Research in Hospitality Management 2024, 14(2): 171–185
https://doi.org/10.1080/22243534.2024.2398479

RHM 2024 Research in Hospitality Management

Hospitality 2.0: Applying the UTAUT model to understand guest perspectives on personalised technologies in hotels

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ABSTRACT: This study evaluates hotel guest perspectives on adopting personalised technology-enabled hospitality services by using a quantitative survey methodology. Applying unified theory of acceptance and use of technology (UTAUT) model constructs, the questionnaire gauges 200 guest views on performance benefits, usage effort and conditions influencing adoption of artificial intelligence (AI), the internet of things (IoT) and mobility. Descriptive and correlational analyses highlight innovation by capability and reveal barriers around complexity, privacy and reliability. Findings can inform hotel technology investment decisions and strategic planning to effectively leverage data-driven customisation capabilities across the entire guest journey — from pre-arrival trip planning to post-stay loyalty building. It will also help towards the Hospitality 2.0 vision of balancing digitisation with human connections. This empirical assessment aims to advance sector transformation and next-generation experience elevation through prudent prioritisation guided by evidence-based user willingness going beyond speculative innovation.

KEYWORDS: personalisation technology, guest experience enhancement, unified theory of acceptance and use of technology

Introduction

The "Hospitality 2.0" vision represents a paradigm shift in the hotel industry, characterised by the integration of advanced technologies to enhance guest experiences while maintaining the essential human element of hospitality (Buhalis & Leung, 2018). Following this vision, major hotel brands have begun implementing a wide array of technologies to transform guest experiences and offer more personalised, seamless stays catered to individual preferences and needs (Bharwani & Mathews, 2021). In this case, an important technology for hotels is online booking systems. Popular third-party sites like Booking.com and Expedia provide a huge marketing reach and allow price comparisons. Meanwhile, branded booking sites like Hilton.com or Marriott.com offer loyalty discounts and personalised offers to repeat guests (Bardukova, 2023).

According to Buhalis and Leung (2018), property management systems (PMS) act as the core system for hotel operations. The PMS allows management to track reservations, room status, rates, payments and guest profiles. Handheld devices or tablets give housekeeping instant access to room status, guest requests and cleaning checklists. Maintenance staff can view equipment issues, respond to guest requests and update resolved complaints and queries. Across departments, staff get notifications when VIP guests arrive so the staff can customise their stay (Piccoli et al., 2017). This way PMS creates a seamless, high-touch experience.

In-room entertainment systems also elevate the guest experience with on-demand movies, TV, music, web browsing, console gaming and more. Streaming platforms like Netflix are often integrated into the TV system (Bardukova, 2023). Tablets allow guests to control lighting, temperature, service requests and other room features. High speed Wi-Fi enables guests' personal devices to connect seamlessly. (Stringam & Gerdes, 2021). Recently, electronic radio frequency identification (RFID) keycards have become popular, and provide secure, convenient access to guest rooms and common areas. Integrated with the PMS, keycards give each registered guest personalised access while enhancing security (Cheong et al., 2017).

In-room voice assistants like Amazon Alexa or Google Home are growing in popularity at hotels. As stated by Buhalis and Leung (2018), guests can ask questions, control room features, request hotel services, play music, get information on local attractions, set alarms and more just by speaking. Voice assistants integrate with the PMS, resort systems and third-party apps to enable a conversational experience for the guests. According to Kasavana (2014), the internet of things (IoT) allows hotels to embed smart technology into rooms to elevate service quality. Networked sensors can detect motion, temperature, humidity, lighting and sound levels. The data collected by these sensors is transmitted to a central management system, which may interface with staff devices, such as tablets or smartphones, allowing real-time monitoring and adjustments.

While hospitality providers are rapidly advancing in digitising and personalising elements of the guest journey, there is limited knowledge related to guest willingness and motivations to accept and utilise these technology-driven personalised experiences (Kabadayi et al., 2019). To address this crucial issue, this study applies the unified theory of acceptance and use of technology (UTAUT) model to understand the factors influencing guest adoption of personalised hotel technologies. By understanding the key drivers of guest acceptance and use of personalised technologies, hotels can more effectively prioritise their technology investments, refine their implementation strategies, and align their offerings with guest expectations and readiness.

Problem statement

While the hospitality industry rapidly advances in digitising and personalising the guest journey, there is a disconnect between these technological innovations and our understanding of guest preferences and behaviours. This discrepancy stems from a lack of comprehensive empirical research into guests' willingness and motivations to adopt technology-driven personalised experiences (Kabadayi et al., 2019). The current body of research mainly provides a limited understanding of the specific factors influencing guests' adoption of personalised technologies. Established models in technology acceptance, such as the unified theory of acceptance and use of technology, identify key constructs like effort expectancy, social influence, facilitating conditions and performance expectancy (Venkatesh et al., 2003). These factors have not yet been thoroughly examined in the context of personalised hospitality technologies (Ozturk et al., 2016).

Objective

To assess the technologies that can enable personalised guest experiences in hotels and evaluate guest perspectives on adopting personalised and technology-enabled hospitality services to help hotels evolve towards the hospitality 2.0 vision. It is imperative to note that hospitality 2.0 envisions integrating advanced technologies with personalised human service to enhance guest experiences, streamline operations and create data-driven, tailored stays across the entire guest journey (Buhalis & Leung, 2018).

Our specific objectives are to:

(1) Identify key technologies like AI, IoT and mobility that can enable personalised guest experiences when applied in hospitality; and
(2) Evaluate guest perceptions, concerns and adoption factors for personalised hospitality technology.

Literature review

This literature review synthesises current research on personalisation in hospitality, guest acceptance of these technologies and the application of the unified theory of acceptance and use of technology model in this context.

Personalisation in hospitality

Personalisation involves tailoring products and services to individual consumer preferences and contexts. In hospitality, Kasavana (2014) argues that personalisation enhances the guest experience by incorporating flexibility, customisation and guest control into service offerings. According to Makki and Chang (2015), key technologies like AI, IoT, mobility, biometrics, VR and big data analytics are driving greater personalisation across the hospitality ecosystem.

As stated by Morosan and DeFranco (2016b), mobile apps allow guests to input preferences, control room features, order amenities and receive personalised suggestions. Markovitch and Willmott (2014) discuss how in-room IoT like smart TVs and tablets also enable personalised entertainment, environment control and service orders. Tung and Au (2018) describe how behind the scenes, AI crunches guest data to predict guest desires. These personalised interactions across platforms aim to provide each guest a unique experience tailored to their needs. Ultimately, the aim is driving guest satisfaction, loyalty and positive word-of-mouth.

Guest perspectives on technology adoption

According to Lashley (2008), the guest experience encompasses every touchpoint between consumers and hospitality brands across the entire journey. Some research explores factors influencing adoption of technologies like automation, IoT, mobility, smart devices and AI in hotels. From an organisational perspective, Morosan and DeFranco (2016b) identify competitive pressure, perceived innovation attributes, technological readiness, managerial support and brand image as drivers of technology adoption. Wang and Sparks (2017) find that hotels with greater technology skills and supporting infrastructure are better positioned to integrate new systems and workflows.

