Check for updates

R&D Management

R&D MANAGEMENT

RESEARCH ARTICLE OPEN ACCESS

Digital Technologies and Innovation Ecosystems in the Post-Pandemic Era

Hello! How Can I Help You? Role of Technology Appetite on AI Adoption in the Post-Pandemic Era

Nitika Sharma[1] | Ruchi Payal[2] | Justin Paul[3,4,5,6]

[1]International Management Institute New Delhi, New Delhi, India | [2]Institute of Management Technology, Ghaziabad, Ghaziabad, India | [3]University of Puerto Rico, San Juan, Puerto Rico, USA | [4]NMIMS School of Business Management, Mumbai, India | [5]University of Economics and Human Sciences, Warsaw, Poland | [6]Korea University Business School, Korea University, Seoul, South Korea

Correspondence: Justin Paul (profjust@gmail.com; justin@drjustinpaul.com)

Received: 11 March 2023 | **Revised:** 12 March 2025 | **Accepted:** 31 March 2025

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | diffusion of innovation theory | perceived enjoyment | perceived fee | perceived usefulness | perceived value | technicality | technology readiness theory | tourism sector | value-based adoption model (VAM) theory

ABSTRACT

Artificial intelligence (AI) has revolutionized many industries, particularly tourism. Using the diffusion of innovation theory, value-based adoption model, and technology readiness theory, this study examines AI adoption through perceived enjoyment, perceived usefulness, perceived fees, and technicality on perceived value in the tour, travel, and hospitality sectors. Data were analyzed using PLS-SEM via SMARTPLS version 3.3.9, and an artificial neural network (ANN). The findings show that perceived fees and usefulness significantly impact perceived value. Travelers are more likely to value AI services if they perceive reasonable fees and enhanced search performance, leading to increased adoption intention. The study revealed that perceived enjoyment and technicality are not primary drivers of perceived value, underscoring the importance of pricing, perceived benefits, convenience, and cost-effectiveness in promoting tourism offerings to enhance AI service value perception. In addition, the high perceived value of benefits, convenience, and cost-effectiveness encourages AI adoption. The moderation effect of age and perceived innovativeness indicates a strong relationship between PV and AI adoption intentions among Gen Z.

1 | Introduction

Artificial intelligence (AI) has revolutionized the travel, tourism, and hospitality sectors through algorithms, voice recognition, machine learning (ML), natural language processing, augmented, mixed, and virtual reality, chatbots, voice assistants, automation, and robotics (Haenlein and Kaplan 2019; Bulchand-Gidumal et al. 2023). AI has enhanced the customer experience, making it more seamless and convenient (Kim and Kim 2024; Paul et al. 2024). It can create personalized itineraries, offer tailored sightseeing recommendations, and facilitate voice-assisted booking and cancellation of flights, hotels, and tickets, transforming the entire travel process into a streamlined bespoke experience. Hotels use chatbots and voice assistants to address customer queries and provide round-the-clock assistance (Forbes 2023a, 2023b; McKinsey 2023b; Bulchand-Gidumal et al. 2023). AI has revolutionized HR, finance, education, and marketing by improving decision-making, predicting behaviors, and optimizing strategies (Pillai and Sivathanu 2020; Setiawan et al. 2021; Chatterjee and Bhattacharjee 2020). AI is essential to address various operational challenges in the travel, tourism, and hospitality industries. Intelligent gadgets assist humans in recommending diverse options and making travel decisions (Hassani et al. 2020). Consequently, consumer preferences for AI-based smart gadgets such as Alexa, bots, and chatbots have increased. AI has significant potential in the travel, tourism, and hospitality industries because it provides personalized suggestions, tailored recommendations, swift responses via chatbots,

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

© 2025 The Author(s). *R&D Management* published by RADMA and John Wiley & Sons Ltd.

online services, and eye-to-eye interactions through AR, VR, and robots (Samala et al. 2020). Therefore, these new technologies might encourage individuals to use AI in the tourism sector, and firms can capitalize on their intentions as a competitive advantage (Samala et al. 2020).

Due to COVID-19 and Volatility, Uncertainty, Complexity, and Ambiguity (VUCA), individuals and firms are increasingly adopting AI because of its cost-effectiveness, sophistication, and efficiency. In emerging markets, such as India, AI is both developed and consumed extensively, with users and investors recognizing its transformative potential (Bhutoria 2022). The perceived value of AI, driven by its usefulness and enjoyment, can influence the intention to use it. Thus, this study explored the impact of positive reinforcement on the perceived value of AI during travel planning and booking. However, the swift evolution of technology and high initial investment in AI (Sohn and Kwon 2020) could affect its perceived value. To address the negative perception of AI's value, this study examined the impact of perceived fees and complexity, which may hinder AI adoption. Some companies that require basic fees or credit card details for travel booking may also restrict AI adoption. Recognizing users' adoption needs and patterns based on perceived value, this study considers perceived usefulness, enjoyment, fee, and technicality as antecedents in the tourism sector. However, this adoption of disruptive technology depends on the tremendous appetite for technology among individuals, which relies on perceived innovativeness (Kwak et al. 2021). The conceptualization of AI-based services relies on technological innovativeness (Coccia and Watts 2020), and technology adoption varies among individuals (Chawla and Joshi 2020). This study investigates the role of the intention to use AI, with perceived innovativeness acting as a moderator in the tourism sector. Highly personalized AI offers varying values to individuals (Lee et al. 2021). Although new technologies can be challenging for older generations, younger users find AI adoption more convenient. Current AI solutions personalize experiences and encourage AI service adoption in travel planning (Tavitiyaman et al. 2022). Therefore, it is essential to explore the generational differences in technology adoption.

This study utilizes the diffusion of innovation theory, value-based adoption model theory, and technology readiness theory to predict AI adoption and to examine technical and facilitating aspects. Marketers and Innovators must understand the factors driving technological interest, particularly in the travel sector, by identifying their influences on AI diffusion. This study aimed to address the following research questions:

- RQ1: How does perceived value activate intention to use AI-based services in the tourism sector?
- RQ2: What are the contingent effects of generation (Y and Z) and perceived innovativeness on perceived value and intentions in the tourism sector?

This study addresses research gaps in the literature by examining the intention to use AI through perceived values, considering the contingent effects of generation (age) and perceived innovativeness. Pillai and Sivathanu (2020) have called for an investigation into perceived value in AI research, while Hollebeek et al. (2024) have emphasized the need for more studies on factors motivating AI user engagement. This study proposes an adoption framework for AI and investigates the technical and functional antecedents of perceived value.

2 | Literature Review

2.1 | Theoretical Background

Diffusion innovation theory (DOI), value-based adoption model (VAM) theory, and technology readiness (TRT).

Currently, AI empowers organizations to provide unique experiences by reimagining personalized strategies, particularly in the travel industry, which demands personalization (Renjith et al. 2020). Hence, firms must understand how and why travel consumers embrace AI technology in their lives. The literature in information technology has adopted multiple theories to discourse intentions to adopt AI-related platforms, including TAM, TAM2, TRA, TPB, and UTAUT (Dissanayake et al. 2022; Lampo 2022; Khan et al. 2021; Lai 2017). However, in 2024, the role of cognition, consumer psychology, value perspective, and experience gained dominance (Sohn and Kwon 2020), which cannot be explained by the theories mentioned above (Zhong et al. 2021). Therefore, this study conceptualized the intention to adopt AI among generations Y and Z using diffusion of innovation theory, value-based adoption model, and technology readiness theory. The diffusion of innovation theory (Rogers 1983) acts as a comprehensive guiding framework for developing the research model. The theory states that characteristics of the innovation itself significantly influence its adoption. Some of these characteristics are facilitating, while some are impeding the innovation adoption. It also emphasizes the innovativeness of the individuals as a significant influencer of the innovation adoption. More innovative individuals tend to adopt new ideas more quickly, thereby accelerating the overall diffusion process. Many recent studies have used diffusion of innovation theory to AI adoption, exploring how new technologies spread in society and how these innovative technologies can be adopted (Patnaik and Bakkar 2024; Uzumcu and Acilmis 2024). Some of these studies have focused on factors that impact the adoption of AI innovation among students and employees (Xu et al. 2024; Raman et al. 2024; Yuen et al. 2021). Some of the studies have focused on the role of innovativeness (Uzumcu and Acilmis 2024) and leadership on AI innovation adoption (Patnaik and Bakkar 2024). The current study is one of the few studies to comprehensively investigate the impact of positive and negative aspects and the moderating role of innovativeness on AI innovation value and adoption in tourism.

The VAM theory considers the perceived values of users, which in general is described as a subjective evaluation of the benefits and cost aspects of using a product/service. It includes both positive and negative facets that critically affect users' adoption intentions (Liao et al. 2022). Kim et al. 2007, conceptualized "usefulness" and "enjoyment" in the positive aspect, that is, benefits and "technicality," and "perceived fee" in the negative aspect, that is, sacrifice. The theory has been widely employed to examine mobile commerce, mobile banking, and IoT

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

(Zhong et al. 2021; Yu et al. 2019), and a handful of studies have employed VAM in AI, particularly in the tourism sector (Cao et al. 2022). Cao et al. (2022) adopted the value adoption model to investigate the adoption of smart voice assistants by Airbnb guests, however, their focus was on perceived functional value, perceived emotional value, perceived privacy, and self-efficacy.

The present study adopts the technology readiness theory to elucidate users' cognitive propensity toward embracing new technology (Parasuraman 2000). Within this framework, consideration is given to both the positive and negative facets that significantly influence readiness to accept and integrate new technological advancements (Lai 2008). Positive facets serve as motivational factors driving users' intentions to adopt new technology, such as optimism and innovativeness, whereas negative facets act as deterrents via discomfort and insecurity, potentially impeding the adoption of such advancements (Gao et al. 2022; Parasuraman and Colby 2015). The technology readiness theory employed in this study serves as a valuable tool for understanding users' psychological states and propensity to engage with technology in pursuit of personal objectives. Beyond its conventional role as a mediator, the TRT framework is herein regarded as a moderator in the context of the adoption of AI technology by users engaged in tour and travel activities. The relationship between perceived innovativeness (PI) and innovation is bidirectional; PI can influence technological innovation, and technological innovation can influence PI. In our study, we examined the role of PI in the intention to use innovative technologies, such as AI-based services in travel, tourism, and hospitality (TTH).

3 | Hypothesis Development

3.1 | Impact of Positive Facets on the Perceived Value of Users

According to value-based adoption theory, the two important positive aspects that impact technology adoption are perceived enjoyment and perceived usefulness. Traveling is an experiential aspect that subscribes to hedonic and eudaimonic facets (Cornet et al. 2022) and planning of traveling leads to similar excitement, enjoyment, and pleasantness (Tandon et al. 2020). Interestingly, previous studies have highlighted perceived enjoyment (PE) as an intrinsic motivation for engaging in new technology to effectively complete a task with fun and involvement (Soares et al. 2021; Lee et al. 2013). AI allows personalization in search that engages customers more, instant replies from chatbots augment participation, and digital platforms provide users with a plethora of options to compare, search, and find the ideal option (Popesku 2019). The latest studies acknowledge the role of AI in showing and presenting hotel rooms, tourist places, and traveling as a delightful experience that influences perceived value (Solakis et al. 2024).

The second positive aspect of any technology that impacts its adoption is perceived usefulness. Perceived usefulness (PU) is the belief that using service/technology can enhance productivity (Davis 1989). It has been identified as a strong motivator for new technology acceptance by providing reliability, assurance, and convenience, leading to enhanced productivity (Tavitiyaman et al. 2022), impacting attitudes and behaviors (Lalicic and Weismayer 2021; Zhu et al. 2023; Melián-González et al. 2021; Pillai and Sivathanu 2020), and invoking positive emotions in customers (Lin et al. 2020). Therefore, the literature has highlighted that perceived usefulness has a substantial impact on creating value for consumers in TTH. Therefore, we proffer the following.

