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Robots at your service: Understanding hotel guest acceptance with meta-UTAUT investigation

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A R T I C L E I N F O

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A B S T R A C T

This study examines the main factors contributing to robot acceptance by UK hotel guests, aiming to increase the acceptance of robot technology and ensure the success of robot initiatives. To reach this aim, it combines the Meta-UTAUT model and four additional factors, including anthropomorphism, aesthetics, interaction, and trust. The study employs a quantitative approach, analysing 358 online surveys from UK hotel guests using AMOS-SEM. The findings reveal that performance expectancy and effort expectancy influence attitudes. However, performance expectancy does not directly impact intentions and effort expectancy was found to significantly affect intention in a negative manner. Also, the social influence, facilitating conditions, anthropomorphism, aesthetics, and trust significantly affect intentions to use robots. Moreover, attitude mediates the relationship between performance expectancy, effort expectancy, and behavioural intentions. This study contributes a more comprehensive framework for understanding robot acceptance in hospitality and offers valuable insights for hoteliers and robot designers. It emphasises the significance of user-centred design, clear communication of benefits, and supportive environments to enhance guest experiences and promote robotic service adoption.

1. Introduction

Robot integration in the hospitality industry revolutionises service delivery and guest experiences (Jung et al., 2023). Robots are emerging as valuable assets in enhancing service efficiency, consistency, and novelty in guest interactions, which reshape the landscape of hotel operations (Wirtz et al., 2018; Ivanov et al., 2019). The growing use of robots in the hospitality sector, such as in hotels, sparks the curiosity of many academics, leading to a significant increase in research about hotel robot assistants impacting guests' view of their experience (Ye et al., 2022). The existing research investigated multiple facets of interactions between guests and robots, looking at the impacts on guest satisfaction, perceived convenience, and overall service quality (Choi et al., 2020; Lee et al., 2021), and the influence of robotic employees on guest expectations, emotional responses, and behavioural intentions (Kim et al., 2022). For example, a study found that robot-aided services can increase guest satisfaction due to their 24/7 availability and consistent performance (Zhong et al., 2021).

Despite the growing body of literature on hotel robots, two crucial gaps in research and practice warrant further investigation. The first gap relates to the absence of specific factors significantly affecting guests' perceptions of using robots. Prior research primarily focused on functional aspects, such as efficiency, accuracy, speed of service, and task completion rates (Ivanov et al., 2019; Leung et al., 2023). However, the

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previous studies lack investigations on crucial factors that lead to certain impacts of guest perception towards robots (e.g., anthropomorphism, aesthetics, interaction, and trust) (Blut et al., 2021; Paauwe et al., 2015). Anthropomorphism refers to ascribing human attributes to non-human things like robots, with its social dimension revealing how human-like characteristics can bridge the psychological distance between guests and technological interfaces (Dubois-Sage et al., 2023). Aesthetics relates to visual appeal and design, which affect first impressions and play a crucial role in creating an emotional connection that facilitates or hinders technological acceptance (Zhou and Liu, 2019). Interaction focuses on the smoothness and naturalness of guest-robot conversations, highlighting the importance of communication dynamics that make technological interactions feel more intuitive and less mechanical (Prentice and Nguyen, 2021). Trust involves a guest's comfort in relying on a robot to perform essential tasks, representing a critical psychological barrier determining the willingness to engage with robotic services (Hasan et al., 2021). By examining these interconnected factors, the study offers a widening approach to understanding guests' perceptions and behavioural intentions towards robotic services.

The second gap lies in the limited application of the Meta-UTAUT model in understanding robotic service adoption in the hospitality industry. While previous studies have explored various aspects of user acceptance, scholars like Chatterjee et al. (2021) and Santiago et al. (2024) critically argued that existing approaches fail to adequately capture the complex psychological, social, and contextual nuances that influence technology adoption, particularly in emerging service domains like robotic interactions. Moreover, emerging research by FakhrHosseini et al. (2024) highlighted that many existing models, such as Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980), Technology Acceptance Model (TAM) (Davis, 1989), Diffusion of Innovation Theory (DOI) (Rogers, 1995), Technology Readiness Index (TRI) (Parasuraman, 2000), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), insufficiently capture the nuanced technology adoption journey. Dwivedi et al. (2019) offered a Meta-UTAUT model with a more sophisticated approach by integrating multiple dimensions—Performance Expectancy, Effort Expectancy, Social Influences, and Facilitating Conditions (Venkatesh et al., 2012), with attitude—that provide a more holistic understanding of technological acceptance. Dwivedi et al. (2019) indicated that future researchers should consider including additional variables that align with the context of the service and the type of technology. Thus, this study demonstrates the model's ability to capture psychological and social factors, particularly by incorporating additional variables, including anthropomorphism, aesthetics, interaction, and trust, often overlooked in traditional technology acceptance frameworks.

Our study addresses the call for more comprehensive models to better explain technological adoption's intricate dynamics in service-oriented contexts (Dwivedi et al., 2019; Santiago et al., 2024). The current study aims to fill the previous two crucial gaps and contribute to the existing literature by embedding the Meta-UTAUT model along with new factors of robot perceptions (Anthropomorphism, Aesthetics, Interaction, Trust) in the hospitality industry. Thus, this research aims to address the following research question:

- *How do the dimensions of the Meta-UTAUT model, combined with anthropomorphism, aesthetics, interaction, and trust, influence guests' intentions to welcome and interact with robot hotel staff?*

Addressing this research question is critical for both theory and practice in the hospitality industry. Theoretically, it will broaden our understanding of service robot adoption in hospitality by integrating the comprehensive Meta-UTAUT model with crucial factors like anthropomorphism, aesthetics, interaction, and trust, potentially leading to a more holistic framework for predicting and explaining guest acceptance of robot staff. In practice, the findings will provide hoteliers and service robot designers with valuable insights into the key factors influencing guest perceptions and acceptance of robotic staff, enabling them to make more informed decisions about implementing and designing robot-assisted services.

2. Literature review

2.1. Robots in the hotel industry

Robots are system-based autonomous machines designed to help humans perform and deliver services (Wirtz et al., 2018). According to role-based typology, there are two main types of robots in hotel workplaces: functional and information-sharing (Wirtz et al., 2018; Fuentes-Moraleda et al., 2020). Functional robots deliver regular and repetitive tasks, such as check-in and check-out procedures and cleaning duties, whereas information-sharing interacts with customers and exchanges information, such as concierge assistance (Ivanov et al., 2019; Byrd et al., 2021; Park et al., 2024). Some hotels use service robots to provide enjoyable, exceptional service and memorable experiences (Choi et al., 2020; Choi et al., 2023). Japan's Henn-na Hotel, for example, was the first in the world to use humanoid service robots (Binesh and Baloglu, 2023). However, the difficulty in perceiving "robot characteristics" as similar to human characteristics like social interactions and how hotel guests accept such technology is a challenge (Blut et al., 2021).

