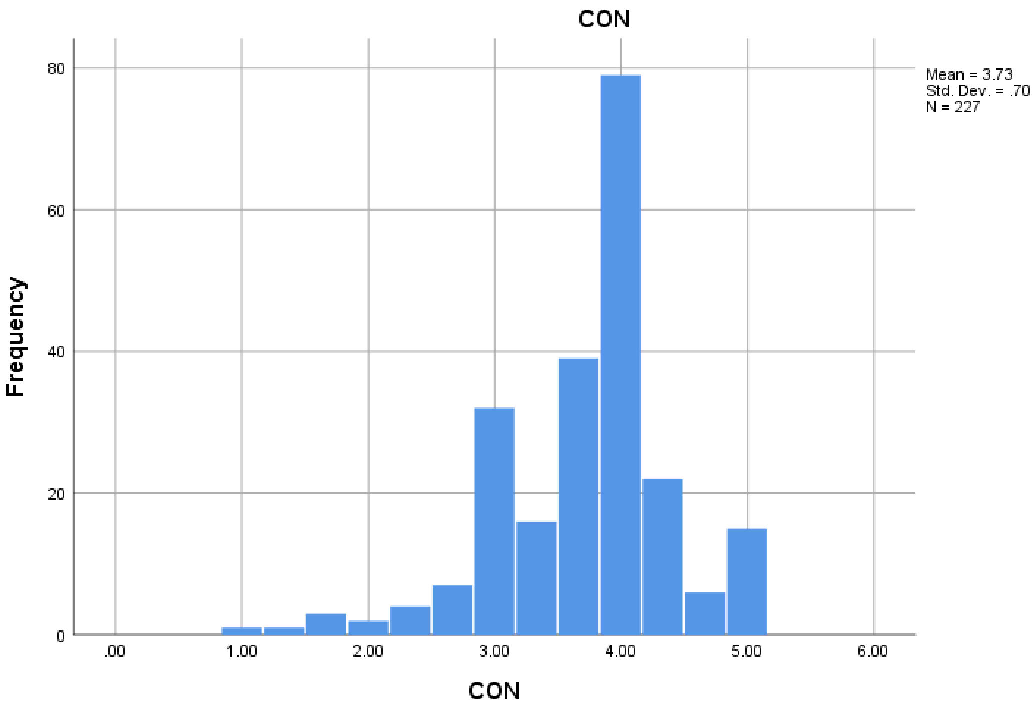


Figure B.11: Histogram and Q-Q plot of response data for construct CON. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".



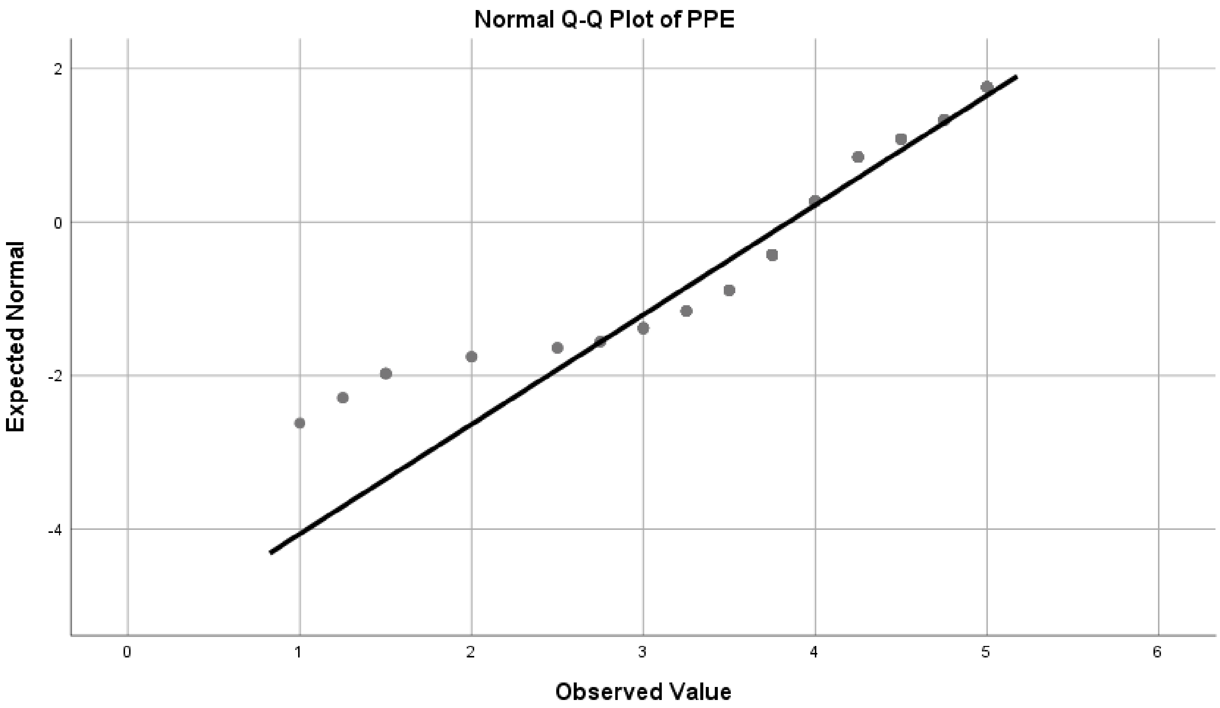
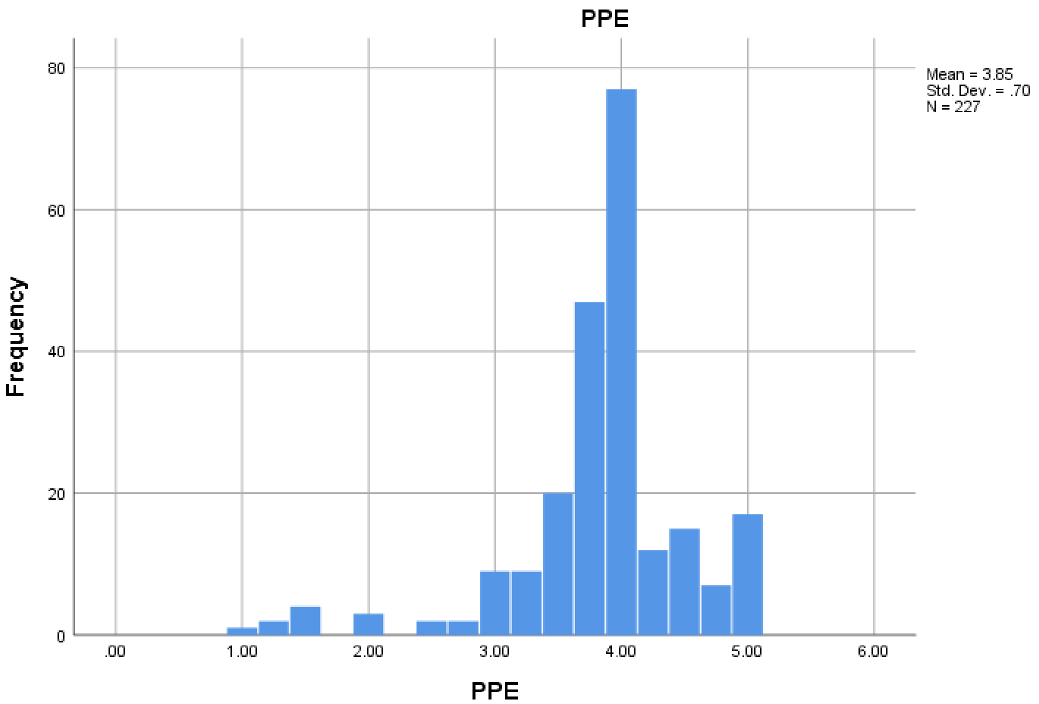