From the guest perspective, Tussyadiah et al (2018) investigated the factors influencing guests' willingness to use hotel technologies. Their study found that perceived ease of use, value, enjoyment and demographic factors play significant roles in technology acceptance. Fuentes-Moraleda et al. (2020) found that younger, frequent travellers are more receptive, while older guests often prefer human interactions. According to Kang and Namkung (2019), guests are often willing to share personal information if they perceive clear benefits, but concerns about data security and misuse can hinder adoption. Critically, Makki and Chang (2015) emphasise that technologies should enhance service and experiences without frustrating guests through complexity or tech issues.

However, Tung and Law (2017) cautioned that the over-reliance on technology diminishes the human touch in hospitality. A survey found that 67% of guests believe technology should enhance but not replace human service. Similarly, Tung and Law (2017) argue technology can augment hospitality productivity, but cannot replicate genuine human experiences. Thus, Fuentes-Moraleda et al. (2020) advocate that a balance is needed between automation and human interaction to optimise guest experiences.

These studies collectively indicate that while guests are generally open to personalisation technologies, their acceptance is contingent on factors such as perceived benefits, ease of use, privacy protection and the preservation of human interaction in service delivery.

The UTAUT model in hospitality technology acceptance

The unified theory of acceptance and use of technology (UTAUT) model, developed by Venkatesh et al. (2003), provides a comprehensive framework for understanding technology acceptance. While originally developed in the context of information technology acceptance in organisations, the UTAUT model has been applied in various contexts, including hospitality technology adoption. For instance, Morosan and DeFranco (2016a) used an extended version of the UTAUT model to examine guests' intentions to use mobile apps for hotel services. They found that performance expectancy and hedonic motivation were strong predictors of intention to use, while effort expectancy had a less significant impact. This suggests that guests are more concerned with the benefits and enjoyment of using hotel mobile apps than with the effort required.

Similarly, Kim and Qu (2014) applied the UTAUT model to investigate hotel guests' adoption of self-service kiosks. Their study revealed that performance expectancy and facilitating conditions were the most significant predictors of behavioural intention to use such kiosks. This highlights the importance of perceived usefulness and adequate support in encouraging guests to adopt self-service technologies. Melián-González et al. (2019) used the UTAUT model to examine the acceptance of AI-enabled personalised hotel services. They found that performance expectancy, effort expectancy and social influence positively impacted guests' intentions to use AI services. However, they also noted that privacy concerns moderated these relationships, emphasising the need to address data protection issues in AI-enabled personalisation.

Research gaps and future directions

Synthesising this literature highlights some gaps representing opportunities for future research. Firstly, few studies take a holistic perspective examining the entire guest journey across pre-arrival, stay and post-stay, as noted by Neuhofer et al. (2014). Research tends to concentrate on specific technologies or touchpoints. Investigating the end-to-end journey experience could reveal points of difficulty and integration challenges.

Secondly, more research is needed on changing guest attitudes towards technology and human versus automated service. As emerging technologies permeate hospitality, will guest tolerance for automation increase? Or will the desire for human connections strengthen? How does technology impact the perceived authenticity and emotional value of guest experiences?

Additionally, while literature explores technology adoption/acceptance factors, Ivanov et al. (2017) point out that less attention is given to implementation challenges and best practices. How can properties overcome integration difficulties, update legacy systems, upskill staff and ensure technologies operate reliably to deliver the promised benefits? Comparative case studies could clarify the leading strategies.

Research methodology

Based on the UTAUT model (Venkatesh et al., 2003), this research aims to use a quantitative research method to determine hotel guests' attitude towards the implementation of personalised and technologically advanced hospitality services. The chosen method is suitable for this study as it enables the systematic collection and analysis of quantitative data to support the hypotheses developed based on the UTAUT model in the context of hospitality technology adoption.

Research design

The study is descriptive, correlational and cross-sectional in design. This design is suitable for assessing the current level of technology usage, consumer characteristics and the interaction of the UTAUT factors at a given time. While the descriptive aspect makes it possible to capture the extent of personalised technology adoption in hospitality, the correlational aspect makes it possible to analyse the performance expectancy, effort expectancy, social influence and facilitating conditions along with the behavioural intention and actual use behaviour (Venkatesh et al., 2003).

Sampling and data collection

A random sampling procedure was used in the study to draw a sample of 200 hotel guests from the target population. This sample size is appropriate for statistical analysis and generalisation of the study. Data collection was conducted through a mixed-mode approach:

(1) An online survey: A personally completed survey on Google Forms was sent to 150 participants who had recently visited hotels; and
(2) An on-site survey: Questionnaires were self-administered and 50 of them were printed and administered to guests who were lodged in some hotels.

This dual approach allowed for a diverse range of respondents, including both potential and current hotel guests, enhancing the study's external validity.

Type of data

Both primary quantitative as well as secondary qualitative data were utilised. The primary data collected through a structured, self-administered questionnaire was quantitative, with UTAUT model-based, 5-point Likert scale statements, measuring agreement levels for 12 to 16 variables as well as demographic questions (Joshi et al., 2015). This data allowed for the testing of relationships among variables. Secondary qualitative data about hospitality technology adoption was gathered through a literature review of previous studies in books, journals, industry reports and online articles.

Instrument development

The primary data collection instrument was a structured questionnaire based on the UTAUT model. It consisted of:

(1) Demographic questions to capture respondent profiles; and
(2) UTAUT construct measures using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) to assess performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioural intention (BI) and actual use behaviour (AU).

The 5-point Likert scale is chosen for its ability to capture nuanced responses and improve the reliability and validity of the measurement (Joshi et al., 2015).

Data analysis

Data analysis was performed using SPSS and AMOS software, employing the following techniques:

(1) Descriptive statistics to summarise demographic information and response patterns;
(2) Structural equation modelling (SEM) to test the hypothesised relationships among UTAUT constructs; and
(3) Moderation analysis to examine the effects of age, gender and experience on the relationships among constructs.

This comprehensive analytical approach allowed for a rigorous examination of the UTAUT model in the context of personalised hospitality technology adoption.

The conceptual framework

The UTAUT model, which is popular for its explanations of user acceptability and adoption of technology, served as the theoretical foundation for this study. Four major constructs are proposed by Venkatesh et al. (2003) as part of the UTAUT paradigm, which determines behavioural intent to utilise technology and impacts actual technology use (Venkatesh et al., 2003):

(1) Performance expectancy (PE): According to Venkatesh et al. (2003), this is the extent to which a person believes that utilising the system would improve their ability to perform their job. This construct can be modified for use in this study to assess how much hotel visitors think tailored technology-enabled services will improve their overall stay.
(2) Effort expectancy (EE): This refers to the system's level of user-friendliness. This concept can be used to gauge how complicated or easy-to-use guests believe personalised technology-enabled services to be.
(3) Social influence (SI): This refers to the extent to which a person believes that other people think they ought to utilise the new system. The influence of social factors, including referrals from friends or family, on hotel guests' intention to use personalised technology-enabled services can be measured using an adaptation of this model.
(4) Facilitating conditions (FC): This refers to the extent to which a person believes that the system's technological and organisational infrastructure will facilitate its use. Personalised technology-enabled services that hotel guests may choose to utilise may be influenced by their perceptions of privacy, dependability and general support, all of which can be assessed with this concept.

