AI service robots in South Africa: Testing and extending the AIDUA Model

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ABSTRACT

Whilst AI Service Robots (AISRs) are transforming Hospitality services worldwide, their adoption in emerging markets remains less explored. In particular, the applicability of the Artificial Intelligence Device Use Acceptance (AIDUA) model within the South African Hospitality industry has received limited empirical attention. This study investigated consumer acceptance of AISRs through the AIDUA framework and tested its validity in a South African context. Data was collected via an online survey from 301 participants using a scenario-based method and analyzed with Structural Equation Modelling (SEM) in Statistical Package for the Social Sciences (SPSS) 29. The findings show that hedonic motivation, social influence, and trust are the strongest predictors of AISR acceptance. Interestingly, anthropomorphism had an adverse effect, indicating that excessive human-like features may lead to rejection. Theoretically, the researchers refine the model by splitting effort expectancy into two aspects, namely time-related and intellect-related, highlighting a dual influence of effort in emerging markets. In practice, to boost AISR acceptance, marketers and retailers should focus on enhancing enjoyment and trust whilst avoiding over-humanization in design and deployment. Limitations of the research include the use of a scenario-based methodology and non-probability sampling. Future research should thus validate these findings with real-world AISR implementations and further assess intellectual and time-based effort expectancy dimensions.

Keywords: AIDUA Model, South African Hospitality industry, AI Service Robots, AI acceptance, technology acceptance

1. INTRODUCTION

Artificial Intelligence Service Robots (AISRs) are transforming the Hospitality industry by enhancing operational efficiency and personalizing customer experience. These systems combine advanced algorithms and machine learning to sense the environment, respond like humans, and learn from interactions with guests (Chi *et al.* 2023; Chen *et al.* 2024). Nevertheless, this transformation remains geographically uneven, as over 80% of AISR development is concentrated in North America, Europe, and China, whilst Africa lags due to infrastructural and financial constraints (Kwinda and Wakelin-Theron 2025). This disparity highlights the need for in-depth research to ensure equitable access to AISRs globally.

South Africa illustrates this disparity. While global pioneers like Japan's Henn-na Hotel deployed AISRs in 2015, Africa's first placement was in 2021 at Hotel Sky in Johannesburg, South Africa (Kwinda and Wakelin-Theron 2025). These installations focused on COVID-19 safety over service innovation. For instance, adoption rates remain 35% below those of international peers, driven by crisis rather than strategy (Schoeman and Seymour 2022).

Multiple barriers explain this lag. Inadequate digital infrastructure, weak governance frameworks, and limited institutional capacity create risks of inappropriate technology transfer and the superficial adoption of Western models (Eke *et al.* 2023). Moreover, socioeconomic problems, including high inequality (Gini ~0.63) and frequent power outages, further complicate deployment (Musakuro and Gie 2024). Critically fewer than 2% of AISRs' adoption studies focus on Africa, resulting in a knowledge and implementation gap (Eke *et al*. 2023).

Existing technology adoption frameworks inadequately capture AISR-specific and context-sensitive factors. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) overlook AISR-specific constructs such as ethical concerns, anthropomorphism, trust in automation and affective response (Davis, 1989; Venkatesh *et al.* 2003; Mogaji *et al.* 2024).

The Artificial Intelligence Device Use Acceptance (AIDUA) model, grounded in Cognitive Appraisal Theory (CAT), offers a more suitable alternative. It captures social and affective mediators through constructs such as hedonic motivation, social influence, performance expectancy, effort expectancy, emotions, trust, behavioral intention and objection factors (Gursoy *et al.* 2019; Chi *et al*. 2023). The model has been validated across Western and Asian contexts. However, its applicability to African emerging markets has not been thoroughly tested (Gursoy *et al.* 2019; Chi *et al*. 2023; Roy *et al.* 2024). A critical gap exists in that acceptance models often fail across cultural and institutional boundaries (Venkatesh *et al.* 2003).