Prior research indicates that several factors significantly influence and drive guests' intentions to accept service robots in hospitality settings, including self-identity, care, willingness, moral obligation, and attitude (Jung et al., 2023), perceived usefulness (influenced by subjective norms and output quality), perceived ease of use (influenced by lack of anxiety and perceived enjoyment), and perceived intelligence and safety (Said et al., 2024). Guest acceptance is also supported by perceived trust (Huang, 2022; Song et al., 2024a), and anthropomorphism (Song et al., 2024b). Moreover, intentions are influenced by functional factors (such as performance expectancy, facilitating conditions, and innovativeness) and emotional factors (including hedonic motivation, social presence, and perceived importance) (Lee et al., 2021). Recently, a sense of closeness, perceived competence, interaction comfort, and pleasant experience were revealed (Fang et al., 2024). Alongside customer studies, previous studies investigated the factors affecting managers and employees' acceptance and adoption of service robots, for example, ease of use, trust, knowledge and skills (Abdelhakim et al., 2023), cost, trust, and relative advantage (Leung et al., 2023), advantage, compatibility, complexity, cost, support, organisational readiness, competition, and innovativeness (Pizam et al., 2022). However, prior research still emphasised a need for further research to understand user perceptions and factors affecting acceptance regarding artificial intelligence (AI) and robotics (Jung et al., 2023; Leung et al., 2023; Soliman et al., 2024), a summary table of relevant previous studies in the field is included in Appendix A.

2.2. Meta-UTAUT model

The Meta-UTAUT model was initially developed from the UTAUT model (Venkatesh et al., 2003), with most results confirming its validity in explaining adoption behaviour in the robot acceptance domain (Abdelhakim et al., 2023; Pande and Gupta, 2023; Pande and Taeihagh, 2024; Zhang, 2024). Dwivedi et al. (2019) conducted a meta-analysis of 162 prior studies to assess aspects of the UTAUT model. The study concluded that attitude plays a significant role in behavioural intention. Prior research has validated this role using fundamental theories such as the Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980), the Technology Acceptance Model (TAM) (Davis, 1989), and the Theory of Planned Behaviour (TPB) (Ajzen, 1991). While the UTAUT model considers four moderators (age, gender, experience, and voluntariness of use), these may not be suitable for all adoption contexts and may not significantly explain individual adoption (Dwivedi et al., 2019).

Therefore, Dwivedi et al. (2019) proposed a revised conceptual model that includes attitude and excludes moderators to address some of the UTAUT model's limitations. Dwivedi and his colleagues introduced the Meta-UTAUT, an improved version of the original model, to overcome UTAUT's limitations by highlighting four independent constructs that directly impact behavioural intention (BI): performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI). In addition, they incorporated the role of attitude on behaviour intention and recommended testing the model in future research to obtain replicable evidence to support its hypotheses. The Meta-UTAUT model has been applied across limited contexts and scopes, including mobile payment adoption among Indian consumers (Patil et al., 2020), Indian travellers' use of the Airbnb platform (Tamilmani et al., 2020), and chatbots in the service industry (Balakrishnan et al., 2022).

Although there are reasons to use the Meta-UTAUT model to predict customers' acceptance of recent technologies like robots (Balakrishnan et al., 2022), the model alone will be inadequate because it ignores the possible impact of some external factors that influence robot technology acceptance in hotel services. Dwivedi et al. (2019) highlighted a lack of Meta-UTAUT model factors, stating that future researchers should consider including additional variables that align with the context of the service and the type of technology. Accordingly, our research extends the Meta-UTAUT model with four additional external variables (i.e., Anthropomorphism, Aesthetics, Interaction, and Trust) to fill the gap and improve the predictive model ability. As shown in Fig. 1, the primary constructs of the UTAUT model (PE, EE, SI, and FC) were considered to be the main predictors of guests' intention to use robots. In keeping with the Meta-UTAUT model (Dwivedi et al., 2019), the model hypothesised the role of attitude and its antecedents (PE, EE) on behavioural Intention (BI), and it also considered the direct effect of four external variables (Anthropomorphism, Aesthetics, Interaction, and Trust) on BI.

2.3. Research model and hypotheses development

2.3.1. Performance expectancy (PE)

PE in the consumer context refers to "the degree to which using a technology will benefit consumers in performing certain activities" (Venkatesh et al., 2012, p. 159). Robots have many benefits, such as accuracy, time-saving, reduced human error, and automated tasks (Pande and Gupta, 2023). Previous literature indicated that these benefits encourage hotel managers to adopt robots in functions and services such as robotic concierge (Prentice and Nguyen, 2021), room service robots (Zhong et al., 2022), housekeeping robots, luggage handling robots (Fuentes-Moraleda et al., 2020), and check-in/check-out robots (Ye et al., 2022). Hotel organisations recently have promoted the benefits of robots, aiming to boost positive beliefs and attitudes towards robot technology (Soliman et al., 2024). Prior studies found different effects of PE on consumers' attitudes using AI technologies in hotel services. While Tamilmani et al. (2020) found a non-significant relationship between PE and attitudes among travellers' usage for Airbnb platform, Bhuiyan et al. (2024) showed that PE positively affects customers' attitudes to using AI in hospitality services. Manzoor et al. (2024) also empirically demonstrated the effect of PE on tourists' attitudes towards AI devices in hotels in Pakistan. Thus, it could be argued that the PE of the robots improves guests' positive attitudes towards using robots. Therefore, this research proposes the following hypothesis:

H1: Performance expectancy will positively impact guests' attitudes to use robots in hotel services.

Hotels introduce robots as one of the modern technologies (Zhang et al., 2023). This supports hotel guests' perception of the usefulness of robots (Lee et al., 2021). Existing studies indicated a significant effect of PE on customers' intention to use robots; for example, Lee et al. (2021) noticed that PE positively affects hotel guests' behavioural intentions to adopt robot assistants in hotel services. Zhang et al. (2023) also showed that consumers have a higher PE of robots, and PE affects consumers' willingness to adopt robots in hospitality service scenarios. Accordingly, the robot's PE not only improves guests' positive attitudes, but also contributes to shaping their intentions toward using such technology. The following hypothesis states:

H2: Performance expectancy will positively impact guests' intention to use robots in hotel services.

2.3.2. Effort expectancy (EE)

EE is "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p. 159). This concept is closely related to the perceived ease of use in TAM and Innovation Diffusion Theory (Patil et al., 2020). Robots in hotels often come with features that make them easy for guests to use, for example, user-friendly interfaces that

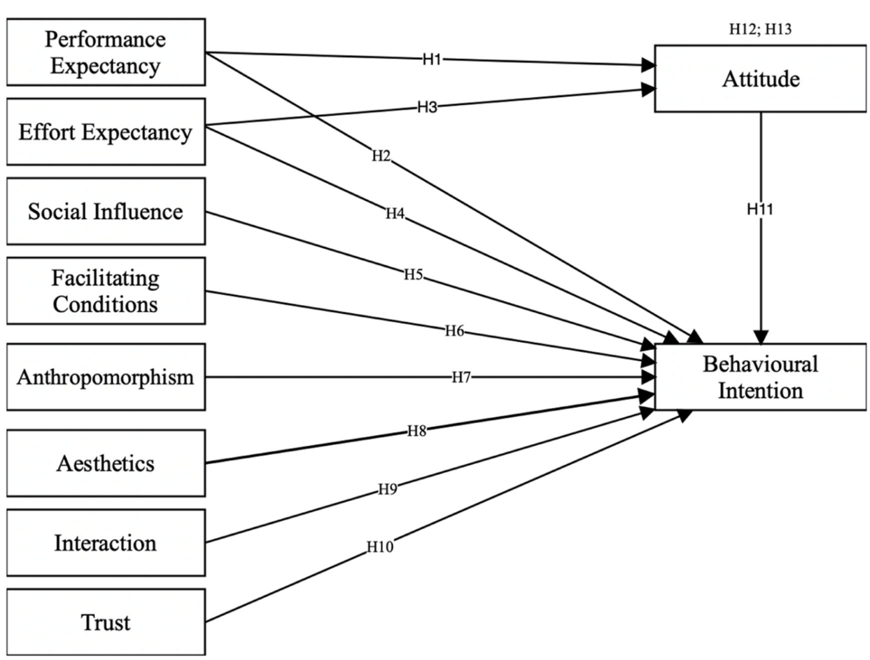

Fig. 1. Research Model.