H1. *Perceived enjoyment (PE) has a positive influence on perceived value (PV) in the tourism sector.*

H2. *Perceived usefulness (PU) has a positive influence on perceived value (PV) in the tourism sector.*

3.2 | Impact of Negative Facets on the Perceived Value of Users

According to value-based adoption theory, the two important negative aspects that impact technology adoption are technicality and perceived fees. Technicality refers to the effort required to use technology (Kim et al. 2007). Technicality demands special skills, competencies, and knowledge (Rahman 2019) and plays a significant role in deciding whether to adopt a new technology (Kim 2021). Technicality impacts customers' attitudes and behaviors toward a technology (Solakis et al. 2024). If the new technology is uncomplicated, simple, and easy to use, the diffusion of technology is more than that of complex technology, which requires more technicality (Pillai and Sivathanu 2020). Previous studies have affirmed the negative impact of technicality on the generation of values from technology. Hsiao (2022) found a negative impact of technicality on PV in mobile payment that hampers the value perception among users, and Sohn and Kwon (2020) reported that technicality harmed perceived value in the context of artificial intelligence.

Similarly, perceived fees have a profound impact on the choice of technology (Sohn and Kwon 2020) and include monetary or non-monetary expenses such as time, search, or psychological expenses (Hsiao 2022). In this study, the perceived fee is monetary and is the search cost that individuals are ready to spend on AI tools for TTH planning. Previous studies have affirmed the negative impact of perceived fees on AI-based service usage (Habibi and Rasoolimanesh 2021; Xu et al. 2019) and confirmed that cost interrupts the acceptance of new innovative technologies (Tom Dieck and Jung 2018). Some studies have debated the above notion and have said that high fees reflect higher quality, which positively influences the value appraisal of the technology (Liao et al. 2022; Zhu et al. 2010; Sweeney and Soutar 2001). Previous research does not agree on the relationship between perceived fees and perceived value.

Therefore, we have proposed the following

H3. *Technicality (T) has a negative influence on perceived value (PV) in the tourism sector.*

H4. *Perceived Fee (PF) has a negative influence on perceived value (PV) in the tourism sector.*

3.3 | PV and Intentions to AI in TTH

Zeithaml (1988) described the term perceived value as "the consumer's overall assessment of the utility of a product (or

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

service) based on perceptions of what is received and what is given," which calculates the benefits and costs of the products/services. Past studies articulated perceived value as both a subjective and objective evaluation of a product that begets the desirability toward the intention to use the product/services (Chen and Lin 2019; Dedeoğlu 2019; Ponte et al. 2015). In tourism, perceived value has been determined as a strong motivator of intention to use technology (Lalicic and Weismayer 2021; de Kervenoael et al. 2020). In addition, the perceived value generated by the trade-off between costs and benefits can attract new users or create intentions to use new technology (Masri et al. 2020). In addition, when TTH companies focus on innovative features that solve consumer problems and address their functional and emotional needs, they can create significant value. This approach may lead to an increased intention to use innovative technologies, such as AI. Hence, we have conjectured the following:

H5. *Perceived value (PV) positively influences the intentions to use AI in the tourism sector.*

3.4 | Perceived Innovativeness as a Moderator

Technology plays a powerful role in changing the world, which is expeditiously growing owing to continuous innovation (Coccia and Watts 2020). Hence, with improved innovative technology, consumers reflect on their exclusiveness and uniqueness to evaluate their usage decision-making (Hwang et al. 2019). Watchravesringkan et al. (2010) defined perceived innovativeness as "the degree to which consumers believe that the product possesses important attributes of innovation such as newness and uniqueness." Perceived innovativeness involves the novel and creative aspect of technology that distinguishes companies and provides a competitive advantage (Hwang et al. 2020). Hence, perceived innovativeness differs from consumer innovativeness. Consumer innovation involves the readiness to use the new innovative technology (Kwak et al. 2021), whereas perceived innovativeness involves the new features or characteristics consumers perceive in the new technology. In line with the technology readiness theory (TRT), Parasuraman and Colby (2015) define innovativeness as "a tendency to be a technology pioneer and thought leader." Hence, it reflects a person's propensity to try and accept advanced technologies. According to TRT, individuals with a high level of innovativeness are more inclined to exhibit openness to novel technologies. Conversely, individuals with lower innovativeness may experience hesitancy or discomfort in adopting new technologies. Previous studies affirmed that users with a high level of perceived innovativeness exhibit more confidence in product/service performance (Kim et al. 2021). Therefore, PI is a significant variable for examining the relationship between PV and intention to use AI as a moderator. Previous studies have discouraged the role of PI in the degree of consumers' perception, which affects their decision to use a product. It is quite possible that users with high PI have a positive contingent effect, and users with low PI have a negative contingent effect on the relationship between PV and intention to use AI in TTH. Hence, we have proposed the following:

H6. *The effect of perceived value (PV) on intentions to use AI in the tourism sector is moderated by perceived innovativeness (PI).*

3.5 | Age (Gen Y and Z) as Moderator

Age has been considered a significant demographic factor in exploring consumer behavior (Di Talia et al. 2019; Martins et al. 2011). Technology is used in everyday activities and is used by people of all ages (Hülür and Macdonald 2020). Generally, the elderly are hesitant to adopt new technology (Niehaves and Plattfaut 2014) compared to the younger generation. Previous studies have examined age as a moderator of technology acceptance and adoption (Chawla and Joshi 2020). Sharma et al. (2023) have affirmed that Generation Z adopts innovative approaches in current times. Zhao et al. (2018) affirm the role of age as a moderator in mobile healthcare technology adoption. Similarly, past studies have observed age as a moderator of technology adoption in banking (Chaouali and Souiden 2019; Chawla and Joshi 2018), social media (Liebana-Cabanillas and Alonso-Dos-Santos 2017), e-commerce and shopping (Natarajan et al. 2018), and education (Yu et al. 2017). Interestingly, in the tour and travel sector, age has been examined profoundly as a moderator to understand its relationship with embracing new technology (Paulo et al. 2018; Tan and Ooi 2018; Kim 2016). Therefore, to recognize the contingent effect of age on the PV and AI eras, we propose the following hypothesis (Figure 1):

H7. *The effect of perceived value (PV) on intentions to use AI in the tourism sector is moderated by age.*

4 | Methodology

4.1 | Sampling and Data Collection

Aligned with the guiding article (Paul 2024), the survey targeted AI-based service users in travel, tourism, and hospitality, primarily tech-savvy millennials (Gen Y) and Zoomers (Gen Z). These cohorts were chosen because of their technical proficiency and acceptance of AI-based services (Bilgihan 2016), particularly hotel bookings and travel planning (PwC 2019). They seek personalized experiences through tailored recommendations and itineraries (Deloitte 2020) and significantly influence travel trends (McKinsey 2023a, 2023b). Thus, Gen Y and Gen Z members are crucial for AI-based tourism, travel, and hospitality services. Invitation messages were sent in January 2022 via messaging platforms and emails. Data were collected using a self-administered cross-sectional survey of 305 participants. After excluding incomplete questionnaires, 283 valid responses were retained for analysis. The respondents' profiles are presented in Table 1.

4.2 | Measuring Instrument

Validated scales were used to measure the study variables (Table 2). Each item uses a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Perceived value was

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

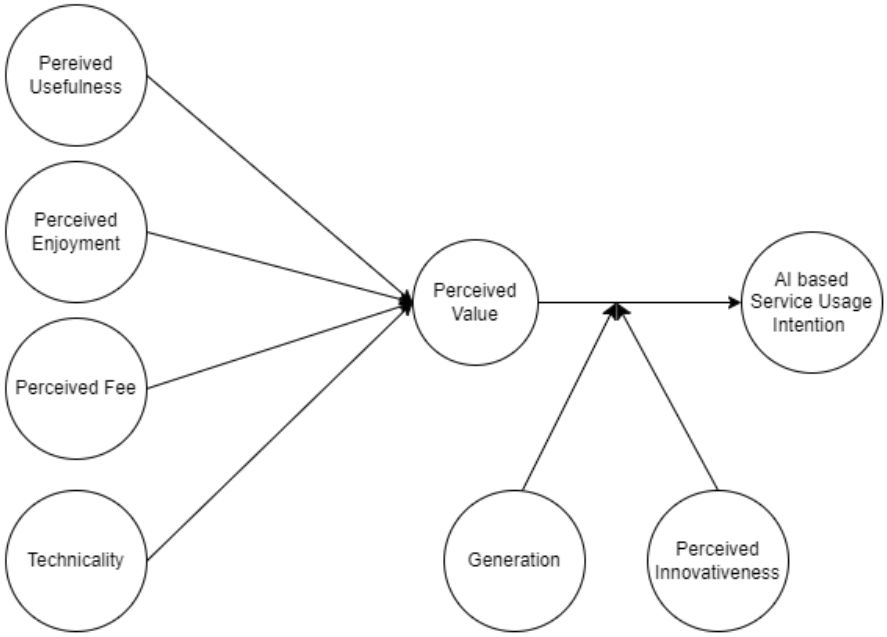


FIGURE 1 | Conceptual model. AGE-Gen, generation Y or Z; IN-AI-based service usage intention; PE-Perceived Enjoyment; PF-Perceived Fee; PI-Perceived Innovativeness; PU-Perceived Usefulness; T-Technicality; PV-Perceived Value. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Respondent demographic profile.

Demographic characteristics ($N = 283$)			
Generation	**Frequency (%)**	**Education**	**Frequency (%)**
Gen Y	174 (62%)	12th	37 (13%)
Gen Z	109 (48%)	Graduation Degree	170 (60%)
		Master's Degree	76 (27%)
Gender		**Used of AI-Based Services**	
Female	98 (35%)	Once	24 (10%)
Male	125 (65%)	Two to five times	73 (30%)
		Once a week	31 (13%)
		More than once a week	71 (29%)
		Once a month	21 (9%)
		Twice a month	21 (9%)

measured using three items from Sirdeshmukh et al. (2002), perceived usefulness (five items) from Davis (1989), and perceived fee (two items) from Voss et al. (1998). Perceived enjoyment included three items from Agarwal and Karahanna (2000) and Wang et al. (2012), while technicality (three items) was adapted from Davis (1989) and DeLone and McLean (2003). Perceived innovativeness (four items) was adapted from Parasuraman and Colby (2015), and intention (three items) from Davis (1989). Two management professors and two doctoral scholars verified the questionnaire's validity. Feedback on face validity and readability was also collected from AI-based service users. The questionnaire began with broad demographic questions to understand the behavioral tendencies of Generation Y and Z, focusing on their use of AI in online reservations and travel planning. Participants were also asked to identify which AI-based services or products were essential to their trip planning processes.

4.3 | Analytic Approach

This study employed PLS-SEM (SMART PLS 4) and artificial neural network analysis. PLS-SEM is suitable for hypothesis testing but cannot fully capture nonlinear relationships, except for quadratic effects (Hair et al. 2011), whereas ANN can capture nonlinear relationships but is inadequate for hypothesis testing. PLS-SEM is deemed suitable for hypothesis testing, as it enables the concurrent estimation of multiple causal relationships among independent and dependent variables (Hair et al. 2011).

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Convergent validity of constructs.

Construct	Item		VIF	Loading
Intentions (IN)	Cronbach's alpha = 0.869, composite reliability = 0.92, average variance extracted (AVE) = 0.793			
	I1	I intend to use AI product in the future for my traveling plans	2.668	0.909
	I2	I intend to use AI product frequently for my traveling plans	2.1	0.874
	I3	I intend to purchase traveling services with AI-based platforms	2.288	0.887
Perceived enjoyment (PE)	Cronbach's alpha = 0.92, composite reliability = 0.95, average variance extracted (AVE) = 0.863			
	PE1	I have fun interacting with AI based services	3.297	0.925
	PE2	Using AI Product provides me with a lot of enjoyment	3.511	0.93
	PE3	I enjoy using AI Product—services	3.31	0.931
Perceived fee (PF)		Cronbach's alpha = 0.823, composite reliability = 0.919, average variance extracted (AVE) = 0.849		
	PF1	The fee that I have to pay for the use of AI product is reasonable	1.955	0.919
	PF2	I am pleased with the fee that I have to pay for the use of AI product	1.955	0.924
Perceived innovativeness (PI)		Cronbach's alpha = 0.917, composite reliability = 0.938, average variance extracted (AVE) = 0.751		
	PI1	I can usually figure out new high-tech products and services without help from others	1.875	0.758
	PI2	I keep up with the latest technological developments in my areas of interest	2.804	0.871
	PI3	I enjoy the challenge of figuring out high-tech gadgets	3.694	0.91
	PI4	I prefer to use the most advanced technology available	3.363	0.899
Perceived usefulness (PU)		Cronbach's alpha = 0.938, composite reliability = 0.953, average variance extracted (AVE) = 0.802		
	PU1	Using AI product enables me to accomplish tasks more quickly	3.559	0.903
	PU2	Using AI product enhances my task effectiveness	3.124	0.881
	PU3	Using AI product makes it easier to do my task	3.286	0.889
	PU4	Using AI product improves my task performance	3.952	0.908
	PU5	Using AI product saves me time and effort in performing tasks	3.582	0.897
Perceived value (PV)		Cronbach's alpha = 0.861, composite reliability = 0.915, average variance extracted (AVE) = 0.783		
	PV1	Compared to the effort I need to put in, the use of AI product is beneficial to me	1.966	0.859
	PV2	Compared to the time I need to spend, the use of AI product is worthwhile to me	2.385	0.89
	PV3	Overall, the use of AI product delivers me good value	2.35	0.904

(Continues)

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | (Continued)

Construct	Item		VIF	Loading
Technicality (T)	Cronbach's alpha = 0.857, composite reliability = 0.903, average variance extracted (AVE) = 0.7			
	T1	It is easy to use AI services	1.764	0.795
	T2	AI services can be connected instantly	1.959	0.827
	T3	AI services takes a short time to respond	2.348	0.877
	T4	It is easy to get AI product to do what I want it to do	2.159	0.845

The sample size for Smart PLS should be ten times the largest number of indicators for one construct and ten times the largest number of structural paths aimed at a particular latent construct. The 283 responses collected in this study exceeded these requirements (Hair et al. 2011).