This study thus validates AIDUA's original constructs in the South African Hospitality industry whilst incorporating trust to reflect communal decision-making norms. This approach serves three purposes: (i) examining cross-contextual generalizability, (ii) testing construct robustness in a new cultural environment, and (iii) identifying theoretical boundary conditions. The current study addresses the question: *What factors influence South African Hospitality consumers' acceptance and use of AISRs?*

contributions are threefold. Theoretically, it refines the AIDUA model by splitting effort expectancy (EE) into time-related and intellect-related, highlighting a dual influence of effort in emerging markets. Moreover, we provide African-centered empirical insights that challenge Western-centric assumptions by also incorporating trust as a mediator, reflecting communal decision-making norms. Practically, this study proffers evidence-based guidance to practitioners on AISR investment, staff training, and culturally aligned customer experience design. This supports both digital transformation and the decolorization of technology adoption frameworks.

The following sections cover the literature review, hypothesis development, research approach, results, and recommendations for practice and future research.

2. LITERATURE REVIEW

2.1 AISR CLASSIFICATION

In Hospitality, AISRs are autonomous systems deployed at the service frontline to perform tasks traditionally requiring human judgment (Chen *et al.* 2025; Ivanov *et al.* 2019). Unlike industrial automation, they are classified by interaction modes and interface types, distinctions that shape consumer perceptions and acceptance. Interaction modes include (i) substitutive robots that perform repetitive tasks like cleaning; (ii) collaborative robots that support staff; and (iii) interactive robots that engage guests through verbal and non-verbal communication as receptionists or concierges (Ivanov *et al.* 2019; Belanche *et al.* 2021). Interfaces can be tangible, such as physical robots, or intangible, like chatbots (Fuentes-Moraleda *et al.* 2020). Their effectiveness hinges on various intelligences, namely analytical, intuitive, emotional and empathetic, that influence service perceptions (Pitardi *et al.* 2022; Ladeira *et al.* 2023). Additionally, the robot's appearance and design should align with local norms to improve acceptance, especially in markets like South Africa (Belanche *et al.* 2021; Kwinda and Wakelin-Theron 2025).

2.2 AISR ADOPTION IN SOUTH AFRICA

AISRs' adoption in South Africa's Hospitality industry is at a nascent stage but evolving. The current deployment is mainly experimental, with a focus on pilot projects in upscale hotels (specifically 4- and 5-star hotels) (May *et al.* 2024; Kwinda and Wakelin-Theron 2025). For example, Hotel Sky in Johannesburg and Cape Town integrated three AISRs: Lexi, Ariel, and Micah, for concierge, room service, cleaning robots, and luggage transport services. Consumer acceptance indicates predominantly favourable dispositions towards robotic assistance, particularly amongst younger and tech-savvy guests, although many still prefer human interaction for personalized experiences (May *et a*l. 2024; Jembere and Revesai 2025; Kwinda and Wakelin-Theron 2025).

Despite the potential of AISRs, their adoption in South Africa is hindered by context-specific challenges. Foundational barriers include unreliable infrastructure, such as electricity and connectivity, and economic constraints like high upfront costs and a 32.9% unemployment rate (Dube 2024; May *et al.* 2024) . Unemployment fuels anxieties about job displacement. Compounding this is a significant skills shortage, as the industry lacks the technical expertise to operate and maintain robotic systems, a problem exacerbated by limited awareness of AISR benefits amongst businesses (Munoriyarwa *et al.* 2023; Sarfo *et al.* 2024). Furthermore, the regulatory landscape lacks clear, AISR-specific frameworks and safety standards, thus creating ambiguity. Collectively, these infrastructural, economic, skills-based, and regulatory hurdles foster staff resistance and the under-use of AISRs.

However, these challenges are accompanied by significant opportunities. The deployment of AISRs can itself generate new economic avenues, such as partnerships between robot manufacturers and local industries. This could help mitigate fears of job displacement and address high unemployment. For sustainable adoption, Jembere and Moodley (2024) state that context-sensitive AI design that aligns with local realities and ethical norms is essential. There is growing market interest in AISRs, driven by the pursuit of operational efficiency and brand differentiation, although guest reactions remain mixed regarding a preference for human versus robotic service (Abdul-Hamid *et al.* 2019; Kwinda and Wakelin-Theron 2025). Ultimately, tailoring AISR solutions to meet specific South African consumer needs offers substantial potential benefits.