include touch screens and voice recognition (Jin, 2024). Moreover, natural language processing (NLP) features allow customers to verbally interact with robots to inquire about room bookings, prices, information, and special offers. Hotels aim to highlight the benefits of modern technologies to their customers and adopt such technologies to improve service quality and gain a competitive advantage (Alsaad, 2023). This can positively shape customers' perceptions and enhance favourable attitudes toward these technologies. Aslam et al. (2017) found a non-significant impact of perceived ease of use (PEOU) on consumer attitudes towards mobile payment, this may no longer be a critical factor in the decision-making process for adopting mobile payment systems. However, many previous studies in the hotel industry revealed a positive relationship between EE and customer attitude towards information systems (Alsaad, 2023; Bhuiyan et al., 2024). Therefore, it is likely that the EE of robots influences hotel guests' attitudes. Based on this understanding, the research proposes the following hypothesis:

H3: Effort expectancy will positively impact guest' attitude to use robots in hotel services.

Based on the UTAUT model, Venkatesh et al. (2012), (2003) established the impact of EE on BI to adopt technology, and the Meta-UTAUT model further confirmed the relationship between EE and intentions to use information systems (Dwivedi et al., 2019). Some studies showed a negative relationship between EE and similar variables like PEOU and BI, for example, tourist adoption of smartphone apps (Gupta et al., 2018) and hotel guests' intention towards smart hotel technology (Yang et al., 2021). On the contrary, Lin et al. (2020) confirmed the perceived effect of EE on BI using an AI robotic device in hospitality services. Similarly, Morosan (2020) indicated that perceived EE greatly influences customers' intention to use facial recognition systems in hotel services (e.g., authentication and payment). Thus, the perceived EE features (e.g., touch screen) embedded in robots could also influence guests' willingness to use robots in hotel services. As a result, we propose the following hypothesis:

H4: Efforts expectancy will positively impact guests' intention to use robots in hotel services.

2.3.3. Social influence (SI)

According to Venkatesh et al. (2012, p.159), SI is defined as "the extent to which consumers perceive that important other (e.g., family and friends) believe they should use a particular technology." This concept of SI is similar to subjective norms in Theory of Reasoned Action and images in Diffusion of Innovation (DOI) (Venkatesh et al., 2003). Hotel customers could share and discuss their experiences and ideas about hotel services and the benefits of using technologies to improve customers' services. Recently, customers have started creating social media groups to easily exchange ideas and opinions about hospitality aspects or technologies (Agag et al., 2024). Theoretically, Venkatesh et al. (2003); (2012) and Dwivedi et al. (2019) found the relationship between SI and customers' intentions to use information systems. Similarly, Azdel et al. (2024) demonstrated that SI significantly influences consumers' behavioural intention to use online travel agents (OTAs) for hotel booking services. Kim et al. (2023) showed that SI significantly affected customers' intentions to use hotel in-room voice assistants. Accordingly, social influence could support guests' intention to use robots in hotel services. Hence:

H5: Social influence will positively impact guests' intention to use robots in hotel services.

2.3.4. Facilitating conditions (FC)

FC refers to "consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh et al., 2012, p.159). Customers require basic skills to use the robots to request hotel services, as they interact with the robot via a touch screen and its options, which are very similar to a smartphone or tablet. In the case of voice interaction, it is like having a conversation with a hotel's employees. Thus, customers can use robots without advanced skills or extensive experience. The FC aspects of robots may impact customers' willingness and intention to use such technology in hotel services. UTAUT and Meta-UTAUT models confirm that the FC significantly influences customers' intentions to use technology (Venkatesh et al., 2012; Dwivedi et al., 2019). Some studies (e.g., Baptista and Oliveira, 2015; Gupta et al., 2018) found this relationship to be non-significant in non-hospitality settings. However, prior studies advocated the impact of FC on BI in using technology in the hotel sector, such as how FCs significantly affect BI in using online travel agents (OTAs) (Azdel et al., 2024) and online booking in hotels' resort service contexts (Baydenïz et al., 2024). Based on the aforementioned discussions, the robot is more likely to reach a high level of guest acceptance if the facilitating conditions are available. Therefore, the formulated hypothesis is:

H6: Facilitating conditions will positively impact guests' intention to use robots in hotel services.

2.3.5. Anthropomorphism

Anthropomorphism refers to how the characteristics of technology resemble those of humans in terms of appearance and interaction (Waytz et al., 2010; Balakrishnan and Dwivedi, 2021). When it comes to hotel robots, anthropomorphism focuses on how much a robot's features, such as appearance and voice recognition, mimic the appearance and interaction style of hotel staff. Essentially, anthropomorphism is enhanced when the robots are designed to resemble humans and are equipped with language capabilities to converse with customers (Cai et al., 2022; Cui and Zhong, 2023). While Song et al. (2024b) found that perceived robot anthropomorphism has negatively influence on guests' intention to use robots in Chinese hotels, Said et al. (2024) revealed that anthropomorphism positively affected the acceptance of humanoid service robots in hotels. Similarly, Cai et al. (2022) discovered that perceived robot anthropomorphism positively affects customers' intentions to use and spread positive word-of-mouth in a hotel context. Therefore, anthropomorphism could positively impact guests' intentions to use robots in hotels. Hence:

H7: Anthropomorphism will positively impact guests' intention to use robots in hotel services.

2.3.6. Aesthetics

Aesthetics refer to "the sensory experience induced by the product and the extent to which it conforms to personal goals and preferences" (Chen et al., 2021, p.5). Aesthetics represent the physical appearance of technology, such as capturing colour, shape, and material (Chen et al., 2021). Robot technologies appear like humans, including a head, eyes, mouth, hands, and feet, and these features aim to make robots more human-like and more capable of effectively interacting with people. Robots possess intelligent eyes, utilising cameras and sensors within their eyes to perceive and evaluate their environment. Presenting robots in this way can attract customers and increase their willingness to try using this technology in a service context (Jin, 2024). Lee (2024a) confirmed that aesthetic branded content experiences over social media platforms positively influenced customers' purchase intentions for hotel services. Zhou and Liu (2019) indicated that the hotel website's aesthetic design positively impacts the guests' intention to use booking services. Similarly, the robot's aesthetics might influence guests' intentions to use robots in hotel services. Hence:

H8: Aesthetics will positively impact guests' intention to use robots in hotel services.

2.3.7. Interaction

Interaction refers to the extent to which customers perceive that technological characteristics will facilitate their communication with the technology (Hasan et al., 2021). In AI technology adoption, interaction presents how customers navigate interface options and communicate or chat with the application or machine (Siddike et al., 2018). Robots possess features that facilitate customer interaction, including hand gestures, facial expressions, and posture to convey emotions or react to user inquiries. Further, NLP can significantly enhance the way robots interact with customers by enabling the robot to understand, process, and naturally generate human language (Jin, 2024). The robot can automatically detect the hotel guest's language and respond in that language, using welcoming and culturally appropriate expressions (e.g., tone and language structure) (Liu et al., 2024; Paauwe et al., 2015). These characteristics can enhance the interaction between robots and customers in hotel services. Hotel guests can converse with robots in their natural language and use touch screens to browse the food menu, select preferred dishes, and make payments (Zhong et al., 2021). Yao et al. (2024) indicated that interaction affects customers' intention to adopt service robots. Prodanova and Chopdar (2024) found that the interaction variable directly impacts BI to use mobile for shopping and purchasing services. These perceptions could positively impact guests' intention to use robots in hotel services. Therefore, this research proposes the following hypothesis:

H9: Interaction will positively impact guests' intention to use robots in hotel services.