Figure B.12: Histogram and Q-Q plot of response data for construct PPE. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".



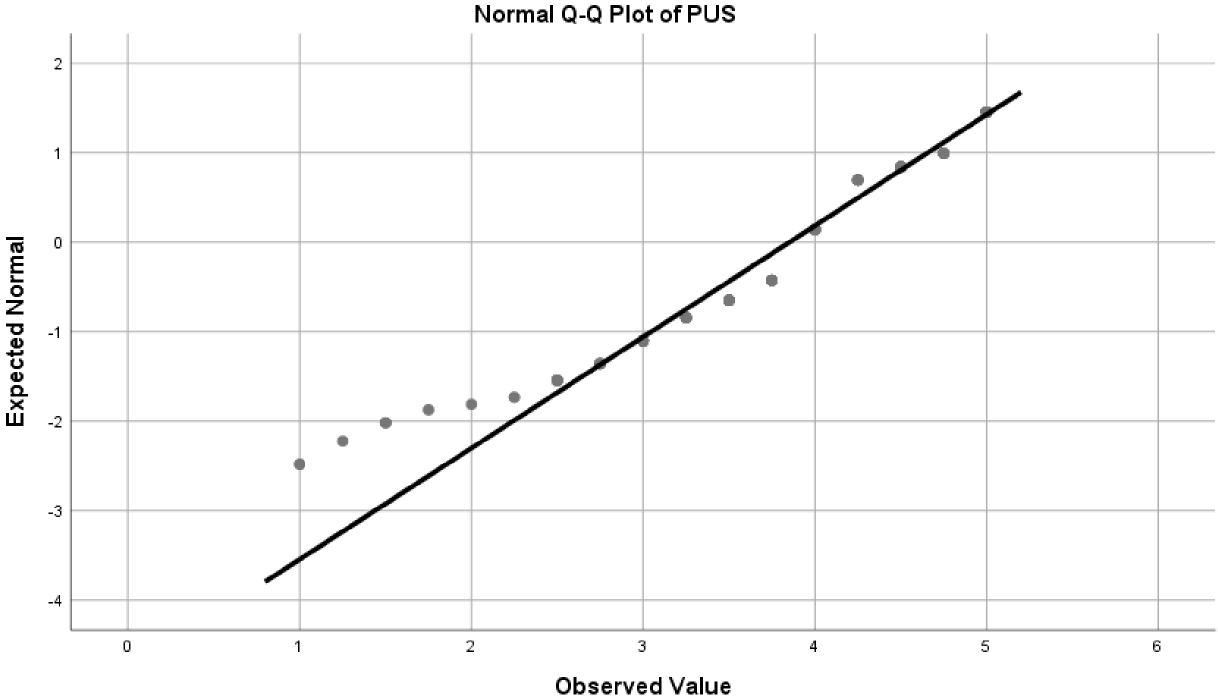
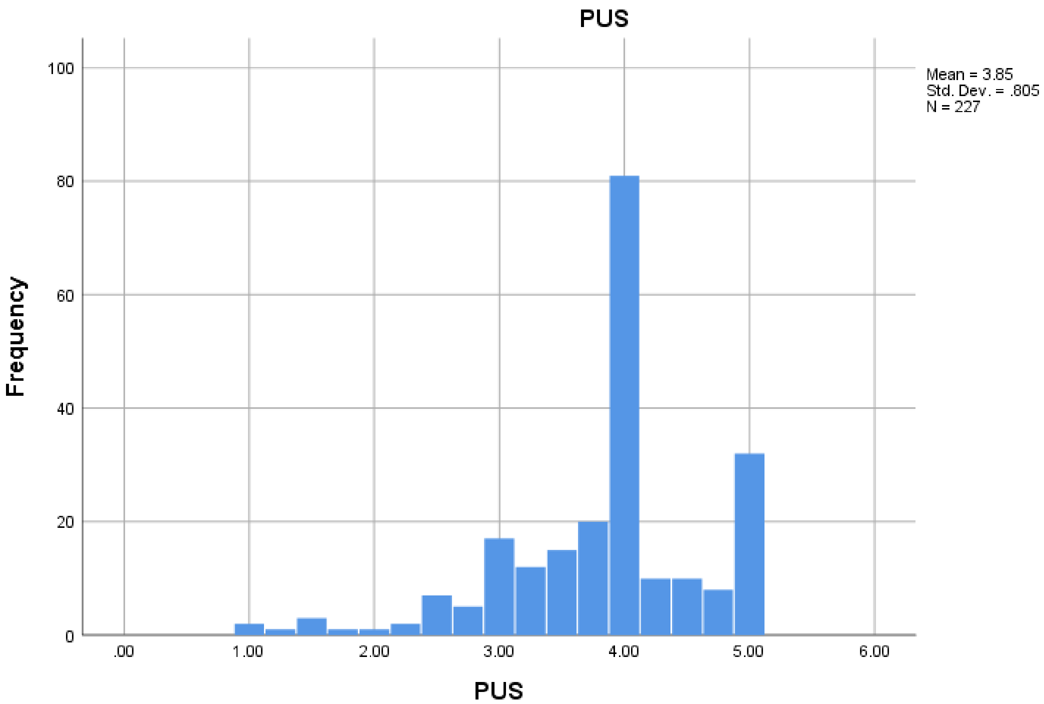


Figure B.13: Histogram and Q-Q plot of response data for construct PUS. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".