Moreover, a number of moderating variables, including age, gender, experience and level of voluntariness, are also included in the UTAUT model and can be taken into account in the analysis if they are pertinent to the study's setting (Venkatesh et al., 2003).

Research hypotheses

The following five hypotheses were developed:

- H1: The behavioural intention of hotel guests to use personalised technology throughout their stay is positively influenced by performance expectancy.
- H2: The intention of hotel customers to use data-driven personalisation services is negatively impacted by effort expectancy.
- H3: The willingness of hotel visitors to accept personalised services is positively impacted by social influence.
- H4: Facilitating conditions directly and positively influence hotel guests' actual use behaviour of personalised technologies.
- H5: The actual use behaviour of hotel visitors is positively influenced by their behavioural intentions to use personalised hospitality technologies.

Figure 1 depicts the proposed conceptual model, which serves as the foundation for the study. This conceptual model graphically represents the hypothesised relationships among the various constructs or factors that are believed to influence the adoption and use of personalised technology in the hotel industry

Data analysis and findings

Sociodemographic information

Table 1 presents the demographic characteristics of the 200 respondents, where 92 (46%) were female and 108 (54%) were male. The majority of respondents (54%) were between the ages of 19 and 25, and only 2.5% of respondents were 45 or older, suggesting that elderly people may be reluctant to travel. 54.5% (109) of the respondents had undergraduate degrees, followed by graduate degrees (23.5%), postgraduate degrees (24.5%), and high school diplomas (15.5%). The information also depicted the diversity in educational attainment among the respondents.

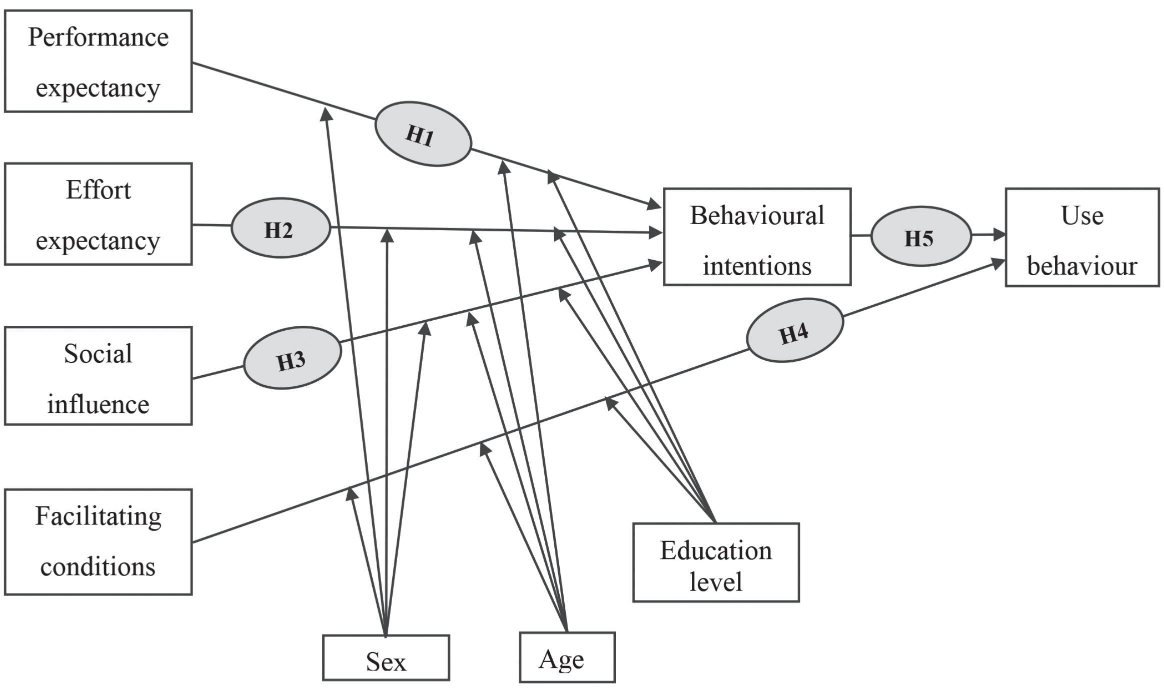

FIGURE 1: Conceptual framework of unified theory of acceptance and use of technology (UTAUT) model

TABLE 1: Demographic characteristics of the respondents

	Frequency	Percentage
Sex		
Male	108	54.0
Female	92	46.0
Total	200	100.0
Age structure		
19–25	108	54.0
26–35	68	34.0
36–45	19	9.5
45+	5	2.5
Total	200	100.0
Education level		
HSC	15	7.5
Undergraduate	109	54.5
Graduate	47	23.5
Postgraduate	29	14.5
Total	200	100.0

Reliability of the study

Table 2 displays the findings of the reliability test utilising Cronbach's alpha, a statistical metric used to evaluate the internal consistency of survey questions for this research. Higher degrees of internal consistency are indicated by values closer to 1, which is the range of the alpha coefficient. Although a higher number, like 0.8 or greater, is preferred and indicates a very good level of reliability, a value of 0.7 or above is commonly accepted in social science research (Taber, 2018). Table 2 indicates that the study's alpha value is 0.925, falling inside the acceptable range. Overall, this indicates great internal consistency among the survey questions.

TABLE 2: Test of reliability

Cronbach's alpha	*N*
0.925	20

Descriptive statistics

Table 3 displays the survey respondents' scores for each variable used to evaluate the adoption of personalised hotel technologies. The analysis showed that, out of the 20 variables that were found, nine had a mean score of more than four ($M > 4.00$), two had a mean score ranging from three and four ($3.00 < M < 4.00$), and three had a mean score of less than three ($M < 3$). As per Pikkemaat (2004), a mean score falling between 3.25 and 4.00 is deemed good, while a score over 4.00 is deemed great. Based on these criteria, nine variables (items 9, 10, 11, 12, 13, 14, 16, and 20) scored excellently. Two variables (items 5 and 6) scored well. Finally, three variables (items 1, 2, and 3) scored poorly ($M \leq 2.75$). Many respondents expressed positive views about the use of personalised technologies in the hospitality industry. The highest mean score of 4.2450 for item 16 suggests that protecting guest privacy is a crucial factor for participants to feel comfortable with data collection for personalisation services (Pikkemaat, 2004). Respondents also recognised the importance of clear instructions and methods for using personalised technologies ($M = 3.8450$), as well as the availability of features to make the self-service experience enjoyable ($M = 3.8850$).

