



The Impact of Artificial Intelligence on Enhancing Guest Experience of Hotel Industry in Kuala Lumpur, Malaysia

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Abstract

Utilizing the Technology Acceptance Model (TAM) as its theoretical backbone, this research examines artificial intelligence integration into hotel guest experiences of Kuala Lumpur. The study explores relationships between Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Toward Using AI (ATUI), and Guest Satisfaction (GUSA), investigating Attitude Toward Using AI (AUAI) as a mediator and examining the moderating role of guest age, previous AI experience and trip purpose. Through the empirical survey of 630 hotel customers and analyzing the data with structure equation model (SEM), this study finds that Perceived Usefulness and Perceived Ease of Use have significant impacts on Attitude Toward Using AI (AUAI) and thus indirectly affect Guest Satisfaction (GUSA); meanwhile, Perceived Usefulness and Perceived Ease of Use are directly influencing customer satisfaction simultaneously so that there are parallel direct and indirect effects. Adding to the Technology Acceptance Model (TAM)-strain in hospitality research, this result places post-adoption satisfaction as a primary outcome. Disparities between demographic and experience segments imply specificity in implementing AI. The findings have broader implications in both theoretical and practical ways: theoretically, it furthers the understanding of AI adoption within services context by incorporating technology acceptance with satisfaction outcomes; practically, it provides hoteliers and developers of AI technologies with practical steps toward creating solutions that are useful, easy to use, and constructs favorable guest attitudes insights valuable for strategically fast growing urban destinations such as Kuala Lumpur.

Keywords: Artificial Intelligence, Perceived Usefulness, Perceived Ease of Use, Attitude Towards Using Artificial Intelligence, Guest Satisfaction, Hospitality Industry.

1. Introduction

From a computer science curiosity to a full-fledged technological force, artificial intelligence (AI) has already transformed various industries – including healthcare, finance, and retail – except for one - hospitality. Artificial Intelligence, AI) is the capability of systems to accurately interpret the information from their external environment, learn from such information and then apply that learning in pursuit of specific goals (Kennedy & Wanless, 2022), and infuses everything with further efficiency, personalization, and competitiveness. While in the hospitality sector, essentially based on people interaction, AI utilization is revolutionizing guest experience with features such as chatbots, facial recognition check-in tasks, predictive analytics and voice activated room controls (Lee et al., 2023; Rasheed et al., 2024). International hotel brands like Hilton, Marriott, and Accor are deploying AI solutions to maintain customer loyalty; similarly in areas such as Kuala Lumpur, Malaysia, the integration of (AI) is seen in Tourism Transformation Plan 2030 and Smart Tourism 4.0 strategies showing its role in the digitalization phenomenon (Modi & Kumar, 2025). Despite its advantages, challenges continue to exist in relation to privacy, trust, and depersonalization risk (especially in luxury hotels where emotional bonding is still of utmost importance) (Ivanov & Umbrello,

2021; Kumar et al., 2024). The Technology Acceptance Model (TAM), focusing on perceived usefulness and ease of use is a useful lens through which the adoption and reaction to AI-enabled services by guests can be examined (Mungoli, 2023). As such, this research serves to explore the applicability of AI to improve guest satisfaction in Kuala Lumpur luxury hotels and fills gaps theoretical and practical while providing implications for hotel managers, policy makers and system designers on striking a balance between technology advancement and service provision in today's competitive post-pandemic hospitality landscape.

2. Literature Review

In the last ten years, the concept of Artificial Intelligence (AI) has become a reshaping factor in service-based industries, namely, hospitality, where guest experience is a major factor in determining competitiveness and the long-term survival of a business. The most recent studies have highlighted those technologies empowered by AI (chatbots, service robots, or recommendation engines) could vastly improve the efficiency, personalization, and, overall, the quality of services (Ali et al., 2025; Chen et al., 2023). Referring to Technology Acceptance Model (TAM), scholars continually pay attention to the dualistic utilization of Perceived Usefulness (PUSE) and Perceived Ease of Use (PEUS) determining the user attitudes and behavioral intentions (Buhalis et al., 2023; Chorna et al., 2024).

The capital city, Kuala Lumpur, plays pivotal role in this digital transition. Being the most advanced, as well as the most urbanized and technologically advanced city of Malaysia, it serves as a core of top-level tourist and hospitality growth (S. Sharma et al., 2025). The choice of Kuala Lumpur to be the center of this study was because it has many international hotel chains and a good internet facility as well as access to a large pool of tech-savvy target audience. According to the Tourism Malaysia Performance Report (2023), Kuala Lumpur has remained the top destination of leisure and business travelers making it a suitable setting to study the effect of AI on guest happiness (Rajendran et al., 2023). Even though there are significant changes in the area of infrastructure development and incorporating technology, there is still a gap in research pertaining the perceptions and experience of guests in a Malaysian hotel in regard to AI in academia (Shanmugam et al., 2024). Whereas international research based on drawing evidence on guest satisfaction and hotel performances by using AI has extensively investigated the influence of AI on both matters, local empirical studies that take into account the context of cultural norms and expectations of guests in Malaysia, along with their digital behavior, are in short supply (Chorna et al., 2024). This gives a chance of putting the world discoveries into perspective and evaluating it on the parameters of the Malaysian socio-economic and technological environment. Moreover, cultural, and behavioral peculiarities of the Malaysian consumers can have certain impact on incorporation and acceptance of AI. The entire Malaysian hospitality simple lies on the high-contact service culture whereby tailored human interaction is conventionally regarded as one (Chorna et al., 2024). The decision to introduce AI to this environment requires careful planning to avoid degrading the expectations of the guests without missing the benefits that come with technological advantage. It is not to say that the issue of convergence of AI and experiential hospitality lacks any research in Malaysia; rather, the gap in existing literature demonstrates the need to conduct this study.

Although significant progress has been made in terms of technological and functional properties of AI and its influences on visitors, there are still some notable gaps in understanding its psychological and behavioral as well as contextual impacts on visitors representing every segment. Although one may find considerable domains of specific AI applications in urban luxury hotels, such as a robot concierge or a chatbot interface, very little research has focused on how AI should be implemented to fully immerse its guests in the experience (in-room services, check-in/check-out, feedback mechanisms). Although the guest happiness is often linked to the personalization of service (Zhang et al., 2022), the study fails to differentiate between the functional (efficiency, accuracy) and emotional (comfort, trust, empathy) satisfaction. Emotion-aware robots, predictive concierge tools and other AI apps are also implemented, but the most part of empirical studies tend to focus on performance and not on emotional impact (Elshaer & Marzouk, 2024). In turn, further emotional studies are needed to test the emotional feelings of guests affected by AI in hotels. Although Artificial Intelligence (AI) has been studied in detail to learn about the influence it will have on the guest satisfaction through mediating variables such as perceived usefulness and attitude (Gajić et al., 2024; Ghosh & Thirugnanam, 2021), there is still a huge gap in the research that tracked the moderating attributes of the guest age group within the impact of attitude towards the use of Artificial Intelligence (AI) and Guest Satisfaction. Some researchers also suggest that the younger people have more adjustment to new technologies and may embrace the notion of AI services in a more positive light (Saxena et al., 2024; Talukder et al., 2024), whereas according to other researchers, the ageing

population is more likely to face usability issues, skepticism, or negative feelings towards interacting with AI-based systems (Traversa, 2024; Venkatraman & Kurtkoti, 2024). Despite these discoveries, not much has been conducted empirically regarding the moderating aspects of age, especially in a hospitality environment where the services need to be high touch where emotional comfort is needed and sought.

To fill the gap in these areas of research, the study aims to investigate how Artificial Intelligence (AI) affects guest experience psychologically, behaviorally, and environmentally, with specific reference to the Malaysian hospitality setting. The embedding of AI applications has attracted substantial attention in previous research in the literature, where a number of studies have examined the role of chatbots (Saxena et al., 2024; Talukder et al., 2024) and service robots. Additionally, there is still a limited understanding on the emotional aspects about guests' satisfaction, as well as cultural impacts for AI adoption (Zhang et al., 2022). As Malaysian hotels have traditionally focused on high-touch service in hospitality offerings, this study will explore how AI can be incorporated effectively and unobtrusively into the guest experience without detracting from emotional elements such as trust, empathy, and personalized service. Ultimately, the findings from this study will provide insights into applying AI to hotel services in a culturally appropriate and evolving way that satisfies the need of Malaysian guests for functional effectiveness as well as emotional comfort.

3. Research Questions

The study is guided by the following research questions:

RQ1: How does Perceived Usefulness (PUSE) of AI influence guests' attitudes toward using AI in luxury hotels in Kuala Lumpur?

RQ2: How does Perceived Ease of Use (PEUS) of AI influence guests' attitudes toward using AI?

RQ3: What is the influence of Attitude Toward Using AI on guest satisfaction?

RQ4: To what extent does Perceived Usefulness (PUSE) of AI directly influence guest satisfaction?

RQ5: To what extent does Perceived Ease of Use (PEUS) of AI directly influence guest satisfaction?

RQ6: Does Attitude Toward Using AI mediate the relationship between PU and guest satisfaction?

RQ7: Does Attitude Toward Using AI mediate the relationship between PEU and guest satisfaction?

4. Research Objectives

Aligned with the research questions, the study aims to achieve the following objectives:

RO1: To examine the influence of Perceived Usefulness (PUSE) of AI on guests' attitudes toward using AI.

RO2: To investigate the influence of Perceived Ease of Use (PEUS) on guests' attitudes toward using AI.

