DOI: 10.30519/ahtr.1392494

Advances in Hospitality and Tourism Research (AHTR)
An International Journal of Akdeniz University Tourism Faculty
ISSN: 2147-9100 (Print), 2148-7316 (Online)
Webpage: https://dergipark.org.tr/en/pub/ahtr

Article in press

DETERMINANTS OF USERS' INTENTIONS TO USE AI-ENABLED TECHNOLOGICAL INNOVATIONS IN HOTELS: A HYBRID APPROACH USING PLS-SEM AND FSQCA

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ABSTRACT

This study investigates the factors influencing hotel guests' intentions to adopt next-generation technologies enabled by artificial intelligence (AI). Both affective and cognitive processes, which led to guests' intentions to adopt these new technologies, were considered to have antecedents in the form of intrinsic and extrinsic motives, respectively. The data collected from 331 respondents were analyzed using a combination of methods, including the asymmetrical fuzzy set qualitative comparative analysis (fsQCA) and the symmetrical partial least square-structural equation modeling (PLS-SEM). The results of the symmetrical study indicated that novelty and compatibility have a good impact on both enjoyment and usefulness, which ultimately lead to behavioral intentions. In contrast, asymmetrical studies have shown that all the criteria are

Article History
Received 9 Dec. 2023
Revised 28 Feb. 2024
Accepted 5 March 2024
Published online 8 May 2024

Keywords
novelty
compatibility
usefulness
enjoyment
next-gen technologies

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Please cite this article as: Terrah, A., Ali, F., Abbasi, G. A., Dogan, S., & Cobanoglu, C. (in press). Advances in Hospitality and Tourism Research, https://doi.org/10.30519/ahtr.1392494

necessary conditions to produce users' intention to embrace AI-based technology. By integrating IDT and TAM, this study extends the comprehension of factors driving customers to use AI-enabled technologies during their hotel stays. This study also adds to the existing literature by exploring configurational modeling with fsQCA, as opposed to prior studies that have relied on net impact modeling via SEM.

INTRODUCTION

Technology use in the hotel industry can be traced back to the 1940s when the earliest versions of property management systems were used. In the decades that followed, the hotel industry adopted computers, reservation systems, in-room phones, electronic locking systems, energy management systems, the internet, websites, and online booking technology. Finally, the 2000s brought about Wi-Fi, the iPhone, mobile technology, and smartphone applications. These technologies gave hoteliers additional capabilities to reach customers, enhance customer relationship management, and develop loyalty programs. As a result, hoteliers have expanded to include a wide range of applications, notably target advertisements, payment services, point-of-sale terminals, high-definition televisions with personalized welcome messages, high-speed Wi-Fi, videos on demand, smart TVs, voice technology, as well as virtual assistants for service requests and in-room controls (Bilgihan et al., 2016; Mercan et al., 2020). All these technologies, including recent developments in augmented and virtual reality, have been assessed to bring repeat business to hotels and attract new customers (Flavian et al., 2020).

The technological progress noted across various economic activity sectors significantly contributed to expanding the adoption of artificial intelligence (AI)-enabled technologies—involving voice technology, biometrics, smartphone integrations, service automation, and robotics. Ivanov et al. (2017) postulated that robotics, service automation, and AI provide the hotel industry with numerous prospects for enhancing the quality of service through consistent performance, leading to improved performance. These novel technologies use AI to offer personalized services and are perceived as attractive because of their newness and coolness (Law et al., 2023). However, Lai (2016) argued that technological progress brings possibilities for innovative service offerings but can also threaten established business models. As many hoteliers have started to adopt AI-based solutions and robotics in their operations (Nam et al., 2021), it is essential to ponder whether they are implementing the right technologies in their properties based on their guests' perceptions. Even though various studies are conducted regarding hotel technologies, only a few have steered their investigations toward AI-enabled technologies.

Several theoretical models were developed to explain consumers' behavioral intentions toward new information technologies. These include the Theory of Planned Behavior (Ajzen, 1991); the Innovation Diffusion Theory (IDT) (Rogers, 1995); the Theory of Task-technology Fit (Goodhue & Thompson, 1995); the Technology Acceptance Model (TAM) (Davis et al., 1989) along with its extensions TAM 2 (Venkatesh & Davis, 2000) and TAM 3 (Venkatesh & Bala, 2008); and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Although these frameworks have proved beneficial to researchers due to their workable applicability in various contexts, they do not capture users' perceptions and evaluations of innovative technologies. AI-enabled technologies are relatively new, and hotels are still adopting them for their operations. The models mentioned above have been updated to provide applicability in various domains. Most current models explaining users' behavioral intentions towards new information technologies consider intrinsic and extrinsic considerations. Both perceptions of usefulness and enjoyment have been recognized as essential factors in hotel guests' adoption of AI-enabled technologies (Chiu & Cho, 2020). Although the intrinsic-extrinsic conceptualization has already been discussed in the literature, only a few investigations focused on the inter-relationships within hotel settings. There is also a lack of models assessing the perceived value of novelty regarding AI-enabled technologies. To the best of the authors' knowledge, the novelty variable did not receive much attention in the hotel context. Novelty can be seen as essential for guests' experiences at the hotel. For instance, the presence of robots and their interactions with customers were found to foster memorable experiences (Mitas & Bastiaansen, 2018). AI-enabled technologies at the hotel—including robots—were also found to elicit curiosity and weigh a lot in the hotel selection process.

As such, the research gap in this study also extends to the comprehension of factors driving customers to use AI-enabled technologies during their hotel stays. To be specific, this study aims to understand the effect of perceived novelty, perceived compatibility, perceived usefulness, and perceived enjoyment on users' behavioral intentions toward using next-gen technologies in hotels. By integrating IDT and TAM, this study’s main contribution is to extend the comprehension of factors driving customers to use AI-enabled technologies during their hotel stays. This study also contributes to the human computer interaction literature at the methodological level. In addition to symmetrical analysis via PLS-SEM, this study uses asymmetrical analysis based on fsQCA to explore how four antecedent conditions (perceived compatibility, perceived enjoyment, perceived novelty, and perceived usefulness) are sufficient for high scores in the outcome condition (i.e., behavioral intentions). Complexity theory provides support for the application of asymmetrical analysis. Complexity theory has been employed for developing theories in several disciplines, including hospitality and tourism (Ali et al., 2023). Complexity theory provides a richer insight into the asymmetric pattern of causal recipes in stimulating outcome conditions (Goel et al., 2022). As such, our study adds to the existing literature by exploring the configurational modeling with fsQCA (fuzzy set qualitative comparative analysis), as opposed to prior studies (Goel et al., 2022; Choi et al., 2020) that have relied on net impact modeling via SEM (structural equation modeling). For this reason, the current research may be seen as an attempt to convey the broad picture of how guests' experiences with AI-enabled technology in hotels shape their impressions of these tools.