2.3.8. *Trust*

Trust represents the extent to which a customer believes a technology is reliable and effective. It allows customers to depend on technology for requesting services (Hasan et al., 2021). Trust as an influencer measures three main characteristics: trustworthiness, honesty, and effective fulfilment of tasks (Pitardi and Marriott, 2021). Hotel robots can meet these trust criteria by providing accurate information and simulating various hospitality service scenarios. Prior research indicated that trust is essential in customers' robot acceptance (Wirtz et al., 2018) and positively links trust to customers' intention to use hotel robots. Other research found that trust could negatively impact customers' acceptance of hotel service robots in China (Huang, 2022). However, recent studies by Kim et al. (2022) and Lee (2024b) found that trust significantly affects customers' intentions to use service robots in hotels. Therefore, it could be argued that the guests' trust in robots shapes their intention toward hotel robots. Hence:

H10: Trust will positively impact guests' intention to use robots in hotel services.

2.3.9. *Attitude*

Attitude refers to the extent to which a user has positive or negative perceptions of technology use (Davis *et al.*, 1989). The attitude construct has been incorporated into many adoption models and theories, such as the TRA (Ajzen and Fishbein, 1980), the TAM (Davis *et al.*, 1989), and Theory of Planned Behaviour (TPB) (Ajzen, 1991). Furthermore, Dwivedi et al. (2019) proposed a Meta-UTAUT model, considering the role of attitude in improving the UTAUT model's predictive capability. Notably, most adoption technology models assume that attitude influences BI. According to Li et al. (2023), customers have stronger positive attitudes towards service robots, and their attitudes influence their behavioural intention to use service. Binesh and Baloglu (2023) also concluded that the attitude of US hotel guests positively influences BI to use service robots. Consequently, the formulated hypothesis is:

H11: Attitude will positively impact guests' intention to use robots in hotel services.

2.3.10. *Attitude as mediation*

According to Meta-UTAUT model, attitude acts as a mediator between EE, PE, and behavioural intention (Dwivedi et al., 2019). When hotel guests perceive the benefits of robots, such as usefulness and ease of use, they could develop a positive attitude. This, in turn, could enhance their behavioural intentions toward the robot usage. Thus, the perceived benefits could promote a favourable attitude towards the robots, affecting guests' intentions to use them in the future. Hence:

H12: Attitude will positively mediate the relationship between performance expectancy and the guests' intention.

H13: Attitude will positively mediate the relationship between effort expectancy and the guests' intention.

3. Methodology

3.1. *Measurement items*

The present study used a seven-point Likert scale, ranging from strongly agree to strongly disagree, to measure the variables. The study model comprises 10 reflective constructs assessed using validated scales, derived from relevant previous studies, and subsequently modified to suit the particular context of the current paper. The variables of PE, EE, SI, FC, and BI were measured using a scale, with 17 items, provided by Venkatesh et al. (2003), (2012) and confirmed by Dwivedi et al. (2019). The measurement of attitude was conducted using a scale, with 5 indicators, adapted from Balakrishnan and Dwivedi (2021), while anthropomorphism was assessed using a 4-item scale constructed by Balakrishnan and Dwivedi (2021), as later adopted by Balakrishnan et al. (2022). A 5-item scale adapted from Chen et al. (2021) was used to measure robot aesthetics, whereas the measurements of interaction and trust were measured by a 4-item scale each adapted from Hasan et al. (2021).

3.2. *Sampling and data collection*

The study employed a non-probability convenience sampling technique, specifically among hotels based in the UK. To target hotel guests, we employed a self-administered online survey that a group of academics reviewed for content validity. We conducted a pilot study to test the questionnaire before the main survey. A group of 30 participants completed the questionnaire and were excluded from the main study. Then, we evaluated the reliability of Cronbach's alpha, showing a threshold of 0.7, ranging from 0.72 to 0.86, ensuring good internal consistency. Additionally, we evaluated the convergent validity, which was further supported as all item loadings on their intended constructs were significant and exceeded 0.5. Average variance extracted (AVE) values exceeded 0.5 for all constructs (Hair Jr *et al.*, 2019).

Out of 398 total responses, 358 were validated and completed. The data collection occurred from early January 2024 to March 2024. The researchers used an internet-based survey platform that connects researchers with hotel guests willing to participate. Before this survey was distributed, the survey company restricted the participants to those who currently live in the UK and have regular hotel experience. This approach was followed to minimise selection bias (e.g., Lim et al., 2024) and to use the platform's ability to generate high-quality, representative samples and increase response rates (Ahmad et al., 2021). Previous robotics studies used a similar approach to select participants (Lee et al., 2021; Jung et al., 2023; Lim et al., 2024). The survey began with a concise introduction to the main research concepts and objectives, a guideline explaining how to complete the questionnaire, and ethical considerations (e.g., anonymity, confidentiality, data usage for study purposes only, etc.). Prior to addressing the main questions, the participants were presented with images of service robots and were posed a screening question about whether they are open to using robots in a future visit or stay in UK hotels. We allowed individuals who answered "Yes" to continue with the survey.

The study analysed the skewness and kurtosis values of all items to determine the normality of the data distribution. The absolute values of skewness and kurtosis for all items were within the acceptable range of -3 to $+3$, as indicated by Hair et al. (2019). Further, Variance Inflation Factors (VIFs) were computed for each observed variable using Kock's (2015) methodology to evaluate any possible common method bias. The findings indicated that common technique bias is not a significant problem in this research since all VIF values were below the recommended cutoff of 3.3.

Concerning the sample (see Table 1), the gender distribution is nearly equal, with 47.5 % identifying as male and 52.5 % as female,

Table 1
Sample Profile.

Characteristics	Descriptions	Statistics	(%)
Gender	Male	170	(47.5)
	Female	188	(52.5)
Age	18–24	78	(21.8)
	25–30	93	(26.0)
	31–40	115	(32.1)
	41–50	37	(10.3)
	51–60	16	(4.5)
	More than 60	19	(5.3)
Education level	High School	41	(11.5)
	Diploma	38	(10.6)
	Undergraduate university degree	140	(39.1)
	Post-graduate university degree	139	(38.8)
Employment status	Full-time	175	(48.9)
	Part-time	113	(31.6)
	Retired	17	(4.7)
	Homemaker	9	(2.5)
	Unemployed	44	(12.3)
In the previous months, what was your monthly income in British Pounds (GBP)?	No income	49	(13.7)
	400–1200 (GBP)	126	(35.2)
	1201–3000 (GBP)	149	(41.6)
	3001–5000 (GBP)	22	(6.1)
	More than 5000 (GBP)	12	(3.4)

ensuring a fair representation. About 80 % of them were between the ages of 18 and 40, and the other 20 % were between the ages of 41 and 60. Around 39 % had a bachelor's degree, 38.8 % had a post-graduate degree, and 22.1 % had a high school diploma. Most participants were working full-time (48.9 %), followed by part-time (31.6 %) and unemployed (12.3 %). Monthly income depicts a wide range of financial situations, with significant proportions earning between 400 and 3000 GBP per month.