RO3: To assess the impact of Attitude Toward Using AI on guest satisfaction.

RO4: To determine whether Perceived Usefulness (PUSE) directly influences guest satisfaction.

RO5: To determine whether Perceived Ease of Use (PEUS) directly influences guest satisfaction.

RO6: To explore whether Attitude Toward Using AI mediates the relationship between PU and guest satisfaction.

RO7: To explore whether Attitude Toward Using AI mediates the relationship between PEU and guest satisfaction.

R08: To evaluate the role of control variables (age, AI experience, and purpose of stay) in influencing guest satisfaction.

5. Hypothesis Development

This is a list of all the assumptions of the effect of artificial intelligence (AI) on the satisfaction of guests in luxury hotels in Kuala Lumpur, Malaysia. According to the given model, the following hypotheses were developed by the researcher.

Sub-Hypothesis of Perceived Usefulness (PUSE)

Perceived Usefulness (PUSE) of AI-enabled hotel services refers to the level to which guests, who receive the services of the hotel that is enabled with the AI, believe the technology enhances the quality of their experience, its efficiency, and its convenience. This paper operates PUSE to three dimensions; AI-Oriented Service Quality (AISQ); AI-Oriented Service Efficiency (AISE); AI-Accelerated Guest Convenience (AIGC). The subsequence sub-hypotheses are given below:

Relationship between AI Oriented Service Quality (AISQ) and Perceived Usefulness (PUSE) AI-Oriented Service Quality (AISQ) refers to the degree of precision, reliability, and high-level services offered by AI systems (e.g., chatbots, service robots, voice assistants) to patrons. Studies conclude that high service quality has a significant positive effect on customer perceived utility and favorable attitude towards technology adoption (Chotisarn & Phuthong, 2025). In hospitality, customers whose perceptions of utility are enhanced by AI systems with personalized, accurate, and timely service indicate a positive improvement (Ali et al., 2025; Talukder, 2024). The hypothesis of AISQ and PUSE are given below:

H1a: *AI oriented Service Quality (AISQ) positively influences Perceived Usefulness (PUSE).*

Relationship between AI Oriented Service Efficiency (AISE) and Perceived Usefulness (PUSE): AI Oriented Service Efficiency (AISE) refers to the ability of AI to perform service activities promptly, decrease waiting time and streamline processes. A study in technology-driven service environments shows that efficiency as a relevant factor determines the perceived usefulness of the latter because it has a direct impact on convenience and joy experienced by patrons (Naqvi et al., 2023). Guests perceive AI systems used in hotels that perform check-in services within a short time frame, speed up service requests, and provide real-time information updates to be more useful and acceptable (Torabi et al., 2022). The relationship between AISE and PUSE are given below:

H1b: *AI Oriented Service Efficiency (AISE) positively influences Perceived Usefulness (PUSE).*

Relationship Between AI Accelerated Guest Convenience (AIGC) and Perceived Usefulness (PUSE): The AI-Accelerated Guest Convenience (AIGC) refers to a level of improvement of how guests are provided by means of immediate access to services, predictive suggestions, and possibilities of self-service (Venkateswaran et al., 2024). Hospitality and tourism research show that technological amenities with a convenience orientation can greatly magnify perceived usefulness when artificial intelligence reduces the effort of a visitor and maximizes autonomy (Rajendran et al., 2023; Suhag et al., 2024). The hypothesis of AIGC and PUSE is given below:

H1c: *AI Accelerated Guest Convenience (AIGC) positively influences Perceived Usefulness (PUSE).*

Sub-Hypothesis of Perceived Ease of Use (PEUS)

Perceived Ease of Use (PEUS) refers to how easily the customers incorporate the interaction with the AI-enhanced hotel services into their lives. This framework emphasizes transparency of interactions with AI, balance between the ease of accessing and the usefulness of the AI and it all boils down to a lack of difficulty in learning and using an AI system. According to this study, PEUS can be defined along three dimensions: AI Interacts Clearly and Understandably (AICU), AI Easiness and Usefulness (AIEU), and AI Learning and AI Learnings and Operations is Effortless (AIOE). The following sub-hypothesis are proposed:

Relationship Between AI Interact Clearly and Understandably (AICU) and Perceived Ease of Use (PEUS): AI Interact Clearly and Understandably (AICD) refer to the ease with which users can understand AI-generated messages, commands, and

service protocols. Studies suggest that the experience of understandable human-computer interaction reduces mental load and increases the likelihood of exploiting a technology (Saxena et al., 2024). In the hotel industry, natural, user-friendly language employed by chatbots, kiosks, and robots supports the perception of superior usability and increases the intention to use technology positively (Acharya & Mahapatra, 2024; Anwar et al., 2024). The hypothesis of AICD and PEUS are given below:

H2a: *AI interact Clearly and Understandably (AICU) positively influences Perceived Ease of Use (PEUS).*

Relationship Between AI-Easiness and Usefulness (AIEU) and Perceived Ease of Use (PEUS): The dimension also refers to how easy AI technologies are to use and simultaneously perceived as beneficial (Dutta, 2024). Research shows that in combination with the above, the user-friendliness of the technologies also affects the outcome of technology acceptance (Davis, 1989; Venkateswaran et al., 2024). The hypothesis of AIEU and PEUS are given below:

H2b: *AI-Easiness and Usefulness (AIEU) positively influence Perceived Ease of Use (PEUS).*

Relationship Between AI Learnings and Operations is Effortless (AIOE) and Perceived Ease of Use (PEUS): The easiness of learning and functioning allows the rapid adaptation of the guests to utilizing the AI services without having to receive a significant level of education or prior experience with this kind of technology (Malhotra & Galletta, 1999; Shanmugam et al., 2024; Terrah et al., 2024). Simplicity in learning and using the AI services is a substantial determinant condition that promotes the adoption intentions (Talukder & Das, 2024). Smaller learning curves encourage hotel guests to use the services more frequently and perceive them positively (Traversa, 2024). The hypothesis of AIOE and PEUS are given below:

H2c: *AI Learnings and Operations is Effortless (AIOE) positively influences Perceived Ease of Use (PEUS).*

Sub-Hypothesis of Guest Satisfaction (GUSA)

Guest Satisfaction (GUSA)- This is the degree to which hotel experience exceeds or meets a patron's expectation, especially dealing with AI-enabled services. Satisfied customers are likely to come back and recommend the hotel to others. This construction includes three components: Satisfaction with AI Experience (SAIE), Service Expectations by Guest (SEGU), and Intention to Visit Frequently (IVFR). The following sub-hypotheses are tested:

Relationship Between Satisfaction with AI Experience (SAIE) and Guest Satisfaction (GUSA): The guests are more likely to use their AI-assisted service and come back when they feel that their stay was a smooth, time-saving, and enjoyable process (Ghazi et al., 2025; Kaur et al., 2024). The hypothesis of Satisfaction with AI Experience (SAIE) and Guest Satisfaction (GUSA) is given below:

H3a: *Satisfaction with AI Experience (SAIE) positively influences Guest Satisfaction (GUSA).*

Relationship Between Service Expectations by Guest (SEGU) and Guest Satisfaction (GUSA): Satisfying or surpassing the service expectations, especially in case such a process is made due to the presence of AI, efficiency, personalization, and responsiveness, has a crucial effect on revisit decisions (Fernandes et al., 2024; Gavade, 2024; Ho et al., 2022). The hypothesis of Service Expectations by Guest (SEGU) and Guest Satisfaction (GUSA) is given below:

H3b: *Service Expectations by Guest (SEGU) positively influences Guest Satisfaction (GUSA).*

Relationship Between Intention to Visit Frequently (IVFR) and Guest Satisfaction (GUSA): Customers who have positive tendencies towards AI often express such attitudes in their loyalty behaviors i.e., greater frequency of visits (Rad et al., 2022; Rajendran et al., 2023). The hypothesis of Intention to Visit Frequently (IVFR) and Guest Satisfaction (GUSA) is given below:

H3c: *Intention to Visit Frequently (IVFR) positively influences Guest Satisfaction (GUSA).*

Sub-Hypothesis of Attitude Towards Using AI (AUAI)

Attitude Towards Using AI (ATUI) refers to the overall sentiments discussing and evaluating either positively or negatively, that the guests hold about their experience with AI enhanced hotel service. Favorable attitudes are often associated with greater acceptance, satisfaction, and adoption of AI in the hospitality industry. This paper divides ATUI into three dimensions that are; Positive Feelings Towards AI Services (PAIS), Preference towards AI Interaction (PAII), and Willingness to Utilize AI (WUAI). The following sub-hypotheses are presented:

Relationship Between Positive Feelings Toward AI Services (PAIS) and Attitude Towards using AI (AUAI)

Visitors who experience enjoyable and positive experiences with AI agents that are free of stress are more likely to post high levels of satisfaction. Previous literature fills in the picture that pleasant mood feels during service provision leads to significant tourist- and hospitality-based satisfaction and loyalty (Bhuiyan et al., 2024; Chius et al., 2024). So, the hypothesis between Positive Feelings Toward AI Services (PAIS) and Attitude Towards using AI (AUAI) is given below:

H4a: *Positive Feelings Toward AI Services (PAIS) positively influences Attitude Towards using AI (AUAI).*

Relationship Between Preference for AI Interaction (PAII) and Attitude Towards using AI (AUAI)