LITERATURE REVIEW

AI Technology Within Hotel Settings

The survival of service businesses' often relies on their financial performance, capacity to respond to changing environments, and services to meet customers' changing customer expectations (Wikhamn, 2019). Recent technological innovations which can be qualified as next-gen technologies are being implemented within hospitality-related businesses, i.e., hotels, food and beverage, and events (Yang et al., 2020). Those cutting-edge technologies are likely to impact several aspects of delivering hospitality as hoteliers gradually adopt AI-enabled technologies and robotics to provide customer service and enhance the guest experience (Choi et al., 2020; Goel et al., 2022). For those reasons, several hotel chains started deploying AI technologies across their properties (Zhang & Jin, 2023). In the United States, butler and concierge robots were introduced in the Sheraton Los Angeles San Gabriel Hotel (Mills, 2018). The Flyzoo Alibaba Hotel in China placed next-gen technologies at the center of the guest experience. The Henn-na Hotel in Japan employed 250 robots. Nevertheless, with those experiences, it is noticeable that hotel guests have also started to accept AI technologies in their service experience as they interact with them, yielding various and differentiated responses (Ivanov & Webster, 2024).

Innovative technologies bring about the prospect of bringing customers' perspectives to the forefront of operations as they contribute to reducing human labor. Redmore (2018) identified four types of representative technologies powered by AI and adopted by hotels: chatbots or voice recognition systems, in-room technologies, robots, and analytics. Chatbots are the most used by hotels, and this may be due to their actual popularity within current smart devices (Louriero et al., 2024). In-room technologies control elements inside the room, including temperature, lighting, and curtains, and are subject to less resistance to guests' acceptance. Delivery and concierge robots are also gaining in popularity and are quickly adopted by guests as they can serve to brighten up experiences on property. In parallel with those technological developments, hotel guests' perceptions and acceptance of AI-enabled technologies are also changing (Law et al., 2023). The 21st-century hotel guest expects technologically driven products and personalized experiences. According to Cai et al. (2022), customers' perceptions about integrating AI-enabled technologies with traditional hotel stays can be an excellent indicator to assist hoteliers in their strategic planning. For this study, hotels' AI-enabled technologies (also referred to as next-gen technologies) are categorized as voice command technology, facial recognition, smartphone integrations, service automation, robotics, and virtual and augmented reality.

Previous literature assessed the multiple ways through which AI-enabled technologies impact hotel operations and guest experiences. As summarized by Nam et al. (2021), those innovations allow guest experiences with innovations such as robots or voice assistants such as Alexa; they attract the millennial segment and contribute to anticipating guests' needs and preferences for the provision of personalized services. It is to say that the use of AI-enabled technologies has become a mean of differentiation between hotel brands and de facto represent a competitive advantage. Consequently, discussing the acceptance of AI-enabled technologies in the hospitality industry is crucial. A combination of various factors influences the adoption of new technologies. Thus, this study investigates factors in users' decisions regarding AI-enabled technology adoption. It is achieved using an extended TAM integrated with the compatibility variable from the IDT, and the perceived novelty of AI-enabled technologies, together proposed as antecedents to behavioral intentions to use.

The Technology Acceptance Model

TAM is studied in hospitality and tourism literature to understand consumers' acceptance of technological innovations (Okumus & Bilgihan, 2014). It originally featured extrinsic motivations—i.e., perceived usefulness and perceived ease of use (Davis et al., 1989; Venkatesh et al., 2003) as the essential antecedents to technology acceptance. The TAM predicts that users are more prone to use new technologies when they experience their usefulness and ease of use. Accordingly, perceived ease of use and perceived usefulness were deemed necessary for determining factors of behavioral intentions toward using different technologies. Nevertheless, prior literature had already assessed that using these sole variables represents a constraint, advocating for more factors in play for predicting behavioral intentions (King & He, 2006). A study by Kucukusta and colleagues (2015) in the context of online booking technologies found that perceived usefulness had a stronger effect than perceived ease of use. They concluded that functionality, efficiency, and effectiveness—all denote usefulness—had a far more critical role than ease of use. This preeminence of perceived usefulness over perceived ease of use has been confirmed by several studies, notably in the contexts of the airline reservation system, e-learning, and human-robot interaction (Song et al., 2022). Moreover, recent technological innovations are relatively easy and do not bring many user challenges. Therefore, recent studies have advised enhancing TAM's explanatory power by adding additional contextual factors (Pillai & Sivathanu, 2020). Considering the preponderance of perceived usefulness over perceived ease of use, the present study considers extrinsic motivation as the construct of perceived usefulness. It extends the original TAM through the inclusion of the perceived enjoyment construct.

Davis et al. (1992) predicted that although extrinsic motivations (e.g., usefulness, ease of use) represent the main determinants for intention to use, intrinsic motivations (e.g., enjoyment) would have much more explanatory power for individual variances in usage intention. A line of researchers argued that the investigation of functional benefits such as perceived usefulness suffers the exclusion of attitudinal effects such as perceived enjoyment, mainly since consumers' attitudes vary accordingly with different internal and external attributes (Ozturk et al., 2016). As such, using TAM within various settings calls for introducing new external constructs to understand better users' acceptance of the technology being studied (Tao et al., 2018). Previous technology acceptance-related studies reported a strong positive influence and antecedence of perceived enjoyment to behavioral intentions (Chiu & Cho, 2020). Therefore, it can be considered that new technologies perceived by hotel guests as fun and useful are more likely to be adopted. Consequently, the present study assumes that perceived enjoyment complements perceived usefulness in predicting users' behavioral intention. The modified TAM is utilized in this study to make sense of the different factors that hotel guests evaluate using AI-enabled technologies (See Figure 1). Although using those technologies has been the subject of many studies in consumer behavior literature, very few focused explicitly on customers' perceptions of AI-enabled technologies within hotel settings. Therefore, this study contributes by providing hoteliers with actionable insights on which technologies they should invest in and heuristics regarding hotel guests' acceptance of AI-enabled technologies.