Data analysis involved two stages. Initially, PLS-SEM was employed to validate the research model and identify the significant predictors. Reliability, convergent validity, and discriminant validity of the measurement model were assessed. The hypotheses were evaluated to verify the structural model, including moderators, as PLS-SEM (Smart PLS 4) accommodates complex models (Becker et al. 2023). The path coefficients were derived using the path-weighting scheme algorithm in Smart PLS. The statistical significance of the structural paths was determined using a two-tailed percentile bootstrap procedure with 10,000 resamples. Model robustness was checked using a post-structural model analysis. In the second stage, artificial neural network (ANN) analysis used significant predictors from the PLS-SEM model to assess the relative importance of each predictor variable.

4.4 | Common Method Bias

This cross-sectional study relied on self-reported measures, necessitating steps to mitigate and evaluate the common method bias. Several procedures and statistical tests were performed. Procedurally, anonymity was ensured via clear survey instructions, avoidance of complex terms, ordering of dependent variables before independent variables, and shuffling items of the same factor (Podsakoff et al. 2003). A full collinearity test of Knock (2015) was applied. A model is deemed free of common method bias if the VIF of all latent factors is below 3.3 (Knock 2015). This criterion was satisfied by the research model.

4.5 | Evaluation of the Measurement Model

To validate the measurement model, reflective indicator loadings were first assessed. Factor loadings should exceed 0.707, indicating greater shared variance between an item and its construct than the error variance (Hair et al. 2011). In this study, all factor loadings exceeded 0.70 (Table 2). Internal consistency reliability was evaluated using composite reliability and Cronbach's alpha, both of which were above 0.7 (Fornell and Larcker 1981; Hair et al. 2011). Convergent validity was assessed using average variance extracted (AVE), with all AVE values above 0.5, indicating that the constructs explained more than 50% of the item variance.

The Fornell–Larcker and heterotrait-monotrait (HTMT) criteria were applied to assess discriminant validity (Fornell and Larcker 1981; Henseler 2017). First, the average shared variance between a construct and its measurement scales must exceed the shared variance between the construct and other constructs in the model, represented by the squared correlation between the constructs (Fornell and Larcker 1981). The square root of AVE surpassed the correlations between the constructs. Second, the HTMT ratio between constructs was below 0.9. As shown in Table 3, both criteria were met, confirming the discriminant validity of the measurement model.

5 | Empirical Results

5.1 | Structural Model

Before analyzing the statistical significance and relevance of the path coefficients, in-sample prediction accuracy was assessed to identify the model's explanatory power (R^2). According to the findings (Table 4), 54.4% of the variance in intention and 67.6% of the variance in perceived value were explained by the independent variables, indicating that the explanatory power of the model was above moderate and acceptable (Hair et al. 2011). The out-of-sample predictive accuracy of the model was computed using PLS prediction with a cross-validation k-fold = 10 parameters (Shmueli et al. 2019), which suggested moderate out-of-sample predictive accuracy of the research model. Additionally, the SRMR value of the structural model was 0.063, which was below the threshold value of 0.08, indicating a good model fit (Henseler 2017).

Subsequently, the statistical significance and relevance of path coefficients were assessed (Figure 2). The results in Table 4 show that H01 and H05 are significant, with H01 and H05 having standardized regression coefficients above the threshold value of 0.2 (Henseler 2017). H02 and H04 levels were not statistically significant. Interestingly, H03 was significant but positive; hence, it was rejected in our study. However, it would be interesting to consider its theoretical and practical implications. The indirect effects are summarized in Table 5. The indirect effect of perceived usefulness on intention through perceived value (beta indirect = 0.389, $p < 0.001$) and the indirect effect of perceived fees on intention through perceived value (beta indirect = 0.087, $p < 0.001$) were found to be significant. Interestingly, the indirect effect of perceived usefulness on intention through perceived

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 3 | Assessment of discriminant validity of constructs.

	IN	PE	PF	PI	PU	PV	T
IN	**0.89**	0.793	0.349	0.579	0.766	0.85	0.681
PE	0.71	**0.929**	0.485	0.728	0.859	0.791	0.786
PF	0.296	0.422	**0.922**	0.525	0.432	0.547	0.658
PI	0.518	0.671	0.435	**0.87**	0.65	0.647	0.739
PU	0.693	0.799	0.381	0.604	**0.896**	0.884	0.804
PV	0.739	0.71	0.461	0.578	0.8	**0.885**	0.791
T	0.586	0.698	0.554	0.643	0.722	0.686	**0.837**

Note: Main diagonal in bold = square root of AVE; Fornell–Larcker criterion is below the main diagonal and the HTMT ratio is above the main diagonal.

TABLE 4 | Structural model results.

		Direct effect$^{\text{significance}}$ (t value) f^2	Result
R^2 (PV) 0.545			
$H_0$1	PU → PV	0.571** (7.559) 0.312	Supported
$H_0$2	PE → PV	0.114^{ns} (1.188) 0.013	Not Supported
$H_0$3	PF → PV	0.127* (2.798) 0.035	Supported
$H_0$4	T → PV	0.123^{ns} (1.786) 0.018	Not Supported
R^2 (IN) 0.676			
$H_0$5	PV → IN	0.740** (19.234) 1.207	Supported

Note: R^2 value of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak (Hair et al. 2018). f^2 values of 0.02, 0.15, and 0.35 are considered small, medium, and large effect size (Guenther et al. 2023).
Abbreviations: IN, AI-based service usage intention; ns, not significant; PE, perceived enjoyment; PF, perceived fee; PU, perceived usefulness; T, technicality.
*$p < 0.01$.
**$p < 0.00$.

value was high, with a standardized beta coefficient of 0.389. The indirect effect of perceived enjoyment on intention through perceived value, as well as the indirect effect of technicality on intention through perceived value, was found to be insignificant.

5.2 | Moderation Analysis

The moderating effects of age (specific focus on Gen Z or Y) and perceived innovativeness on the relationship between perceived value and intention to use AI-based services are established by including moderators in the structural model. Table 6 presents the moderation results. The results showed that both age ($\beta = -0.105$, $p = 0.047$, t-value = 1.987) and perceived innovativeness ($\beta = -0.072$, $p = 0.031$, t-value = 1.077) significantly moderated the relationship between perceived value and intention to use AI-based services. Interestingly, the standardized regression coefficient of perceived innovativeness and age has a low negative value. This shows that perceived innovativeness has a significant but very low suppressing impact on the relationship between perceived value and intention to use AI-based services. For age (Generation Z or Y), the negative standardized regression coefficient means that the relationship between perceived value and the intention to use AI-based services is stronger for Generation Z than for Generation Y.

A simple slope analysis was conducted to better understand the significant moderators. For the moderating variable "perceived innovativeness," the simple slope diagram (Figure 3) indicates that at −1 SD (low innovativeness), the plot is steeper with a positive gradient compared to +1 SD (high innovativeness). This means that for individuals with low perceived innovativeness, an increase in perceived value enhances their intention to adopt AI-based services. Conversely, for highly innovative individuals, an increase in perceived value (cost/benefit trade-off) reduces their intention to adopt AI-based services. Thus, as user innovativeness decreases, the relationship between perceived value and intention to adopt AI-based services strengthens. Conversely, higher perceived innovativeness weakens this relationship, potentially because less-innovative users view perceived value as a crucial factor, making them more likely to adopt AI-based services. By contrast, highly innovative users may find the service complex, unnecessary, or have high expectations, leading to lower adoption intentions despite increased perceived value. For the moderating variable "age," the simple slope diagram (Figure 4) shows that at 0 (Generation Z), the plot is steeper with a positive gradient compared to 1 (Generation Y). Simple slope analysis reveals that for Generation Z, perceived value has a stronger impact on the intention to use AI-based services than for Generation Y. These findings are consistent with those of the statistical analysis.

5.3 | Model Robustness Check

To perform multivariate analysis using SMART PLS, several prerequisites need to be assessed, such as multicollinearity, homoscedasticity, normality of distribution, endogeneity, and nonlinearity (Sarstedt et al. 2020). To assess the multicollinearity problem, we examined the VIFs (Table 1). The results showed that the VIFs fell within the standard threshold of five, which indicates that there was no multicollinearity issue.

To assess homoscedasticity, we examined the standard residual scatter plot (Figure 5) and found that residuals dispersed along a diagonal line. Further analysis using Sarstedt et al.'s (2020) systematic procedure involved running FIMIX-PLS for five

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

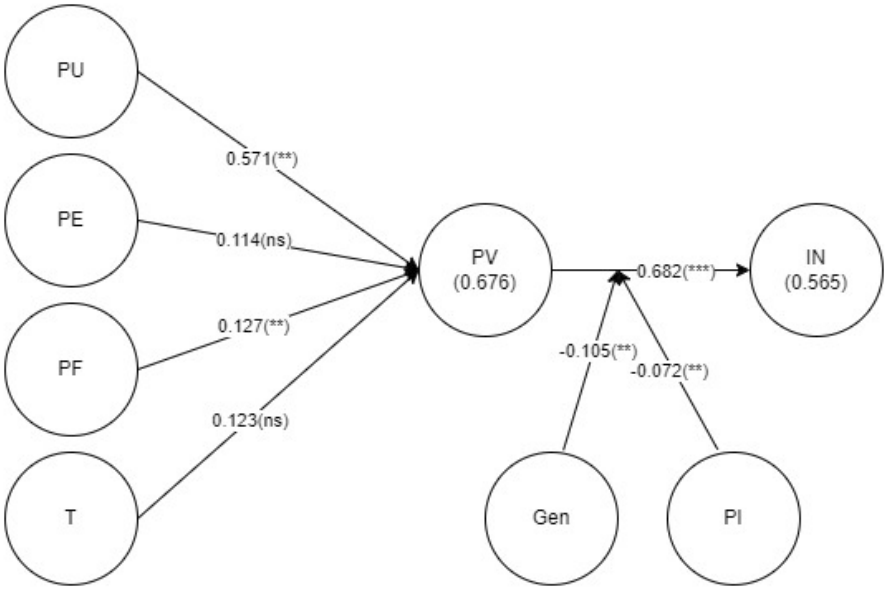


FIGURE 2 | Structural model predicting the direct, indirect, and conditional direct relationships. Gen, generation Y or Z; IN, AI-based service usage intention; PE, perceived enjoyment; PF, perceived fee; PI, perceived innovativeness; PU, perceived usefulness; T, technicality. **$-p \leq 0.01$, ***$-p \leq 0.001$, ns-not significant.

TABLE 5 | Indirect effects.

	Indirect effect$^{\text{significance}}$/t value	Total effect	Result
PU → PV → IN	0.389*** (5.730)	0.389*** (5.730)	Supported
PE → PV → IN	0.078^{ns} (1.179)	0.078^{ns} (1.179)	Not supported
PF → PV → IN	0.087** (2.645)	0.087** (2.645)	Supported
T → PV → IN	0.084^{ns} (1.803)	0.084^{ns} (1.803)	Not supported

Abbreviations: IN, AI-based service usage intention; ns, not significant; PE, perceived enjoyment; PF, perceived fee; PU, perceived usefulness; T, technicality.
***$p < 0.01$.
**$p < 0.00$.