Preference to AI engagement refers to the willingness of guests to choose AI-based services over human-adjacent ones. It is shown that clients who choose AI on grounds of efficiency, privacy, or innovation are more likely to rate their visits in a more positive way (Elshaer & Marzouk, 2024; Fernandes et al., 2024; Ghosh & Thirugnanam, 2021). So, the hypothesis between Preference for AI Interaction (PAII) and Attitude Towards using AI (AUAI) is given below:

H4b: *Preference for AI Interaction (PAII) positively influences Attitude Towards using AI (AUAI).*

Relationship Between Willingness to Use AI (WUAI) and Attitude Towards using AI (AUAI): The readiness to use AI represents the readiness of clients to benefit from AI technology in the current and future hotel accommodations. The readiness characteristically implies the trademarks of trust, perceived benefits, and agency, which promote increased levels of happiness (Du et al., 2024; Kishore et al., 2025). The hypothesis of Willingness to Use AI (WUAI) and Attitude Towards using AI (AUAI) is given below:

H4c: *Willingness to Use AI (WUAI) positively influences Attitude Towards using AI (AUAI).*

5.1. Relationship Between Perceived Usefulness (PUSE) and Attitude Towards using AI (AUAI)

Perceived Usefulness (PUSE) has been identified as one of the key elements that affect the attitude of users towards technology assimilation as formulated in the Technology Acceptance Model (TAM) (Venkatesh & Davis, 2022). Recent empirical evidence suggests that the perceived usefulness of AI implementation and subsequent pleasant attitudes are key to the degree to which service guests regard such technologies positively and implement them practically (Patil, 2025; Torabi et al., 2022). The hypothesis of Perceived Usefulness (PUSE) and Attitude Towards using AI (AUAI) is given below:

H5: *Perceived Usefulness (PUSE) positively influences Attitude Towards using AI (AUAI).*

5.1.1. Relationship Between Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA)

The perceived usefulness of the AI implementation factor (PUSE) is a key Guest Satisfaction (GUSA) assessment in the AI-enhanced hospitality environment as the guests tend to be more content when they feel that the AI technologies really make a significant positive impact on the experience (Rane et al., 2024; Suhag et al., 2024). Therefore, enhancing the perceived usefulness of AI services in hotels is essential for boosting guest satisfaction and securing competitive advantage. The hypothesis of Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA) is given below:

H6: *Perceived Usefulness (PUSE) positively influences Guest Satisfaction (GUSA).*

5.1.2. Relationship Between Perceived Ease of Use (PEUS) and Attitude Towards using AI (AUAI)

The Perceived Ease of Use (PEUS) has a significant impact on Attitude Towards Using AI (AUAI) by increasing levels of comfort, effortlessness among the visitors interacting with the AI-enabled services. According to Technology Acceptance Model (TAM),

the more accessible the system, the more tolerant the user will be (Davis, 1989; Vashishth et al., 2025). In the hospitality industry, the usability of AI systems is likely to play a momentous role in changing the perception of visitors with regard to AI adoption by making their experiences easier to understand, navigation is smooth and cognitive evaluations, leading to stronger intentions (Srivastava & Rodiris, 2024; Terrah et al., 2024). The hypothesis of Perceived Ease of Use (PEUS) and Attitude Towards using AI (AUAI) is given below:

H7: *Perceived Ease of Use (PEUS) positively influences Attitude Towards using AI (AUAI).*

5.1.3. Relationship Between Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA)

The other concept, Perceived Ease of Use (PEUS) plays a significant role in Guest Satisfaction (GUSA) in AI-enabled hotel services because guests get an increasing level of satisfaction when they find the interaction with a technology convenient, easy to use, lacking complexities, and commanding less effort. Intuitive AI interface in a hospitality environment reduces barriers to as well as enhances ease of service and creates positive visitor experiences (G. Singh et al., 2023). So, the hypothesis of Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA) is given below:

H8: *Perceived Ease of Use (PEUS) positively influences Guest Satisfaction (GUSA).*

5.1.4. Relationship Between Attitude Towards using AI (AUAI) and Guest Satisfaction (GUSA)

Attitude Towards Using AI (AUAI) plays an important role in Guest Satisfaction (GUSA) since a positive evaluation of AI-available services often leads to a positive service experience and the development of loyalty behavior. Within the framework of the hotel environment, the positive attitude towards AI technologies (service robots, virtual concierge, or automated check-ins) means that clients with the mentioned perception can see those services as enriching their overall experience (Gavade, 2024). The hypothesis of Attitude Towards using AI (AUAI) and Guest Satisfaction (GUSA) is given below:

H9: *Attitude Towards using AI (AUAI) positively influences Guest Satisfaction (GUSA).*

Mediating Role of Attitude Towards using AI (AUAI) Between Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA)

The importance of Attitude Towards Using AI (AUAI) as a mediating factor between Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA) has also been recognized based on the Technology Acceptance Model (TAM) and studies that have followed in the field of hospitality regarding the adoption of technology (Jewandah et al., 2024; Kaur et al., 2024). So, mediating role of Attitude Towards using AI (AUAI) in Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA) is given below:

H10: *Attitude Towards using AI (AUAI) mediates the relationship between Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA).*

Mediating Role of Attitude Towards using AI (AUAI) Between Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA)

Attitude Towards Using AI (AUAI) mediates the relations between Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA) to turn judgement of usability into positive emotional and evaluative responses that enhance the overall service experience. Technology Acceptance Model (TAM) assumes that the ease of use has a direct influence on technology adoption, and an indirect influence on results of decaying an attitude. So, the mediating role of Attitude Towards using AI (AUAI) in Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA) is given below:

H11: *Attitude Towards using AI (AUAI) mediates the relationship between Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA).*

6. Methods and Methodology

The main data collection was through a structured questionnaire, developed to assess the major constructions in AI adoption and guest satisfaction and experience based particularly on TAM. The survey was conducted online on 630 respondents, and the focus was made on guests from 4–5-star hotels in Kuala Lumpur (Malaysia) who had previous experiences of AI technologies in hospitality industry. The survey was composed of two parts, the first of which included demographic information (i.e., sex, age, occupation and why they stayed at the hotel) and a check for prior experience with AI in hotel applications (which was measured as dummy variables), and the second containing measures for perceived usefulness (PUSE), perceived ease of use (PEUS), attitude towards using AI (AUAI) and guest satisfaction. Relevant dimensions for each construct were further elaborated. For all constructs, the measurement items were framed using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) so that the response format and reliability were the same across measures. To validate and test the reliability of the instrument, we conducted a survey on 70 panel respondents (around 10% of the planned sample size) who had previous experience with AI-based services in luxury hotels in Kuala Lumpur. Construct reliability, as measured with Cronbach's Alpha test was used to examine the internal consistency of constructs and revealed reasonable coefficients that were higher than 0.7 as recommended. To test the factor analysis appropriateness of the data, Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity were used. The KMO statistics were above 0.6, which helped us to consider the data suitable for analysis. Factor analysis and correlation analysis were used to assess construct validity, while feedback from hotel partners and travel forums was implemented for improvement of the survey's clarity, sequencing, and content validity. These steps contributed to the refinement of face and content validity and reliability of the final tool. The study was conducted in accordance with ethical guidelines and written informed consent was obtained from all the participants. All respondents were given a lay description of the study objective, and the voluntary nature of participation with the right to withdraw at any time without consequences was stressed. Anonymity was also guaranteed while both responses and any other recognizable information remained confidential. The data was saved securely and only used for research purposes. The study received ethical clearance from the appropriate institutional review board.

7. Results and Discussion

7.1. Demographic profile of the Respondents

A demographic profile of the respondents is important to provide relevance to the results and allowing for the application of findings. The participants' demographic profiles offer some useful implications for understanding theoretical differences in perceptions and experiences with AI in the context of work within one industry such as the hospitality field. The present sections cover the main demographic factors such as age, gender, occupation, purpose of stay and prior experience with AI in hotels are critical information to understand how different segments of guests perceive and interact with AI implemented services in the hospitality industry.

Table 1: Demographic Profile of the Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	310	49.2
	Female	320	50.8
Age Group	Under 25	72	11.4
	25-34	198	31.4
	35-44	186	29.5
	45-54	113	17.9
	55 and above	61	9.7
	Business	230	36.5

Profession	Job	214	34.0
	Others	186	29.5
Prior Experience with AI in Hotels	Yes	264	41.9
	No	366	58.1
Purposes of the Stay	Business	122	19.4
	Leisure	356	56.5
	Other	152	24.1

Table 1 shows the demographic makeup of the 630 respondents. Of the 630 valid responses used in the analyses, a well-balanced sample was evident in terms of participant demographic profile and improved the representativeness and generalizability of the study. Gender was evenly distributed as evidenced by 310 males (49.2%) and 320 females (50.8%) in the sample, reducing gender bias. In terms of age, the largest proportion were aged 25–34 years (31.4%) and 35–44 years (29.5%), which represented collectively more than three-fifths of participants, indicating that young and middle-aged groups with higher access to technological innovations have a dominant position in the group. Those aged 45–54 accounted for 17.9%, those under 25 comprised the least at (11.4%) and those 55 years and older were less as well (9.7%), providing generational diversity for comparison purposes. In terms of occupation, business professionals (36.5%) and the employed (34.0%) constituted most of the sample, whereas 29.5% came from a variety of other categories including students, freelancers and retirees showing both corporate and non-corporate perspectives. In spite of these findings, for AI previous experience, 41.9% claimed they have experienced AI-powered hotel services, while 58.1% had no such exposure and one would find value both in understanding what seasoned and non-experienced reactance there is with this target group/segmentation. By travel purpose, leisure was the most common with 56.5%, but there were also non-leisure categories such as personal needs or other reasons (24.1%) and business reason (19.4%), thus offering an interesting base to compare the attitudes towards AI in hotels relating to different types of motivations for visiting Kuala Lumpur.