Research Model and Hypotheses Development

Theories Integration Rationale

Researchers in this study proposed a model on the foundations of the critical factors related to TAM and IDT. In addition, they perceived novelty in understanding the intention to use AI-enabled technologies. Research has shown that human behavior toward accepting a technology is multifaceted and warrants more than a single model, i.e., an integrated approach. Integrated models offer an all-inclusive and wide-ranging view of the causal mechanism underlying the relationships and bring an entire understanding which cannot be accomplished by models grounded on a single theory (Thusi & Maduku, 2020). Consequently, owing to the above discussions, it can be fair to assume that integrating TAM, IDT, and perceived novelty will provide a comprehensive viewpoint on AI Technological Innovations-adoption in hotel settings.

Novelty and Users' Evaluations

Technological innovations' innate characteristics are their novelty and newness (Yuan et al., 2020). The word novelty is usually linked with positive attributes and outcomes of technology use and adoption, also referred to as a honeymoon effect (Fichman & Kemerer, 1993). Wells et al. (2010) advanced that innovation novelty is viewed as fostering affective reactions, including excitement. A novelty that can be experienced through certain technologies is related to fun or pleasure. As users seek novelty, instant gratification favors the elicitation of enjoyment (Koenig-Lewis et al., 2015). Perceived enjoyment thus denotes the excitement or fun an individual derives when using a particular technology (Rosenbaum &

Wong, 2015). In the context of blog usage, Chen et al. (2013) noted that novelty positively influences perceived enjoyment. Similarly, Merikivi et al. (2017) also found novelty to influence perceived enjoyment significantly. Robots, for instance, perform actions that humans usually perform. Service robots and other next-gen technologies spark guests' interests as they elicit enjoyment, a motivation towards adopting such technologies. Thus, novel products can be viewed as eliciting intrinsic motivations in users. As perceived enjoyment is considered an intrinsic motivation, perceptions of AI-enabled technologies' novelty are bound to enhance hotel guests' perceived enjoyment. Therefore, the following hypothesis is proposed:

H1: Perceived novelty has a significantly positive impact on perceived enjoyment

Regarding extrinsic reactions, Lin and Yu (2006) explained that individuals seeking novelty in technologies were more likely to increase their perceived usefulness. It is confirmed by Baccarella et al. (2021), who also found that perceptions of novelty influenced perceived usefulness in the context of autonomous vehicles' use. Furthermore, regarding mobile payments technology, Flavian et al. (2020) contended that knowing its novelty heightens perceived usefulness, especially when users can acknowledge how they differ from other payment methods, for example, in terms of convenience and usefulness. In addition, Kristi and Kamasuwati (2021) focused on augmented reality and found novelty to impact perceived usefulness positively. Recent studies assessed that using new products or technologies goes to subjective judgments or evaluations of these products. During this process, consumers proceed to an evaluation of the risks versus rewards of using a novel technology, which represents a cognitive process of evaluating the extrinsic benefits of using that technology. As such, users tend to find innovative products that meet their needs useful. In other words, products and technologies that users view as increasing their efficiency are more likely to adopt new technologies. In this context, perceived novelty can be viewed as supporting cognitive beliefs such as the perceived usefulness of adopting technological innovation. However, studies assessing the relationship between perceived novelty and perceived usefulness are scarce in the hotel context. To fill this gap in the literature, we propose the following:

H2: Perceived novelty has a significantly positive impact on perceived usefulness

Compatibility and User Evaluations

Compatibility is the degree to which new information technologies fit the lifestyle and experiences of individuals (Ozturk et al., 2016). In the present study, compatibility is best understood from the lifestyle lens, comprising beliefs, ideas, values, and needs that users identify to adopt new technologies. There have not been many studies done to investigate the connection between perceived compatibility and perceived enjoyment. Lai and Ulhas (2012, p. 332) stated that technological features such as compatibility "strengthen intrinsic motivations, i.e., perceived enjoyment, then intensify extrinsic motivation, i.e., perceived usefulness, and finally reinforce intention to use". Oh and Yoon (2014) investigated haptic-enabling technologies and found that product compatibility positively affected perceived enjoyment. Regarding m-learning, Cheng (2015) found that compatibility positively influenced perceived enjoyment. Tan and Chou (2008) found that perceived compatibility regarding mobile information and entertainment services is positively linked to perceived playfulness. The concept of playfulness relates to the pleasure and psychological drive for intrinsically interesting interactions (Moon & Kim, 2001). It thus can be equated to enjoyment, which denotes in this study the extent to which AI-enabled technologies are perceived as enjoyable, regardless of external rewards. In mobile banking, Mohammadi (2015) associated high compatibility with a higher tendency to adopt the technology. In the context of online learning, Ifinedo (2017) found that students finding the technology to fit their learning needs were more likely to be pleased with the experience. The current study uses the previous discussion to propose a positive influence of perceived compatibility on the perceived enjoyment of AI-enabled hotel technologies. Thus, the following hypothesis is tested:

H3: Perceived compatibility has a significantly positive impact on perceived enjoyment

Wu and Wang (2005) further explained that the influence of compatibility on behavioral intention occurs through perceived usefulness. The construct of usefulness proposed by Davis (1989) within the original TAM has previously been used extensively in studies related to hospitality technologies (e.g., Bilgihan et al., 2016; Chang et al., 2012; Kim & Qu, 2014). Perceived usefulness is a belief that influences consumers' attitudes and behavioral intentions toward using information technologies. For example, Chau and Hu (2001) found that compatibility strongly impacted perceived usefulness in a study evaluating long-distance medical technologies. Similarly, Kanchanatanee et al. (2014) found that perceived compatibility directly impacts the perceived usefulness of e-marketing. Moreover, empirical support has also been provided for the significant positive association between compatibility and perceived usefulness (Park & Kim, 2020). Within the context of mobile banking, Hanafizadeh et al. (2014) found compatibility to be one of the factors influencing technology adoption, as influencing the perceived usefulness. It implies that the high compatibility of AI-enabled technologies with hotel guests' lifestyles will likely shape their adoption decisions. However, the relationship between compatibility and usefulness was not much tested within hotel settings. Therefore, the impact of compatibility on AI-enabled technologies at hotels is evaluated through perceived usefulness in the current study:

H4: Perceived compatibility has a significantly positive impact on perceived usefulness