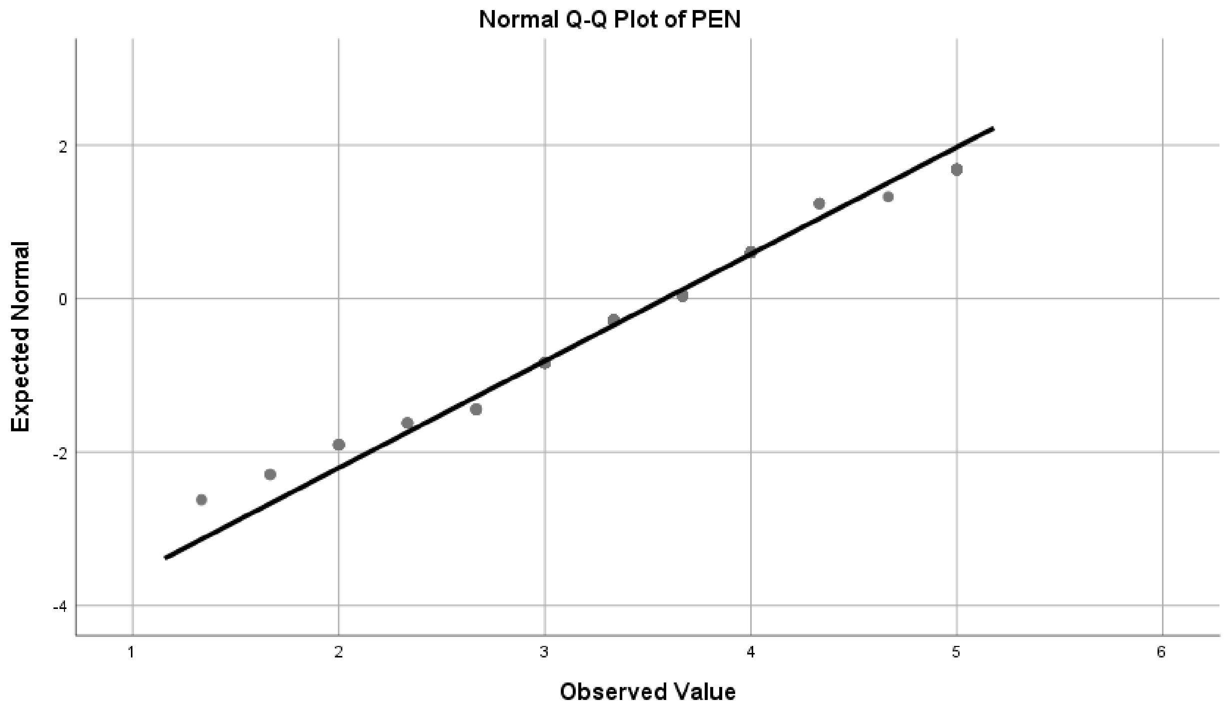
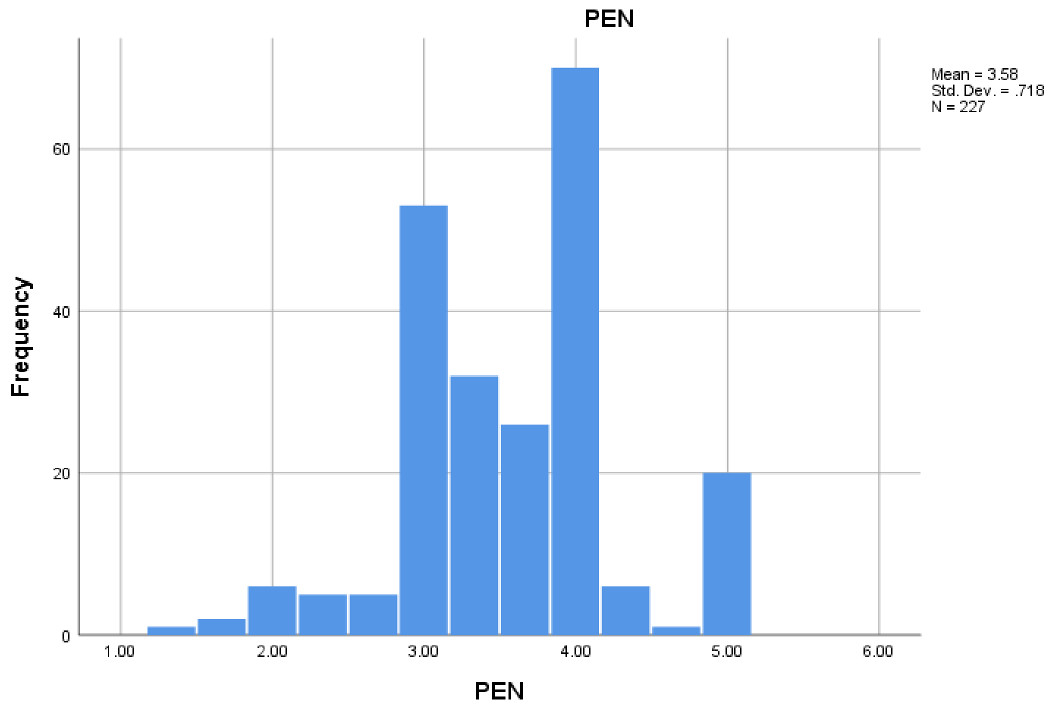


Figure B.14: Histogram and Q-Q plot of response data for construct PEN. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".