4. Results

As suggested by Hair Jr *et al.* (2020), this study employed a two-step approach. The first involved assessing the reliability and validity of the measurement model using Confirmatory Factor Analysis (CFA). The second involved evaluating the structural model by Structural Equation Modelling (SEM), facilitated by high-efficiency software AMOS 24. They noted that SEM assesses the proposed model's fit with the observed data and investigates the relationships between several dimensions. The Sobel test was also used to investigate the meditation of the attitude and certain variables (i.e., PE, EE, and BI).

4.1. Measurement model and model fit

Table 2 presents significant factor loadings for all the study constructs (t-value ≤ 0.001), indicating that the measures accurately represent their underlying constructs (Hair et al., 2011). All component factor loadings were notably higher than 0.60, emphasising the robustness of the study's measurement instruments. The study also examines the two key elements of measurement quality: reliability and validity. Reliability, the consistency and accuracy of the measures employed to represent a construct (Aldridge et al., 2017), was assessed using Composite Reliability (CR) and Cronbach's Alpha (α) for each construct. CR and α scrutinise internal consistency, or how effectively the measures representing a construct reflect the same underlying concept. This study constructs met the thorough values for CR and α set at 0.70 or above, demonstrating the measurements are dependable and consistently reflect the constructs (Hair Jr *et al.*, 2019).

Validity is whether a measure accurately captures its intended measure (Podsakoff et al., 2013). The study's validity assessment relies on Average Variance Extracted (AVE), a vital method that indicates the variance in the measures the construct explains (Hair Jr *et al.*, 2020). An AVE value of 0.50 or greater is acceptable, signifying the construct accounts for at least half of the variance in its measurements. In this study, the constructs had AVE values exceeding 0.50, indicating their significant contribution to the variance in the indicators (Hair Jr *et al.*, 2019). The study also includes each construct's mean and standard deviation values, providing a comprehensive understanding of the data. The mean, representing the average score for each construct's indicators, offers an overall impression of participants' responses to the linked survey questions (Wan et al., 2014). The averages of all the constructs range from 3.84 to 4.8, indicating a generally favourable opinion of the measured constructs. However, the relatively high standard deviations for certain constructs reflect a wide range of participant perspectives, recognising the diversity of opinions and enhancing the study's credibility. Further, the predictive significance of the model was evaluated using Stone-Geisser's Q^2, as suggested by Hair et al. (2013). The findings showed that attitude ($Q^2 = 0.590$) and behavioural intention ($Q^2 = 0.757$) had substantial predictive significance. In line with Hair et al. (2013), these results show that the model can reliably predict out-of-sample values for these essential constructs, proving its practicality.

The fit of the measurement model was assessed employing several fit indices (Hair Jr *et al.*, 2020). The relative chi-square ($2\chi^2/df$) value of 2.6 suggests an acceptable fit ($\chi^2 = 1854$, df = 691, $p < .001$), considering it falls below the recommended cutoff of 3.0 (Hu and Bentler, 1999). Also, the fit indices indicative of overall model fit (AGFI = 0.94, NFI = 0.95, GFI = 0.91) and parsimony-adjusted fit (CFI = 0.92, TLI = 0.95) all above the recommended threshold of 0.90 (Byrne, 2013). Ultimately, the RMSEA value of 0.041 fell below the benchmark of 0.08, suggesting a good approximation error (Steiger, 2007). Hence, the combined evidence from these fit indices unequivocally suggests a satisfactory measurement model that adeptly captures the underlying constructs.

Table 3 shows the discriminant validity analysis, determining whether the measurement model's constructs are distinct (Fornell and Larcker, 1981). The results show that the correlations between any two constructs (off-diagonal elements) are smaller than the square root of the AVE for each construct (diagonal elements). Hence, each construct's variance is more closely associated with its measures than with measures of other constructs. Additionally, the study assessed the discriminant validity using the Heterotrait-Monotrait Ratio (HTMT) (Hair et al., 2020). Results indicated that discriminant validity was demonstrated, with all values meeting the HTMT below the 0.9 threshold (see Table 4).

4.2. Hypothesis testing

Table 5 presents the path coefficients of the direct relationships influencing hotel guests' acceptance of robotic services. The results indicate that PE, as hypothesized in H1, has a strong and statistically significant influence on attitudes toward robotic services ($\beta = 0.000$, $p < .001$). Similarly, EE, as hypothesized in H3, positively affects attitude ($\beta = 0.000$, $p < .001$). Moreover, path analysis shows that various factors highly influence behavioural intention (H5, H6, H7, H8, H10, H11). These comprise the following factors: social pressure to use the service (SI) ($\beta = 0.004$, $p < .01$); availability of learning resources (FC) ($\beta = 0.000$, $p < .001$); human-like features (anthropomorphism) ($\beta = 0.000$, $p < .001$); its aesthetic appeal ($\beta = 0.000$, $p < .001$); trust in its capabilities (Søraa et al., 2023) ($\beta = 0.000$, $p < .001$); and overall customer attitude ($\beta = 0.000$, $p < .001$). Fig. 2

Bottom of Form

Surprisingly, there was no evidence to support the hypotheses that suggested behavioural intention was directly impacted by PE (H2: $\beta = 0.654$, $p > .05$) and by interaction (H9: $\beta = 0.287$, $p > .05$). Further, Table 6 provides insights into the indirect effects. Both the interaction of PE and attitude (H12: $\beta = 0.000$, $p < .001$) and EE and attitude (H13: β

Table 2
Analysis of Measurement Model.

Constructs	Standardized loading (t- value)	AVE	CR	α	Mean	Standard deviation
Performance Expectancy		0.67	0.86	0.86	4.80	1.36
PE1	0.82					
PE2	0.82					
PE3	0.83					
Effort Expectancy		0.71	0.90	0.91	4.70	1.39
EE1	0.81					
EE2	0.87					
EE3	0.83					
EE4	0.86					
Social Influences		0.77	0.91	0.91	4.05	1.46
SI1	0.84					
SI2	0.91					
SI3	0.89					
Facilitating Conditions		0.59	0.85	0.84	4.79	1.24
FC1	0.77					
FC2	0.73					
FC3	0.82					
FC4	0.77					
Behavioural Intention		0.67	0.86	0.86	4.22	1.54
BI1	0.86					
BI2	0.77					
BI3	0.83					
Attitude		0.76	0.94	0.94	4.58	1.47
ATT1	0.88					
ATT2	0.86					
ATT3	0.91					
ATT4	0.88					
ATT5	0.85					
Anthropomorphism		0.63	0.87	0.78	3.84	1.33
ATH1	0.83					
ATH2	0.87					
ATH3	0.78					
ATH4	0.71					
Aesthetics		0.67	0.91	0.91	4.06	1.41
A1	0.81					
A2	0.86					
A3	0.91					
A4	0.71					
A5	0.81					
Interaction		0.68	0.89	0.89	4.33	1.42
I1	0.88					
I2	0.89					
I3	0.77					
I4	0.77					
Trust		0.63	0.87	0.87	4.52	1.36
TR1	0.77					
TR2	0.89					
TR3	0.81					
TR4	0.70					

Note: All factor loadings were significant at ≤ .001; CR = Composite Reliability (≥ 0.70); α = Alpha Reliability (≥ 0.70); AVE = Average Variance Extracted (≥ 0.50). Source: Created by authors.

Table 3
Discriminant Validity (Fornell-Larcker).