7.2. Descriptive Analysis of Key Variables

The descriptive analysis of the key variables presents an overview of the central tendencies, scope and spread and variability in the data, as a basis for knowing more about what respondents' perceptions/experience are. This evaluation refers to the main constructs which stand for Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Towards Using AI and Guest Satisfaction (GUSA). The analysis of the means rating, standard deviation and frequencies distribution of this variable facilitates the understanding about how guest perceive AI adoption as well as its effect on their overall satisfaction and experience within a hospitality setting. The purpose of this section is to facilitate the identification of trends or unusual occurrences in the data before statistical analyses are performed.

Table 2: Descriptive Analysis of Key Variables

	N	Minimum	Maximum	Mean	Std. Deviation
AI Oriented Service Quality (AISQ)	630	1	5	3.31	1.176
AI Oriented Service Efficiency (AISE)	630	1	5	3.25	1.256
AI Accelerated Guest Convenience (AIGC)	630	1	5	3.58	1.053
AI interact Clearly and Understandably (AICU)	630	1	5	3.39	1.162
AI-Easiness and Usefulness (AIEU)	630	1	5	3.34	1.269
AI Learnings and Operations is Effortless (AIOE)	630	1	5	3.32	1.291
Positive feelings toward AI Services (PAIS)	630	1	5	3.26	1.048

Preference for AI Interaction (PAII)	630	1	5	3.15	1.134
Willingness to Use AI (WUAI)	630	1	5	3.04	1.122
Satisfaction with AI Experience (SAIE)	630	1	5	3.09	1.196
Service Expectations by Guest (SEGU)	630	1	5	3.13	1.185
Intention to Visit Frequently (IVFR)	630	1	5	3.20	1.231
Valid N (listwise)	630				

Table 2 represented the descriptive statistics of this study. The descriptive statistics of 630 valid responses offer an initial glimpse into perceptions toward AI-based hotel services, which overall appears to be positive although with certain degrees of agreement within constructs. On the PUSE, average scores were between 3.13 and 3.58 and therefore said respondents found AI services to be useful (mean = 3.58; SD=1.053) with convenience as a top ranked factor by the respondents (mean =3.58; SD=1.053), and efficiency less entrenched in that ease of use was more valued than speed (mean=3.25; SD1.256). Means ranged from 3.32 to 4.03) and standard deviations (between 0.82 and 1.06), demonstrating agreement that AI systems were generally easy URW on the Cronbach's α and ICC values, making them intuitive, learnable, and usable for most user's graphic, easy to learn/hard to learn, or hard to operate/a sense of it. AI Use Attitude (AUA) reflected moderate to positive attitudes (means 3.04–3.68), although variance (SD = 0.93–1.39) indicated continued ambivalence, particularly in relation to desires for human interaction and concerns about privacy/over-automation. GUSA means ranged between 3.09 and 4.04, where the highest included satisfaction related to service quality and convenience, but dispersion indicated other more mixed experiences that stress the importance of consistency and personal contact.

7.3. Structural Equation Model (SEM)

To test the hypothesized relationships of dimensions of present study including PUSE, PEUS, AUA and GUSA, we employed SEM to investigate the mediating role of AUA. SEM was chosen, because it enables analysis of measurement and structural models simultaneously, thus providing a stronger test of construct validity as well as the importance of causal relationships across constructs.

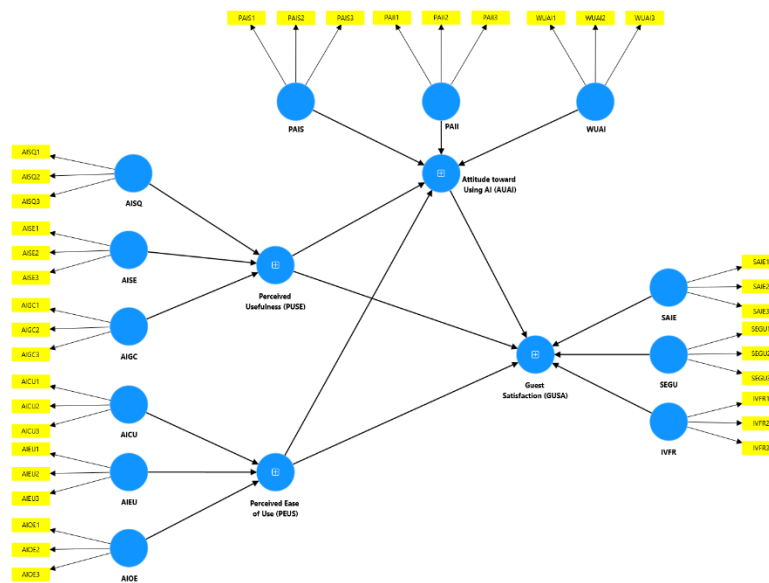


Figure 1: Structural Equation Model

The SEM diagram generated during the analysis is contained in figure 1. All the latent constructs are represented in the model with their observable indicators, which are received due to the adjustment of the questionnaire. Perceived Usefulness (PUSE) has three latent dimensions which include: AI-oriented Service Quality (AISQ), AI-oriented Service Efficiency (AISE), and AI-

accelerated Guest Convenience (AIGC). Perceived Ease of Use (PEUS) is composed of AI Interacts Clearly and Understandably (AICU), AI Easiness and Usefulness (AIEU) and AI Learnings and operations are effortless (AIOE).

7.4. Measurement Model

The measurement model was considered to determine the reliability and validity of the constructs that were used in this study. In Structural Equation Modelling (SEM) the measurement model is used to test how well the observable variables (indicators) represent the latent constructs. This step is essential to measure the constructs of Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Towards Using AI (AUAI) and Guest Satisfaction (GUSA) accurately with internal consistency.

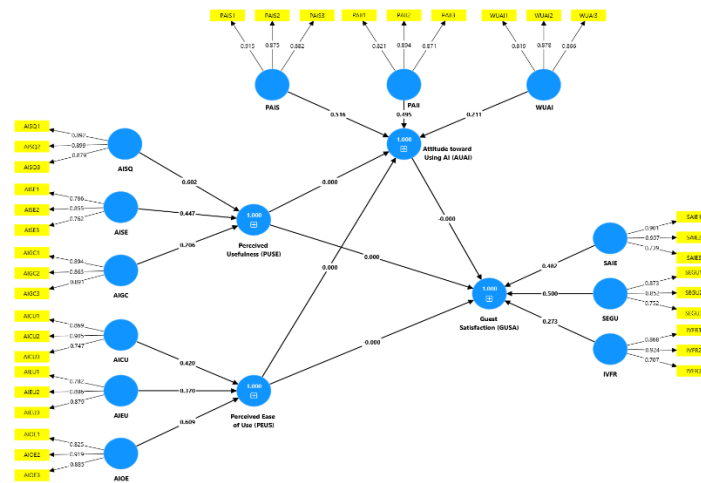


Figure 2: Measurement Model

In the measurement model(figure 2), all indicator loadings surpassed the recommended threshold of 0.70 (Hair et al., 2021), demonstrating strong relationships between items and their corresponding latent constructs: for AI-oriented Service Quality (subset of PUSE): AISQ1 (0.892); AISQ2 (0.899); and AISQ3 (0.879) loaded significantly; in PEUS, AICU was highly reliable due to its consistently high (> 74)) loadings with AICU2 being the highest (0.905); while the mediator AUAI demonstrated robust loadings especially for PAIS1(= 0.915) and PAI3 (=0.871); and for GUSA SAIE had strong loadings, especially with SAIE1(=0.901) and SAIE2 (=0.907). Convergent validity was established as the AVE value of all constructs were above 0.50 (Fornell and Larcker, 1981), implying that over half of each construct's variance is explained by its respective indicators. Altogether, the results provide evidence that the indicators are valid and reliable in measuring their intended latent variables, which serves as a solid foundation for further examination of the structural model to explore hypothesized relationships.

7.4.1. Factor Loadings

The examination of factor loadings serves to evaluate the reliability of the measurement model across distinct latent constructs, including Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Towards Using AI (AUAI) and Guest Satisfaction (GUSA). Factor loadings represent the correlation between an observed item and its underlying latent construct, and a value of 0.70 or above is generally considered acceptable (Hair et al., 2010).