Perceived Usefulness, Perceived Enjoyment, and Behavioral Intentions

Verma et al. (2018, p. 795) provide an updated definition of perceived usefulness: "the degree to which an individual believes that the use of an innovation helps to enhance his/her work". According to the TAM, perceived usefulness positively influences users of new technologies (Davis et al., 1992). Several studies within various contexts have confirmed this positive relationship. Chang et al. (2012) found perceived usefulness positively related to purchase intention in the context of the quality of travel agency websites. Kim and Qu (2014) also assessed perceived usefulness as positively impacting behavioral intentions. In the context of online booking, several studies assessed perceived usefulness as one of the determinants for predicting usage intention (Kucukusta et al., 2015). In the context of AI-enabled voice assistants at hotels, Cai et al. (2022) found a positive influence of perceived usefulness on intentions to use. Perceived usefulness influences consumers' decision-making toward new technologies, e.g., virtual reality (Holdack et al., 2020). In addition, the construct was also found to be a powerful predictor of behavioral intentions to purchase, as consumers are more engaged when they assess the high usefulness of using a technology (Lee & Koo, 2015). It means that if hotel guests perceive a high level of usefulness for the presence of AI-enabled technologies on a property, they would be more prone to experience an enhanced stay. Thus, in the context of hotel AI-enabled technologies, perceived usefulness refers to the hotel guests feeling that using those technologies presents valuable advantages for their stay.

H5: Perceived usefulness has a significantly positive impact on behavioral intentions

Compared to usefulness, enjoyment is an intrinsic motivation. It has been assessed by previous information systems and technology acceptance literature as contributing factor to users' intention towards adopting new systems (e.g., Alalwan et al., 2018; Davis et al., 1992). Prior studies have also confirmed perceived enjoyment's positive relationship with consumers' behavioral intentions (e.g., tom Dieck et al., 2017). In the context of online booking, perceived enjoyment was found to have a positive influence on booking intentions (Sahli & Legoherel, 2015). Therefore, perceived enjoyment was incorporated into the modified TAM to evaluate how this attitudinal construct plays besides functional variables (i.e., perceived usefulness) for influencing hotel guests' behavioral intention toward using AI-enabled technologies. Furthermore, several studies used other hedonic constructs like enjoyment, recognizing their influence on users' attitudes toward using new technologies (Chen et al., 2019). Therefore, hedonic perceptions such as perceived enjoyment are crucial for users' intention to use adaptation to the technology. The following hypothesis is then proposed for the context of AI-enabled technologies:

H6: Perceived enjoyment has a significantly positive impact on Behavioral intentions

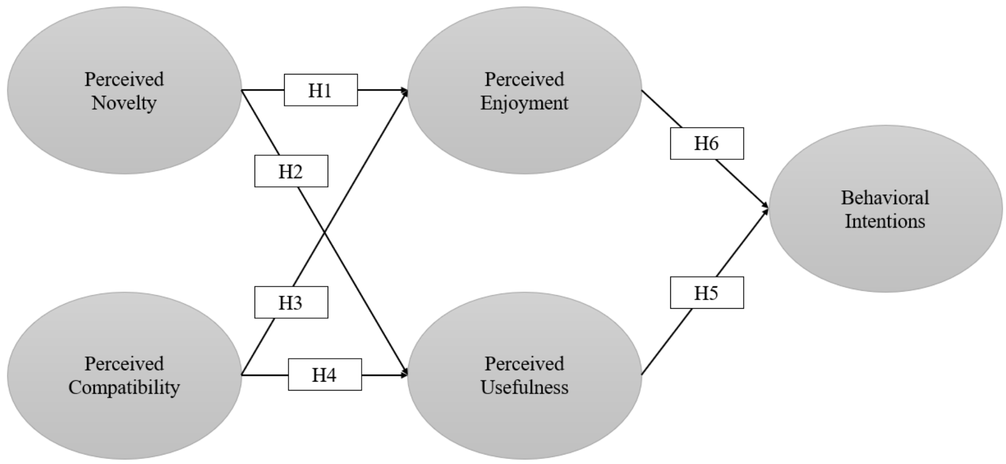

Figure 1. *Research Model*

METHODOLOGY

As an online survey platform used by several scholars within hospitality and tourism studies (Ali et al., 2021), Amazon Mechanical Turk (MTurk) was used to collect the necessary data to conduct this investigation. A self-selection sampling method was deemed relevant since respondents' decision to participate in the research is based on their free will, an essential characteristic of digital surveys (El-Manstrly et al., 2020). The target population consisted of users above 18 years old who have stayed in a US hotel at least once during the past 24 months. Due to the novel character of the technologies presented in this study, and in the optic of providing context for the respondents, survey participants were exposed to a three-minute video clip featuring next-gen technologies used in Alibaba Flyzoo futuristic hotel in China[2]. The Flyzoo hotel was chosen as it features a quasi-comprehensive package of guest-facing AI technologies used at hotels. The clip was judged as most appropriate to present next-gen technologies. It featured mobile check-in, facial recognition technology for room entry, voice technology to control room amenities, service robots, and augmented reality. For data quality purposes, the online survey targeted respondents who scored a minimum of 95% in the Human Intelligence Task Approval due to their high reputation on the MTurk platform. In addition, two attention checks were included in the online survey to ensure that respondents effectively watched and understood the video. Data collection through Amazon MTurk yielded a total of 1033 responses. The validity and reliability of the data were ensured through several attention-check questions disseminated in various steps of the survey. All respondents who failed attention check questions were excluded from the final data set. In addition, a bot check tool was used to prevent bots from taking the surveys (i.e., humans need to click on the circles with traffic lights). After this cleaning, a net of 405 respondents was used for the final analysis. Then, respondents not meeting the exclusion criteria were removed from the study, and incomplete survey responses were excluded from the final dataset. At the end of the process, 331 valid responses were accepted for analysis.

The study's sample encompasses a rich demographic tapestry, capturing a wide array of participants. Gender distribution is well-balanced, with approximately 45% identifying as female and 55% as male. Age-wise, a predominant 40% falls within the 25-34 age range, highlighting a significant representation of the younger demographic, while another 30% belong to the 35-44 age group, ensuring a diverse age distribution. Educational backgrounds exhibit diversity, with 25% holding undergraduate degrees, 35% possessing postgraduate qualifications, and 10% holding doctoral degrees. In addition to demographic characteristics, participants' technology usage behaviors are integral to the sample, with a noteworthy 61% reporting frequent use of technology during their travel. Moreover, approximately 70% reported engaging in frequent travel, showcasing a sample that actively participates in the hospitality and tourism domains.