Constructs	1	2	3	4	5	6	7	8	9	10
1. Performance Expectancy	**0.81**									
2. Effort Expectancy	0.72	**0.84**								
3. Social Influences	0.70	0.69	**0.87**							
4. Facilitating Conditions	0.79	0.77	0.72	**0.76**						
5. Behavioral Intention	0.72	0.73	0.65	0.74	**0.81**					
6. Attitude	0.62	0.62	0.65	0.61	0.75	**0.87**				
7. Anthropomorphism	0.72	0.69	0.69	0.74	0.77	0.74	**0.79**			
8. Aesthetics	0.70	0.77	0.58	0.75	0.79	0.75	0.71	**0.81**		
9. Interaction	0.75	0.73	0.62	0.75	0.79	0.73	0.73	0.68	**0.82**	
10. Trust	0.70	0.74	0.72	0.75	0.72	0.73	0.61	0.73	0.69	**0.79**

Note: All correlations are significant at $p < .001$. Source: Created by authors.

Table 4
Heterotrait-Monotrait Ratio (HTMT) – Matrix.

Constructs	1	2	3	4	5	6	7	8	9	10
1. Performance Expectancy										
2. Effort Expectancy	0.820									
3. Social Influences	0.710	0.709								
4. Facilitating Conditions	0.824	0.828	0.721							
5. Behavioral Intention	0.791	0.738	0.733	0.836						
6. Attitude	0.821	0.733	0.660	0.815	0.813					
7. Anthropomorphism	0.678	0.659	0.681	0.659	0.824	0.804				
8. Aesthetics	0.726	0.702	0.719	0.732	0.819	0.787	0.827			
9. Interaction	0.717	0.784	0.610	0.762	0.802	0.808	0.836	0.830		
10. Trust	0.731	0.715	0.621	0.722	0.778	0.790	0.803	0.821	0.831	

Note: All correlations are significant at $p < .001$. Source: Created by authors.

Table 5
Path Coefficients (Direct Influences).

Hypothesis	**Path**	**Standardised coefficient**	**t-value**	**p-value**	**Conclusion**
H1	Performance Expectancy → Attitude	0.675	12.485	0.000***	Supported
H2	Performance Expectancy → Behavioural Intention	−0.036	−.448	0.654	Rejected
H3	Effort Expectancy → Attitude	0.361	8.216	0.000***	Supported
H4	Effort Expectancy → Behavioural Intention	−0.151	−2.573	0.010*	Supported
H5	Social Influences → Behavioural Intention	0.139	2.886	0.004**	Supported
H6	Facilitating Conditions → Behavioural Intention	0.334	5.998	0.000***	Supported
H7	Anthropomorphism → Behavioural Intention	0.310	4.762	0.000***	Supported
H8	Aesthetics → Behavioural Intention	0.371	7.064	0.000***	Supported
H9	Interaction → Behavioural Intention	0.051	1.065	0.287	Rejected
H10	Trust → Behavioural Intention	0.467	8.016	0.000***	Supported
H11	Attitude → Behavioural Intention	0.565	6.286	0.000***	Supported

Note:
* Absolute *t*-value > 1.96, $p < 0.05$;
** Absolute *t*-value > 2.58, $p < 0.01$;
*** Absolute *t*-value > 3.29, $p < 0.001$. Source: Created by authors.

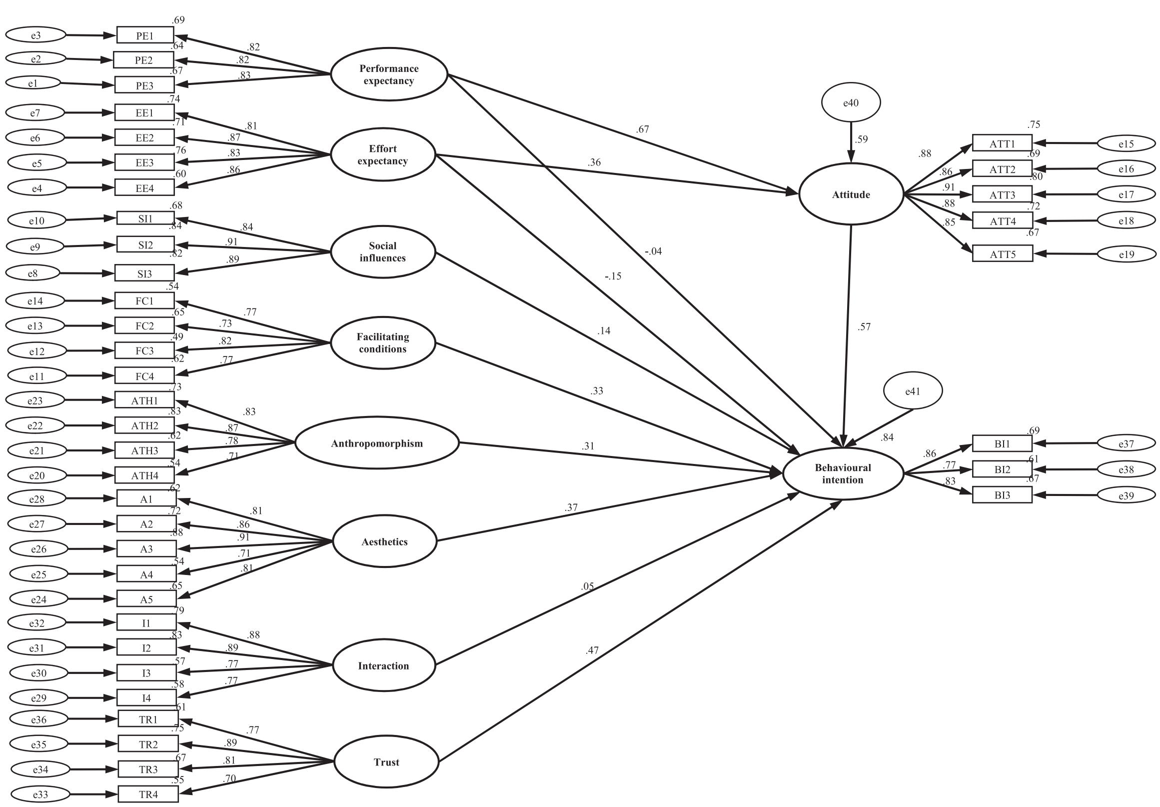

Fig. 2. Research Model Results.

Table 6
Path Coefficients (Indirect Influences).

Hypothesis	Path	Standardised coefficient	t-value	p-value	Conclusion
H12	Performance Expectancy × Attitude → Behavioural Intention	0.382	5.578	0.000***	Supported
H13	Effort Expectancy × Attitude → Behavioural Intention	0.204	4.955	0.000***	Supported

Note: *Absolute *t*-value > 1.96, p < 0.05; **Absolute *t*-value > 2.58, p < 0.01; ***Absolute *t*-value > 3.29, p < 0.001. Source: Created by authors.

= 0.000, p < .001) on behavioural intention were supported.

5. Discussion and conclusion

An evolution of the UTAUT framework, the Meta-UTAUT model explains robot acceptance behaviours but ignores context-specific external variables (Dwivedi et al., 2019). The current study expands the Meta-UTAUT model to accurately predict the guest acceptance of robots in hotels. The present research finds that guests who perceive technology services as beneficial (PE) develop a more favourable attitude toward these technologies. This result is in line with prior research about the beneficial influence of PE on consumers' adoption of AI technologies in the hospitality (Manzoor et al., 2024). The study shows hospitality providers can improve guest perceptions and adoption by building robotic systems that effectively express their benefits (Huang et al., 2023). Surprisingly, the findings showed that PE does not affect BI. While PE is often considered a strong predictor of BI (Tamilmani et al., 2020; Lee et al., 2021; Zhang et al., 2023), some studies reported its limited impact on BI towards emerging technologies, such as smartphone fitness apps (Dhiman et al., 2019) and the Internet of Things (Arfi et al., 2021). The rejection of PE in the current study highlights that participants may be unable to gain a holistic view of emerging technologies in some contexts, like hotels, affecting their perception of technological characteristics. Additionally, the limited prior experience of participants with robots might contribute to their inability to perceive the usefulness of robots in hotel settings.