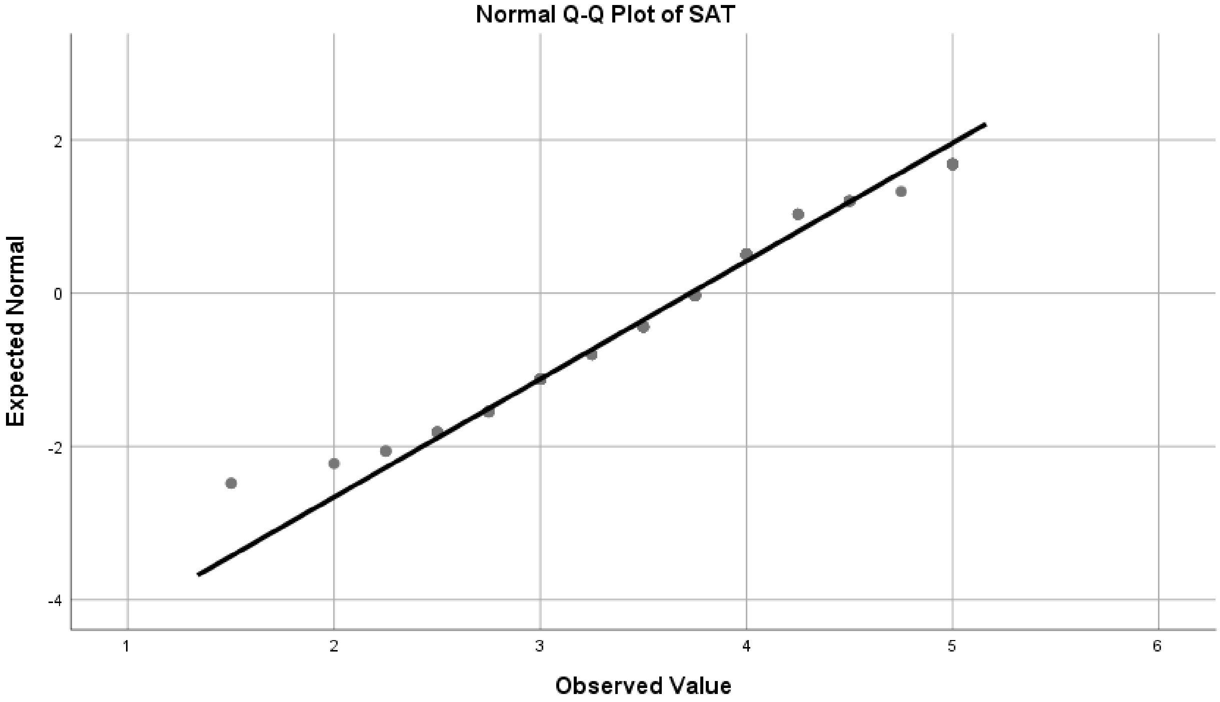
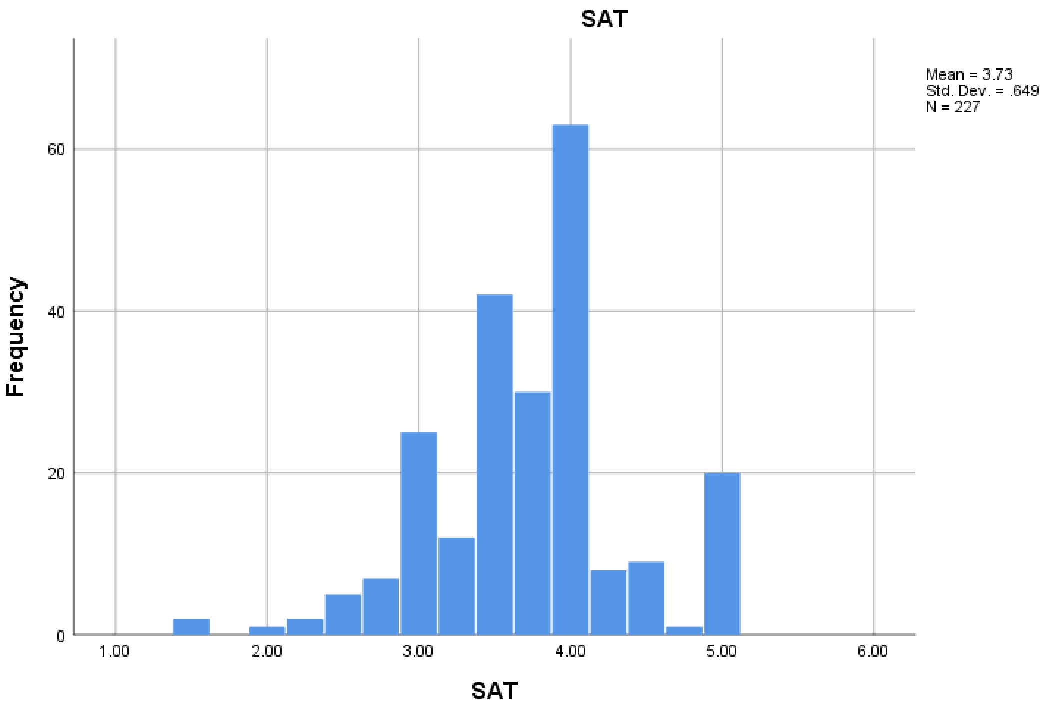


Figure B.15: Histogram and Q-Q plot of response data for construct SAT. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".



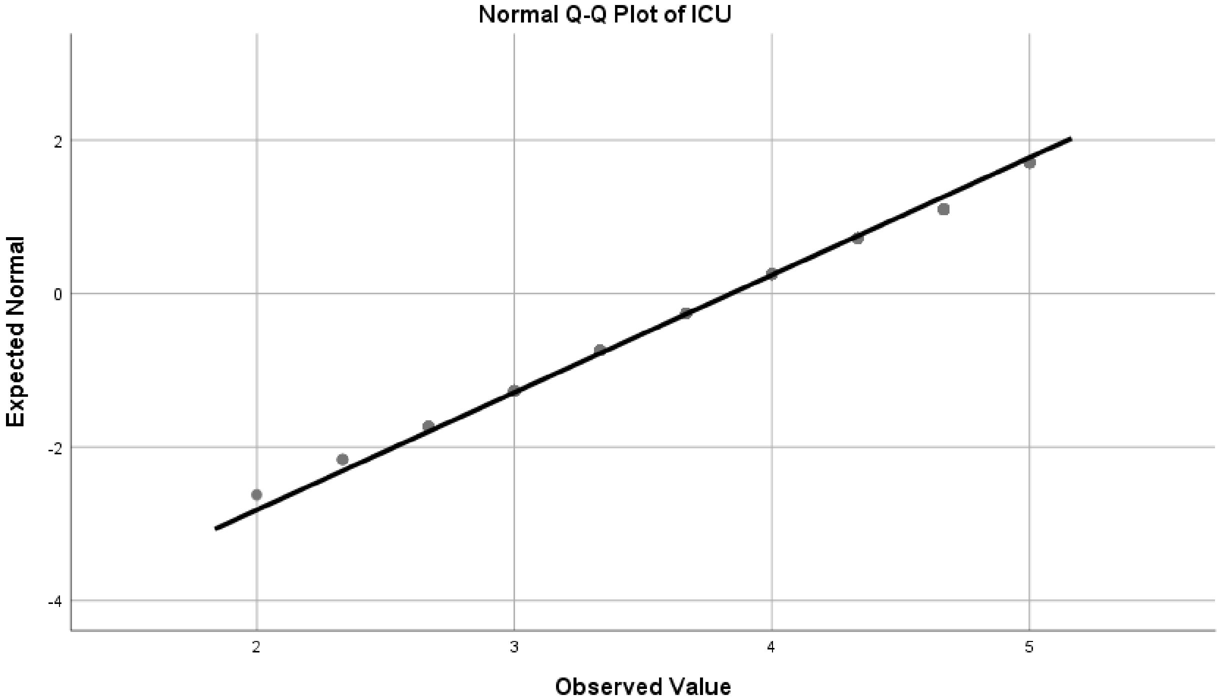


Figure B.16: Histogram and Q-Q plot of response data for construct ICU. Source: Kyriakaki, E. (2026) "An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services".