[2] (https://www.youtube.com/watch?v=kn28gSlQUMc)

Regarding measurement, the scales used in this examination were derived from previous studies in consumer behavior, marketing, and technology acceptance literature (Table 1). While only the behavioral intentions variable was measured through a seven-point Likert scale, all other measures employed a five-point Likert scale. Before data collection, the instrument was dispatched to six hospitality and hotel technology experts to confirm face validity. Their valuable comments improved the questionnaire's readability from users' hands-on involvement with next-gen technologies.

Common Method Variance

Common method variance was justified using various methodological and statistical tools. Psychological separation among respondents was also achieved using different cover stories for each scale. The survey instrument had 30 questions, which presents the advantage of being short to avoid confusion and tiredness, which can have an adverse impact on the respondents' cognitive capabilities/efforts to provide accurate answers to the questions. Results from Harman's single-factor test confirmed that a single factor did not account for the majority of the variance. As such, this investigation could not be affected significantly by common method bias.

FINDINGS AND ANALYSIS

This study used Partial least squares (PLS-SEM) performed on the SmartPLS 3.3.3 software to test the linear relationships in the research model depicted in Figure 1. Similarly, for configurational modeling, authors have used fsQCA software (Ragin, 2009). Recently, the scholarly community in hospitality and tourism has suggested employing causal asymmetrical analysis to understand the complex issues within consumer behavior (Kumar et al., 2023). The asymmetrical approach suggests that a high value of X is both necessary and sufficient for a high value of Y to occur and that a low value of Y occurs with low values of X (Woodside, 2016). In addition, the asymmetrical approach suggests that the four antecedent conditions leading to high scores in an outcome condition are often not the mirror opposites of the antecedent conditions leading to low scores (Woodside, 2016). Failure to examine asymmetric analysis can lead to incomplete results, implying an unfitting causal understanding of the issue. Also, the asymmetric analysis provides richer and deeper insights to explain reality than the symmetric analysis, allowing researchers to understand the complex causal relationships and the effects of causal recipes of outcome conditions (Ali et al., 2023). There are three main components of fsQCA analysis, i.e., data calibration, truth table analysis, and necessary component analysis. First, data calibration converts raw data to more exact standard values (Pappas & Woodside, 2021). Subsequently, transforming the Likert-type scale data from a discrete value (1 to 5) into a fuzzy form (0 to 1), where 1 signifies complete participation, .5 marks the crossover point, and 0 denotes an entire absence of membership. Since the dataset did not follow a multivariate normal distribution as indicated by Mardia's coefficients, PLS-SEM was considered suitable for testing the model, especially since the study is exploratory per se (Ali et al., 2018). Moreover, the independent t-test revealed that all measures had a statistically non-significant difference, thus confirming the absence of non-response bias.

Measurement Model Assessment

PLSc algorithm was applied, given that the variables used in this study are reflective. First, the model fit using Standardized Root Mean Square Residual Value (SRMR) yielded a value of .074, indicating a good fit to the data (Ali et al., 2018). Second, d_ULS and d_G values were 2.513 and .077, less than the 95% bootstrapped quantile. Third, the discriminant validity, convergent validity, and internal consistency reliability were evaluated through rho_A, composite reliability (CR), and Cronbach's alpha (CA). The results show that CR is above .70 (See Table 1)—the suggested lower limit for these measures (Ali et al., 2018). In addition, the AVE is also above the threshold of .5. Consequently, the model presents acceptable results regarding convergent validity and intrinsic reliability values. Additionally, discriminant validity was assessed for the variables through the Fornell-Larker criterion. Correlations in the respective rows and columns were lower than all the AVE square roots (See Table 2). Table 2 also displays all values for HTMT, which satisfy the condition of HTMT .90 and support the satisfactory discriminant validity for all study constructs.

Table 1. *Validity and Reliability*

Variables	Items	Statements	Loadings	CA	Rho_A	CR	AVE
Perceived novelty (Im et al., 2015)	PN1	Compared to other technologies used in hotels, the AI-enabled technologies presented in the video clip: Are very novel for me	.701	.889	.889	.901	.534
	PN2	Are very innovative for me	.766				
	PN3	Are very original to me	.746				

	PN4	Are radically different	.738				
	PN5	Can be considered revolutionary	.771				
	PN6	Are really out of the ordinary	.753				
	PN7	Provide something not commonly found	.590				
	PN8	Incorporates new ideas/concepts	.769				
Perceived compatibility (Wu & Wang, 2005)	PC1	Using AI-enabled services is compatible with many aspects of my transactions	.866	.854	.857	.911	.775
	PC2	Using AI-enabled services fit my lifestyle	.865				
	PC3	Using AI-enabled services fit well with the way I like to engage in online transactions	.908				
Perceived enjoyment (Nysveen et al., 2005)	PE1	Using AI-enabled services is fun	.835	.89	.891	.924	.752
	PE2	Using AI-enabled services is enjoyable	.882				
	PE3	Using AI-enabled services is exciting	.867				
	PE4	Using AI-enabled services is pleasant	.883				
Perceived usefulness (Nysveen et al., 2005)	PU1	Using AI-enabled services make me save time	.858	.841	.846	.904	.758
	PU2	Using AI-enabled services improve my efficiency	.866				
	PE3	AI-enabled services are useful to me	.888				
Behavioral intentions (Ali et al., 2021)	BI1	I think that I will be using AI-enabled services	.891	.894	.896	.934	.825
	BI2	I would leave positive comments about AI-enabled services	.906				
	BI3	I would recommend my friends and family to use AI-enabled services	.926				

Table 2. *Discriminant Validity*

Constructs	**1**	**2**	**3**	**4**	**5**
	F&L criterion				
Behavioral intentions	.908				
Perceived compatibility	.768	.880			
Perceived enjoyment	.736	.756	.867		

Perceived novelty	.495	.552	.483	.732	
Perceived usefulness	.759	.773	.700	.559	.871
	HTMT criterion				
Behavioral intentions					
Perceived compatibility	.848				
Perceived enjoyment	.823	.844			
Perceived novelty	.543	.558	.531		
Perceived usefulness	.850	.808	.821	.633	

Structural Model Assessment

The variance inflation factor (VIF) results revealed no multicollinearity concerns in the structural model since the values found were lower than the threshold of 5. Also, path estimates were calculated along with 5,000 subsamples. As displayed in Figure 2, the perceived novelty has a significant positive impact on perceived enjoyment, and perceived compatibility positively impacts perceived usefulness. Moreover, perceived enjoyment and perceived usefulness were found to have a positive impact on behavioral intentions.