TABLE 6 | Moderation analysis.

		$\beta^{\text{significance}}$ (t value)	f^2	Result
$H_0$6	Gen → PV → IN	−0.105** (1.987)	0.009	Supported
$H_0$7	PI → PV → IN	−0.072** (2.158)	0.021	Supported

Abbreviations: Gen, Generation Y or Z; IN, AI-based service usage intention; ns, not significant; PI, perceived innovativeness.
**$p < 0.00$.

segments (minimum sample size = 85, effect size = 0.15, and power = 80%) with consistent initial settings. However, the analysis did not clearly indicate a specific segment solution (Table 7). Unobserved heterogeneity is not critical and supports complete data results.

A one-sample Kolmogorov–Smirnov test revealed that all p-values were below 0.05, indicating a non-normal data distribution. Given this non-normality, variance-based structural equation modeling (SEM) using partial least squares (PLS) was suitable for this study because of its robustness against non-normal distributions, unlike covariance-based SEM (Hair et al. 2011).

Hult et al. (2018) guidelines build on Park and Gupta (2012) Gaussian copula approach was followed to test the endogeneity. There were five estimator variables in the analysis; a total 31 models with one copula, two copulas, three copulas, four copulas, and five copulas were developed and analyzed. Coefficient copula significance was tested using bootstrapping (Park and Gupta 2012). The results in Table 8 show that there was no significant Gaussian copula in the models.

A two-step approach was used to test model nonlinearity. First, Ramsey's (1969) test was conducted using R-programming. Interaction terms were then included to represent quadratic effects in the PLS-SEM (Basco et al. 2022). The results revealed that three out of the five quadratic effects were nonlinear (Table 9). Thus, the original model was extended to incorporate significant nonlinear effects, assess changes in R-squared and BIC values, and compare models for fit and explanatory power (Basco et al. 2022). The nonlinear model showed a better fit (BIC of −217.728 compared with −213.762) and higher explanatory power (adjusted R^2 of 0.559 vs. 0.545). It also demonstrated

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

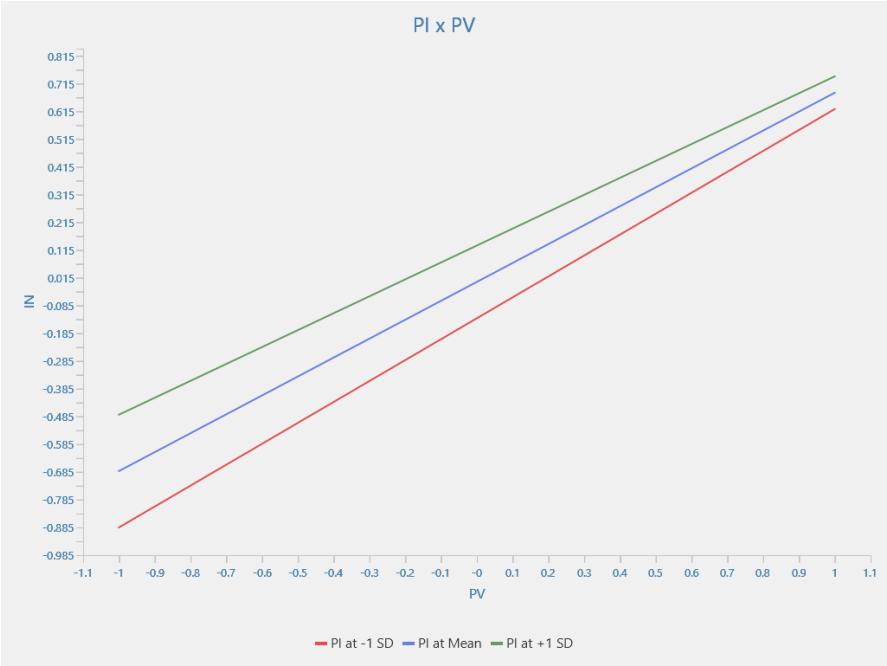


FIGURE 3 | Moderating effect of perceived innovativeness on perceived value and intention to adopt AI-based services. [Colour figure can be viewed at wileyonlinelibrary.com]



FIGURE 4 | Moderating effect of Gen Y and Z on perceived value and intention to adopt AI-based services. [Colour figure can be viewed at wileyonlinelibrary.com]

slightly better predictive relevance (0.489 vs. 0.486). PLS prediction analysis results are presented in Table 10.

5.4 | ANN Analysis

To confirm and strengthen the results, an ANN analysis was applied using IBM's SPSS ANN algorithm, which captures both linear and nonlinear relationships, and does not require normally distributed data for complex models (Table 11). ANNs are often used along with PLS-SEM for similar reasons (Chen et al. 2023; Chong et al. 2023; Leong et al. 2023; Mishra et al. 2023; Nayal et al. 2023; Xu et al. 2023). The multilayer perceptron and sigmoid activation functions were employed for the input and hidden layers, respectively. Ninety percent of the sample was used for training, and the remainder was

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

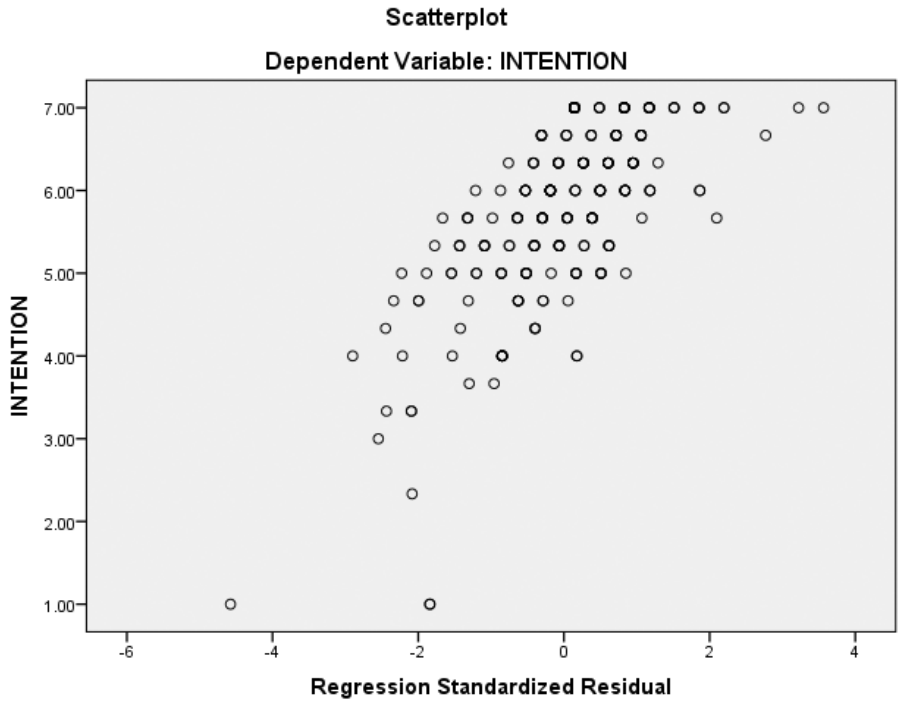


FIGURE 5 | Homoscedasticity (standard residual plot).

TABLE 7 | Unobserved heterogeneity.

	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
AIC (Akaike's information criterion)	1065.752	817.349	784.43	744.055	727.735
AIC3 (modified AIC with Factor 3)	1076.752	840.349	819.43	791.055	786.735
AIC4 (modified AIC with Factor 4)	1087.752	863.349	854.43	838.055	845.735
BIC (Bayesian information criterion)	1105.852	901.195	912.02	915.391	942.816
CAIC (consistent AIC)	1116.852	924.195	947.02	962.391	1001.816
HQ (Hannan–Quinn criterion)	1081.831	850.968	835.589	812.755	813.975
MDL5 (minimum description length with Factor 5)	1354.252	1420.576	1702.383	1976.735	2275.142
LnL (log likelihood)	−521.876	−385.675	−357.215	−325.027	−304.868
EN (normed entropy statistic)	0	0.965	0.69	0.82	0.823
NFI (non-fuzzy index)	0	0.977	0.681	0.807	0.79
NEC (normalized entropy criterion)	0	9.89	87.622	50.995	50.038
Criteria	**Suggested number of segments**		**Criteria**	**Suggested number of segments**	
AIC3	5		AIC4	4	
CAIC	2		BIC	2	
Criteria	**Suggested number of segments**				
MDL5	1				

Note: Sarstedt's (2020) systematic procedure involved running FIMIX-PLS for five segments (minimum sample size = 85, effect size = 0.15, and power = 80%) was used to check for unobserved heterogeneity. Shades doesn't have any significance values. AIC/BIC and entropoy values are used to identify if there are any optimal segment solution.

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 8 | Gaussian copula analysis for endogeneity.

Construct	Original model beta/*p* value	Gaussian copula Model 1 (EV: PU) beta/*p* value	Gaussian copula Model 2 (EV: PE) beta/*p* value	Gaussian copula Model 3 (EV: PF) beta/*p* value	Gaussian copula Model 4 (EV: T) beta/*p* value	Gaussian copula Model 5 (EV: PV) beta/*p* value
PU	0.571/0	0.498/0	0.571/0	0.577/0	0.565/0	0.571/0
PE	0.114/0.227	0.117/0.215	0.097/0.563	0.11/0.246	0.115/0.224	0.114/0.227
PF	0.127/0.006	0.128/0.006	0.128/0.005	0.265/0.076	0.133/0.005	0.127/0.006
T	0.123/0.078	0.119/0.088	0.123/0.077	0.126/0.071	0.269/0.018	0.123/0.078
PV	0.74/0	0.74/0	0.74/0	0.74/0	0.74/0	0.82/0
GC (PU) → PV		0.06/0.262				
GC (PE) → PV			0.013/0.868			
GC (PF) → PV				−0.124/0.293		
GC (T) → PV					−0.128/0.118	
GC (PV) → IN						−0.068/0.381

	Gaussian copula Model 6 (EV: PU, PE) beta/*p* value	Gaussian copula Model 7 (EV: PU, PF) beta/*p* value	Gaussian copula Model 8 (EV: PU, T) beta/*p* value	Gaussian copula Model 9 (EV: PU, PV) beta/*p* value	Gaussian copula Model 10 (EV: PE, PF) beta/*p* value	Gaussian copula Model 11 (EV: PE, T) beta/*p* value
PU	0.485/0	0.462/0	0.422/0	0.498/0	0.58/0	0.564/0
PE	0.145/0.464	0.111/0.238	0.12/0.2	0.117/0.215	0.041/0.835	0.028/0.882
PF	0.127/0.006	0.354/0.039	0.138/0.004	0.128/0.006	0.323/0.082	0.139/0.003
T	0.119/0.093	0.121/0.085	0.351/0.008	0.119/0.088	0.127/0.07	0.327/0.033
PV	0.74/0	0.74/0	0.74/0	0.82/0	0.74/0	0.74/0
GC (PU) → PV	0.071/0.401	0.099/0.134	0.116/0.077	0.06/0.262		
GC (PE) → PV	−0.021/0.845				0.051/0.606	0.066/0.511
GC (PF) → PV		−0.203/0.146			−0.174/0.256	
GC (T) → PV			−0.208/0.051			−0.18/0.115
GC (PV) → IN				−0.068/0.381		

(Continues)

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 8 | (Continued)

	Gaussian copula Model 12 (EV: PE, PV)	Gaussian copula Model 13 (EV: PF, T)	Gaussian copula Model 14 (EV: PF, PV))	Gaussian copula Model 15 (EV: T, PV)	Gaussian copula Model 16 (EV: PU, PE, PF)	Gaussian copula Model 17 (EV: PU, PE, T)
PU	0.571/0	0.569/0	0.577/0	0.565/0	0.47/0.001	0.434/0.001
PE	0.097/0.563	0.113/0.232	0.11/0.246	0.115/0.224	0.091/0.671	0.085/0.687
PF	0.128/0.005	0.191/0.309	0.265/0.076	0.133/0.005	0.366/0.049	0.14/0.003
T	0.123/0.077	0.246/0.087	0.126/0.071	0.269/0.018	0.122/0.088	0.368/0.014
PV	0.82/0	0.74/0	0.82/0	0.82/0	0.74/0	0.74/0
GC (PU) → PV					0.093/0.28	0.106/0.218
GC (PE) → PV	0.013/0.868				0.015/0.899	0.027/0.816
GC (PF) → PV		−0.053/0.741	−0.124/0.293		−0.213/0.162	
GC (T) → PV		−0.107/0.348		−0.068/0.381		−0.222/0.051
GC (PV) → IN	−0.068/0.381		−0.068/0.381	−0.128/0.118		