Hypothesis analysis

- Hypothesis 1 (H1): The behavioural intention of hotel guests to use personalised technology throughout their stay is positively influenced by performance expectancy

The analysis strongly supports this hypothesis (Table 4). Two key performance expectancy factors exhibited significant positive impacts on behavioural intention (BI) to adopt personalised hotel technologies. PE2 (experience with hotel mobile app for check-in/room access, $\beta = 0.259616$, $p = 0.001$) indicates

TABLE 3: The perception score given to the factors by the respondents

No.	Factor	*N*	*M*	Variance
1	Ease of using hotel website for booking (PE1)	200	3.1800	1.043
2	Experience with hotel mobile app for check-in/room access (PE2)	200	3.1450	1.059
3	Satisfaction with in-room technology controls (PE3)	200	3.6750	0.894
4	Value of AI chatbots for answering questions (PE4)	200	3.3900	0.782
5	Ease of learning personalised hotel technologies (EE1)	200	3.7500	0.691
6	Clarity of experience with hotel technologies (EE2)	200	3.7900	0.629
7	Need for technical support with personalised services (EE3)	200	3.7350	0.839
8	Effort required to connect devices to smart hospitality system (EE4)	200	3.4900	1.075
9	Influence of positive peer reviews on using personalised hotel app (SI1)	200	3.8600	0.784
10	Impact of media reviews on decisions to use hotel technologies (SI2)	200	3.8950	0.939
11	Interest level based on reviews of smooth tech check-in/out (SI3)	200	4.0650	0.413
12	Perception of luxury hotels' personalised tech practices (SI4)	200	3.8350	0.691
13	Clarity of hotel instructions for using personalised tech (FC1)	200	3.8450	0.725
14	Sufficiency of personalised tech features for enjoyable self-service (FC2)	200	3.8850	0.836
15	Motivation from clear alerts about available personalised services (FC3)	200	3.9100	0.494
16	Comfort with data collection for personalization based on privacy protection (FC4)	200	4.2450	0.658
17	Intent to use personalised hotel technologies (BI1)	200	3.8400	0.758
18	Using personalised services based on recommendations/social influence (BI2)	200	3.9150	0.752
19	Adopt personalised hotel technologies (BI3)	200	3.8900	0.551
20	Actual usage of personalised technologies offered by the hotel (AU1)	200	4.1750	0.688
	Valid *N* (listwise)	200		

TABLE 4: Hypothesis test for H1

Regression analysis summary for performance expectancy predictors of adoption of personalised hotel technologies								
				Change statistics				
R	R^2	Adjusted R^2	SE	R^2 change	F change	df1	df2	Sig. F change
0.632[a]	0.399	0.387	0.58098	0.399	32.411	4	195	<0.001

a. Predictors: (Constant), Value of AI chatbots for answering questions, Ease of using hotel website for booking, Satisfaction with in-room technology controls, Experience with hotel mobile app for check-in/room access

Model	ANOVA				
	Sum of squares	df	M^2	F	Sig.
Regression	43.760	4	10.940	32.411	<0.001[b]
Residual	65.820	195	0.338		
Total	109.580	199			

a. Dependent variable: Adopt personalised hotel technologies

b. Predictors: (Constant), Value of AI chatbots for answering questions, Ease of using hotel website for booking, Satisfaction with in-room technology controls, Experience with hotel mobile app for check-in/room access

Model		Coefficients				
		Unstandardised coefficients		Standardised coefficients	t	Sig.
		B	SE	Beta		
1	(Constant)	1.872	0.214		8.732	<0.001
	Ease of using hotel website for booking	−0.009	0.050	−0.012	−0.174	0.862
	Experience with hotel mobile app for check-in/room access	0.177	0.056	0.246	3.165	0.002
	Satisfaction with in-room technology controls	0.341	0.052	0.435	6.564	<0.001
	Value of AI chatbots for answering questions	0.069	0.051	0.082	1.337	0.183

a. Dependent variable: Adopt personalised hotel technologies

that guests who had positive experiences using mobile apps for check-in and room access are likely to use personalised technologies. Similarly, PE3 (satisfaction with in-room technology controls, $\beta = 0.456373$, $p < 0.001$) suggests that guests that are satisfied with the performance of in-room tech controls, such as for lighting, temperature and entertainment systems, are more inclined towards adopting personalisation offerings (Venkatesh et al., 2003). These findings highlight that providing user-friendly mobile apps and intuitive in-room technology interfaces can drive guest adoption of personalised services.

- Hypothesis 2 (H2): The intention of hotel customers to use data-driven personalisation services is negatively impacted by effort expectancy

The results for this hypothesis are inconclusive and do not provide clear support (Table 5). While EE3 (need for technical support with personalised services, $\beta = 0.304823$, $p < 0.001$) shows a significant positive relationship with BI1 (intent to use personalised hotel technologies), the analysis does not comprehensively examine whether effort expectancy factors, such as ease of use and learnability, had an overall negative impact on adoption intentions (Venkatesh et al., 2003). As this hypothesis is not supported, it means that effort expectancy positively affects hotel guests' intention to use data-driven personalisation offerings.

- Hypothesis 3 (H3): The willingness of hotel visitors to accept personalised services is positively impacted by social influence

The findings strongly support this hypothesis (Table 6). Three social influence factors demonstrated significant positive effects on BI2 (using personalised services based on recommendations/social influence). SI2 (impact of media reviews on decisions to use hotel technologies, $\beta = 0.187203$, $p = 0.003$) indicates that positive media coverage and reviews influenced guests' intentions to enable personalised services (Venkatesh et al., 2003). SI3 (interest level based on reviews of smooth tech check-in/out, $\beta = 0.400578$, $p < 0.001$) suggests that reviews highlighting seamless and convenient technology-enabled check-in and checkout processes piqued guests' interest in adopting personalisation (Venkatesh et al., 2003). Additionally, SI4 (perception of luxury hotels' personalised technology practices, $\beta = 0.29822$, $p < 0.001$) shows that perceiving luxury hotels as leaders in personalised technology practices positively swayed guests' intentions (Venkatesh et al., 2003). These findings underscore the potent influence of social factors like reviews, media coverage and industry perceptions on driving guest adoption of personalised hospitality technologies.