Further, guests who find robot services need low EE have better attitudes and low BI. The EE and attitude result emphasises hotels' need to prioritise user-centred design principles when implementing robot services (De Kervenoael et al., 2020; Fang et al., 2024). Therefore, straightforward interfaces and explanations can reduce frustration and help guests use the technology (Huang et al., 2023). However, EE and BI result shows that hotel guests' BI to accept service robots is reduced when they perceive little effort. This finding is surprising since earlier research has established a positive association between EE and BI (Lin et al., 2020), where minimal effort improves guest technology usage. This negative relationship might be attributed to guests' privacy concerns (Boo and Chua, 2022) which exposes them to cyber-attack risks. This justification confirms Seo and Lee's (2021) result that trusted systems considerably boosts PEOU for a service robot, lowers perceived risk, and increases satisfaction.

Beyond PE and EE, the study uncovered various indicators impacting guest intentions toward robot service. SI strongly influenced guests' intentions to use robots. According to Agag et al. (2024), social media platforms should create a favourable social atmosphere surrounding robot services. Hotels may boost word-of-mouth, social buzz, and robot technology perception by showing successful visitor interactions with robots and promoting peer-to-peer sharing (Huang et al., 2023). Moreover, the study finds the FC critical in guests' robot use intentions. The study highlights the importance of simple interfaces, clear instructions, and suitable support systems for better guest experiences and adoption (Azdel et al., 2024; Baydenïz et al., 2024).

Additionally, our study highlights the crucial influence of anthropomorphism on guest intentions regarding robot service in hotel settings. The study confirmed prior findings (Cai et al., 2022; Kim et al., 2023; Said et al., 2024) that human-like features such as expressive facial expressions, natural language processing, emotional reactivity, and engaging conversational abilities improve visitor perceptions and technology adoption. Therefore, hotels can make their guest experiences more relevant and engaging by endowing robots with human-like characteristics (Cui and Zhong, 2023; Baltaci et al., 2024; So et al., 2024). For example, hotels may use Christou et al. (2020) multi-level paradigm to understand robot anthropomorphism, distinguishing between internal factors (perceived internal state and personality), functional (capabilities), and surface (physical appearance).

In addition, our research significantly contributes by highlighting the importance of aesthetics in affecting guests' intentions toward robot service in hotel environments. The results indicate visually appealing robot designs can positively impact guest intentions and promote trialability (Lee, 2024a). This outcome aligns with previous studies on the relationship between aesthetics and BI use of technology (Zhou and Liu, 2019; Lee, 2024a). Hotels can improve the guest experience and establish a favourable first impression by investing in modern and aesthetically appealing robot designs (Zhou and Liu, 2019). Hotels can pay attention to the robot's "surface" characteristics to promote guests' willingness to use, like uniform, facial, and body movements (Christou et al., 2020). Hotels can design service robots with humanoid, streamlined shapes with interacting screens, smooth curves with interesting features, and welcoming, expressive displays (Paauwe et al., 2015; Mende et al., 2019). The study also shows that trust influences guest robot service intentions. According to Søraa et al. (2023), trust is crucial in guest views of robot reliability and effectiveness. Hotels can create guest trust by consistently performing and being honest about limits (Zhong et al., 2021).

However, there was no indication that interaction impacts directly affected hotel guest robot use intentions. This result contradicts prior research that indicated the positive impact of interaction on guests' BI to use hotel technology (Prodanova and Chopdar, 2024; Yao et al., 2024). Since the interaction variable depends mostly on direct system use, non-adopters were unaware of robot interaction characteristics, including navigation, chat, and discourse (Siddike et al., 2018). The absence of direct experience may lead to diminished perceived attractiveness of the robot, resulting in a reduced propensity to interact with the technology (Li et al., 2023). Also, the novelty effect and the degree of technology adoption within hotel environments may impact customers' expectations and interactions with robots (Horng et al., 2024). Previous research indicates that the influence of interaction on adoption intentions may differ according to familiarity with the technology, prior exposure, and the perceived usefulness of the system (Fang et al., 2024; Yao et al., 2024). Therefore, the relationship between interaction and BI could be more complex and contingent on factors such as guest experience.

Furthermore, this study extends the prior research on the relationship between attitudes and behavioural intentions (Fishbein & Ajzen, 1975; Davis, 1989; Dwivedi et al., 2019) by examining how attitudes toward robot services influence hotel guests' intentions to adopt these technologies (Binesh and Baloglu, 2023; Li et al., 2023). In contrast to previous research, the current study emphasises the role of attitudes as a mediator between PE and EE on behavioural intentions. The results show, however, that PE and EE indirectly affect behavioural intention via the favourable attitude they foster toward robot services. These results align with earlier studies that highlighted the importance of attitude as a mediator (Zhong et al., 2021). These results imply that, rather than relying only on perceived utility, it may be more beneficial to promote a positive attitude by communicating the value proposition of robot services clearly and concisely and including user-friendly design (Dwivedi et al., 2019).

5.1. Theoretical implications

This study suggests significant theoretical contributions. Firstly, the study advances our understanding of how guests accept robots in hotels by extending the Meta-UTAUT model to include factors of anthropomorphism, aesthetics, interaction, and trust. This study is the first to test the Meta-UTAUT model, examining new insights into guest behaviour towards hotel robot adoption. The results offer additional evidence and validation for the Meta-UTAUT model and respond to repeated calls for studies to test this model (e.g., Dwivedi et al., 2019) in different contexts. Secondly, while our empirical data analysis supported most of the proposed hypotheses, the results did not support those related to PE and Interaction to BI, contradicting prior studies that examined PE (Patil et al., 2020; Lee et al., 2021; Balakrishnan et al., 2022) and Interaction (Hasan et al., 2021), thus providing a new area for further research of the hotel guests' characteristics and circumstances of use. However, the study did confirm that factors like anthropomorphism, aesthetics, and trust, alongside the original Meta-UTAUT variables and the role of attitude as a mediator, significantly affect guests' acceptance of robot technology in UK hotels. This result enhances the Meta-UTAUT model's ability to predict behavioural intentions towards technology adoption in hospitality organisations. Lastly, previous research has investigated the use of service robots in tourism and hospitality in various regions, including Bulgaria (Ivanov et al., 2020), China and Korea (Jung et al., 2023), Japan and the United States (Said et al., 2024), and Oman (Soliman et al., 2024). However, research in the United Kingdom was scarce. This study is the first known, to our knowledge, to investigate guests' intentions for using service robots in UK hotels. As a result, it lays the groundwork for future research into guest acceptance of robot services across different cultural and socio-economic contexts.