	Gaussian copula Model 18 (EV: PU, PE, PV) beta/*p* value	Gaussian copula Model 19 (EV: PU, PF, T) beta/*p* value	Gaussian copula Model 20 (EV: PU, PF, PV) beta/*p* value	Gaussian copula Model 21 (EV: PU, T, PV) beta/*p* value	Gaussian copula Model 22 (EV: PE, PF, T) beta/*p* value	Gaussian copula Model 23 (EV: PE, PF, PV) beta/*p* value
PU	0.485/0	0.415/0	0.462/0	0.422/0	0.571/0	0.58/0
PE	0.145/0.464	0.117/0.215	0.111/0.238	0.12/0.2	0.007/0.972	0.041/0.835
PF	0.127/0.006	0.262/0.175	0.354/0.039	0.138/0.004	0.251/0.207	0.323/0.082
T	0.119/0.093	0.311/0.044	0.121/0.085	0.351/0.008	0.295/0.071	0.127/0.07
PV	0.82/0	0.74/0	0.82/0	0.82/0	0.74/0	0.82/0
GC (PU) → PV	0.071/0.401	0.127/0.063	0.099/0.134	0.116/0.077		
GC (PE) → PV	−0.021/0.845				0.079/0.463	0.051/0.606
GC (PF) → PV		−0.113/0.494	−0.203/0.146		−0.101/0.549	−0.174/0.256
GC (T) → PV		−0.17/0.174		−0.208/0.051	−0.15/0.237	
GC (PV) → IN	−0.068/0.381		−0.068/0.381	−0.068/0.381		−0.068/0.381

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 8 | (Continued)

	Gaussian copula Model 24 (EV: PE, T, PV) beta/*p* value	Gaussian copula Model 25 (EV: PF, T, PV) beta/*p* value	Gaussian copula Model 26 (EV: PV, PU, PE, PF) beta/*p* value	Gaussian copula Model 27 (EV: PV, PU, PE, T) beta/*p* value	Gaussian copula Model 28 (EV: PV, PU, PF, T) beta/*p* value	Gaussian copula Model 29 (EV: PV, PE, PF, T) beta/*p* value
PU	0.485/0	0.569/0	0.47/0.001	0.434/0.001	0.415/0	0.571/0
PE	0.145/0.464	0.113/0.232	0.091/0.671	0.085/0.687	0.117/0.215	0.007/0.972
PF	0.127/0.006	0.191/0.309	0.366/0.049	0.14/0.003	0.262/0.175	0.251/0.207
T	0.119/0.093	0.246/0.087	0.122/0.088	0.368/0.014	0.311/0.044	0.295/0.071
PV	0.82/0	0.82/0	0.82/0	0.82/0	0.82/0	0.82/0
GC (PU) → PV	0.071/0.401	−0.068/0.381	0.093/0.28	0.106/0.218	0.127/0.063	
GC (PE) → PV	−0.021/0.845		0.015/0.899	0.027/0.816		0.079/0.463
GC (PF) → PV		−0.053/0.741	−0.213/0.162		−0.113/0.494	−0.101/0.549
GC (T) → PV		−0.107/0.348		−0.222/0.051	−0.17/0.174	−0.15/0.237
GC (PV) → IN	−0.068/0.381	−0.068/0.381	−0.068/0.381	−0.068/0.381	−0.068/0.381	−0.068/0.381

	Gaussian copula Model 30 (EV: PU, PE, PF, T) beta/*p* value	Gaussian copula Model 31 (EV: PV, PU, PE, PF, T) beta/*p* value
PU	0.286/0.151	0.432/0.001
PE	0.432/0.001	0.061/0.78
PF	0.061/0.78	0.286/0.151
T	0.329/0.043	0.329/0.043
PV	0.74/0	0.82/0
GC (PU) → PV	0.114/0.186	0.114/0.186
GC (PE) → PV	0.041/0.734	0.041/0.734
GC (PF) → PV	−0.132/0.437	−0.132/0.437
GC (T) → PV	0.114/0.147	−0.186/0.147
GC (PV) → IN		−0.068/0.381

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 9 | Non-linearity (Ramsay RESET test and quadratic effects in PLS-SEM).

Non-linear relationship	Coefficient	*p*	f^2	Ramsay's RESET
QE (PU) → PV	0.027	0.622	0.040	RESET test data: PV ~ PU + PF + PE + T RESET = 5.2121, df1 = 8, df2 = 270, *p*-value = 4.515e−06
QE (PE) → PV	−0.107	0.201	0.04	
QE (PF) → PV	0.081	0.032	0.021	
QE (T) → PV	−0.009	0.856	0	
QE (PV) → IN	−0.074	0.002	0.035	RESET test data: IN ~ PV RESET = 5.1276, df1 = 2, df2 = 279, *p*-value = 0.006502

TABLE 10 | $PLS_{predict}$ analysis.

	Q^2 predict	PLS-SEM_ RMSE	LM_RMSE	Diff
IN1	0.394	0.891	0.875	0.016
IN2	0.327	1.062	1.074	−0.012
IN3	0.416	0.935	0.961	−0.026

Abbreviation: IN, AI-based service usage intention.

TABLE 11 | Comparison of original model with non-linear model.

	Original model	Non-linear model
R-square adjusted (intention)	0.545	0.559
BIC (Bayesian information criterion) (intention)	−213.762	−217.728
Q^2 predict (Intention)	0.486	0.489

TABLE 12 | RMSE values.

Training			Testing		
N	SSE	RMSE	*N*	SSE	RMSE
249	1.791	0.0848	34	0.176	0.0719
252	1.769	0.0838	31	0.197	0.0797
254	1.757	0.0832	29	0.159	0.0740
255	1.883	0.0859	28	0.112	0.0632
254	1.769	0.0835	29	0.165	0.0754
251	1.851	0.0859	32	0.225	0.0839
256	1.682	0.0811	27	0.236	0.0935
264	2.098	0.0891	19	0.054	0.0533
263	1.824	0.0833	20	0.195	0.0987
247	1.618	0.0809	36	0.346	0.0980
Mean	1.8042	0.0841	Mean	0.1865	0.0792
Standard deviation	0.1289	0.0024	Standard deviation	0.0774	0.0148

used for testing. A 10-fold cross-validation procedure and root mean square error (RMSE) calculations were conducted to prevent overfitting. Table 12 shows that the average RMSE values for training and testing were 0.0841 and 0.0792, respectively, indicating an excellent model fit. Sensitivity analysis was used to measure the predictive power of each input neuron (Table 13), with normalized importance determined by dividing the relative importance by the maximum importance. The results indicate that perceived value is the most critical predictor, followed by perceived usefulness, innovativeness, and fees.

TABLE 13 | Sensitivity analysis.

	PV	PU	PF	PI
ANN1	0.511	0.355	0.074	0.060
ANN2	0.550	0.375	0.055	0.020
ANN3	0.579	0.272	0.084	0.084
ANN4	0.463	0.315	0.045	0.045
ANN5	0.534	0.336	0.092	0.092
ANN6	0.492	0.374	0.017	0.017
ANN7	0.508	0.295	0.106	0.106
ANN8	0.489	0.354	0.009	0.009
ANN9	0.616	0.265	0.011	0.011
ANN10	0.583	0.320	0.058	0.058
Average importance	0.533	0.326	0.055	0.086
Normalized importance (%)	100	61.2316	10.3386	16.1977

6 | Discussion

The study adopted the diffusion of innovation theory, value adoption model, and technology readiness theory to investigate the impact of the value perception of users on the behavioral intention to adopt AI products. The study found that perceived value significantly impacts the intention to adopt AI-based services for travel, tourism, and hospitality. These results are corroborated by several previous studies (Sohn and Kwon 2020;

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Paul et al. 2024). As long as consumers value AI services, they will want to engage with, use, and continue using AI-based services for travel, tourism, and hospitality (Lee et al. 2013; Shaw and Sergueeva 2019).

Perceived fees were found to significantly impact the perceived value of AI-based services for travel, tourism, and hospitality. The results contradict the results of Pal et al. (2020) and Zietsman et al. (2018), who affirmed that the value perception of the customer of the AI-based service increases with a decrease in the fee of the AI-based services and vice versa. However, previous studies have confirmed a positive relationship between high prices and the generation of more value from the technology used (Liao et al. 2022; Zhu et al. 2010; Sweeney and Soutar 2001).

This study established that perceived utility significantly impacts the perceived value of AI-based services for travel, tourism, and hospitality. These results are in accord with several recent studies that reiterate that utility is a crucial antecedent to understanding the customer adoption intention toward artificially intelligent products such as healthcare devices (Huarng et al. 2022). However, the results differ from those of studies conducted by Sohn and Kwon (2020), Pal et al. (2020), and Moriuchi (2019). The research studies showed that perceived utility is not an important variable affecting the intention of AI-based services, such as the use of digital voice assistants for travel recommendations and bookings. AI-based services lack utility, and their adoption intention is driven more by pleasure than by their usefulness. A possible explanation for such contradictory results is that the type of AI service may affect the utility perception of the customer. Some AI-based services that are utility-oriented are liked and used by the users more for their usefulness than enjoyment, while other AI-based services that are oriented toward enjoyment are adopted by the user more because of the enjoyment and pleasure they provide than the utility aspect (Sohn and Kwon 2020).

This study found that perceived enjoyment does not impact the perceived value of an AI-based service. However, the findings of the current study do not support those of previous research. These results differ from those of several previous studies (Moussawi et al. 2021; Pal et al. 2020; Yang and Lee 2019; Lee et al. 2013). Earlier studies established that perceived enjoyment significantly impacts the intention to adopt AI-based services (Moussawi et al. 2021; Pal et al. 2020; Yang and Lee 2019; Lee et al. 2013). Perceived enjoyment is a critical factor affecting the effort expectations and the performance expectations of the user, which in turn influences the user's attitude toward the AI-based service (Pitardi and Marriott 2021; Lin et al. 2020).

The study found that technicality did not impact the perceived value of AI-based services for travel, tourism, and hospitality. However, this result has not been previously reported. These results differ from previous studies' results (Sohn and Kwon 2020; Pal et al. 2020). Technicality affects the value of AI-based services. If technically it is easy to use the AI-based service, the users value it more and tend to engage with the AI-based service; however, if technically it is difficult to operate the AI-based service, the user value perception plummets, leading to disengagement with the AI-based service (Sohn and Kwon 2020; Pal et al. 2020). This implies that when travelers perceive AI services in the travel, tourism, and hospitality industries as innovative, they are more likely to have a higher perceived value of these services and adopt and use them.

7 | Theoretical Implications

7.1 | Theoretical Contribution to Innovation Management Literature

This study extends the innovation management literature, especially related to technology. The study adapts the diffusion of innovation theory as a guiding framework to integrate the value-based adoption theory and technology readiness theory and investigate the perceived value and adoption intention of AI innovation in tourism. This study is one of the few studies to establish that technology innovation diffusion/adoption is a multi-faceted concept and requires a comprehensive approach focusing on both facilitating and impeding aspects of the technology innovation, along with the innovativeness of the users intending to adopt the technology. Prior studies focused on integrating diffusion of innovation theory with other theories like the threat of technology (Xu et al. 2024), communication flow and self-efficacy (Kim and Chakraborty 2024), security and privacy aspects (Shaw et al. 2022), the use and gratification theory, and the privacy calculus theory (Attié and Meyer-Waarden 2022), and the unified theory of acceptance and use of technology (Nordhoff et al. 2021). This study uniquely employs diffusion of innovation theory as a guiding framework to integrate with value-based adoption theory and technology readiness theory to study AI adoption. Further, the study focuses on both positive and negative aspects of the technology, providing a balanced approach to understanding AI innovation in Tourism.

7.2 | Other Theoretical Contributions

The present study proposes a comprehensive theoretical framework for disruptive technology in TTH regarding intentions to use AI and responds to studies that demand further research on AI adoption, usage, and intention in TTH (Solakis et al. 2024; Filieri et al. 2021; Pillai and Sivathanu 2020; Samara et al. 2020; Popesku 2019), which is a dearth in the literature. Technological development outdated swiftly (Filieri et al. 2021), but the implications of the current study can be extended to marketers and TTH planners to understand the users' perspective as predicting what motivates users to operate AI to contemplate their tours and travel to use AI via perceived enjoyment, perceived usefulness, perceived fee, and technicality.