- Hypothesis 4 (H4): Facilitating conditions directly and positively influence hotel guests' actual use behaviour of personalised technologies

The analysis provides robust support for this hypothesis. Three key facilitating conditions exhibited significant positive relationships with AU (actual usage of personalised technologies offered by the hotel; Table 7). FC1 (clarity of hotel instructions for using personalised tech, $\beta = 0.426552$, $p < 0.001$) suggests that clear guidance from hotels on how to use personalised services directly enables guests to actually adopt and use them. FC2 (sufficiency of personalised technology features for enjoyable self-service, $\beta = 0.156942$, $p = 0.032$) indicates

TABLE 5: Hypothesis test for H2

Regression analysis summary for effort expectancy predictors of intent to use personalised hotel technologies								
				Change Statistics				
R	R^2	Adjusted R^2	SE	R^2 change	*F* change	df1	df2	Sig. *F* Change
0.544[a]	0.296	0.282	0.73798	0.296	20.509	4	195	<0.001

a. Predictors: (Constant), Effort required to connect devices to smart hospitality system, Ease of learning personalised hotel technologies, Need for technical support with personalised services, Clarity of experience with hotel technologies

ANOVA				
Model	Sum of squares	M^2	*F*	Sig.
Regression	44.679	11.170	20.509	<0.001[b]
Residual	106.201	0.545		
Total	150.880			

a. Dependent variable: Intent to use personalised hotel technologies

b. Predictors: (Constant), Effort required to connect devices to smart hospitality system, Ease of learning personalised hotel technologies, Need for technical support with personalised services, Clarity of experience with hotel technologies

Model		Coefficients				
		Unstandardised coefficients		Standardised Coefficients	*t*	Sig.
		B	SE	Beta		
1	(Constant)	1.089	0.324		3.358	0.001
	Ease of learning personalised hotel technologies	0.180	0.078	0.172	2.298	0.023
	Clarity of experience with hotel technologies	0.168	0.079	0.153	2.115	0.036
	Need for technical support with personalised services	0.297	0.067	0.312	4.460	<0.001
	Effort required to connect devices to smart hospitality system	0.095	0.054	0.113	1.740	0.083

a. Dependent variable: Intent to use personalised hotel technologies

TABLE 6: Hypothesis test for H3

Model	Regression analysis summary for social influence predictors of using personalised hotel services								
					Change statistics				
	R	R^2	Adjusted R^2	SE	R^2 change	*F* change	df1	df2	Sig. F change
1	0.661[a]	0.437	0.425	0.65715	0.437	37.829	4	195	<0.001

a. Predictors: (Constant), Perception of luxury hotels' personalised tech practices, Interest level based on reviews of smooth tech check-in/out, Impact of media reviews on decisions to use hotel technologies, Influence of positive peer reviews on using personalised hotel app

ANOVA						
Model		Sum of Squares	df	M^2	*F*	Sig.
1	Regression	65.346	4	16.336	37.829	<0.001[b]
	Residual	84.209	195	0.432		
	Total	149.555	199			

a. Dependent Variable: Using personalised services based on recommendations/social influence

b. Predictors: (Constant), Perception of luxury hotels' personalised tech practices, Interest level based on reviews of smooth tech check-in/out, Impact of media reviews on decisions to use hotel technologies, Influence of positive peer reviews on using personalised hotel app

Model		Coefficients				
		Unstandardised coefficients		Standardised coefficients	*t*	Sig.
		SE	Beta			
1	(Constant)	0.162	0.321		0.506	0.614
	Influence of positive peer reviews on using personalised hotel app	−0.108	0.074	−0.110	−1.455	0.147
	Impact of media reviews on decisions to use hotel technologies	0.141	0.059	0.158	2.383	0.018
	Interest level based on reviews of smooth tech check-in/out	0.620	0.085	0.460	7.315	<0.001
	Perception of luxury hotels' personalised tech practices	0.287	0.078	0.275	3.696	<0.001

a. Dependent variable: Using personalised services based on recommendations/social influence

TABLE 7: Hypothesis test for H4

Model	Regression analysis summary for facilitating condition predictors of actual usage of personalised hotel technologies							
	R	R^2	SE	Change statistics				
				R^2 change	F change	df1	df2	Sig. F Change
1	0.877[a]	0.768	0.764	0.40313	0.768	1	0.877[a]	0.768

a. Predictors: (Constant), Comfort with data collection for personalization based on privacy protection, Sufficiency of personalised tech features for enjoyable self-service, Motivation from clear alerts about available personalised services, Clarity of hotel instructions for using personalised tech

Model	ANOVA				
	Sum of squares	df	M^2	*F*	Sig.
Regression	105.184	4	26.296	161.805	0.000[b]
Residual	31.691	195	0.163		
Total	136.875	199			

a. Dependent Variable: Actual usage of personalised technologies offered by the hotel

b. Predictors: (Constant), Comfort with data collection for personalization based on privacy protection, Sufficiency of personalised tech features for enjoyable self-service, Motivation from clear alerts about available personalised services, Clarity of hotel instructions for using personalised tech

Model		Coefficients				
		Unstandardised coefficients		Standardised coefficients	*t*	Sig.
		B	SE	Beta		
1	(Constant)	0.025	0.189		0.131	0.896
	Clarity of hotel instructions for using personalised tech	0.217	0.048	0.223	4.550	0.000
	Sufficiency of personalised tech features for enjoyable self-service	−0.038	0.042	−0.042	−0.917	0.360
	Motivation from clear alerts about available personalised services	0.034	0.050	0.029	0.682	0.496
	Comfort with data collection for personalization based on privacy protection	0.784	0.041	0.767	19.330	0.000

a. Dependent Variable: Actual usage of personalised technologies offered by the hotel

that offering adequate personalised technology capabilities to support self-service facilitates actual usage. Moreover, FC4 (comfort with data collection for personalisation based on privacy protection, $\beta = 0.667817$, $p = 0.000$) demonstrates that ensuring guests' comfort with data practices by implementing robust privacy safeguards is a critical facilitating condition for actual technology use. These findings highlight that providing comprehensive support, extensive personalisation features and stringent data privacy measures can facilitate guests' adoption and continued usage of personalised hotel technologies.

- Hypothesis 5 (H5): The actual use behaviour of hotel visitors is positively influenced by their behavioural intentions to use personalised hospitality technologies

The results strongly substantiate this hypothesis (Table 8). BI3 (adopt personalised hotel technologies, $\beta = 0.195706$, $p = 0.000$) exhibits a significant positive effect on AU (actual usage of personalised technologies offered by the hotel). This finding aligns with the core tenet of the UTAUT model, which posits that behavioural intentions are a direct determinant of technology use behaviour (Venkatesh et al., 2003). Consequently, fostering positive intentions among guests to adopt personalised hospitality technologies through performance benefits, social influence and facilitating conditions is crucial for translating intentions into actual sustained usage.

Unified theory of acceptance and use of technology (UTAUT) model analysis

In Figure 2, we observe the structural factors of the unified theory of acceptance and use of technology (UTAUT) model. This figure provides a comprehensive visualisation of the factor analysis conducted using structural equation modelling (SEM). The SEM approach allows for a rigorous examination of the relationships among the various factors, enabling us to gain profound insights into the underlying dynamics influencing technology adoption and usage behaviour.

Performance expectancy

The results indicate that performance expectancy had a significant positive influence on behavioural intention to use personalised hotel technologies (see Table 9). Specifically, positive experiences with hotel mobile apps for functions like check-in and room access (PE2, $\beta = 0.259616$, $p = 0.001$) and satisfaction with in-room technology controls (PE3, $\beta = 0.456373$, $p = 0.000$) were associated with greater intention to adopt personalisation offerings. These findings are consistent with the UTAUT model, which suggests that people are more inclined to embrace a technology if they believe it can be beneficial and improve their performance. (Venkatesh et al., 2003). Hotels should prioritise developing user-friendly mobile apps and intuitive in-room tech interfaces to leverage the positive impact of performance expectancy on guests' adoption intentions. Ensuring that guests have positive experiences with these interfaces can significantly increase their willingness to adopt personalised hotel technologies.