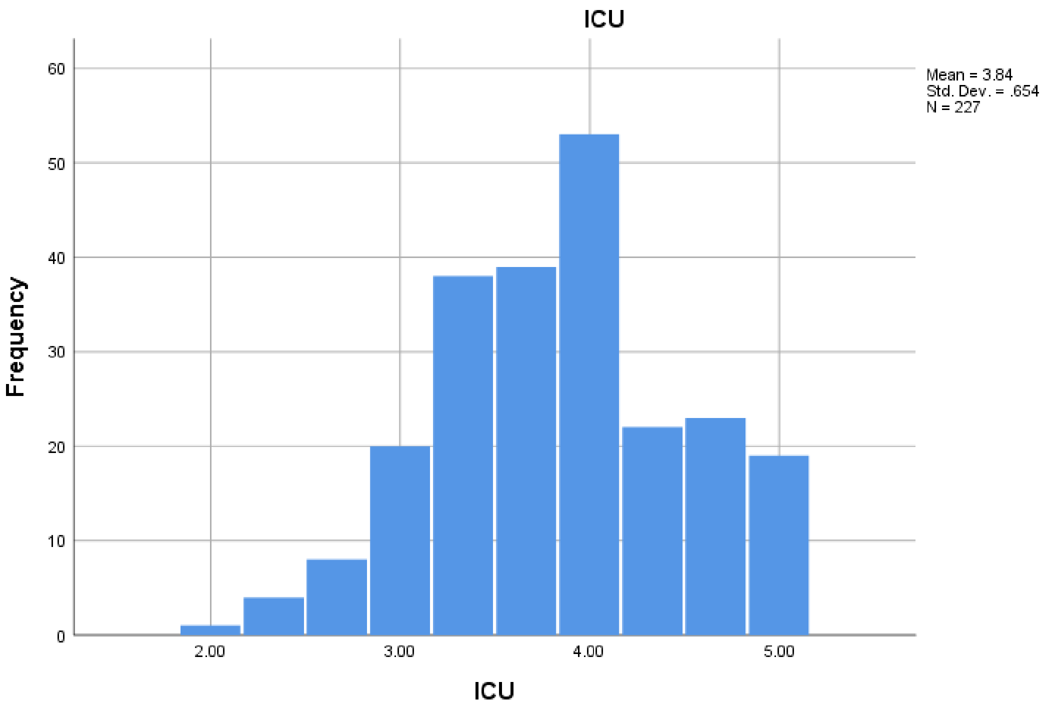


Table B.1
Descriptive Statistics of Questionnaire Items and Grouped Constructs (N = 227)

Variable	Valid	Missing	Mean	Std. Deviation
My experience from using AI was better than I expected	227	0	3.7621	0.79588
The level of service from using AI was better than I expected	227	0	3.6916	0.78823
Overall, most of my expectations from using AI were confirmed	227	0	3.7269	0.76154
Using AI enhances my effectiveness in managing tourism and hospitality services	227	0	3.8458	0.79156
My tourism and hospitality-related tasks were easier to complete with AI	227	0	3.6344	0.84312
I can save time in managing tourism and hospitality services by using AI	227	0	3.9339	0.84667
Overall, AI is useful in managing tourism and hospitality services	227	0	3.9736	0.72820
AI helped me improve my performance in managing multiple tasks	227	0	3.8590	0.85053
I find AI very useful in my daily work	227	0	3.8590	0.86087
Using AI enhances my effectiveness in carrying out my planned work	227	0	3.7885	0.93565
Using AI helps me perform many tasks more easily	227	0	3.8987	0.84840
Using AI was entertaining	227	0	3.5683	0.79180
Using AI was enjoyable	227	0	3.4714	0.80530
Using AI was pleasant	227	0	3.7093	0.74907
I was satisfied with my overall experience with AI	227	0	3.9075	0.72581
I was pleased with my overall experience with AI	227	0	3.9207	0.67369
I was happy with my overall experience with AI	227	0	3.4890	0.80574
I was excited about my overall experience with AI	227	0	3.5903	0.79517
I intend to continue using AI rather than stop using it	227	0	4.0485	0.73613
I intend to continue using AI rather than use alternative means	227	0	3.8590	0.87109
If I could, I would like to stop using AI	227	0	2.3833	1.15914
CON	227	0	3.7269	0.69961
PPE	227	0	3.8469	0.70040
PUS	227	0	3.8513	0.80491
PEN	227	0	3.5830	0.71805
SAT	227	0	3.7269	0.64942

Variable	**Valid**	**Missing**	**Mean**	**Std. Deviation**
ICU	227	0	3.8414	0.65353

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.2
Distribution of Responses per Questionnaire Item (N = 227)

Item	**Strongly Disagree n (%)**	**Disagree n (%)**	**Neutral n (%)**	**Agree n (%)**	**Strongly Agree n (%)**
My experience was better than expected	2 (0.9%)	12 (5.3%)	57 (25.1%)	123 (54.2%)	33 (14.5%)
Service level better than expected	3 (1.3%)	12 (5.3%)	62 (27.3%)	125 (55.1%)	25 (11.0%)
Expectations confirmed	3 (1.3%)	10 (4.4%)	57 (25.1%)	133 (58.6%)	24 (10.6%)
AI enhances effectiveness	6 (2.6%)	7 (3.1%)	34 (15.0%)	149 (65.6%)	31 (13.7%)
Tasks easier with AI	6 (2.6%)	12 (5.3%)	65 (28.6%)	120 (52.9%)	24 (10.6%)
Save time with AI	9 (4.0%)	3 (1.3%)	26 (11.5%)	145 (63.9%)	44 (19.4%)
AI is useful	3 (1.3%)	6 (2.6%)	27 (11.9%)	149 (65.6%)	42 (18.5%)
Improve performance	5 (2.2%)	10 (4.4%)	40 (17.6%)	129 (56.8%)	43 (18.9%)
Useful in daily work	4 (1.8%)	11 (4.8%)	45 (19.8%)	120 (52.9%)	47 (20.7%)
Enhances planned work	7 (3.1%)	13 (5.7%)	47 (20.7%)	114 (50.2%)	46 (20.3%)
Helps perform tasks easily	4 (1.8%)	8 (3.5%)	46 (20.3%)	118 (52.0%)	51 (22.5%)
Entertaining	1 (0.4%)	15 (6.6%)	90 (39.6%)	96 (42.3%)	25 (11.0%)
Enjoyable	3 (1.3%)	15 (6.6%)	102 (44.9%)	86 (37.9%)	21 (9.3%)
Pleasant	1 (0.4%)	12 (5.3%)	64 (28.2%)	125 (55.1%)	25 (11.0%)
Satisfied	3 (1.3%)	5 (2.2%)	38 (16.7%)	145 (63.9%)	36 (15.9%)
Pleased	0 (0.0%)	6 (2.6%)	43	141	37 (16.3%)