This study contributes theoretically by empirically validating the aspects that influence the values of users while planning tours and travels and searching in the hospitality sector. It is worth noting that the value created by positive and negative aspects leads to the intention to use AI-based services in TTH. However, this relationship is moderated by perceived innovativeness and age, as in this study, which shows that both constructs have a moderating effect. Hence, TTH companies should focus on developing innovative features to attract consumers

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

with high perceived innovativeness. To maximize benefits, companies should market their innovative services through social media, press releases, and campaigns. This model elucidates the importance of the amalgamation of AI in TTH with traditional approaches using technologies such as chatbots, online services, AR, VR, and robots.

8 | Practical Implications

This study provides profound insight to practitioners, policymakers, and managers in the TTH sector and suggests the implementation of AI-based services in TTH to commercialize the current low-priced sophisticated technology. Managers can understand and appreciate the factors that potentially influence the values of users when using AI while planning their travel. For example, travel chatbots provide consumers with a 24×7 live support service, which saves time and cost; voice assistance helps in prompt and engaging responses; AR/VR shows them the virtual look of a place and hotel to make the experience more real, and data analysis can help in individualizing the experience of consumers. This implies that in the current changing context, the usage of AI in TTH is occurring in tandem, that is, at the managerial and operational levels to effectiveness and efficiency (Tavitiyaman et al. 2022), which can also motivate users to adopt these AI services for planning their travel. The current study reveals that rather than enjoying the perceived usage of an AI solution, it influences the values. It is quite possible that users look forward to functional and experiential utility rather than concentrating on amusement and gratification while using AI-based services to plan their tours. Therefore, companies should provide user-friendly interfaces, simple processes, and smooth navigation to increase PV among users, rather than only creating fun, interesting, and exciting experiences. Companies should personalize user experiences and provide customized recommendations. Additionally, managers should price fair fees, as this study shows that users find it reasonable to pay fees to avail of high-tech services while planning their tours and travel. It is possible that, with reasonable fees, they estimate value generation. Hence, companies should strategize their fees.

8.1 | Implications of Innovative Technologies in TTH From a Consumer and Marketers Perspective

The results show that when it comes to give and take, users find AI services to be more beneficial when they intend to adopt AI solutions while planning their tours and travels. This shows that PV positively reinforces intentions to use AI-based services in TTH. Hence, companies should ensure that they provide innovative AI solutions, such as chatbots, individualized recommendations, and interactive robots. As suggested by eminent professors Kartajaya et al. (2016), companies should add 3E to generate WOW through enjoyment, engagement, and experience to create consumer journeys. This study encourages practitioners and managers to create 3E via innovative AI solutions for TTH. Chatbots, personalized recommendations, and easy navigation can assist in exploring enjoyment. Interactive robots, chatbots, and 24×7 services promote engagement. Finally, AR and VR can provide a virtual experience. These 3E's can generate the WOW factor for innovative technologies and influence the adoption of AI-based tools for travel planning.

In addition, AI should be new and unique to create a competitive advantage among competitors, as the present manifests that users' perceived innovativeness (PI) tends to lead to the usage of AI-based services in TTH. Additionally, the higher the PI, the stronger the relationship between perceived value and the intention to use AI in TTH. In the context of innovation management, a stronger perceived innovativeness (PI) to develop the latest and most advanced technologies, encouraging users to engage with and utilize AI solutions. Additionally, interventions can be customized for users by understanding their levels of perceived innovativeness (PI). For instance, users with a high level of PI may require less guidance but benefit from increased engagement. On the other hand, users with a low PI may need more training and guidance to effectively utilize AI-based services when planning travel. By capitalizing on strong PI, TTH companies can create a competitive advantage, increase travelers' perceived value of innovative services, and encourage greater adoption and usage. This could serve as a significant market differentiator. In addition, this relationship between PV and intention to use AI is strong among younger users, as the study showed that the moderation effect of Gen Z is high. The tourism industry can better target its efforts to promote and facilitate the adoption of AI services among travelers of different ages. AI technologies like e-services, service robots, chatbots, voice assistants, metaverse tourism, and AR and VR can be opted for by travelers (Solakis et al. 2024; Bulchand-Gidumal et al. 2023) and our study suggests this choice is more likely to be made by Gen Z (Appendix A).

9 | Conclusions and Directions for Future Research

AI is rapidly changing the way we live and work, and the tourism industry is no exception to this. This study conceptualized a model using diffusion of innovation theory, value adoption model, and technology readiness theory to examine the factors impacting the perceived values of users and their intentions to use AI solutions in TTH. This model introduces a framework for a smart tourism environment based on AI, emphasizing the significant role of perceived innovativeness across generations. The integration of AI in tourism provides new and exciting opportunities for businesses and travelers. Any mundane task can be automated with AI, with the benefits of personalized recommendations, improved efficacy, real-time information, virtual tours, and AR-based destination guides. AI cannot replace human interaction, but it can be a tool to facilitate business with better services and experiences for customers. As technology continues to develop and become more sophisticated, we can expect even more exciting advancements in the tourism industry that can create better experiences in consumer journeys. Hence, AI has the potential to revolutionize the TTH industry.

However, this study is subject to some limitations and challenges. AI is still at an early stage of development, and many applications are in the testing stage and are not fully mature. With the upgrading of new technology, the perception of AI adoption will change. Hence, future research on this topic is essential and

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

needs to be conducted frequently until AI reaches maturity. The current study did not consider a particular need for tourism or tour planning. Future research can concentrate on different dimensions of tourism, such as the impact of AI on sustainable, rural, and hospital tourism. In addition, this study analyzed a sample from one of the fastest-growing emerging economies in India. Future studies can compare user perceptions regarding AI solution adoption in TTH in developed and developing nations.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the first author. The data are not publicly available due to privacy or ethical restrictions.

References

Agarwal, R., and E. Karahanna. 2000. "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs About Information Technology Usage." *MIS Quarterly* 24: 665–694. https://doi.org/10.2307/3250951.

Attié, E., and L. Meyer-Waarden. 2022. "The Acceptance and Usage of Smart Connected Objects According to Adoption Stages: An Enhanced Technology Acceptance Model Integrating the Diffusion of Innovation, Uses and Gratification and Privacy Calculus Theories." *Technological Forecasting and Social Change* 176: 121485.

Basco, R., J. F. Hair Jr., C. M. Ringle, and M. Sarstedt. 2022. "Advancing Family Business Research Through Modeling Nonlinear Relationships: Comparing PLS-SEM and Multiple Regression." *Journal of Family Business Strategy* 13, no. 3: 100457.

Becker, J. M., J. H. Cheah, R. Gholamzade, C. M. Ringle, and M. Sarstedt. 2023. "PLS-SEM's Most Wanted Guidance." *International Journal of Contemporary Hospitality Management* 35, no. 1: 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474.

Bhutoria, A. 2022. "Personalized Education and Artificial Intelligence in United States, China, and India: A Systematic Review Using a Human-In-The-Loop Model." *Computers and Education: Artificial Intelligence* 3: 100068.

Bilgihan, A. 2016. "Gen Y Customer Loyalty in Online Shopping: An Integrated Model of Trust, User Experience and Branding." *Computers in Human Behavior* 61: 103–113. https://doi.org/10.1016/j.chb.2016.03.014.

Bulchand-Gidumal, J., E. W. Secin, P. O'Connor, and D. Buhalis. 2023. "Artificial Intelligence's Impact on Hospitality and Tourism Marketing: Exploring Key Themes and Addressing Challenges." *Current Issues in Tourism* 27, no. 14: 2345–2362. https://doi.org/10.1080/13683500.2023.2229480.

Cao, D., Y. Sun, E. Goh, R. Wang, and K. Kuiavska. 2022. "Adoption of Smart Voice Assistants' Technology Among Airbnb Guests: A Revised Self-Efficacy-Based Value Adoption Model (SVAM)." *International Journal of Hospitality Management* 101: 103124.

Chaouali, W., and N. Souiden. 2019. "The Role of Cognitive Age in Explaining Mobile Banking Resistance Among Elderly People." *Journal of Retailing and Consumer Services* 50: 342–350.

Chatterjee, S., and K. K. Bhattacharjee. 2020. "Adoption of Artificial Intelligence in Higher Education: A Quantitative Analysis Using Structural Equation Modelling." *Education and Information Technologies* 25, no. 5: 3443–3463.

Chawla, D., and H. Joshi. 2018. "The Moderating Effect of Demographic Variables on Mobile Banking Adoption: An Empirical Investigation." *Global Business Review* 19, no. 3_suppl: S90–S113.

Chawla, D., and H. Joshi. 2020. "The Moderating Role of Gender and Age in the Adoption of Mobile Wallet." *Foresight* 22, no. 4: 483–504.

Chen, S. C., and C. P. Lin. 2019. "Understanding the Effect of Social Media Marketing Activities: The Mediation of Social Identification, Perceived Value, and Satisfaction." *Technological Forecasting and Social Change* 140: 22–32.

Chen, Y., Y. Hu, S. Zhou, and S. Yang. 2023. "Investigating the Determinants of Performance of Artificial Intelligence Adoption in Hospitality Industry During COVID-19." *International Journal of Contemporary Hospitality Management* 35, no. 8: 2868–2889.

Chong, H. X., A. H. Hashim, S. Osman, J. L. Lau, and E. C. X. Aw. 2023. "The Future of e-Commerce? Understanding Livestreaming Commerce Continuance Usage." *International Journal of Retail & Distribution Management* 51, no. 1: 1–20.

Coccia, M., and J. Watts. 2020. "A Theory of the Evolution of Technology: Technological Parasitism and the Implications for Innovation Management." *Journal of Engineering and Technology Management* 55: 101552.

Cornet, Y., G. Lugano, C. Georgouli, and D. Milakis. 2022. "Worthwhile Travel Time: A Conceptual Framework of the Perceived Value of Enjoyment, Productivity and Fitness While Travelling." *Transport Reviews* 42, no. 5: 580–603.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13: 319–340. https://doi.org/10.2307/249008.

de Kervenoael, R., R. Hasan, A. Schwob, and E. Goh. 2020. "Leveraging Human-Robot Interaction in Hospitality Services: Incorporating the Role of Perceived Value, Empathy, and Information Sharing Into Visitors' Intentions to Use Social Robots." *Tourism Management* 78: 104042.

Dedeoğlu, B. B. 2019. "Shaping Tourists' Destination Quality Perception and Loyalty Through Destination Country Image: The Importance of Involvement and Perceived Value." *Tourism Management Perspectives* 29: 105–117.

Deloitte. 2020. "Hyper-Personalizing the Customer Experience Using Data, Analytics, and AI." https://www2.deloitte.com/content/dam/Deloitte/ca/Documents/deloitte-analytics/ca-en-omnia-ai-marketing-pov-fin-jun24-aoda.pdf.

DeLone, W. H., and E. R. McLean. 2003. "The DeLone and McLean Model of Information Systems Success: A Ten-Year Update." *Journal of Management Information Systems* 19, no. 4: 9–30. https://doi.org/10.1080/07421222.2003.11045748.

Di Talia, E., M. Simeone, and D. Scarpato. 2019. "Consumer Behaviour Types in Household Food Waste." *Journal of Cleaner Production* 214: 166–172.

Dissanayake, C. A. K., W. Jayathilake, H. V. A. Wickramasuriya, U. Dissanayake, K. P. P. Kopiyawattage, and W. M. C. B. Wasala. 2022. "Theories and Models of Technology Adoption in Agricultural Sector." *Human Behavior and Emerging Technologies* 2022. https://doi.org/10.1155/2022/9258317.

Filieri, R., E. D'Amico, A. Destefanis, E. Paolucci, and E. Raguseo. 2021. "Artificial Intelligence (AI) for Tourism: An European-Based Study on Successful AI Tourism Start-Ups." *International Journal of Contemporary Hospitality Management* 33, no. 11: 4099–4125.

Forbes. 2023a. "How AI in Travel and Hospitality is Enhancing Experiences and Optimising Operations." https://www.forbesindia.com/article/take-one-big-story-of-the-day/how-ai-in-travel-and-hospitality-is-enhancing-experiences-and-optimising-operations/87027/1.