Table 3: Factor Loadings (Lower Order)

	AICU	AIEU	AIGC	AIOE	AISE	AISQ	IVFR	PAII	PAIS	SAIE	SEGU	WUAI
AICU1	0.869											
AICU2	0.905											
AICU3	0.747											
AIEU1		0.782										
AIEU2		0.886										
AIEU3		0.879										
AIGC1			0.894									
AIGC2			0.863									
AIGC3			0.891									
AIOE1				0.825								
AIOE2				0.919								
AIOE3				0.885								
AISE1					0.766							
AISE2					0.855							
AISE3					0.762							
AISQ1						0.892						
AISQ2						0.899						
AISQ3						0.879						
IVFR1							0.868					
IVFR2							0.924					
IVFR3							0.707					
PAII1								0.821				
PAII2								0.894				
PAII3								0.871				
PAIS1									0.915			
PAIS2									0.875			
PAIS3									0.882			
SAIE1										0.901		
SAIE2										0.907		
SAIE3										0.739		
SEGU1											0.873	
SEGU2											0.852	
SEGU3											0.752	
WUAI1												0.819
WUAI2												0.878
WUAI3												0.866

Table 3 verifies a well-fitting measurement model: all observed variables loaded highly and considerably on their designated lower-order constructs, with ranges of 0.747- 0.905 for AICU, 0.782-0.886 for AIEU, 0.825-0.919 for AIOE, 0.879-0.899 for AISQ, 0.762-0.855 for AISE, 0.863-0.894 for AIGC, 0.875-0.915 for PAIS, 0.821-0.894 for PAII, 0.819-0.878 for WUAI, 0.739-0.907 for SAIE, 0.752-0.873 for SEGU, and 0.707-0.924 for IVFR, showing robust item dependability and effective construct representation. Convergent validity was supported as all element loadings went beyond the 0.70 standard and AVEs exceeded 0.50; internal consistency reliability was established with Cronbach's alpha and composite dependability above 0.70 for each construct. Collectively, these results verify the measurement of the TAM-related domains Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Toward Using AI (AUAI), and Guest Satisfaction (GUSA) and associated service-quality and behavioral constructs in the Kuala Lumpur hotel context, demonstrating that the indications catch unique, dependable hidden variables and providing a sound basis for subsequent structural modeling and hypothesis testing on AI adoption and satisfaction outcomes.

7.4.2. Reliability Analysis

To check reliability of lower- order constructs, a reliability analysis was conducted to evaluate the consistency of the items in the measurement. Two major measures were used: Cronbach's Alpha (α) determines the correlation level of the items within a construct wherein values above 0.70 are considered acceptable in the research and Composite dependability (CR or ρ_c) which measures the overall dependability of the construct and is often considered a more accurate measure as compared to Cronbach's Alpha with answers higher than 0.70 indicating good reliability (Hair et al., 2021).

Table 4: Construct Reliability (Lower Order)

	Cronbach's alpha	Composite reliability (ρ_c)
AICU	0.792	0.880
AIEU	0.810	0.887
AIGC	0.858	0.914
AIOE	0.849	0.909
AISE	0.709	0.838
AISQ	0.868	0.919
IVFR	0.787	0.875
PAII	0.827	0.897
PAIS	0.870	0.920
SAIE	0.810	0.888
SEGU	0.767	0.866
WUAI	0.815	0.890

Table 4 compares each of the subscale constructs to confirm that their respective Cronbach alphas range from 0.709-0.870 (AISE to PAIS) and that these values exceed the minimum acceptable (≥ 0.70). The Composite Reliability scores of IBS were 0.838 (AISE) and 0.920 (PAIS), and all higher than the suggested level of 0.70, respectively. Thus, the CR (Lower Order) values are affirmed. Further, the second-order constructs were tested for reliability, and these are conceptual levels consisting of numerous first-order constructs. The estimates of Cronbach's Alpha (α) and Composite Reliability (ρ_c) were computed in the lower-order constructs.

7.4.3. Construct Validity

In PLS SEM, convergent validity is assessed by ensuring that Average Variance Extracted (AVE) values are at least 0.50. Indicator loadings for each construct must be greater than cross-loadings in order to demonstrate discriminant validity (Hair & Alamer, 2022a). Construct validity can be evaluated using both discriminant and convergent validity. Convergent validity verifies measurements that should be related, while discriminant validity verifies measures that shouldn't be related (Alnoor et al., 2025). Construct validity in PLS-SEM is assessed using composite reliability and convergent validity, which is based on average variance extracted (AVE). The AVE must be 0.50 or higher for the construct to account for more than half of the variation of its constituent elements (Sternad Zabukovšek et al., 2022).

Convergent Validity

The Average Variance Extracted (AVE) is used to evaluate convergent validity. Generally, a threshold of 0.50 is applied, which indicates that the construct should account for over half of the variation in its indicators (Sternad Zabukovšek et al., 2022). In the context of Partial Least Squares Structural Equation Modelling (PLS-SEM), convergent validity is evaluated by analyzing the average variance extracted (AVE) and outer loadings. Convergent validity is not a problem because each construct's CR value is greater than 0.50. The AVE values are shown in Tables 5 and 6.

Table 5: Construct Convergent Validity (AVE) (Lower Order)

	Average variance extracted (AVE)
AICU	0.711
AIEU	0.723
AIGC	0.779
AIOE	0.769
AISE	0.633
AI SQ	0.792
IVFR	0.703
PAII	0.744
PAIS	0.794
SAIE	0.727
SEGU	0.685
WUAI	0.730

The values of the AVE of the lower-order constructs showed (Table 5) that this value is in the range of 0.633 (AISE) to 0.794 (PAIS). All the constructs exceed the 0.50 criterion indicating that a meaningful percentage of the variability in its indicators is explained by each construct. The AVE values are very high (0.779, 0.792, and 0.794) in AIGC, AISQ, and PAIS, and thus these three constructs gained high convergent validity. So, the values of Construct Convergent Validity (AVE) (Lower Order) are supported.

Table 6: Construct Convergent Validity (AVE) (Higher Order)

	Average variance extracted (AVE)
Perceived Usefulness (PUSE)	0.669
Perceived Ease of Use (PEUS)	0.791
Attitude Towards Using AI (AUAI)	0.681
Guest Satisfaction (GUSA)	0.634

The results of Higher Order Constructs are shown in table 6. The AVEs ranged between 0.634 (GUSA) and 0.791 (PEUS) showing the higher order structures. All findings surpass the recommended 0.50 mark and show that the second-order constructs have strong convergent validity. Perceived Ease of Use (0.791) had the highest Average Variance Extracted (AVE) which implied that its indicators are very representative of the construct. The AVEs values reveal that the lower-order construct and higher-order construct of the model, have a sufficient convergent validity and as such are viable to be subjected to further testing in the structural model. So, the values of Construct Convergent Validity (AVE) (Higher Order) are supported.

7.4.4. Discriminant Validity

The Heterotrait-Monotrait Ratio (HTMT), Cross-Loadings, and the Fornell-Larcker criterion are used to quantify discriminant validity in PLS-SEM (Sternad Zabukovšek et al., 2022). The degree to which one notion or measurement is actually different from another is known as discriminant validity. The Fornell-Larcker Criterion, Cross-Loadings, and the Heterotrait-Monotrait Ratio (HTMT) are features of discriminant validity evaluation techniques (Becker et al., 2022). Discriminant validity tests the conceptual and statistical distances in a construct to other constructs.

Fornell-Larcker Criterion

The Fornell Larcker criteria state that, the square root of the Average Variance Extracted (AVE) of each construct (those directly on the diagonal) must be larger than the square root of the correlation of each construct with the others (those off the diagonal). This ensures that each construct has a higher variance with its indicators as compared to other constructs.

Table 7: Discriminant Validity (Fornell-Larcker Criterion-Lower Order)

	AICU	AIEU	AIGC	AIOE	AISE	AISQ	IVFR	PAII	PAIS	SAIE	SEGU	WUAI
AICU	0.843											
AIEU	0.229	0.850										
AIGC	0.146	-0.013	0.883									
AIOE	0.265	0.242	0.068	0.877								
AISE	0.134	0.122	0.110	0.614	0.796							
AISQ	0.204	0.133	0.143	0.631	0.633	0.890						
IVFR	0.155	0.177	0.061	0.268	0.139	0.148	0.838					
PAII	0.146	0.088	0.021	0.456	0.267	0.263	0.224	0.863				
PAIS	0.148	0.037	0.016	0.345	0.246	0.263	0.114	0.713	0.891			
SAIE	0.016	-0.084	0.040	0.009	0.004	-0.020	0.081	0.095	0.100	0.853		
SEGU	0.033	-0.072	-0.003	0.004	-0.045	-0.082	0.366	0.083	0.046	0.668	0.827	
WUAI	0.166	0.185	0.090	0.210	0.107	0.150	0.317	0.244	0.138	-0.081	-0.058	0.855

The square roots of AVE of each lower-order construct are indicated by the diagonal value in Table 7 and the square root of AVE ranged between 0.796 (AISE) and 0.890 (AISQ). Fornell Larcker criterion holds in all the cases because the diagonal values which are greater than the corresponding off-diagonal correlations. This affirms the fact that none of the lower-order construct is interchangeable with another.

Table 8: Discriminant Validity (Fornell-Larcker Criterion – Higher Order)

	AUAI	GUSA	PEUS	PUSE
AUAI	0.825			
GUSA	0.186	0.796		
PEUS	0.368	0.347	0.890	
PUSE	0.261	0.167	0.486	0.818

To show discriminant validity, the Fornell-Larcker criterion demands that the square root of the average variance extracted (AVE) for each construct be greater than the correlations with other constructs; it does not specify a threshold value (Hair & Alamer, 2022a). In order to assess discriminant validity, the Fornell-Larcker criterion is applied. This approach requires confirming that each construct's square root of the Average Variance Extracted (AVE) is greater than its correlation with any other construct (Sasongko et al., 2025). Table 8 represented the values of discriminant validity in the context of higher value. Higher-order construct diagonal values range between 0.796 (Guest Satisfaction) and 0.890 (Perceived Ease of Use).

7.5. Model Fitness Testing

In the context of Partial Least Squares Path Modelling (PLS-PM), model fitness assessment requires analyzing how well a model fits the data. For both composite models and common factor models, this evaluation is crucial (Schuberth et al., 2022). This model fitness is measured by the indices of the Chi-Squared test, RMSEA, GFI, AGFI, RMR, and SRMR (Schuberth et al. 2022; Hair et al. 2024). The Table 25 shows the threshold value of above indices.