2.3 THE AIDUA FRAMEWORK: A THREE-STAGE COGNITIVE MODEL

Grounded on the CAT, the AIDUA model (Figure 1) frames consumer acceptance of AISRs as a three-stage sequential process (Gursoy *et al.* 2019). The primary appraisal (Stage 1) involves an initial evaluation driven by Social Influence (SI), Hedonic Motivation (HM), and the system's Anthropomorphism (AN). In the secondary appraisal (Stage 2), consumers weigh the anticipated benefits, Performance Expectancy (PE), against the anticipated costs Effort Expectancy (EE). This cost-benefit assessment generates key mediating states: a cognitive state of Trust (T) and an affective state of Emotion (EM). Finally, in the outcome stage, these states of trust and emotion directly determine the consumer's Behavioral Intention (BI), namely the decision to use or reject the AISR.

2.4 STRENGTHS, LIMITATIONS, AND CONTEXTUAL VARIABILITY OF THE AIDUA MODEL

Proponents argue that AIDUA's integration of cognitive, emotional, and social factors offers a richer explanation than utilitarian models, especially for capturing the complexity of human-AI interaction, where emotional engagement is key (Gursoy *et al.* 2019; Espinoza-Bravo *et al.* 2025). Empirical evidence supports its predictive validity across multiple industries and cultural contexts, effectively accounting for diverse antecedents and their interactions (Mei *et al.* 2024; Jembere and Revesai 2025).

However, critics state significant limitations. The model's multi-stage structure and numerous constructs complicate practical application and data collection, particularly in resource-limited settings (Cintamür 2024). A core criticism leveraged by Espinoza-Bravo *et al.* (2025) is that its effectiveness varies substantially across cultures, requiring localized adjustments that challenge its claims of universality. This variability is evident in non-Western contexts. Whilst PE consistently predicts AISR acceptance when users perceive tangible efficiency gains (Mei *et al.* 2024), EE is highly context sensitive. In infrastructure-poor settings, factors like unreliable connectivity, power outages, and inadequate training substantially undermine perceived ease of use and reduce adoption (Kwinda and Wakelin-Theron 2025; Ivanov *et al.* 2019).

Moreover, SI's effects are stronger in collectivist African societies, where peer and community influence shape adoption (Al-Mawali *et al.* 2025; Maimela and Mbonde 2025). AN boosts engagement by making AISR more relatable (Christou *et al.* 2020), but high human-like qualities can backfire, increasing perceived effort and triggering the uncanny valley effect (Grazzini *et al.* 2023; Shum *et al.* 2024). HM promotes acceptance in urban and service sectors, where enjoyment is key (Barrett *et al.* 2024; Khan and Khan 2024), but less so in rural or utilitarian settings (Lu *et al.* 2024; Reid *et al.* 2024). Critics also note that limited digital literacy hampers acceptance, regardless of other factors (Mei *et al.* 2024).

2.5 EXTENSIONS AND UNRESOLVED GAPS OF THE AIDUA MODEL

This variability has led researchers to extend the AIDUA framework with various moderations. Its adaptability has allowed successful use across industries and technological contexts. The framework includes individual variables like technology anxiety, risk aversion, and digital literacy to improve predictions in high-stakes settings (Cintamür 2024; Mei *et al.* 2024). Technology-specific constructs, including accuracy, transparency, fairness, and task-technology fit, have been integrated to capture nuances of generative AI and autonomous systems (Wang *et al.* 2025; Zhang *et al.* 2025). Context-specific adaptations for service robots have introduced non-instrumental factors, such as personality traits, to explain variations in acceptance (Vitezić and Perić 2021; Jembere and Revesai 2025). These systematic extensions demonstrate AIDUA's flexibility in responding to emerging technological and contextual challenges.

Despite adaptations, a significant gap persists, risking reliance on Western-centric frameworks that overlook local realities. In South Africa, trust may be a prerequisite and mediator, reflecting Ubuntu's communal emphasis. Infrastructural constraints may heighten EE, whilst high unemployment could worsen emotional reactions to labour-replacing technology.