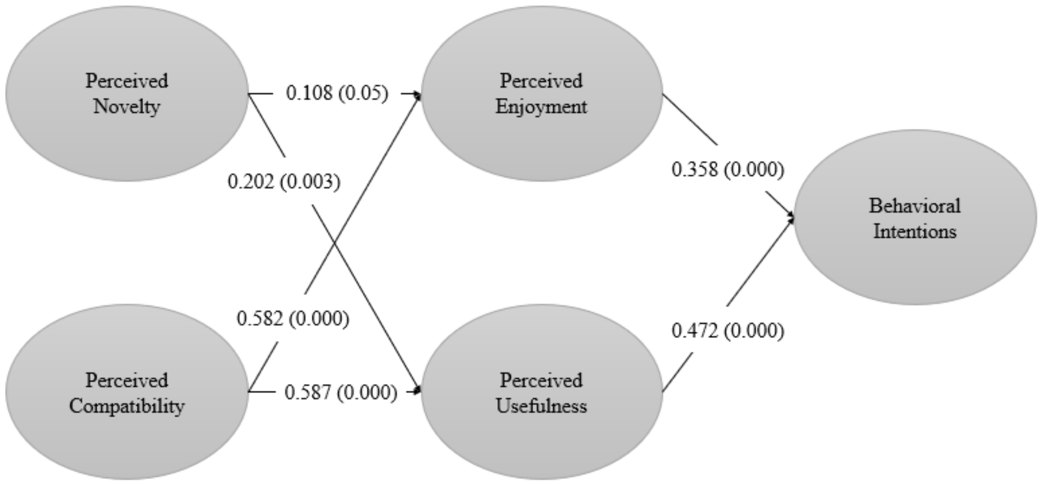

Figure 2. *Structural model*

Table 3. *Hypotheses Testing*

Paths		**Original sample**	**T Statistics**	**P Values**	**Decision**
H1	Perceived novelty -> Perceived enjoyment	.108	2.331	.05	Supported
H2	Perceived novelty -> Perceived usefulness	.202	3.032	.003	Supported
H3	Perceived compatibility -> Perceived enjoyment	.582	7.384	.000	Supported
H4	Perceived compatibility -> Perceived usefulness	.587	8.285	.000	Supported
H5	Perceived usefulness -> Behavioral intentions	.472	6.732	.000	Supported
H6	Perceived enjoyment -> Behavioral intentions	.358	4.637	.000	Supported

Necessary Conditions Analysis (NCA)

NCA was conducted to identify the critical necessary factors for the study's high and low outcome, i.e., intentions to adopt and use next-gen/AI-enabled technologies by hotel guests (See Table 4). Whenever the values of consistency and coverage are more than .9 and .5, a condition is necessary (Pappas & Woodside, 2021). Findings in Table 4 reveal that all conditions, including perceived novelty (PN), perceived compatibility (PC), perceived enjoyment (PE), and perceived usefulness (PU), were necessary for developing the high intention intentions to adopt and use next-gen/AI-enabled technologies. It means that the user's high behavioral intention will not be developed without the presence of PV, PC, PE, and PU.

Table 4. *Table for NCA for both high and low outcomes*

Conditions Tested High BI.	Consistency	Coverage
PN	**.915**	**.915**
~PN	.185	.896
PC	**.909**	**.961**
~PC	.209	.804
PE	**.948**	**.934**
~PE	.152	.795
PU	**.912**	**.948**
~PU	.191	.803
Conditions Tested Low BI.		
PN	.896	.186
~PN	.509	.592
PC	.754	.165
~PC	.820	.652
PE	.810	.165
~PE	.677	.730
PU	.774	.165
~PU	.755	.658

Note: PN: Perceived novelty; PC: Perceived compatibility; PE: Perceived enjoyment; PU: Perceived Usefulness.

1. **Conditions in bold represent necessary conditions.**

Configurational Analysis

We used truth table analysis to determine if the sample data adequately explained the expected results. Outcomes from the fsQCA (see Table 5) indicate that the configurations were enough to forecast high and low scores of the study outcome based on evaluating the complex set of interconnected studied components leading to users' behavioral intention. Because coverage and consistency were above the preset standards of >.2 and .80, respectively, the solutions were accepted (Ragin, 2009). In addition, Pappas and Woodside (2021) recommended that the recognition and recording of both peripheral and core components in each configuration be conducted to achieve a deeper understanding. In Table 5, the absence of a condition is represented by a circle with a cross through it (⊗), whereas the presence of a causal event is represented by a black circle (●). The vacant spaces denote circumstances regarded to be "do not care" scenarios. Larger circles depict more significant conditions, smaller ones less so.

Table 5. *Configurational Analysis*

Conditions	Solutions for High BI. frequency cut off: 1 consistency cut off: .828			Solutions for Low BI. frequency cut off: 1 consistency cut-off: .705	
	M1	**M2**	**M3**	**M1**	**M2**
Perceived Novelty		●		^	●
Perceived Compatibility	⊗	⊗	●	⊗	⊗
Perceived Enjoyment	⊗	●	●	⊗	⊗
Perceived Usefulness	⊗		●		
Raw Coverage	.132	.204	.877	.625	.690
Unique Coverage	.004	.003	.680	.024	.090
Consistency	.804	.928	.968	.788	.736
Overall Coverage		.889		.715	
Overall Consistency		..935		.734	

Note:

1. (Black circle (●) indicates the existence of a causal condition, blank cross circle (⊗) indicates the absence or negation of a condition, and blank cells belong to situations where the presence or absence of such a condition does not matter for the outcome.
2. ^ represents the core conditions, whereas a small black circle (●) represents the peripheral conditions.

The overall solution consistency (.935) demonstrates how the three causal solutions lead to a high level of behavioral intent to use AI-based technology. In particular, the overall solution coverage (.889) indicates the probability that the three causal configurations will predict a high proposed outcome. For example, considering Table 5's data, configuration 1 had a consistency of 80% and a coverage of 13.2%. Comparatively, configuration 2 explained 92.7% of the result's variance with coverage values of 20%. Ultimately, solution 3 had the maximum coverage and consistency values (.877 and .968, respectively) to generate high intention toward AI-based technologies. Accordingly, two causal solutions with overall consistency and coverage values of .734 and .715, respectively, were developed for low behavioral intention regarding AI-based technology. Model 1 of the two causal models has 62% coverage and 78.6% consistency, including the lack of PC, PE, and PU. Nevertheless, model 2 has greater coverage (.690) and a consistency score of 73.6%, including the existence of PN and the lack of PC and PU.