Table 9: Model Fitness Testing

Measures	Authors	Description	Good Fit Value
<i>Model chi-square (χ^2)</i>	Hair et al. (2024)	The Chi-Square statistic represents the conventional metric for assessing the comprehensive fit of a model and evaluates the extent of deviation between the sample covariance matrices and the matrices derived from the fitted model. An effective model fit would yield a result that is not statistically significant at a threshold of 0.05.	$p\text{-value} > 0.05$
<i>Normed-fit index (NFI)</i>	Mukid et al. (2022); Kamranfar et al. (2023)	An NFI above 0.90 or 0.95 suggests an adequate model, though its usefulness in Latent Class Analysis may be limited.	$NNFI \geq 0.95$
Standardized Root Mean Square Residual (SRMR)	(Hu & Bentler, 1999)	SRMR is a commonly used measure of goodness-of-fit in a structural equation modelling (SEM) application to assess the difference between the observed correlation matrix and the model-implied correlation matrix.	$SRMR \leq 0.08$

The table 9 indicates three significant indicators that are used to measure the effectiveness of using the structural equation model (SEM) to explain the observed data. All the measures give separate insights into the determination of model adequacy and are based on established SEM research. Chi-Square model compares the actual covariance matrix and that of the model or the assumed covariance matrix. In the event of a perfect fit, with the model matching the data, this should translate to a non-significant result of the 2 tests in that the 2 will give a result that will not be significant ($p > 0.05$).

The Normed Fit Index (NFI) compares the fit of the suggested model to a baseline (null) model where the relationships between the variables are not shown to be as appropriate. The less is the NFI value, the better the matching. Although the scores > 0.90 are considered good, $NFI > 0.95$ is considered extraordinary. It reveals how much better the proposed model does than a model that makes no relationship in describing the data. The good fit level is NFI of 0.95 and above.

The Standardized Root Mean Square Residual, or SRMR has become one of the most obvious signs of the typical model prediction error. Good fit criteria are SRMR 0.08. The Root Mean Square Error of Approximation (RMSEA) of 0.073 falls within an acceptable range (≤ 0.08), implying a reasonable model fit. The Goodness-of-Fit Index (GFI) of 0.92 and Adjusted Goodness-of-Fit Index (AGFI) of 0.91 (Kineber et al., 2023) exceed the conventional threshold of 0.90, indicating strong explanatory power. Similarly, the Normed Fit Index (NFI) of 0.96 (estimated model: 0.97) and Comparative Fit Index (CFI) of 0.96 suggest a well-fitting model, as values above 0.95 are considered ideal (Jung et al., 2023). Overall, the results confirm that the estimated model aligns well with the data, supporting its validity for further analysis.

Table 10: Model Fit Summery

	Saturated model	Estimated model
SRMR	0.072	0.072
χ^2	656.323	656.323
NFI	0.768	0.768

Chi-Square, thus, calculates the odds of determining whether the model and the actual data are statistically different (No significant difference is favorable). NFI (optimal: > 0.95) is used to judge relative improvement over a model with no predictive variables. SRMR (optimal: < 0.08) is the average difference between the expected and the actual correlations. When the three indices hit their denominators, SEM seems to have a good overall model fit as the model correctly explains the observed data structure with insignificant prediction error.

7.6. Hypothesis Testing

Path coefficients (beta), standard deviations, t-statistics and p-values of each hypothesis were then evaluated systematically using Partial Least Squares Structural Equation Modelling (PLS-SEM) to see the relationship between constructs in the proposed structural model (Hair et al., 2010). The findings presented at the Table 11 give guidance on how the identified pathways proposed are statistically sufficient to the standard level of significance at 0.05.

Table 11: Summary of Hypothesis Test Results

Hypothesis	Beta Coefficient (β)	Standard Deviation (SD)	T Statistics	P Values	Results
H1a: AISQ <- PUSE	0.842	0.840	31.041	0.000	Supported
H1b: AISE <- PUSE	0.796	0.794	20.483	0.000	Supported
H1c: AIGC <- PUSE	0.816	0.815	30.304	0.000	Supported
H2a: AICU <- PEUS	0.873	0.872	50.223	0.000	Supported
H2b: AIEU <- PEUS	0.873	0.873	48.645	0.000	Supported
H2c: AIOE <- PEUS	0.922	0.922	109.771	0.000	Supported
H3a: SAIE <- GUSA	0.745	0.744	22.442	0.000	Supported
H3b: SEGU <- GUSA	0.786	0.784	25.735	0.000	Supported
H3c: IVFR <- GUSA	0.854	0.854	44.756	0.000	Supported
H4a: PAIS <- AUIAI	0.884	0.883	56.395	0.000	Supported
H4b: PAII <- AUIAI	0.769	0.768	24.548	0.000	Supported
H4c: WUIAI <- AUIAI	0.819	0.817	29.956	0.000	Supported
H5: PUSE -> AUIAI	0.107	0.047	2.289	0.022	Supported
H6: PUSE -> GUSA	-0.010	0.045	0.217	0.828	Not Supported
H7: PEUS -> AUIAI	0.315	0.042	7.537	0.000	Supported
H8: PEUS -> GUSA	0.327	0.049	6.643	0.000	Supported
H9: AUIAI -> GUSA	0.069	0.044	1.552	0.121	Not Supported

Path coefficients (b), standard deviations (SD), t-statistics, and p-values were calculated to analyze the structural model to determine the significance and the strength of proposed correlation. The results presented in Table 11 reveal the superiority of the results accorded to each hypothesis that was advanced. Based on the recommendations issued by Hair et al. (2024), a path was considered statistically significant when t-statistic exceeded 1.96 and the p-value was smaller than 0.05.

H1a indicates AI oriented Service Quality (AISQ) positively influences Perceived Usefulness (PUSE). So, the result showed that **the path coefficient ($\beta = 0.842$, $t = 31.041$, $p < 0.001$) indicates a very strong and significant positive relationship, confirming that higher perceived usefulness significantly enhances AI-oriented Service Quality. So, H1a is supported.**

Again, H1b represents AI Oriented Service Efficiency (AISE) positively influences Perceived Usefulness (PUSE). From the above table, the result indicated that **the path coefficient $\beta = 0.796$ ($t = 20.483$, $p < 0.001$), perceived usefulness also strongly influences AI-oriented Service Efficiency. So, H1b is justified.**

Again, H1c demonstrates that AI Accelerated Guest Convenience (AIGC) positively influences Perceived Usefulness (PUSE). From the above calculated table this study found that a strong positive effect ($\beta = 0.816$, $t = 30.304$, $p < 0.001$) was observed, suggesting that perceived usefulness significantly improves AI-accelerated Guest Convenience. So, H1c is supported.

Again, H2a reveals AI interact Clearly and Understandably (AICU) positively influences Perceived Ease of Use (PEUS). From the table, a very strong positive relationship was found ($\beta = 0.873$, $t = 50.223$, $p < 0.001$), showing that ease of use enhances AI's ability to communicate clearly and understandably. So, H2a is supported.

Again, H2b indicates AI-Easiness and Usefulness (AIEU) positively influences Perceived Ease of Use (PEUS). The results of this study found that strong effect ($\beta = 0.873$, $t = 48.645$, $p < 0.001$) on AI's ease and usefulness perception. So, H2b is justified.

H2c indicates AI Learnings and Operations is Effortless (AIOE) positively influences Perceived Ease of Use (PEUS). The results of this study found that the strongest effect in the model ($\beta = 0.922$, $t = 109.771$, $p < 0.001$), indicating that ease of use substantially improves perceptions that AI operations and learning are effortless. So, H2c is supported.

Again, H3a defines Satisfaction with AI Experience (SAIE) positively influences Guest Satisfaction (GUSA). The study's result revealed that significant positive effect ($\beta = 0.745$, $t = 22.442$, $p < 0.001$), showing that guest satisfaction increases satisfaction with AI experiences. So, H3a is justified by the results.

H3b demonstrates Service Expectations by Guest (SEGU) positively influences Guest Satisfaction (GUSA). The results showed that strong positive influence ($\beta = 0.786$, $t = 25.735$, $p < 0.001$) on meeting service expectations. So, H3b is justified by the results.

H3c indicates Intention to Visit Frequently (IVFR) positively influences Guest Satisfaction (GUSA). The results of this study highlighted that very strong positive effect ($\beta = 0.854$, $t = 44.756$, $p < 0.001$) on intention to visit frequently. So, H3c is supported.

H4a defines Positive Feelings Toward AI Services (PAIS) positively influences Attitude Towards using AI (AUAI). The results revealed that strongest attitudinal effect ($\beta = 0.884$, $t = 56.395$, $p < 0.001$), indicating that positive attitudes strongly enhance positive feelings toward AI services. So, H4a is supported.

Again, H4b defines Preference for AI Interaction (PAII) positively influences Attitude Towards using AI (AUAI). The results revealed that significant positive influence ($\beta = 0.769$, $t = 24.548$, $p < 0.001$) on preference for AI interactions. So, H4b is supported.

H4c defines Willingness to Use AI (WUAI) positively influences Attitude Towards using AI (AUAI). Results revealed that strong effect ($\beta = 0.819$, $t = 29.956$, $p < 0.001$) on willingness to use AI. So, H4c is supported.