5.2. Practical implications

This study also suggests practical contributions for hotel operations. First, the study indicates important factors that promote guests' acceptance of service robots. Hotels should consider functional, social, and aesthetic factors before incorporating robots. As demographics and guest interactions can significantly impact the decision to use robots, it is beneficial for hotels to use robots that show human-like features, such as facial expressions, gestures, blinking eyes, or head tilts. Also, incorporating advanced NLP capabilities allows robots to interact in a human-like manner, understanding and responding to the tone, context, and even humour. Second, hotels can collaborate with service robot designers to maintain a user-friendly and consistent design that reflects a proper body shape, appearance, animated face, touchscreen interface, personalised and data storage capabilities, language options, and emotion recognition characteristics. They should avoid mechanical or alien shapes, which may be unpleasant or lead to technophobia and techno-anxiety. AI tools and systems can help robots show facial gestures, engage in dialogues, and share information with guests to make them feel comfortable with the technology. In doing so, hotels can build trust between guests and robots using conversational-appealing cognitive service robots. However, it is occasionally essential to offer service delivery that involves human engagement to guests to prevent monotony or dissatisfaction with the service and to enhance personalised service, manage guest complaints, or assist in high-stress situations. Lastly, robots have advantages, such as improving the capacity and efficiency of services and eliminating service waits (Choi et al., 2020). This study also highlights the possibility of promoting robots to hotel guests and understanding their intentions by collecting guests' opinions via surveys or employing a pilot programme to test the robots as a preliminary stage. Hotels should also create a favourable first impression to ensure guests are comfortable and open to the new technology and follow up promptly with them. In addition, this may help second-movers and new entrants save time, effort, and money when understanding the nuances of robot technology adoption in their hotels.

5.3. Limitations and future research

This study is not without limitations. It examined the Meta-UTAUT variables as the main technology adoption constructs, alongside four new variables: anthropomorphism, aesthetics, interaction, and trust. A notable area for further research could be testing the Meta-UTAUT model and these additional variables in other hospitality organisations. Researchers could also add other variables such as emotions, anxiety, enjoyment, experience, or readiness, or consider the role of size, type, ownership, service, or target demographics. This model can also be applied to recent technologies like virtual reality, AI, or chatbots, and to a variety of samples such as employees or visitors. Another limitation is that this research used a quantitative approach and focused on hotel guests in the UK. Future research could use qualitative or mixed methods in countries with different cultures to gain a comprehensive understanding of guests' acceptance of robots and their behaviour. Researchers could also focus on a multi-group analysis of service robot users and non-users in different hospitality organisations, such as restaurants or the aviation industry.

CRediT authorship contribution statement

Marghany Mostafa: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Data curation, Conceptualization. **Helal Mohamed:** Writing – original draft, Visualization, Validation, Resources, Formal analysis. **Ghazy Khaled:** Writing – original draft, Visualization, Resources. **Elmohandes Nirmeen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Data curation, Conceptualization. **Mohamad Ibrahim:** Writing – original draft, Validation, Resources, Conceptualization. **El-Shawarbi Nabila:** Writing – original draft, Resources, Formal analysis. **Saleh Mahmoud:** Writing – review & editing, Writing – original draft, Supervision, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. : A summary of customer-focused robot adoption studies in the hotel industry

Research Aim	Theory /Model	Internal /External Factors	Sample	Source
Examined the antecedents of customers' willingness and objection to use AI robotic devices in hospitality service (full-service and limited-service hotels).	Artificially Intelligent Device Use Acceptance (AIDUA)	Social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotions.	605 participants, USA	Lin et al. (2020)

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(*continued*)

Research Aim	Theory /Model	Internal /External Factors	Sample	Source
Explored hotel guests' perceptions of using hotel robot assistants.	Unidentified	Facilitating conditions, performance expectancy, innovativeness, social presence, hedonic motivation, and perceived importance.	494 participants, USA.	Lee et al. (2021)
Investigated the relationship between technology readiness and technology amenities as antecedents to visiting intentions	TAM	Technology readiness, technology amenities, ease of use, and perceived usefulness	648 participants, China	Yang et al. (2021)
Investigated the factors affecting customers' adoption of service robot in hotels.	TAM	Perceived usefulness, perceive ease of use, attitude, perceived enjoyment, robot anxiety, trust.	598 participants, Turkey.	Çallı et al. (2022)
Investigated the factors affecting customers' acceptance and use of hotel service robots.	Quality service theory TAM	Perceived usefulness, perceived ease of use, trust, empathy, perceived value.	218 participants, China.	Huang (2022)
Explored the impact of different types of service robots' usage in hotels.	TAM	Perceived ease of use (PEOU), perceived usefulness (PU), room division, food, beverage and secondary services, attitude.	638 participants, Turkey.	Alma Çallı et al. (2023)
Explored hotel-goers' adoption of robot service.	Self-identity-based model	Self-identity, moral obligation, attitudes, care for negative aspects of human services, customer innovativeness.	451 participants, China and South Korea.	Jung et al. (2023)
Examined the impact of anthropomorphic factors on consumer acceptance of service robots.	Social identity theory	Anthropomorphism (physical, Psychological), social mechanism (consumer resistance, human identity threats).	402 participants, South Korea.	Kim et al. (2023)
Investigated the reasons for the differences in customers' acceptance of service robots (CARS) in actual experience and credence service settings.	RC-TAM Role theory	Ability, role clarity, anthropomorphism, autonomy, perceived usefulness, ease of use, attitude	426 participants from hotels, China	Li et al. (2023)
Investigated the effect of multidimensional anthropomorphism and technology readiness on attitudes and usage intentions towards hospitality service robots.	Technology readiness	Technology readiness (innovativeness, optimism, discomfort, insecurity), anthropomorphism (physical, functional, internal), attitude.	1018 participants, Turkey.	Baltaci et al. (2024)
Investigated guest-robot interaction experience in hotel context.	Unidentified	Perceived anthropomorphism, perceived competence, sense of closeness, interactive comfort, pleasant experience.	652 Participants, China.	Fang et al. (2024)
Identified the drivers of hotel guests' choice of smart products (i.e., robotics, artificial intelligence AI, ChatGPT).	Technology readiness TAM TPB	Perceived ease of use, perceived usefulness, optimism, innovativeness, discomfort, insecurity, attitude, subjective norm, perceived behavioural control, positive anticipated emotion, negative anticipated emotion.	315 participants, USA.	Han et al. (2024)
Identified the impact of robot anthropomorphism on consumers' expectations of service robots.	Expectation-confirmation theory Dual-congruity theory Task-technology fit	Anthropomorphism, social capability, social presence, performance expectancy, perceived importance, Luxury-Technology Fit, Task-Technology Fit.	556 participants, Taiwan.	Horng et al. (2024)
Explored the role of different types of perceived benefits on customers' intention to use service robots in the hotel industry.	Social exchange theory	Functional, hedonic, social, empathy benefits, engagement, trust	347 participants, USA.	Lee (2024b)
Identified the factors impact on customer acceptance of humanoid service robots in hotels.	TAM3	Perceived usefulness, perceived ease of use, enjoyment, anxiety, anthropomorphism, perceived intelligence, safety.	395 Participants, Japan and USA.	Said et al. (2024)
Explored the effects of anthropomorphism and functional perceptions on consumers' acceptance of service robots.	Task-technology fit TAM	Anthropomorphism, perceived ease of use (PEOU), perceived usefulness (PU), trust, receptivity, satisfaction, task complexity.	273 participants, USA.	So et al. (2024)
Investigated the effect of customers' perceptions, emotions expectations, perceptions on adoption service robots.	Technology Readiness Cognitive Appraisal Theory Attachment Theory	Optimism, anxiety, discomfort, insecurity, attitude, innovativeness, emotions expectations, brand attachment, Brand experience.	419, participants, Oman.	Soliman et al. (2024)
Explored the effect anthropomorphism and perceived intelligence on hotel guests' intention to use robots.	Heuristic-systematic model Consumption value	Perceived intelligence, perceived control, anthropomorphism, utilitarian value and hedonic value.	248 participants, China.	Song et al. (2024)

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijhm.2025.104227.

Data Availability

Data will be made available on request.

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