Effort expectancy

The results regarding effort expectancy were inconclusive (see Table 9). While the need for technical support with personalised services (EE3, $\beta = 0.304823$, $p = 0.000$) positively influenced

TABLE 8: Hypothesis test for H5

Model	Regression analysis summary for behavioral intention predictors of actual usage of personalised hotel technologies								
	R	R^2	Adjusted R^2	SE	Change statistics				
					R^2 change	F change	df1	df2	Sig. F change
1	0.515[a]	0.265	0.254	0.71638	0.265	23.569	3	196	0.000

a. Predictors: (Constant), Adopt personalised hotel technologies, using personalised services based on recommendations/social influence, Intent to use personalised hotel technologies

Model		ANOVA				
		Sum of squares	df	M^2	F	Sig.
1	Regression	36.287	3	12.096	23.569	0.000[a]
	Residual	100.588	196	0.513		
	Total	136.875	199			

a. Dependent variable: Actual usage of personalised technologies offered by the hotel

Model		Coefficients				
		Unstandardised coefficients		Standardised coefficients	t	Sig.
		SE	Beta			
1	(Constant)	1.688	0.305		5.542	0.000
	Intent to use personalised hotel technologies	0.095	0.081	0.100	1.177	0.240
	Using personalised services based on recommendations/social influence	0.102	0.076	0.107	1.341	0.181
	Adopt personalised hotel technologies	0.443	0.080	0.396	5.554	0.000

a. Dependent variable: Actual usage of personalised technologies offered by the hotel

the intention to use personalised technologies (BI1) (Venkatesh et al., 2003), the analysis does not comprehensively examine whether factors like ease of use and learnability had an overall negative effect on adoption intentions, as hypothesised. The UTAUT model suggests that effort expectancy, or the degree of ease associated with using a technology, can influence adoption, especially among users who are older or less experienced (Venkatesh et al., 2003). Hotels need to invest more in user-friendly interfaces and mobile apps that are easy to navigate and require minimal effort to use the personalised features. Operationalising guest data and preferences from previous stays to pre-populate personalisation settings can minimise the effort required for setup. Further research is needed to better understand the specific effort-related barriers or facilitators in this context.

Social influence

The analysis provides strong evidence that social influence positively impacts guests' intention to enable personalised services. Factors like the impact of media reviews (SI2, $\beta = 0.187203$, $p = 0.003$), interest based on reviews of smooth tech check-in/out (SI3, $\beta = 0.400578$, $p = 0.000$) and perceptions of luxury hotels as leaders in personalised technology (SI4, $\beta = 0.29822$, $p = 0.000$) significantly influenced guests' intentions to use personalised services (BI2) (see Table 9). These findings are consistent with the UTAUT paradigm, which contends that people are impacted by the beliefs and actions of others, particularly those in their social and professional networks (Venkatesh et al., 2003). Hotels should leverage positive social influences, such as encouraging guest reviews, fostering media coverage and positioning themselves as technology leaders to drive the adoption of personalised offerings. Promoting a strong positive presence across media channels and review platforms, and joining forces with influential travel bloggers, industry experts and media outlets can generate promising coverage highlighting the convenience and innovative nature of personalised services.

Facilitating conditions

The results strongly indicate that facilitating conditions directly and positively influenced guests' actual use of personalised hotel technologies (see Table 9). Clear hotel instructions for using personalised tech (FC1, $\beta = 0.426552$, $p = 0.000$), sufficient personalised tech features for enjoyable self-service (FC2, $\beta = 0.156942$, $p = 0.032$) and comfort with data collection based on privacy protections (FC4, $\beta = 0.667817$, $p = 0.000$) were all significantly associated with increased actual usage (AU) (Venkatesh et al., 2003). These findings align with the UTAUT model, which posits that individuals are more likely to adopt and use a technology when they have access to resources and support, including training, guidance and compatible infrastructure (Venkatesh et al., 2003). Hotels should focus on providing comprehensive support, extensive personalisation features and robust data privacy measures to facilitate guests' continued usage of personalised technologies. Developing clear and user-friendly guidance materials (e.g. tutorials, FAQs, in-app instructions) to educate guests on effectively use of the personalised services and leveraging available features can help train staff to provide knowledgeable and proactive assistance to guests in using personalised technologies, ensuring a seamless and supportive experience.

Behavioural intention and actual use

The analysis confirms the core relationship between behavioural intention and actual use behaviour proposed by the UTAUT model (see Table 9). Guests' intentions to adopt personalised

TABLE 9: Structural model estimates from the unified theory of acceptance and use of technology (utaut) model

Structural	Structural model estimates from the unified theory of acceptance and use of technology (UTAUT) model					
	Standardised	Coefficient	SE	Z	$P > z$	95% CI
B13						
PE1	−0.02267	0.068333	-0.33	0.74	−0.1566	0.111259
PE2	0.259616	0.076169	3.41	0.001	0.110328	0.408904
PE3	0.456373	0.062881	7.26	0	0.333129	0.579617
PE4	0.0683	0.062363	1.1	0.273	−0.05393	0.190529
Age	−0.03562	0.057551	−0.62	0.536	−0.14842	0.077179
Gender	0.053387	0.06081	0.88	0.38	−0.0658	0.172571
_cons	2.44683	0.432851	5.65	0	1.598458	3.295
AU						
BI3	0.195706	0.055847	3.5	0	0.086248	0.305164
BI1	−0.33246	0.044385	−7.49	0	−0.41945	−0.24547
BI2	−0.17298	0.07363	−2.35	0.019	−0.3173	−0.02867
FC1	0.426552	0.043064	9.9	0	0.342147	0.510956
FC2	0.156942	0.07336	2.14	0.032	0.013159	0.300726
FC3	−0.13967	0.055384	−2.52	0.012	−0.24822	−0.03112
FC4	0.667817	0.0305	21.9	0	0.608038	0.727596
Age	0.008439	0.02659	0.32	0.751	−0.04368	0.060554
_cons	0.145302	0.187258	0.78	0.438	−0.22172	0.512322
BI1						
EE1	0.190098	0.070814	2.68	0.007	0.051305	0.328891
EE2	0.119849	0.069678	1.72	0.085	−0.01672	0.256416
EE3	0.304823	0.066393	4.59	0	0.174695	0.43495
EE4	0.116521	0.061711	1.89	0.059	−0.00443	0.237472
Age	0.215673	0.057221	3.77	0	0.103521	0.327824
Sex	−0.05815	0.061287	−0.95	0.343	−0.17827	0.06197
_cons	0.789263	0.47596	1.66	0.097	−0.1436	1.722128
BI2						
SI1	-0.13513	0.071113	−1.9	0.057	−0.27451	0.004247
SI2	0.187203	0.063096	2.97	0.003	0.063536	0.310869
SI3	0.400578	0.058486	6.85	0	0.285948	0.515208
SI4	0.29822	0.067993	4.39	0	0.164957	0.431483
Age	0.098156	0.051998	1.89	0.059	−0.00376	0.200071
Sex	−0.23756	0.051875	-4.58	0	−0.33924	−0.13589
_cons	0.841643	0.482914	1.74	0.081	−0.10485	1.788137
var(e.BI3)	0.5978492	0.0479241			0.5109267	0.6995595
var(e.AU)	0.1234462	0.0146795			0.0977819	0.1558466
var(e.BI1)	0.6593776	0.0495728			0.5690361	0.7640619
var(e.BI2)	0.508299	0.0437737			0.4293539	0.6017597