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Forbes. 2023b. "Revolutionizing the Hospitality Industry With Artificial Intelligence." https://www.forbes.com/sites/forbesbusinesscouncil/2023/09/11/revolutionizing-the-hospitality-industry-with-artificial-intelligence/?sh=5ff9a87b23d1.

Fornell, C., and D. F. Larcker. 1981. "Evaluating Structural Equation Models With Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18, no. 1: 39–50. https://doi.org/10.1177/002224378101800104.

Gao, J., L. Ren, Y. Yang, D. Zhang, and L. Li. 2022. "The Impact of Artificial Intelligence Technology Stimuli on Smart Customer Experience and the Moderating Effect of Technology Readiness." *International Journal of Emerging Markets* 17: 1123–1142.

Guenther, P., M. Guenther, C. M. Ringle, G. Zaefarian, and S. Cartwright. 2023. "Improving PLS-SEM Use for Business Marketing Research." *Industrial Marketing Management* 111: 127–142.

Habibi, A., and S. M. Rasoolimanesh. 2021. "Experience and Service Quality on Perceived Value and Behavioral Intention: Moderating Effect of Perceived Risk and Fee." *Journal of Quality Assurance in Hospitality & Tourism* 22, no. 6: 711–737.

Haenlein, M., and A. Kaplan. 2019. "A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence." *California Management Review* 61, no. 4: 5–14.

Hair, J. F., C. M. Ringle, and M. Sarstedt. 2011. "PLS-SEM: Indeed a Silver Bullet." *Journal of Marketing Theory and Practice* 19, no. 2: 139–152. https://doi.org/10.2753/MTP1069-6679190202.

Hair, J. F., M. Sarstedt, C. M. Ringle, and S. P. Gudergan. 2018. *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage.

Hassani, H., E. S. Silva, S. Unger, M. TajMazinani, and S. Mac Feely. 2020. "Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future?" *AI* 1, no. 2: 8.

Henseler, J. 2017. "Bridging Design and Behavioral Research With Variance-Based Structural Equation Modeling." *Journal of Advertising* 46, no. 1: 178–192. https://doi.org/10.1080/00913367.2017.1281780.

Hollebeek, L. D., C. Menidjel, M. Sarstedt, J. Jansson, and S. Urbonavicius. 2024. "Engaging Consumers Through Artificially Intelligent Technologies: Systematic Review, Conceptual Model, and Further Research." *Psychology & Marketing* 41: 880–898.

Hsiao, M. H. 2022. "Post-Purchase Behavior From Customer Perceived Value of Mobile Payment Services." *Journal of Modelling in Management* 17, no. 4: 1524–1543. https://doi.org/10.1108/JM2-11-2020-0293.

Huarng, K. H., T. H. K. Yu, and C. fang Lee 2022. "Adoption Model of Healthcare Wearable Devices." *Technological Forecasting and Social Change* 174: 121286.

Hult, G. T. M., J. F. Hair Jr., D. Proksch, M. Sarstedt, A. Pinkwart, and C. M. Ringle. 2018. "Addressing Endogeneity in International Marketing Applications of Partial Least Squares Structural Equation Modeling." *Journal of International Marketing* 26, no. 3: 1–21. https://doi.org/10.1509/jim.17.0151.

Hülür, G., and B. Macdonald. 2020. "Rethinking Social Relationships in Old Age: Digitalization and the Social Lives of Older Adults." *American Psychologist* 75, no. 4: 554–566.

Hwang, J., J. S. Lee, and H. Kim. 2019. "Perceived Innovativeness of Drone Food Delivery Services and Its Impacts on Attitude and Behavioral Intentions: The Moderating Role of Gender and Age." *International Journal of Hospitality Management* 81: 94–103.

Hwang, J., K. W. Lee, D. Kim, and I. Kim. 2020. "Robotic Restaurant Marketing Strategies in the Era of the Fourth Industrial Revolution: Focusing on Perceived Innovativeness." *Sustainability* 12, no. 21: 9165.

Kartajaya, H., P. Kotler, and I. Setiawan. 2016. *Marketing 4.0: Moving From Traditional to Digital*. John Wiley & Sons.

Khan, R., H. Qudrat-Ullah, R. A. Khan, and H. Qudrat-Ullah. 2021. "Technology Adoption Theories and Models." In *Adoption of LMS in Higher Educational Institutions of the Middle East*, 27–48. Springer.

Kim, E. 2021. "In-Store Shopping With Location-Based Retail Apps: Perceived Value, Consumer Response, and the Moderating Effect of Flow." *Information Technology and Management* 22, no. 2: 83–97.

Kim, H. M., and S. Chakraborty. 2024. "Exploring the Diffusion of Digital Fashion and Influencers' Social Roles in the Metaverse: An Analysis of Twitter Hashtag Networks." *Internet Research* 34, no. 1: 107–128.

Kim, H. W., H. C. Chan, and S. Gupta. 2007. "Value-Based Adoption of Mobile Internet: An Empirical Investigation." *Decision Support Systems* 43, no. 1: 111–126.

Kim, J. J., I. Kim, and J. Hwang. 2021. "A Change of Perceived Innovativeness for Contactless Food Delivery Services Using Drones After the Outbreak of COVID-19." *International Journal of Hospitality Management* 93: 102758.

Kim, J. S. 2016. "An Extended Technology Acceptance Model in Behavioral Intention Toward Hotel Tablet Apps With Moderating Effects of Gender and Age." *International Journal of Contemporary Hospitality Management* 28, no. 8: 1535–1553. https://doi.org/10.1108/IJCHM-06-2015-0289.

Kim, M., and J. Kim. 2024. "Artificial Intelligence in Voice Assistants: User Benefits Explored." *International Journal of Consumer Studies* 48, no. 2: e13019.

Knock, N. 2015. "Common Method Bias in PLS-SEM." *International Journal of E-Collaboration* 11, no. 4: 1–10.

Kwak, M. K., J. Lee, and S. S. Cha. 2021. "Senior Consumer Motivations and Perceived Value of Robot Service Restaurants in Korea." *Sustainability* 13, no. 5: 2755.

Lai, M. L. 2008. "Technology Readiness, Internet Self-Efficacy and Computing Experience of Professional Accounting Students." *Campus-Wide Information Systems* 25: 18–29.

Lai, P. C. 2017. "The Literature Review of Technology Adoption Models and Theories for the Novelty Technology." *JISTEM-Journal of Information Systems and Technology Management* 14, no. 1: 21–38. https://doi.org/10.4301/s1807-17752017000100002.

Lalicic, L., and C. Weismayer. 2021. "Consumers' Reasons and Perceived Value Co-Creation of Using Artificial Intelligence-Enabled Travel Service Agents." *Journal of Business Research* 129: 891–901.

Lampo, A. 2022. "How Is Technology Accepted? Fundamental Works in User Technology Acceptance From Diffusion of Innovations to UTAUT-2." In *Proceedings of the 8th International Conference on Industrial and Business Engineering*, 260–266. ACM Publications.

Lee, H. G., S. Chung, and W. H. Lee. 2013. "Presence in Virtual Golf Simulators: The Effects of Presence on Perceived Enjoyment, Perceived Value, and Behavioral Intention." *New Media & Society* 15, no. 6: 930–946.

Lee, J., M. K. Kwak, and S. S. Cha. 2021. "The Effect of Motivated Consumer Innovativeness on Perceived Value and Intention to Use for Senior Customers at AI Food Service Store." *Journal of Distribution Science* 19, no. 9: 91–100.

Leong, L. Y., J. J. Hew, V. H. Lee, G. W. H. Tan, K. B. Ooi, and N. P. Rana. 2023. "An SEM-ANN Analysis of the Impacts of Blockchain on Competitive Advantage." *Industrial Management & Data Systems* 123, no. 3: 967–1004.

Liao, Y. K., W. Y. Wu, T. Q. Le, and T. T. T. Phung. 2022. "The Integration of the Technology Acceptance Model and Value-Based Adoption Model to Study the Adoption of e-Learning: The Moderating Role of e-WOM." *Sustainability* 14, no. 2: 815.

Liebana-Cabanillas, F., and M. Alonso-Dos-Santos. 2017. "Factors That Determine the Adoption of Facebook Commerce: The Moderating

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Effect of Age." *Journal of Engineering and Technology Management* 44: 1–18.

Lin, H., O. H. Chi, and D. Gursoy. 2020. "Antecedents of Customers' Acceptance of Artificially Intelligent Robotic Device Use in Hospitality Services." *Journal of Hospitality Marketing & Management* 29, no. 5: 530–549.

Martins, J. M., F. Yusuf, and D. A. Swanson. 2011. *Consumer Demographics and Behaviour: Markets Are People*. Vol. 30. Springer Science & Business Media.

Masri, N. W., J. J. You, A. Ruangkanjanases, S. C. Chen, and C. I. Pan. 2020. "Assessing the Effects of Information System Quality and Relationship Quality on Continuance Intention in e-Tourism." *International Journal of Environmental Research and Public Health* 17, no. 1: 174.

McKinsey. 2023a. "The Promise of Travel in the Age of AI." https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/the-promise-of-travel-in-the-age-of-ai.

McKinsey. 2023b. "What AI Means for Travel—Now and in the Future." https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/what-ai-means-for-travel-now-and-in-the-future.

Melián-González, S., D. Gutiérrez-Taño, and J. Bulchand-Gidumal. 2021. "Predicting the Intentions to Use Chatbots for Travel and Tourism." *Current Issues in Tourism* 24, no. 2: 192–210.

Mishra, A. K., R. Bansal, P. K. Maurya, S. K. Kar, and P. K. Bakshi. 2023. "Predicting the Antecedents of Consumers' Intention Toward Purchase of Mutual Funds: A Hybrid PLS-SEM-Neural Network Approach." *International Journal of Consumer Studies* 47, no. 2: 563–587.

Moriuchi, E. 2019. "Okay, Google!: An Empirical Study on Voice Assistants on Consumer Engagement and Loyalty." *Psychology & Marketing* 36, no. 5: 489–501.

Moussawi, S., M. Koufaris, and R. Benbunan-Fich. 2021. "How Perceptions of Intelligence and Anthropomorphism Affect Adoption of Personal Intelligent Agents." *Electronic Markets* 31, no. 2: 343–364.

Natarajan, T., S. A. Balasubramanian, and D. L. Kasilingam. 2018. "The Moderating Role of Device Type and Age of Users on the Intention to Use Mobile Shopping Applications." *Technology in Society* 53: 79–90.

Nayal, K., R. D. Raut, B. E. Narkhede, P. Priyadarshinee, G. B. Panchal, and V. V. Gedam. 2023. "Antecedents for Blockchain Technology-Enabled Sustainable Agriculture Supply Chain." *Annals of Operations Research* 327, no. 1: 293–337.

Niehaves, B., and R. Plattfaut. 2014. "Internet Adoption by the Elderly: Employing IS Technology Acceptance Theories for Understanding the Age-Related Digital Divide." *European Journal of Information Systems* 23, no. 6: 708–726.

Nordhoff, S., V. Malmsten, B. Van Arem, P. Liu, and R. Happee. 2021. "A Structural Equation Modeling Approach for the Acceptance of Driverless Automated Shuttles Based on Constructs From the Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovation Theory." *Transportation Research Part F: Traffic Psychology and Behaviour* 78: 58–73. https://doi.org/10.1016/j.trf.2021.01.001.

Pal, D., C. Arpnikanondt, S. Funilkul, and W. Chutimaskul. 2020. "The Adoption Analysis of Voice-Based Smart IoT Products." *IEEE Internet of Things Journal* 7, no. 11: 10852–10867.

Parasuraman, A. 2000. "Technology Readiness Index (TRI) a Multiple-Item Scale to Measure Readiness to Embrace New Technologies." *Journal of Service Research* 2, no. 4: 307–320.

Parasuraman, A., and C. L. Colby. 2015. "An Updated and Streamlined Technology Readiness Index: TRI 2.0." *Journal of Service Research* 18, no. 1: 59–74. https://doi.org/10.1177/1094670514539730.

Park, S., and S. Gupta. 2012. "Handling Endogenous Regressors by Joint Estimation Using Copulas." *Marketing Science* 31, no. 4: 567–586. https://doi.org/10.1287/mksc.1120.0718.

Patnaik, P., and M. Bakkar. 2024. "Exploring Determinants Influencing Artificial Intelligence Adoption, Reference to Diffusion of Innovation Theory." *Technology in Society* 79: 102750.