DISCUSSION AND CONCLUSIONS

This study examined the main factors shaping users' behavioral intentions toward using next-gen technologies in hotels. As such, extrinsic (i.e., perceived usefulness) and intrinsic (i.e., perceived enjoyment) aspects were considered the main drivers of users' behavioral intentions to use next-gen technologies in hotels. In addition, the study hypothesized that perceived novelty and compatibility significantly impact both perceived enjoyment and usefulness, leading to behavioral intentions. All hypothetical relationships between constructs in this study were tested, and empirical support was provided for these hypotheses. Thus, this study underlined the importance of including extrinsic and intrinsic motivations in shaping users' behavioral intentions toward using AI-enabled technologies. The outcomes of this analysis are consistent with previous studies that assessed the significant influence of perceived usefulness on behavioral intentions (Alalwan et al., 2018; Cobanoglu et al., 2015). The positive relationship between perceived enjoyment and behavioral intention is also corroborated by similar studies, reinforcing the importance of intrinsic motivations in users' adoption of new technologies (Alalwan et al., 2018; Chang & Chen, 2021; Holdack et al., 2020). Furthermore, this study uncovered that perceived novelty positively impacted perceived enjoyment and perceived compatibility positively impacted perceived usefulness. Again, these findings are in line with findings from previous studies (Chen et al., 2013; Kanchanatanee et al., 2016; Koenig-Lewis et al., 2015; Merikivi et al., 2017). In addition, the present study demonstrated the impact of intrinsic motivators on extrinsic evaluations in that perceived novelty had a positive impact on perceived usefulness. However, perceived compatibility had a positive impact on perceived enjoyment. It implies that hotel guests can evaluate next-gen technologies based on how well these fit with their beliefs, ideas, and needs (compatibility). Guests will likely consider these technologies useful, enjoyable and use them if these technologies are novel. Thus, the extended TAM and IDT interpretation offers a detailed understanding of users' beliefs, impacting their intention to use next-gen technologies. The following paragraph compares these findings with those of previous studies.

First, the study found support for the positive impact of perceived novelty on perceived enjoyment and usefulness. These results suggest that users perceive the novelty of technological innovation shapes their evaluations of the intrinsic and extrinsic benefits they gain from using those technologies. It is in line with Kristi and Kamasuwati (2021), who found that novelty in augmented reality positively influenced perceived usefulness and enjoyment. Contradictorily and apropos of novelty-seeking, Baccarella et al. (2021) could not confirm a positive relationship between novelty-seeking and perceived usefulness. Secondly, perceived compatibility was found to have a positive impact on perceived enjoyment and perceived usefulness. It suggests that the degree to which technological innovations align with users' beliefs, ideas, values, and needs, is also a function of their perceptions of benefits, both on affective and cognitive levels. This understanding is also consistent with previous studies. For example, Cheng (2015) found a positive effect of compatibility on both perceived enjoyment and usefulness in mobile learning. Oh and Yoon (2014) also assessed compatibility to impact the perceived enjoyment and usefulness of haptic-enabled technologies positively. Finally, concerning e-textbook applications, Lai and Ulhas (2012) also found compatibility to affect both perceived enjoyment and perceived usefulness positively. Lastly, perceived usefulness and perceived enjoyment were found to have a positive impact on behavioral intentions. These findings support the rationale that about technological innovations, intrinsic and extrinsic factors significantly influence users' behavioral intentions toward using those technologies, regardless of the technological context. For example, Chang and Chen (2021) found that perceived enjoyment and usefulness positively affected behavioral intention in online shopping. It is also confirmed in several other studies: Chiu and Cho (2020) about health and fitness apps; Alalwan et al. (2018) about mobile internet adoption in Saudi Arabia; Han and Conti (2020) in the context of telepresence robots in an educational setting. As such, this study provides empirical findings in a hotel setting. While Koenig-Lewis et al. (2015)—referring to the context of mobile payment technology—also found a positive effect of perceived usefulness on behavioral intentions, they did not find a significant direct relationship between perceived enjoyment and behavioral intentions. Nevertheless, Cha's (2020) investigation regarding the intention to use robot services in restaurants corroborated the positive influence of perceived enjoyment on behavioral intentions. The direct relationship between perceived usefulness and behavioral intentions is also supported in various studies (e.g., Cobanoglu et al., 2015; Lin & Chang, 2011).

Finally, this research presents a novel asymmetrical approach to confirming the preliminary assumptions of complexity theory, complementing the standard symmetrical analysis. Equality of outcomes, asymmetry, and conjunctural causation are the three cornerstones of complexity theory. All the crucial assumptions of complexity theory are proven true, and the results fill a crucial context absent from the more common SEM study. The results of applying fsQCA to the key concepts of complexity theory are summarized in Table 5. To begin with, the results of the fsQCA analyses provide credence to the idea that asymmetrical correlations exist between the variables in the research, proving a key premise of fsQCA. The findings demonstrate that the suggested consequence, namely the purpose of employing AI-based technology, may be explained by several conditions. The context for the result is provided by the fact that both high and low PE and PC components can be found in different configurations (M2 and M3). The results of the truth table analysis further showed that numerous conditions (PE and PU) did not matter. Meanwhile, the more traditional PLS-SEM-based analysis showed that they did matter significantly. These results suggest that the relationship between the investigated factors and the outcome is complex and multifaceted. Equifinality refers to the idea that there are many ways to arrive at the same destination (in this case, BI). Findings of the dataset's asymmetrical relationships show that the results from using either PE or PC are consistent and comprehensive, further justifying equifinal outcomes. Conjectural causality was proven to be an acceptable research premise. Multiple combinations of antecedents contribute to BI, and the researchers concluded that each of these accounts for the predicted outcome. Moreover, the findings in Table 4 also reveal that all conditions are found to be necessary to generate the desired outcome.