LR test of model vs. saturated: $chi^2(52) = 786.45$
Prob > $chi^2 = 0.0000$

hotel technologies (BI3, $\beta = 0.195706$, $p = 0.000$) significantly and positively influence their actual usage of such offerings (AU) (Venkatesh et al., 2003). This finding underscores the importance of shaping positive intentions among guests as a precursor to driving sustained adoption and usage of personalised hospitality technologies.

To explore the significant positive influence of behavioural intention on actual technology usage, hotels must prioritise strategies that foster positive intentions among guests towards adopting personalised services. Safeguarding a seamless and user-friendly adoption process, with clear guidance and support, can minimise barriers and encourage initial usage. However, sustaining guest engagement requires continuously improving the personalisation features, implementing incentives for active usage and regularly gathering feedback to adapt offerings to guest preferences. Leveraging social proof and amplifying positive experiences across channels can further support social influence and drive sustained adoption. By focusing on shaping positive behavioural intentions and addressing usage barriers, hotels can effectively interpret guests' intentions into long-term adoption and engagement with personalised technologies, leading to enhanced satisfaction, loyalty and potential revenue opportunities.

The UTAUT model analysis reveals valuable insights into the factors influencing guests' acceptance and use of personalised hotel technologies. By leveraging performance benefits, social influences and facilitating conditions to foster positive behavioural intentions, hotels can effectively translate these intentions into actual, sustained usage of data-driven personalisation offerings across the guest journey.

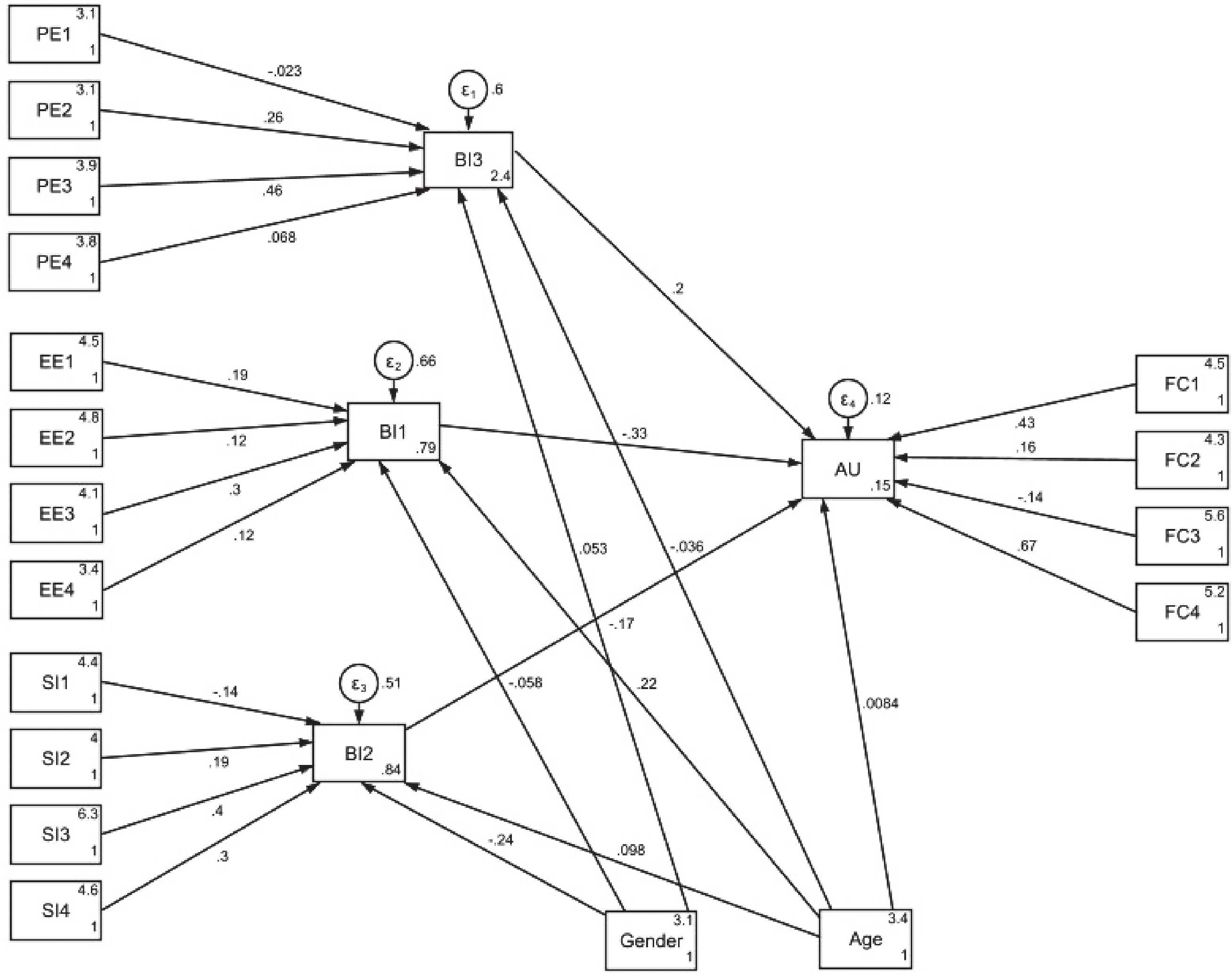

FIGURE 2: Structural factors of UTAUT model from survey data using structural equation modelling

Conclusion and discussion

The purpose of this research was to understand how various antecedent determinants affect the intention of hotel guests to accept and use technology-enabled hospitality services. Based on the UTAUT model, the research reveals that performance expectancy, social influence and facilitating conditions are the central factors that affect guests' acceptance and usage of personalised hotel technologies. Performance expectancy, as related to guests' previous experiences with mobile apps for check-in/room access and satisfaction with in-room technology controls, had a significant positive impact on the behavioural intentions of guests to use personalised hotel technologies. The analysed social influence factors include media reviews, the perceived image of luxury hotels as the "tech-savvy" industry leaders and interest driven by efficient technical check-in/out processes influenced guests' intentions to use other personalisation services. Actual sustained technology use by the guests depended on facilitating conditions as defined in the hotel instructions, adequate individualised client enjoyment of the self-service applications and the strong data protection measures that were provided by the hotel.