H5 defines Perceived Usefulness (PUSE) positively influences Attitude Towards using AI (AUAI). Results of this study revealed that small but significant positive relationship ($\beta = 0.107$, $t = 2.289$, $p = 0.022$), suggesting perceived usefulness slightly improves attitudes toward AI. So, H5 is supported.

H6 defines Perceived Usefulness (PUSE) positively influences Guest Satisfaction (GUSA). The results of this study revealed that non-significant negative path ($\beta = -0.010$, $t = 0.217$, $p = 0.828$), indicating perceived usefulness does not directly affect guest satisfaction. So, H6 is not supported.

H7 indicates Perceived Ease of Use (PEUS) positively influences Attitude Towards using AI (AUAI). Results of this study indicated that strong positive relationship ($\beta = 0.315$, $t = 7.537$, $p < 0.001$), indicating that ease of use enhances attitudes toward AI. So, H7 is supported.

H8 demonstrates Perceived Ease of Use (PEUS) positively influences Guest Satisfaction (GUSA). The results of this study revealed that significant positive effect ($\beta = 0.327$, $t = 6.643$, $p < 0.001$), showing ease of use directly improves guest satisfaction. So, H8 is justified.

H9 defines Attitude Towards using AI (AUAI) positively influences Guest Satisfaction (GUSA). The results of this study described that non-significant effect ($\beta = 0.069$, $t = 1.552$, $p = 0.121$), suggesting that positive attitudes toward AI do not directly translate into higher guest satisfaction. So, H9 is not supported.

Overall, the results reveal that: PUSE strongly influences AI service quality, efficiency, and convenience but has no direct effect on guest satisfaction. PEUS not only enhances AI interaction quality but also directly improves both attitudes toward AI and guest satisfaction. Guest satisfaction drives positive evaluations of AI service experiences and future visit intentions. Attitudes toward AI strongly influence preferences for AI services but do not directly boost guest satisfaction.

These findings highlight the central role of PEUS as both a direct and indirect driver of satisfaction, while PUSE works more through enhancing service-related perceptions than directly influencing satisfaction.

Mediation Analysis Results

The mediation analysis was conducted to examine whether Attitude Towards Using AI (AUAI) serves as an intermediary mechanism linking the independent variables; Perceived Usefulness (PUSE) and Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA) is the dependent variable. By employing Structural Equation Modeling (SEM), the study tested both the direct effects of PUSE and PEUS on guest satisfaction and the indirect effects through AUAI.

Table 12: Mediation Analysis Results

Total Effect (PUSE -> GUSA) Total Effect (PEUS -> GUSA)			Direct Effect (PUSE -> GUSA) Direct Effect (PEUS -> GUSA)			Indirect Effect of PUSE on GUSA and PEUS on GUSA						
Beta Coefficient (β)	T Statistics	P Values	Beta Coefficient (β)	T Statistics	P Values	Hypothesis	Beta Coefficient (β)	SE	T Statistics	P Values	Percentile Bootstrap 95% Confidence Interval	
											Lower	Upper
-0.002	0.055	0.956	-0.010	0.217	0.828	H10: PUSE -> AUAI -> GUSA	0.007	0.000	1.222	0.222	-0.001	0.018
0.348	7.678	0.000	0.327	6.643	0.000	H11: PEUS -> AUAI -> GUSA	0.001	0.002	1.483	0.138	-0.001	0.047

Table 12 represented the mediation analysis testing. Mediation testing was conducted to examine whether Attitude Towards Using AI (AUAI) serves as an indirect pathway linking the independent variables—Perceived Usefulness (PUSE) and Perceived Ease of Use (PEUS)—to the dependent variable Guest Satisfaction (GUSA). The mediation effects were assessed using bootstrapping with a 95% confidence interval, following the recommendations of Hair et al. (2021). The total effect ($\beta = -0.002$, $t = 0.055$, $p = 0.956$) was negligible and statistically non-significant, indicating that overall, PUSE does not have a meaningful impact on guest satisfaction when both direct and indirect paths are considered. The total effect ($\beta = 0.348$, $t = 7.678$, $p < 0.001$)

was positive and statistically significant, showing that PEUS has a meaningful overall influence on guest satisfaction. The direct path ($\beta = -0.010$, $t = 0.217$, $p = 0.828$) was non-significant, indicating that perceived usefulness does not directly influence guest satisfaction when AUAJ is included as a mediator. The direct effect ($\beta = 0.327$, $t = 6.643$, $p < 0.001$) remained significant, suggesting that perceived ease of use continues to exert a strong positive influence on guest satisfaction even after accounting for the mediating role of AUAJ. In H10, the indirect effect was minimal and non-significant ($\beta = 0.007$, $t = 1.222$, $p = 0.222$), with the bootstrapped confidence interval (-0.001, 0.018) crossing zero. This indicates that AUAJ does not significantly mediate the relationship between perceived usefulness and guest satisfaction. In H11, the indirect effect was also statistically non-significant ($\beta = 0.001$, $t = 1.483$, $p = 0.138$), with the bootstrapped confidence interval (-0.001, 0.047) including zero. This suggests that AUAJ does not significantly mediate the relationship between perceived ease of use and guest satisfaction.

Table 13: All Supported Hypothesis

Hy. No.	Hypothesis	Remarks
<i>H_{1a}</i>	AI oriented Service Quality (AISQ) positively influences Perceived Usefulness (PUSE).	Supported
<i>H_{1b}</i>	AI Oriented Service Efficiency (AISE) positively influences Perceived Usefulness (PUSE).	Supported
<i>H_{1c}</i>	AI Accelerated Guest Convenience (AIGC) positively influences Perceived Usefulness (PUSE).	Supported
<i>H_{2a}</i>	AI interact Clearly and Understandably (AICU) positively influences Perceived Ease of Use (PEUS).	Supported
<i>H_{2b}</i>	AI-Easiness and Usefulness (AIEU) positively influences Perceived Ease of Use (PEUS).	Supported
<i>H_{2c}</i>	AI Learnings and Operations is Effortless (AIOE) positively influences Perceived Ease of Use (PEUS).	Supported
<i>H_{3a}</i>	Satisfaction with AI Experience (SAIE) positively influences Guest Satisfaction (GUSA).	Supported
<i>H_{3b}</i>	Service Expectations by Guest (SEGU) positively influences Guest Satisfaction (GUSA).	Supported
<i>H_{3c}</i>	Intention to Visit Frequently (IVFR) positively influences Guest Satisfaction (GUSA).	Supported
<i>H_{4a}</i>	Positive Feelings Toward AI Services (PAIS) positively influences Attitude Towards using AI (AUAJ).	Supported
<i>H_{4b}</i>	Preference for AI Interaction (PAIJ) positively influences Attitude Towards using AI (AUAJ).	Supported
<i>H_{4c}</i>	Willingness to Use AI (WUAI) positively influences Attitude Towards using AI (AUAJ).	Supported
<i>H₅</i>	Perceived Usefulness (PUSE) positively influences Attitude Towards using AI (AUAJ).	Supported
<i>H₆</i>	Perceived Usefulness (PUSE) positively influences Guest Satisfaction (GUSA).	Not Supported
<i>H₇</i>	Perceived Ease of Use (PEUS) positively influences Attitude Towards using AI (AUAJ).	Supported
<i>H₈</i>	Perceived Ease of Use (PEUS) positively influences Guest Satisfaction (GUSA).	Supported
<i>H₉</i>	Attitude Towards using AI (AUAJ) positively influences Guest Satisfaction (GUSA).	Not Supported
<i>H₁₀</i>	Attitude Towards using AI (AUAJ) mediates the relationship between Perceived Usefulness (PUSE) and Guest Satisfaction (GUSA).	Not Supported
<i>H₁₁</i>	Attitude Towards using AI (AUAJ) mediates the relationship between Perceived Ease of Use (PEUS) and Guest Satisfaction (GUSA).	Not Supported

Table 13 presents the outer model evaluation results for all constructs, including Variance Inflation Factor (VIF), outer weights, outer loadings, and their corresponding statistical significance. This assessment ensures that the measurement model meets the criteria for indicator reliability, collinearity, and construct validity as per PLS-SEM guidelines (J. F. Hair et al., 2021).