Item	Strongly Disagree n (%)	Disagree n (%)	Neutral n (%)	Agree n (%)	Strongly Agree n (%)
			(18.9%)	(62.1%)	
Happy	2 (0.9%)	16 (7.0%)	101 (44.5%)	85 (37.4%)	23 (10.1%)
Excited	2 (0.9%)	12 (5.3%)	89 (39.2%)	98 (43.2%)	26 (11.5%)
Continue using AI	2 (0.9%)	7 (3.1%)	23 (10.1%)	141 (62.1%)	54 (23.8%)
Continue vs alternatives	1 (0.4%)	18 (7.9%)	44 (19.4%)	113 (49.8%)	51 (22.5%)
Would stop using AI	56 (24.7%)	85 (37.4%)	41 (18.1%)	33 (14.5%)	12 (5.3%)

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.*

Table B.3
Internal Consistency Reliability of Study Constructs (N = 227)

Construct	Items (n)	Cronbach's α	Corrected Item-Total Correlation (Range)	Cronbach's α if Item Deleted (Range)
Confirmation of Expectations (CON)	3	.875	.722 - .792	.794 - .857
Perceived Performance (PPE)	4	.894	.682 - .828	.845 - .896
Perceived Usefulness (PUS)	4	.940	.830 - .873	.916 - .929
Perceived Enjoyment (PEN)	3	.906	.765 - .841	.841 - .905
Satisfaction (SAT)	4	.886	.716 - .820	.833 - .870
Intention to Continue Use (ICU)	3	.468	.127 - .447	.175 - .747

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services.*

Table B.4. Spearman Correlations between the 6 scales of the research

			CON	PPE	PUS	PEN	SAT	ICU
Spearman's rho	CON	Correlation Coefficient	1.000	.593**	.440**	.567**	.651**	.424**
		Sig. (2-tailed)	.	.000	.000	.000	.000	.000
		N	227	227	227	227	227	227
	PPE	Correlation Coefficient	.593**	1.000	.640**	.482**	.610**	.477**
		Sig. (2-tailed)	.000	.	.000	.000	.000	.000
		N	227	227	227	227	227	227
	PUS	Correlation Coefficient	.440**	.640**	1.000	.383**	.597**	.382**
		Sig. (2-tailed)	.000	.000	.	.000	.000	.000
		N	227	227	227	227	227	227
	PEN	Correlation Coefficient	.567**	.482**	.383**	1.000	.702**	.308**
		Sig. (2-tailed)	.000	.000	.000	.	.000	.000
		N	227	227	227	227	227	227
	SAT	Correlation Coefficient	.651**	.610**	.597**	.702**	1.000	.367**
		Sig. (2-tailed)	.000	.000	.000	.000	.	.000
		N	227	227	227	227	227	227
	ICU	Correlation Coefficient	.424**	.477**	.382**	.308**	.367**	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.
		N	227	227	227	227	227	227

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention t continue use AI technology for hospitality and tourism services*.

Table B.5. Regression fit

Hypothesis	DV	IV	β (Linear)	R^2	F(1,225)	p	ΔR^2	ΔF p	Polynomial Supported
H1	PPE	CON	.620	.385	140.59	<.001	.003	.314	No
H2	PUS	CON	.430	.185	51.16	<.001	.002	.509	No
H3	PEN	CON	.544	.296	94.77	<.001	.034	.001	Yes
H4	SAT	PPE	.621	.385	141.12	<.001	.049	<.001	Yes
H5	SAT	PUS	.597	.356	124.63	<.001	.042	<.001	Yes
H6	SAT	PEN	.731	.535	258.52	<.001	.003	.201	No
H7	ICU	PEN	.354	.125	32.23	<.001	.012	.082	No
H8	ICU	PUS	.430	.185	51.12	<.001	.012	.069	No
H9	ICU	SAT	.434	.189	52.34	<.001	.004	.288	No

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.6. CFA including Q32_ICU3

Confirmatory Factor Analysis including Q32_ICU3

Model fit

Chi-square test

Model	X^2	df	p
Baseline model	3466.358	171	
Factor model	304.557	137	< .001

Note. The estimator is ML. The test statistic is standard. The standard error method is standard.

Parameter estimates

Factor loadings

						95% Confidence Interval	
Factor	Indicator	Estimate	Std. Error	z-value	p	Lower	Upper
CON	Q12_CON1	1.000	0.000			1.000	1.000
	Q13_CON2	1.052	0.066	15.92	< .001	0.923	1.182
	Q14_CON3	0.897	0.066	13.55	< .001	0.767	1.027
PPE	Q15_PPE1	1.000	0.000			1.000	1.000
	Q16_PPE2	0.940	0.074	12.68	< .001	0.795	1.086
	Q17_PPE3	1.022	0.072	14.12	< .001	0.880	1.164
PUS	Q19_PUS1	1.000	0.000			1.000	1.000
	Q20_PUS2	1.048	0.053	19.64	< .001	0.944	1.153
	Q21_PUS3	1.144	0.058	19.80	< .001	1.031	1.257
	Q22_PUS4	1.014	0.054	18.89	< .001	0.909	1.119
PEN	Q23_PEN1	1.000	0.000			1.000	1.000
	Q24_PEN2	1.026	0.052	19.70	< .001	0.924	1.128
	Q25_PEN3	0.857	0.053	16.31	< .001	0.754	0.960
SAT	Q26_SAT1	1.000	0.000			1.000	1.000
	Q27_SAT2	0.928	0.041	22.49	< .001	0.847	1.009
	Q28_SAT3	0.834	0.065	12.85	< .001	0.707	0.961
ICU	Q30_ICU1	1.000	0.000			1.000	1.000
	Q31_ICU2	1.054	0.105	10.08	< .001	0.849	1.259
	Q32_ICU3	0.236	0.139	1.694	.090	-0.037	0.508

Factor variances

					95% Confidence Interval	
Factor	Estimate	Std. Error	z-value	p	Lower	Upper
CON	0.442	0.059	7.516	< .001	0.327	0.558
PPE	0.451	0.059	7.630	< .001	0.335	0.567
PUS	0.549	0.067	8.234	< .001	0.418	0.680
PEN	0.507	0.059	8.533	< .001	0.390	0.623
SAT	0.447	0.050	8.966	< .001	0.349	0.545
ICU	0.368	0.056	6.621	< .001	0.259	0.476

Factor Covariances

							95% Confidence Interval	
			Estimate	Std. Error	z-value	p	Lower	Upper
CON	↔	PPE	0.325	0.044	7.404	< .001	0.239	0.411
CON	↔	PUS	0.234	0.041	5.717	< .001	0.154	0.315
CON	↔	PEN	0.287	0.042	6.797	< .001	0.204	0.369
CON	↔	SAT	0.330	0.042	7.827	< .001	0.247	0.413
CON	↔	ICU	0.243	0.038	6.304	< .001	0.167	0.318