In addition, the various relationships revealed by the structural conditions of the different determinants were analysed. The results suggest that facilitating conditions have a positive impact on performance expectancy and effort expectancy. The audience held more favourable impressions of tailored technologies if the appropriate assistance and frameworks were provided. Additionally, performance expectancy also moderates the relationship between facilitating conditions and behavioural intentions and social influence and behavioural intentions.

Theoretical implications

The major theoretical contribution of this study is the extension of the UTAUT model to the context of personalised hotel technologies and its empirical validation. Of all these determinants, performance expectancy has the biggest impact on increasing the guests' technology acceptance. This underlines the fact that there is a need to provide tangible values through customisation to encourage the use of the services.

Social influence comes second as the most influential factor in the decision-making of guests, which underscores the significance of social norms and industry trends in the adoption of new technologies. This study also reveals that facilitating conditions have a highly significant relationship with guests' behavioural intention to use personalised technologies, underscoring the importance of support infrastructure and user trust for sustaining engagement.

Thus, this research contributes to the generalisation of the UTAUT model in the context of technological innovation with an emphasis on personalised services in the hospitality industry. Despite prior work focusing on technology adoption in the hospitality context, this study specifically addresses a research gap about the use of personalised technologies from the guest's point of view. Thus, this research adds value to the literature by providing insights into the antecedents of acceptance of personalised technology as perceived by hotel guests.

Managerial implications

This research has several managerial implications relevant to hospitality firms and provides new insights into how innovative personalised service design can enhance guests' emotional attachment to and cognitive evaluation of hospitality brands. The study provides hospitality practitioners with a precise and proactive set of determinants to improve guests' acceptance of personalised services.

Findings from the analysis shed light on the role of determinants and thus provide suggestions for effective managerial and marketing strategies. To improve guests' acceptance of personalised technology, hospitality managers should prioritise enhancing performance expectancy by ensuring that personalised services deliver clear and tangible benefits to guests. This could involve developing user-friendly mobile apps and intuitive in-room technology interfaces that demonstrably improve the guest experience.

The second priority should focus on leveraging social influence. Hotels should invest in positive media relations, showcase technology leadership and encourage satisfied guests to share their experiences of personalised services. Additionally, managers should ensure robust facilitating conditions by providing clear instructions, comprehensive support systems and stringent data privacy measures to build trust and facilitate sustained usage of personalised technologies.

Limitations and future research

This research has some limitations that scholars should consider when conducting similar research in the future. First, the sample size of 200 respondents is statistically enough, but it does not cover the population of global hotel guests perfectly. Future research should apply the UTAUT model to a greater number of participants in different regions and across different categories of hotels.

Second, this study only presents cross-sectional data to gain insights into the guests' perceptions, but it fails to answer how the perceptions and behaviours of guests might change over time. Longitudinal research could provide more information about the process and subsequent usage of personalised hotel technologies. Third, the quantitative approach, although methodologically more accurate, may not reveal much about the richness of the guests' attitudes and experiences. Subsequent studies could employ further quantitative approaches, like interviews or focus groups, to obtain more profound information about the users' attitudes toward the employed hotel technologies. Finally, as the application of personalised technologies increases in the hospitality industry, it would be beneficial to examine the effect of behavioural intention on actual behaviour and its consequences for a hotel's performance, including guest satisfaction, loyalty and revenue. Consequently, this study offers important empirical findings to enhance the understanding of the factors that affect the acceptance of personalised technologies among hotel guests. With these insights, hospitality providers can better assess the potential of certain technologies and plan on how to integrate them to create a more effective and customer-oriented hospitality industry.

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Appendix 1: Questionnaire

We are conducting a research study to understand guest preferences and opinions on the use of personalised technology in hotels. Please take a few minutes to complete this survey to help us gather insights. Your participation is completely voluntary and your responses will be kept anonymous.

1. Gender
o Male
o Female
2. Age
o Below 18
o 19–25
o 26–35
o 36–45
o 45+
3. Education Level
o SSC
o HSC
o Under- graduate
o Graduate
o Post- graduate
4. In the past year, how many nights have you stayed at a hotel?
o 0 night
o 1–3 nights
o 4–6 nights
o 6–8 nights
o 9+ nights
5. How would you rate the uses of the hotel website to find and book your room?
o Extremely easy
o Very easy
o Easy
o Slightly difficult
o Very difficult
6. The use of hotel's mobile app for checking in and accessing your room was-
o Extremely easy
o Very easy
o Easy
o Slightly difficult
o Very difficult
7. The satisfaction level with the in-room controls for lighting, temperature, entertainment, etc. were-
o Strongly Satisfied
o Satisfied
o Neutral
o Dissatisfied
o Strongly Dissatisfied
8. Having AI chatbots that can easily answer your questions during your stay would be:
o Extremely helpful
o Very helpful
o Helpful
o Somewhat helpful
o Not helpful at all
9. Learning how to use personalised technologies in the hotel is easy for you.
o Strongly Agree
o Agree
o Neutral
o Disagree
o Strongly Disagree
10. Your experience with technologies for various services in the hotel is clear and understandable.
o Strongly agree
o Agree
o Neutral
o Disagree
o Strongly disagree
11. You might need technical support to assist you in using personalised hospitality services
o Strongly agree
o Agree
o Neutral
o Disagree
o Strongly disagree
12. Connecting your mobile apps and devices to a smart hospitality system would require too much time and effort from you.
o Strongly agree
o Agree
o Neutral
o Disagree
o Strongly disagree
13. If your friends speak positively about personalised recommendations from a hotel's app, you would be more likely to use it.
o Strongly agree
o Agree
o Neutral
o Disagree
o Strongly disagree
14. Media influence, such as positive reviews, affects your decision to use personalised technologies during your hotel stay.
o Strongly agree
o Agree
o Neutral
o Disagree
o Strongly disagree
15. If you see reviews mentioning smooth check-ins/check-outs through technology, your interest level would.
o Definitely increase
o Increase
o Remain neutral
o Decrease
o Definitely decrease

16. If many luxury hotels promoted their use of personalization, you would likely have positive opinions about those hospitality technology practices.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

17. The hotel offers clear instructions and methods for using personalised technologies.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

18. The hotel provides personalised technologies with enough features to make the self-service experience enjoyable.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

19. Clear and simple notifications and alerts about available personalised services would motivate you to make use of those offerings during your stay
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

20. Protecting guest privacy would make you feel more comfortable with data collection used to enable personalization service.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

21. You intend to use personalised technologies during your hotel stay.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

22. You plan to use the personalization features and services recommended by friends or social influence.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

23. You are likely to adopt personalised technologies during your hotel stay.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree

24. You actually use the personalised technologies offered by the hotel.
- o Strongly Agree
- o Agree
- o Neutral
- o Disagree
- o Strongly Disagree