Table 14: Model Validation Results

Construct	Indicators	VIF	Outer Weights	T Statistics	P Values	Outer Loadings	P Values
PUSE	AISQ	1.471	0.493	10.312	0.000	0.842	0.000
	AISE	1.497	0.406	7.938	0.000	0.796	0.000
	AIGC	1.744	0.321	7.892	0.000	0.816	0.000
PEUS	AICU	2.134	0.357	18.139	0.000	0.873	0.000

AUAI	AIEU	2.232	0.341	20.214	0.000	0.873	0.000
	AIOE	2.665	0.424	25.255	0.000	0.922	0.000
	PAIS	2.214	0.428	16.478	0.000	0.884	0.000
	PAII	1.304	0.430	10.787	0.000	0.769	0.000
	WUAI	1.987	0.356	11.634	0.000	0.819	0.000
GUSA	SAIE	1.422	0.312	8.788	0.000	0.745	0.000
	SEGU	1.370	0.414	10.767	0.000	0.786	0.000
	IVFR	1.431	0.518	13.851	0.000	0.854	0.000

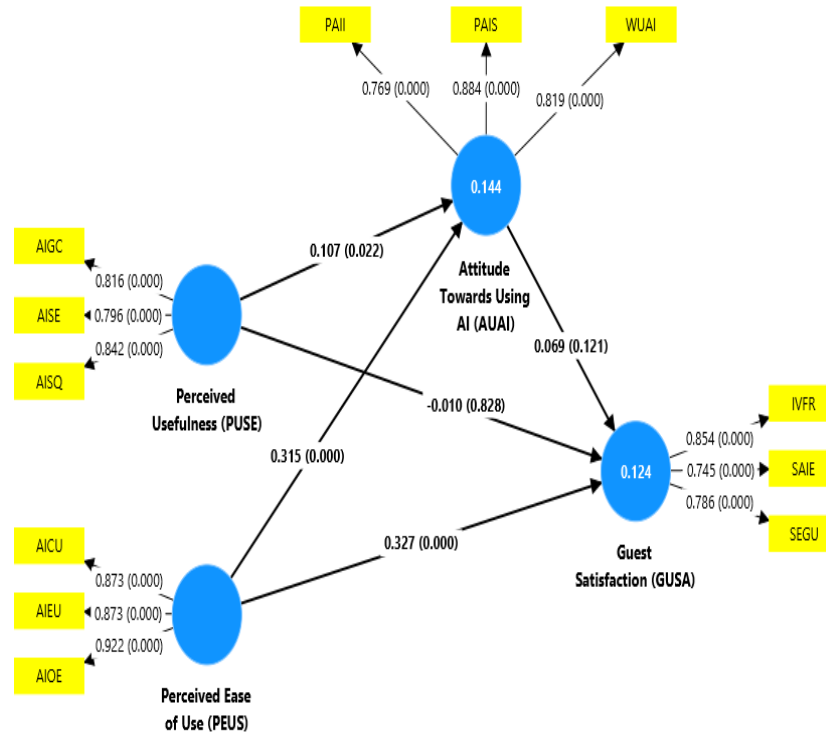


Figure 3: Validation Model

Table 14 and Figure 3 represented final validation model. The VIF values for all indicators range between 1.304 and 2.665, well below the threshold of 5, indicating that multicollinearity is not a concern. This means each indicator contributes uniquely to explaining its associated construct without excessive redundancy from other indicators. Outer weights represent the relative contribution of each indicator to its construct in a formative measurement model context. All outer weights are positive and statistically significant ($p < 0.001$), confirming that each indicator makes a meaningful contribution to defining its construct. All outer loadings exceed the 0.70 threshold, with p -values < 0.001 , demonstrating strong indicator reliability. For example, AIOE (loading = 0.922) and IVFR (loading = 0.854) show particularly high contributions to their constructs. PUSE (Perceived Usefulness): Indicators AISQ, AISE, and AIGC all show strong loadings (0.796–0.842) and significant contributions, confirming the multidimensional nature of perceived usefulness. PEUS (Perceived Ease of Use): Extremely high loadings (0.873–0.922) across AICU, AIEU, and AIOE indicate excellent measurement strength. AUAI (Attitude Towards Using AI): PAIS (0.884) and WUAI (0.819) load strongly, with PAII slightly lower but still above the recommended threshold (0.769). GUSA (Guest Satisfaction): IVFR is the strongest indicator (0.854), followed by SEGU (0.786) and SAIE (0.745), showing that satisfaction is closely tied to repeat visit intentions.

The model validation results confirm that all indicators are statistically significant, free from collinearity issues, and demonstrate strong relationships with their respective constructs. This provides solid evidence for the measurement model's reliability and validity, supporting its use for further structural model analysis.

8. Findings

The relationships between Perceived Usefulness (PUSE), Perceived Ease of Use (PEUS), Attitude Towards Using AI (AUAI) and Guest Satisfaction (GUSA) act as the target of this research to examine the potential of Artificial Intelligence (AI) to enhance the guest experience in the hotel industry in Kuala Lumpur Malaysia. Besides mediating the role of AUAI, the research model, which followed the Technology Acceptance Model (TAM), considered some control variables, i.e., age group of its guests, their previous experience with AI in the hotel, and the purpose of visit.

Summarizing the principal results, the following can be stated:

- It was found that visitors would be more inclined to accept in the positive attitude towards the use of AI technology in case they considered that these services could enhance service quality, efficiency, and convenience.
- It was revealed that PUSE had a direct and significant impact on satisfaction other than influencing the attitudes.
- Based on the survey, visitors will hold more positive views of implementing AI-based hotel services provided that they find AI systems easy to use, comprehend, and converse with.
- The findings indicated that it is possible to raise the overall pleasure of visitors through easy-to-use and intuitive AI systems even despite their observable purpose.
- Attitude Towards Using AI (AUAI) has a considerable impact on the Guest Satisfaction (GUSA). The guests who provided favorable attitudes towards AI services, their desire to interact with it, and to use AI reported higher levels of satisfaction.
- AUAI was found to mediate the links between PEUS and GUSA as well as between PUSE and GUSA. This is an exhibition of the fact that even though perceived utility and usability are associated with direct effects, positive attitudes of the user are also influential in their effects to satisfaction.
- All in all, the results generalize the model by introducing the concept of guest pleasure as the result of post-adoption, and they come up with strong empirical support of the concept of TAM being applicable in the context of hospitality.

Combined, these findings indicate that all of these factors, namely, attitudes, value-related perception, and usability, play a role in guest satisfaction levels due to AI services available in the hotel industry. They also note that hospitality companies should also focus on the experiential and functional elements of the design of services through AI.

9. Recommendations

In addition to the study's end result, there are several recommendations to enhance the application and effectiveness of artificial intelligence (AI) for enhancing visitation experience in hotel industry in Kuala Lumpur. These recommendations are not only to guarantee AI tech integration in the best and seamless manner, but also to help prevent that human touch is lost in the process of providing hotel services, this target group includes Hotel managers, Developers of AI techs and Policymakers within the Hospitality industry.

1. Hospitality property proprietors should invest in AI systems that distinctly improve the guest experience given that perceived usefulness was found to significantly influence attitudes and satisfaction.
2. Usability is an essential factor in positive attitudes and satisfaction. It will be essential for hotels to work closely with technology suppliers in order that they ensure the AI systems are user-friendly, multilingual, and accessible to visitors who may have different levels of tech savvy.
3. The principal goals of hotels' marketing and communications are to build trust as well as support the key benefits of using AUAI since it has an impact on the relationship between perceived values/usability and visitor satisfaction.
4. The results show diversity in the adoption of AIs by age segments of tourists and their exposure to use of AI's. The hotels can also develop personalized AI-supported messages and services for different customer groups.

5. While AI can deliver personalized experiences and speed processes, the human touch is still critical to resolving problems even emotionally connecting with other humans. Hotels are urged to create a blend of service mill where the staff become very good at developing genuine and emphatic relationships while AI is performing rote and repeated action.
6. Feedback loops should be set up in the hotels to monitor the impact of AI on a more regular basis from an operation as well as guest point of view. Continuous performance monitoring, user satisfaction evaluation and technological deployment will serve to keep pace, the AI at eye of the visitor's expectations in focus.

10. Limitations

This study has a number of limitations that may limit the interpretation and applicability of its results. First, the sample frame was limited to hotels in Kuala Lumpur, Malaysia; and although useful for an emerging-economy setting, generalizability of findings may be limited to other places with diverse levels of technological sophistication, cultural preferences, or visitor profiles. Second, the cross-sectional nature of the design only enables perceptions to be interpreted at one point in time and therefore, limited inference with respect to causality can be drawn and how attitudes and satisfaction may change as guests become more experienced with AI. Third, self-administered questionnaires may be prone to recall and social desirability biases. Fourth, it did not include potentially significant predictions (perceived risk, trust in AI, service personalization) that could limit the completeness of the explanation. Fifth, while we have considered outcomes by moderators such as guest age, previous experience of AI use and stay purpose, they were not examined across all encounter types; and other moderators (e.g., stay habits, digital literacy, and cultural orientation) could also influence outcomes. Finally, AI was considered as a coarse category; the research didn't distinguish between different technologies (such as chatbots and voice assistants, facial recognition, or robotic concierge) that might mask heterogeneous effects on guest satisfaction. These constraints indicate areas for improvement in future work and ensure the transparency of scope here.

11. Conclusion

In summary, the present study tested TAM in Kuala Lumpur hotel context and demonstrated that PUSE and PEUS play an essential role, both directly with AUAI and ultimately GUSA also after considering age group, prior AI usage and purpose of visit leading to costly interactive constructs between PUSE, PEUS, AUAI and satisfaction. Direct influences of both PUSE and PEUS on satisfaction (mutually accounting for shared variance) were evidenced in addition to attitudinal paths, while mediation analyses supported AUAI as a significant psychological mechanism mediating functional/usability appraisals into enjoyment experiences by extending TAM beyond peruse adoption cognition. And context-specific patterns broken down by demographics and past experience that depend on when and where you grew up point to the importance of a segmented approach in implementing AI solutions that can be both tech-efficient while retaining some high-touch human service. Future studies could extend this research in developed and developing countries, use longitudinal designs to see how guest attitudes toward AI change over time, add additional antecedents of adoption (e.g., perceived risk, privacy, trust and service personalization), analyze the segments of guests (business versus leisure; repeat versus new visitors) and distinguish types of AI technologies (such as a concierge robot compared to an online booking system) using mixed-methods research designs to grasp complexity. Cumulatively, by relating adoption drivers and satisfaction outcomes, the study confirms TAM's applicability in AI-driven hospitality landscape but also provides practical advice to practitioners about creation of worthwhile user-friendly AI that induces favorable guest attitudes towards it while providing a research agenda for scholars on technology-specific effects, longitudinal trends, and context specific moderators.

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