PPE	↔	PUS	0.368	0.048	7.711	< .001	0.274	0.462
PPE	↔	PEN	0.241	0.041	5.926	< .001	0.161	0.321
PPE	↔	SAT	0.309	0.041	7.472	< .001	0.228	0.390
PPE	↔	ICU	0.276	0.040	6.822	< .001	0.196	0.355
PUS	↔	PEN	0.198	0.041	4.838	< .001	0.118	0.278
PUS	↔	SAT	0.307	0.043	7.198	< .001	0.223	0.391
PUS	↔	ICU	0.271	0.042	6.509	< .001	0.189	0.352
PEN	↔	SAT	0.338	0.043	7.901	< .001	0.254	0.422
PEN	↔	ICU	0.267	0.040	6.631	< .001	0.188	0.346
SAT	↔	ICU	0.289	0.039	7.377	< .001	0.212	0.365

Residual variances

					95% Confidence Interval	
Indicator	Estimate	Std. Error	z-value	p	Lower	Upper
Q12_CON1	0.188	0.024	7.776	< .001	0.141	0.236
Q13_CON2	0.129	0.021	6.075	< .001	0.087	0.170
Q14_CON3	0.221	0.025	8.738	< .001	0.172	0.271
Q15_PPE1	0.172	0.024	7.060	< .001	0.125	0.220
Q16_PPE2	0.308	0.035	8.921	< .001	0.241	0.376
Q17_PPE3	0.242	0.030	7.999	< .001	0.183	0.301
Q19_PUS1	0.171	0.020	8.616	< .001	0.132	0.210
Q20_PUS2	0.134	0.017	7.773	< .001	0.100	0.168
Q21_PUS3	0.153	0.020	7.644	< .001	0.114	0.192
Q22_PUS4	0.152	0.018	8.284	< .001	0.116	0.188
Q23_PEN1	0.117	0.018	6.408	< .001	0.082	0.153
Q24_PEN2	0.112	0.019	6.020	< .001	0.075	0.148
Q25_PEN3	0.186	0.021	8.807	< .001	0.145	0.228
Q26_SAT1	0.077	0.013	5.969	< .001	0.052	0.103
Q27_SAT2	0.067	0.011	5.961	< .001	0.045	0.088
Q28_SAT3	0.335	0.034	9.979	< .001	0.269	0.401
Q30_ICU1	0.172	0.032	5.337	< .001	0.109	0.235
Q31_ICU2	0.347	0.045	7.712	< .001	0.259	0.435
Q32_ICU3	1.317	0.124	10.62	< .001	1.074	1.560

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.7. CFA omitting Q32_ICU3

Confirmatory Factor Analysis omitting Q32_ICU3

Model fit

Chi-square test

Model	Χ²	df	P
Baseline model	3756.010	171	
Factor model	309.466	137	< .001

Note. The estimator is ML. The test statistic is standard. The standard error method is standard.

Parameter estimates

Factor loadings

						95% Confidence Interval	
Factor	Indicator	Estimate	Std. Error	z-value	p	Lower	Upper

Factor loadings

						95% Confidence Interval	
Factor	Indicator	Estimate	Std. Error	z-value	p	Lower	Upper
CON	Q12_CON1	1.000	0.000			1.000	1.000
	Q13_CON2	1.054	0.066	15.85	< .001	0.924	1.184
	Q14_CON3	0.897	0.066	13.50	< .001	0.767	1.027
PPE	Q15_PPE1	1.000	0.000			1.000	1.000
	Q16_PPE2	0.917	0.072	12.68	< .001	0.775	1.059
	Q17_PPE3	1.063	0.067	15.78	< .001	0.931	1.195
	Q18_PPE4	0.979	0.056	17.61	< .001	0.870	1.087
PUS	Q19_PUS1	1.000	0.000			1.000	1.000
	Q20_PUS2	1.049	0.054	19.49	< .001	0.944	1.155
	Q21_PUS3	1.148	0.058	19.77	< .001	1.034	1.262
	Q22_PUS4	1.018	0.054	18.90	< .001	0.913	1.124
PEN	Q23_PEN1	1.000	0.000			1.000	1.000
	Q24_PEN2	1.026	0.052	19.69	< .001	0.924	1.128
	Q25_PEN3	0.858	0.053	16.32	< .001	0.755	0.961
SAT	Q26_SAT1	1.000	0.000			1.000	1.000
	Q27_SAT2	0.930	0.041	22.49	< .001	0.848	1.011
	Q28_SAT3	0.835	0.065	12.85	< .001	0.707	0.962
ICU	Q30_ICU1	1.000	0.000			1.000	1.000
	Q31_ICU2	1.048	0.103	10.17	< .001	0.846	1.250

Factor variances

					95% Confidence Interval	
Factor	Estimate	Std. Error	z-value	p	Lower	Upper
CON	0.442	0.059	7.502	< .001	0.327	0.558
PPE	0.448	0.058	7.769	< .001	0.335	0.561
PUS	0.547	0.067	8.206	< .001	0.416	0.677
PEN	0.507	0.059	8.533	< .001	0.390	0.623
SAT	0.447	0.050	8.956	< .001	0.349	0.544
ICU	0.368	0.055	6.652	< .001	0.260	0.476

Factor Covariances

							95% Confidence Interval	
			Estimate	Std. Error	z-value	p	Lower	Upper
CON	↔	PPE	0.299	0.042	7.135	< .001	0.217	0.381
CON	↔	PUS	0.234	0.041	5.709	< .001	0.153	0.314
CON	↔	PEN	0.286	0.042	6.793	< .001	0.204	0.369
CON	↔	SAT	0.330	0.042	7.818	< .001	0.247	0.412
CON	↔	ICU	0.242	0.038	6.296	< .001	0.167	0.318
PPE	↔	PUS	0.370	0.047	7.837	< .001	0.278	0.463
PPE	↔	PEN	0.233	0.039	5.902	< .001	0.156	0.310
PPE	↔	SAT	0.294	0.040	7.358	< .001	0.216	0.373
PPE	↔	ICU	0.281	0.040	7.039	< .001	0.203	0.360
PUS	↔	PEN	0.197	0.041	4.834	< .001	0.117	0.277
PUS	↔	SAT	0.306	0.043	7.185	< .001	0.222	0.389
PUS	↔	ICU	0.270	0.042	6.507	< .001	0.189	0.352
PEN	↔	SAT	0.338	0.043	7.900	< .001	0.254	0.422
PEN	↔	ICU	0.270	0.040	6.688	< .001	0.191	0.350
SAT	↔	ICU	0.290	0.039	7.406	< .001	0.213	0.367