3. THEORETICAL FRAMEWORK

This study is primarily based on the original AIDUA model. However, it incorporates trust as a key element, as suggested by Gursoy *et al.* (2019). Trust is considered an important cognitive response in a South African context and is drawn from Chi *et al.* (2023). The research also draws on Social Learning Theory (SLT), Flow Theory, and the Uncanny Valley Theory to develop some hypotheses.

3.1 DEVELOPMENT OF HYPOTHESIS

3.1.1 Social Influence, Performance Expectancy, and Effort Expectancy

Social Influence (SI) is a critical antecedent in technology adoption. Drawing on Bandura's (1969) SLT, consumers reduce uncertainty with AISRs through observation, outcome expectations, and social context. In a collectivist African society, the adoption of AISRs may be influenced by the Ubuntu Philosophy (UP), a humanist perspective emphasizing interconnectedness, collective well-being, and mutual care, often summarized as "I am because we are" (Jembere *et al.* 2025; Mangaroo-Pillay *et al.* 2023). The philosophy suggests that consumer attitudes towards technology extend beyond personal networks to include broader community leaders and norms, fostering shared value creation (Ngubelanga and Duffett 2021; Mogaji *et al.* 2024). Consequently, social approval can boost the performance expectancy (PE) of AISR, which is viewed as community-endorsed (Gursoy *et al.* 2019). Thus, this study proposes that

H1: Social influence positively relates to AISRs' performance expectancy in South Africa.

However, this influence is not uniformly positive. In disadvantaged South African communities with limited digital exposure, social cues and absent direct experience, people may portray AISRs as complex, and a threat to humanity (digital illiterate, threat to job loss) or misaligned with communal wellbeing, thereby creating scepticism (Kondo and Diwani 2023; Kwinda and Wakelin-Theron 2025). This scepticism can amplify the perceived difficulty of using AISRs (EE). Thus,

H2: Social influence negatively impacts AISRs' effort expectancy in South Africa.

3.1.2 Hedonic Motivation, Performance Expectancy, and Effort Expectancy

Hedonic Motivation, the pleasure, fun, and novelty derived from using AISRs, shapes instrumental evaluations through psychological need fulfilment (Gursoy *et al.* 2019). An enjoyable experience satisfies intrinsic needs, which enhances the technology's PE (Gursoy *et al.* 2019). In South Africa's digital landscape, where curiosity can be a primary driver, the novelty of an AISR may signal sophistication and elevate service expectations, thereby strengthening this link. This is exemplified by AI chatbots, where initial adoption is often driven by delight (Cai *et al.* 2022). Thus,

H3: Hedonic motivation is a positive predictor of AISRs' Performance Expectancy.

Furthermore, HM reduces effort expectancy through affective and cognitive pathways. By lowering anxiety and fostering engaging "flow states", HM makes interactions feel more intuitive and less effortful (Venkatesh *et al.* 2012). Design elements like gamification operationalize this by boosting engagement. In communal contexts informed by

Ubuntu, shared positive experiences can socially validate and reinforce this collective perception of ease (EE). Consequently, the study hypothesizes that

H4: Hedonic motivation negatively relates to AISRs' effort expectancy.

3.1.3 Anthropomorphism, Performance Expectancy, and Effort Expectancy

Anthropomorphism, attributing human-like characteristics to AISRs, has a complex, often negative, influence on consumer evaluations. Whilst theories such as Social Response Theory (SRT) suggest that AN can signal competence and intelligence, this study argues that excessive human resemblance often backfires. It raises user expectations to human-level standards and triggers the uncanny valley effect (Vitezić and Perić, 2021). The Expectancy Disconfirmation Theory (EDT) adds that if AISRs' performance fails to meet these unrealistic expectations, users experience negative disconfirmation and a diminished perception of robots' utility, reliability, and appearance (Gursoy *et al.* 2019; Oliver 1980). Thus,

H5: Anthropomorphism is negatively related to the performance expectancy of AISR.