Theoretical Implications

This study explores the determinants of hotel guests' intentions to adopt and use next-gen/AI-enabled technologies, employing a dual approach of symmetrical and asymmetrical methods while integrating aspects of Innovation Diffusion Theory (IDT) and Technology Acceptance Model (TAM). Symmetrically, our investigation advances the comprehension of perceived enjoyment and usefulness in influencing hotel guests' behavioral intentions toward the adoption of next-gen technologies, aligning with TAM. The research model posits that perceived enjoyment and usefulness positively influence hotel guests' behavioral intentions, with intrinsic and extrinsic motivations serving as antecedents impacting cognitive and affective processes. This study contributes to the theoretical landscape by enhancing the combination of IDT and TAM, providing greater clarity on how the integration enriches our understanding within the framework of AI technology in the hospitality industry. We extend traditional TAM by underscoring the pivotal role of intrinsic motivations in users' assessments of adopting newer technologies, emphasizing the need for affective considerations in technology adoption. Aligning with IDT, we acknowledge the evolving nature of technology adoption in the hospitality sector, shifting from predominantly utilitarian guest-facing technologies to the current emphasis on hedonic facets. Specifically, the "fun" aspect of these technologies cannot be ignored, and this study delves into the factors contributing to their adoption by users. The hedonic aspect of AI-enabled technologies, particularly their degree of personalization, is a focal point, integrating both IDT and TAM perspectives. Recent studies, incorporating perceived enjoyment, highlight intrinsic motivations as potent predictors of behavioral intentions, prompting the inclusion of additional variables. Drawing on IDT and TAM principles, personalized services within hotel operations, offering special attention and treatment, are posited to significantly contribute to guests' enjoyment and usefulness, reducing information search time and providing intrinsic and extrinsic benefits. In employing asymmetrical techniques rooted in complexity theory, this research uncovers nuanced phenomena in human behavior, particularly in the tourism industry's use of AI-based technology. Beyond detailing the overall impact of each variable, the study utilizes fsQCA to present alternative pathways for achieving desired goals, optimizing for both low or high behavioral intention (BI). This approach enhances our theoretical contribution by providing a more comprehensive understanding of the adoption of AI-enabled technologies in the hospitality industry, firmly grounded in the integrated perspectives of IDT and TAM.

Practical Implications

In terms of practical implications, new technologies are vital for the hotel guest experience and can provide hoteliers with a satisfactory return on substantial investments in AI-enabled technologies. This study thus contributes by extending to hoteliers willing to gain further insights regarding guests' acceptance of next-gen technologies, leading to a better selection and implantation policy. Although the novelty of those technologies may elicit enjoyment and other intrinsic benefits to users, they should answer to specific demands and needs of customers. It shows that hoteliers should not neglect the human factor beyond the system itself, likely to elicit extrinsic motivations. To achieve this, hoteliers should tailor technology offerings, providing alternatives or flexible usage conditions to accommodate the varied expectations of their clientele. A practical example involves implementing a smart room system with customizable features, allowing guests to personalize their experiences based on individual preferences. In addition, hoteliers should make sure that their investments in technologies are of quality products, as related to the example of Hen-na hotel in Japan, which was aimed to be entirely operated by robots but ended as a fiasco due to malfunctioning robots. Some users may not find all AI-enabled technologies useful; as such, there should be alternatives or flexibility in the conditions of their use. It can also be recommended that hoteliers focus on innovative technologies that align with their customer base's beliefs, values, and needs. For instance, a hotel focusing on millennials may invest in mobile technology because of this generation's heavy usage of smartphones.

Ultimately, our study assessed the importance of intrinsic motivations, i.e., perceived enjoyment, in justifying behavioral intentions toward using next-gen technology in hotels. It can be said that guests at a hotel would be less inclined to use technologies that do not offer intrinsic benefits. It can be attributed to the fact that technologies enabled by artificial intelligence usually involve personalized features, which tend to increase customers' feelings of pleasure and enjoyment from using those technologies. A contradicting viewpoint is from Koenig-Lewis et al. (2015), who found that perceived enjoyment did not strongly influence the intention to use mobile payment services but assessed a significant indirect effect through perceived usefulness. Koenig-Lewis et al. (2015) also argued that perceived enjoyment is not essential in adopting financial services. As financial services are designed for their productivity and convenience attributes rather than the fun aspect, enjoyment's effect on behavioral intentions is not uniform across various sectors. Nevertheless, the present study assessed the critical role of enjoyment in the context of hotel technologies. Within hospitality, perceived enjoyment is a critical factor for leisure travelers, who tend to place more importance on amusement over productivity. With the panoply of technologies competing for consumers' attention, adoption, and use, hoteliers must provide technologies that users may find fun and enjoyable. Koenig-Lewis et al. (2015) also noted that perceptions of novelty and instant gratification are essential for young people, thus emphasizing the importance of intrinsic evaluations and benefits for consumers. If guests perceive AI-enabled technologies in hotels as enjoyable, they are also more likely to be perceived as productive and beneficial. As such, by enhancing levels of perceived enjoyment, hoteliers would benefit from an increased willingness to adopt and improve the perceived usefulness levels. Hoteliers' promotional and marketing efforts should be directed at positioning AI-enabled technologies from an affective standpoint. Along with those efforts, practitioners also need to provide services with assured quality and reliability to not fail on the perceived usefulness of those technologies.

Limitations and Future Research Suggestions

While the present study yielded intriguing and meaningful insights, it is essential to acknowledge certain limitations that may guide future research endeavors. The study's nature, centered on next-gen technologies in hotels, necessitated the utilization of a video clip showcasing the innovative Flyzoo Hotel in China. However, it is worth noting that these technologies are still in the introductory stage, limiting the number of hotel guests with direct, hands-on experiences. To address this limitation, future research could intentionally focus on guests who have had firsthand encounters with these technologies, providing a more nuanced understanding of their perceptions and attitudes. Furthermore, as the adoption of next-gen technologies unfolds, it becomes evident that flexibility is paramount to cater to users' specific needs. Subsequent studies could enhance the model employed in this research by incorporating additional variables, such as exploring the intricate dynamics of trust and privacy concerns. This expansion would contribute to a more comprehensive understanding of the factors influencing users' intentions to adopt and use these technologies in a dynamic hotel environment. Another avenue for future research lies in exploring the evolving landscape of user experiences with next-gen technologies in diverse hospitality settings. This could involve investigating how users from various demographic backgrounds and technological familiarity levels engage with these innovations. Moreover, delving into the potential cultural nuances influencing technology adoption and acceptance could provide valuable insights for hoteliers and technology developers aiming to tailor their offerings to different markets. Additionally, recognizing the rapid evolution of technology, longitudinal studies tracking the changes in user perceptions and behaviors over time would offer valuable insights into the long-term impact of next-gen technologies in the hotel industry. This could involve periodic assessments of user experiences, preferences, and concerns as these technologies mature and become more ingrained in the hospitality landscape.

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