Residual variances

Indicator	Estimate	Std. Error	z-value	p	95% Confidence Interval	
					Lower	Upper
Q12_CON1	0.189	0.024	7.734	< .001	0.141	0.236
Q13_CON2	0.128	0.021	5.971	< .001	0.086	0.169
Q14_CON3	0.222	0.025	8.717	< .001	0.172	0.272
Q15_PPE1	0.176	0.021	8.401	< .001	0.135	0.217
Q16_PPE2	0.331	0.034	9.670	< .001	0.264	0.398
Q17_PPE3	0.208	0.024	8.505	< .001	0.160	0.256
Q18_PPE4	0.099	0.015	6.832	< .001	0.071	0.128
Q19_PUS1	0.173	0.020	8.675	< .001	0.134	0.213
Q20_PUS2	0.136	0.017	7.850	< .001	0.102	0.170
Q21_PUS3	0.151	0.020	7.625	< .001	0.112	0.190
Q22_PUS4	0.149	0.018	8.258	< .001	0.114	0.185
Q23_PEN1	0.118	0.018	6.416	< .001	0.082	0.154
Q24_PEN2	0.112	0.019	6.032	< .001	0.076	0.149
Q25_PEN3	0.186	0.021	8.803	< .001	0.145	0.227
Q26_SAT1	0.078	0.013	5.998	< .001	0.052	0.103
Q27_SAT2	0.066	0.011	5.923	< .001	0.044	0.088
Q28_SAT3	0.335	0.034	9.978	< .001	0.269	0.401
Q30_ICU1	0.172	0.032	5.390	< .001	0.109	0.234
Q31_ICU2	0.351	0.045	7.858	< .001	0.264	0.439

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.8: Mediation analysis- Effect of CON on SAT through PUS. CON: Confirmation of Expectations, SAT: Satisfaction, PUS: Perceived Usefulness.

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 4

Y : SAT

X : CON

M : PUS

Sample

Size: 227

****

OUTCOME VARIABLE:

PUS

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4304	.1853	.5302	51.1612	1.0000	225.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.0058	.2625	7.6407	.0000	1.4885	2.5231
CON	.4952	.0692	7.1527	.0000	.3588	.6316

****
*

OUTCOME VARIABLE:

SAT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7556	.5710	.1826	149.0513	2.0000	224.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.7828	.1729	4.5280	.0000	.4421	1.1234
CON	.4763	.0450	10.5828	.0000	.3876	.5650
PUS	.3035	.0391	7.7587	.0000	.2264	.3806

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI

```
   .4763     .0450   10.5828     .0000     .3876     .5650
```

Indirect effect(s) of X on Y:

```
       Effect     BootSE   BootLLCI   BootULCI
PUS     .1503      .0475      .0678      .2513
```

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.9: Mediation Analysis-Effect of CON on ICU through PUS. CON: Confirmation of Expectations, ICU: Intention to Continue Use, PUS: Perceived Usefulness.

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 4

Y : ICU

X : CON

M : PUS

Sample

Size: 227

****

OUTCOME VARIABLE:

PUS

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4304	.1853	.5302	51.1612	1.0000	225.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.0058	.2625	7.6407	.0000	1.4885	2.5231
CON	.4952	.0692	7.1527	.0000	.3588	.6316

****

OUTCOME VARIABLE:

ICU

Model Summary

R	R-sq	MSE	F	df1	df2	p
.5116	.2617	.3181	39.7006	2.0000	224.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.8413	.2282	8.0684	.0000	1.3916	2.2910
CON	.2864	.0594	4.8201	.0000	.1693	.4035
PUS	.2422	.0516	4.6901	.0000	.1404	.3440

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.2864	.0594	4.8201	.0000	.1693	.4035

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
PUS	.1199	.0369	.0590	.2025

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.10: Mediation Analysis- Effect of CON on SAT through PEN. CON: Confirmation of Expectations, SAT: Satisfaction, PEN: Perceived Enjoyment.

Run MATRIX procedure:

*************** PROCESS Procedure for SPSS Version 4.2 ***************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****
*

Model : 4

Y : SAT

X : CON

M : PEN

Sample

Size: 227

****
*

OUTCOME VARIABLE:

PEN

Model Summary

R	R-sq	MSE	F	df1	df2	p
.5444	.2964	.3644	94.7646	1.0000	225.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.5006	.2176	6.8951	.0000	1.0717	1.9294
CON	.5587	.0574	9.7347	.0000	.4456	.6718

****

OUTCOME VARIABLE:

SAT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.8023	.6437	.1516	202.3288	2.0000	224.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.6900	.1545	4.4661	.0000	.3855	.9945
CON	.3654	.0441	8.2788	.0000	.2784	.4524
PEN	.4675	.0430	10.8720	.0000	.3828	.5523

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI

.3654	.0441	8.2788	.0000	.2784	.4524

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
PEN	.2612	.0394	.1861	.3397

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B. 11: Mediation Analysis- Effect of CON on ICU through PEN. CON: Confirmation of Expectations, ICU: Intention to Continue Use, PEN: Perceived Enjoyment.

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

Written by Andrew F. Hayes, Ph.D. www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 4

Y : ICU

X : CON

M : PEN

Sample

Size: 227

****

OUTCOME VARIABLE:

PEN

Model Summary

R R-sq MSE F df1 df2 p

.5444	.2964	.3644	94.7646	1.0000	225.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.5006	.2176	6.8951	.0000	1.0717	1.9294
CON	.5587	.0574	9.7347	.0000	.4456	.6718

****
*

OUTCOME VARIABLE:

ICU

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4569	.2087	.3410	29.5433	2.0000	224.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.0996	.2317	9.0621	.0000	1.6430	2.5562
CON	.3216	.0662	4.8593	.0000	.1912	.4521
PEN	.1516	.0645	2.3508	.0196	.0245	.2787

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.3216	.0662	4.8593	.0000	.1912	.4521

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
PEN	.0847	.0440	.0041	.1754

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Table B.12: Mediation Analysis- Effect of CON on SAT through PPE. CON: Confirmation of Expectations, SAT: Satisfaction, PPE: Perceived Performance.

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 4

Y : SAT

X : CON

M : PPE

Sample

Size: 227

****

OUTCOME VARIABLE:

PPE

Model Summary

R	R-sq	MSE	F	df1	df2	p
.6201	.3845	.3033	140.5846	1.0000	225.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.5332	.1985	7.7224	.0000	1.1419	1.9244
CON	.6208	.0524	11.8568	.0000	.5176	.7240

****

OUTCOME VARIABLE:

SAT

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7226	.5221	.2033	122.3702	2.0000	224.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.9244	.1829	5.0556	.0000	.5641	1.2847
CON	.4375	.0547	8.0042	.0000	.3298	.5452
PPE	.3047	.0546	5.5813	.0000	.1971	.4123

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.4375	.0547	8.0042	.0000	.3298	.5452

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
PPE	.1892	.0651	.0762	.3302

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Source: Kyriakaki, E. (2026). *An exploration of the roles of perceived performance, perceived usefulness and perceived enjoyment on intention to continue use AI technology for hospitality and tourism services*.

Author's Statement:

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