Paul, J. 2024. "Publishing in Premier Journals With High Impact Factor and Q1 Journals: Dos and Don'ts." *International Journal of Consumer Studies* 48, no. 3: e13049.

Paul, J., A. Ueno, C. Dennis, et al. 2024. "Digital Transformation: A Multidisciplinary Perspective and Future Research Agenda." *International Journal of Consumer Studies* 48, no. 2: e13015. https://doi.org/10.1111/ijcs.13015.

Paulo, M. M., P. Rita, T. Oliveira, and S. Moro. 2018. "Understanding Mobile Augmented Reality Adoption in a Consumer Context." *Journal of Hospitality and Tourism Technology* 9, no. 2: 142–157.

Pillai, R., and B. Sivathanu. 2020. "Adoption of Artificial Intelligence (AI) for Talent Acquisition in IT/ITeS Organizations." *Benchmarking: An International Journal* 27, no. 9: 2599–2629.

Pitardi, V., and H. R. Marriott. 2021. "Alexa, She's Not Human but... Unveiling the Drivers of Consumers' Trust in Voice-Based Artificial Intelligence." *Psychology & Marketing* 38, no. 4: 626–642.

Podsakoff, P. M., S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* 88, no. 5: 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Ponte, E. B., E. Carvajal-Trujillo, and T. Escobar-Rodríguez. 2015. "Influence of Trust and Perceived Value on the Intention to Purchase Travel Online: Integrating the Effects of Assurance on Trust Antecedents." *Tourism Management* 47: 286–302.

Popesku, J. 2019. "Current Applications of Artificial Intelligence in Tourism and Hospitality." In *Sinteza 2019-International Scientific Conference on Information Technology and Data Related Research*, 84–90. Singidunum University.

PwC. 2019. "Hospitality and Leisure Trends 2019." https://www.pwc.com/gx/en/ceo-survey/2019/Theme-assets/reports/hospitality-leisure-trends-report-2019.pdf.

Rahman, M. K. 2019. "Medical Tourism: Tourists' Perceived Services and Satisfaction Lessons From Malaysian Hospitals." *Tourism Review* 74: 739–758.

Raman, R., S. Mandal, P. Das, T. Kaur, J. P. Sanjanasri, and P. Nedungadi. 2024. "Exploring University Students' Adoption of ChatGPT Using the Diffusion of Innovation Theory and Sentiment Analysis With Gender Dimension." *Human Behavior and Emerging Technologies* 2024, no. 1: 3085910.

Ramsey, J. B. 1969. "Test for Specification Errors in Classical Linear Least-Squares Regression Analysis." *Journal of the Royal Statistical Society, Series B* 31, no. 2: 350–371.

Renjith, S., A. Sreekumar, and M. Jathavedan. 2020. "An Extensive Study on the Evolution of Context-Aware Personalized Travel Recommender Systems." *Information Processing & Management* 57, no. 1: 102078.

Rogers, E. M. 1983. *Diffusion of Innovations*. 3rd ed. Free Press, a division of Macmillan Publishing.

Samala, N., B. S. Katkam, R. S. Bellamkonda, and R. V. Rodriguez. 2020. "Impact of AI and Robotics in the Tourism Sector: A Critical Insight." *Journal of tourism futures* 8, no. 1: 73–87.

Sarstedt, M., C. M. Ringle, J. H. Cheah, H. Ting, O. I. Moisescu, and L. Radomir. 2020. "Structural Model Robustness Checks in PLS-SEM." *Tourism Economics* 26, no. 4: 531–554. https://doi.org/10.1177/1354816618823921.

Setiawan, B., D. P. Nugraha, A. Irawan, R. J. Nathan, and Z. Zoltan. 2021. "User Innovativeness and Fintech Adoption in Indonesia." *Journal of Open Innovation: Technology, Market, and Complexity* 7, no. 3: 188.

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Sharma, N., P. Goel, R. Nunkoo, A. Sharma, and N. P. Rana. 2023. "Food Waste Avoidance Behavior: How Different Are Generation Z Travelers?" *Journal of Sustainable Tourism*: 1–15.

Shaw, N., B. Eschenbrenner, and B. M. Brand. 2022. "Towards a Mobile App Diffusion of Innovations Model: A Multinational Study of Mobile Wallet Adoption." *Journal of Retailing and Consumer Services* 64: 102768.

Shaw, N., and K. Sergueeva. 2019. "The Non-Monetary Benefits of Mobile Commerce: Extending UTAUT2 with Perceived Value." *International Journal of Information Management* 45: 44–55.

Shmueli, G., M. Sarstedt, J. F. Hair, et al. 2019. "Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict." *European Journal of Marketing* 53, no. 11: 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189.

Sirdeshmukh, D., J. Singh, and B. Sabol. 2002. "Consumer Trust, Value, and Loyalty in Relational Exchanges." *Journal of Marketing* 66, no. 1: 15–37. https://doi.org/10.1509/jmkg.66.1.15.18449.

Soares, A. M., J. C. M. Pinho, T. Heath, and A. Alves. 2021. "Can Virtual Customer Service Agents Improve Consumers' Online Experiences?: The Role of Hedonic Dimensions." In *Research Anthology on E-Commerce Adoption, Models, and Applications for Modern Business*, 764–780. IGI Global.

Sohn, K., and O. Kwon. 2020. "Technology Acceptance Theories and Factors Influencing Artificial Intelligence-Based Intelligent Products." *Telematics and Informatics* 47: 101324.

Solakis, K., V. Katsoni, A. B. Mahmoud, and N. Grigoriou. 2024. "Factors Affecting Value Co-Creation Through Artificial Intelligence in Tourism: A General Literature Review." *Journal of Tourism Futures* 10, no. 1: 116–130.

Sweeney, J. C., and G. N. Soutar. 2001. "Consumer Perceived Value: The Development of a Multiple Item Scale." *Journal of Retailing* 77, no. 2: 203–220.

Tan, G. W. H., and K. B. Ooi. 2018. "Gender and Age: Do They Really Moderate Mobile Tourism Shopping Behavior?" *Telematics and Informatics* 35, no. 6: 1617–1642.

Tandon, U., M. Ertz, and H. Bansal. 2020. "Social Vacation: Proposition of a Model to Understand Tourists' Usage of Social Media for Travel Planning." *Technology in Society* 63: 101438.

Tavitiyaman, P., X. Zhang, and W. Y. Tsang. 2022. "How Tourists Perceive the Usefulness of Technology Adoption in Hotels: Interaction Effect of Past Experience and Education Level." *Journal of China Tourism Research* 18, no. 1: 64–87.

Tom Dieck, M. C., and T. Jung. 2018. "A Theoretical Model of Mobile Augmented Reality Acceptance in Urban Heritage Tourism." *Current Issues in Tourism* 21, no. 2: 154–174.

Uzumcu, O., and H. Acilmis. 2024. "Do Innovative Teachers Use AI-Powered Tools More Interactively? A Study in the Context of Diffusion of Innovation Theory." *Technology, Knowledge and Learning* 29, no. 2: 1109–1128.

Voss, G. B., A. Parasuraman, and D. Grewal. 1998. "The Roles of Price, Performance, and Expectations in Determining Satisfaction in Service Exchanges." *Journal of Marketing* 62, no. 4: 46–61. https://doi.org/10.1177/002224299806200404.

Wang, Y. S., H. H. Lin, and Y. W. Liao. 2012. "Investigating the Individual Difference Antecedents of Perceived Enjoyment in Students' Use of Blogging." *British Journal of Educational Technology* 43, no. 1: 139–152.

Watchravesringkan, K., N. N. Hodges, and Y. H. Kim. 2010. "Exploring Consumers' Adoption of Highly Technological Fashion Products: The Role of Extrinsic and Intrinsic Motivational Factors." *Journal of Fashion Marketing and Management: An International Journal* 14, no. 2: 263–281.

Xu, F., S. S. Huang, and S. Li. 2019. "Time, Money, or Convenience: What Determines Chinese Consumers' Continuance Usage Intention and Behavior of Using Tourism Mobile Apps?" *International Journal of Culture, Tourism and Hospitality Research* 13, no. 3: 288–302.

Xu, S., K. F. Kee, W. Li, M. Yamamoto, and R. E. Riggs. 2024. "Examining the Diffusion of Innovations From a Dynamic, Differential-Effects Perspective: A Longitudinal Study on AI Adoption Among Employees." *Communication Research* 51, no. 7: 843–866.

Xu, X. Y., Y. X. Gao, and Q. D. Jia. 2023. "The Role of Social Commerce for Enhancing Consumers' Involvement in the Cross-Border Product: Evidence From SEM and ANN Based on MOA Framework." *Journal of Retailing and Consumer Services* 71: 103187.

Yang, H., and H. Lee. 2019. "Understanding User Behavior of Virtual Personal Assistant Devices." *Information Systems and e-Business Management* 17: 65–87.

Yu, H., I. Seo, and J. Choi. 2019. "A Study of Critical Factors Affecting Adoption of Self-Customisation Service–Focused on Value-Based Adoption Model." *Total Quality Management & Business Excellence* 30, no. sup1: S98–S113.

Yu, T. K., M. L. Lin, and Y. K. Liao. 2017. "Understanding Factors Influencing Information Communication Technology Adoption Behavior: The Moderators of Information Literacy and Digital Skills." *Computers in Human Behavior* 71: 196–208.

Yuen, K. F., L. Cai, G. Qi, and X. Wang. 2021. "Factors Influencing Autonomous Vehicle Adoption: An Application of the Technology Acceptance Model and Innovation Diffusion Theory." *Technology Analysis & Strategic Management* 33, no. 5: 505–519.

Zeithaml, V. A. 1988. "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence." *Journal of Marketing* 52, no. 3: 2–22.

Zhao, Y., Q. Ni, and R. Zhou. 2018. "What Factors Influence the Mobile Health Service Adoption? A Meta-Analysis and the Moderating Role of Age." *International Journal of Information Management* 43: 342–350.

Zhong, L., X. Zhang, J. Rong, H. K. Chan, J. Xiao, and H. Kong. 2021. "Construction and Empirical Research on Acceptance Model of Service Robots Applied in Hotel Industry." *Industrial Management & Data Systems* 121, no. 6: 1325–1352.

Zhu, G., S. Sangwan, and T. J. Lu. 2010. "A New Theoretical Framework of Technology Acceptance and Empirical Investigation on Self-Efficacy-Based Value Adoption Model." *Nankai Business Review International* 1, no. 4: 345–372. https://doi.org/10.1108/20408741011082543.

Zhu, Y., R. Zhang, Y. Zou, and D. Jin. 2023. "Investigating Customers' Responses to Artificial Intelligence Chatbots in Online Travel Agencies: The Moderating Role of Product Familiarity." *Journal of Hospitality and Tourism Technology* 14, no. 2: 208–224.

Zietsman, M. L. 2018. *Establishing the Antecedents and Outcomes of a Value Creation Strategy in Business Banking*. Doctoral dissertation, University of Pretoria.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Appendix A

Benefits of innovative technology in TTH	Suggestions	Strategic recommendations
Customer benefits		• Create 3E's for consumer journey • Optimize pricing strategy that align perceived value • Focus on user-friendly interfaces and it can different for different generations • Leverage data analytics for personalization
24/7 live support	The AI solutions like chatbots and virtual assistant can provide better customer service and can be time and cost effective for travelers	
Enhanced engagement	AI solutions like voice assistance can enable prompt and interactive responses and it help in assistant travel planning and accordingly enhance customer satisfaction	
Seamless experience	With innovative immersive experiences with AR/VR, TTH can provide virtual tours of destinations and accommodations to make travel experiences more vivid and realistic	
Personalized recommendations	AI solutions can utilize data of consumers to tailor travel suggestions based on individual preferences, enhancing the relevance of travel plans	
Marketer benefits		
Achieving objectives	By incorporating innovative solutions, marketers can offer customer satisfaction and loyalty	
Competitive advantage	Innovative AI solutions with hyper personalization and engaging interactions can differentiate businesses	
Market differentiation	Strong PI drives adoption of innovative AI services, this can attract tech-savvy travelers	
Personalization according to different generation	Recognizing different needs of different generations and tailoring innovation accordingly as GenZ propensity to adopt AI tech in travel, marketers can create high tech solution for GenZ and user-friendly operations for other generations	
Enhanced partner integration	Enables seamless linking of benefits from official hotels on their website, enhancing the attractiveness of travel packages and promotions to potential customers	

14679310, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/radm.12771, Wiley Online Library on [06/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License