The effect of EE on AN is bidirectional, but negative mechanisms predominate. Although human-like cues can leverage familiar social schemas to reduce EE (Chi *et al.* 2023), AN raises EE by violating expectations for intuitive, effortless interaction (Della Corte *et al.* 2023; Qian *and* Wan 2024). EDT clarifies that an anthropomorphic design creates an expectation of effortless, natural communication (Della Corte *et al.*, 2023). When the AISR's communication or behavior is ambiguous or confusing, consumers expend more mental effort in attempting to interpret it, a phenomenon linked to the Uncanny Valley (Lu *et al.* 2020). This cognitive burden, stemming from violated expectations, heightens perceived effort. Consequently, the researchers hypothesize

H6: Anthropomorphism is positively associated with the Effort Expectancy of AISRs.

3.1.4 Performance Expectancy, Effort Expectancy, and Emotions

According to CAT, emotions stem from an individual's evaluation of an event (Lazarus 1991). Applied to the adoption of AISRs, the appraisal of anticipated benefits is key. Thus, when consumers believe that AISRs improve efficiency and competence (PE), they evaluate them as valuable, which generates positive emotional states such as excitement and anticipation (Alsaad 2023; Chi *et al.* 2023).

H7: PE has a positive influence on emotions toward AISR in South Africa's Hospitality industry.

Conversely, emotions are also shaped by the appraisal of anticipated costs. Lazarus's Cognition-Motivation-Emotion framework posits that evaluating a situation as challenging triggers negative affect. When consumers perceive AISRs as sophisticated and challenging to use, EE, they appraise them as a cognitive threat, leading to a negative response (Ma and Huo 2023). This response can be amplified by AI identity threats, where AISRs are sophisticated, intimidating consumers, and amplifying anxiety and frustration (Alsaad, 2023). Therefore,

H8: EE negatively impacts emotions toward AISR in the South African Hospitality industry.

3.1.5 Performance Expectancy, Effort Expectancy and Trust

Chi *et al.* (2023) introduced trust (T) into AIDUA, noting that accurate, consistent AISR performance influences perceptions of dependability and competence. High-performing AISRs (PE) display reliability and dependability, reducing technological uncertainty and fostering trustworthiness (Chi *et al.* 2023). Thus,

H9: Performance expectancy positively influences trust towards AISR.

Conversely, if consumers perceive AISRs as requiring effort to use (EE), this signals risk and uncertainty, thereby reducing trust. This adverse effect is particularly pronounced in high-power distance cultures, such as South Africa, as consumers are more sensitive to negative service experiences (Chi *et al.* 2023; Jembere *et al.* 2023; Mohammed and Seymour 2023). Thus,

H10: Effort expectancy negatively relates to Trust in AISR.

3.1.6 Emotions, Behavioural Intention and Objection

According to the AIDUA framework and CAT, emotions drive behavioural intention through situational evaluations (Heber and Schneider 2020). PE and EE generate positive emotions such as anticipation and joy, thereby enhancing willingness to engage (Jameel *et al.* 2024). Emotional trust from SI and AN strengthens AISR acceptance (Vafaei-Zadeh *et al.* 2024).

H11: Positive emotions significantly enhance behavioural intention toward AISRs.

Conversely, Cognitive Dissonance Theory (CDT) explains how technology-belief conflicts evoke negative emotions, such as frustration, fear, and anxiety, thereby creating resistance (Rasheed *et al.* 2023). When AISRs disrupt personalised service expectations, negative emotions intensify objections.

H12: Negative emotions contribute to heightened AISR adoption objections.

3.1.7 Trust, Behavioural Intention and Objection

Trust influences AISR behavioral intentions by reducing uncertainty and fostering positive attitudes through assessments of reliability, competence, and benefits, particularly in high-uncertainty cultures like South Africa (Chi *et al.* 2023; Della Corte *et al.* 2023). Behavioral Reasoning Theory explains that individuals weigh the reasons for adoption when making decisions (Westaby, 2005). T facilitates positive reasoning: when users perceive AISRs as dependable and safe, they develop strong pro-adoption justifications, boosting intention. *H13: Trust positively relates to AISR behavioral intention.* Conversely, low trust increases perceived risks, leading to OBJ such as hesitation or rejection (Rasheed *et al.* 2023). T functions as a cognitive buffer, amplifying positive reasoning whilst mitigating negative concerns. *H14: Trust negatively relates to AISR adoption objections.* The figure below summarises the proposed framework, which outlines the fourteen hypotheses.
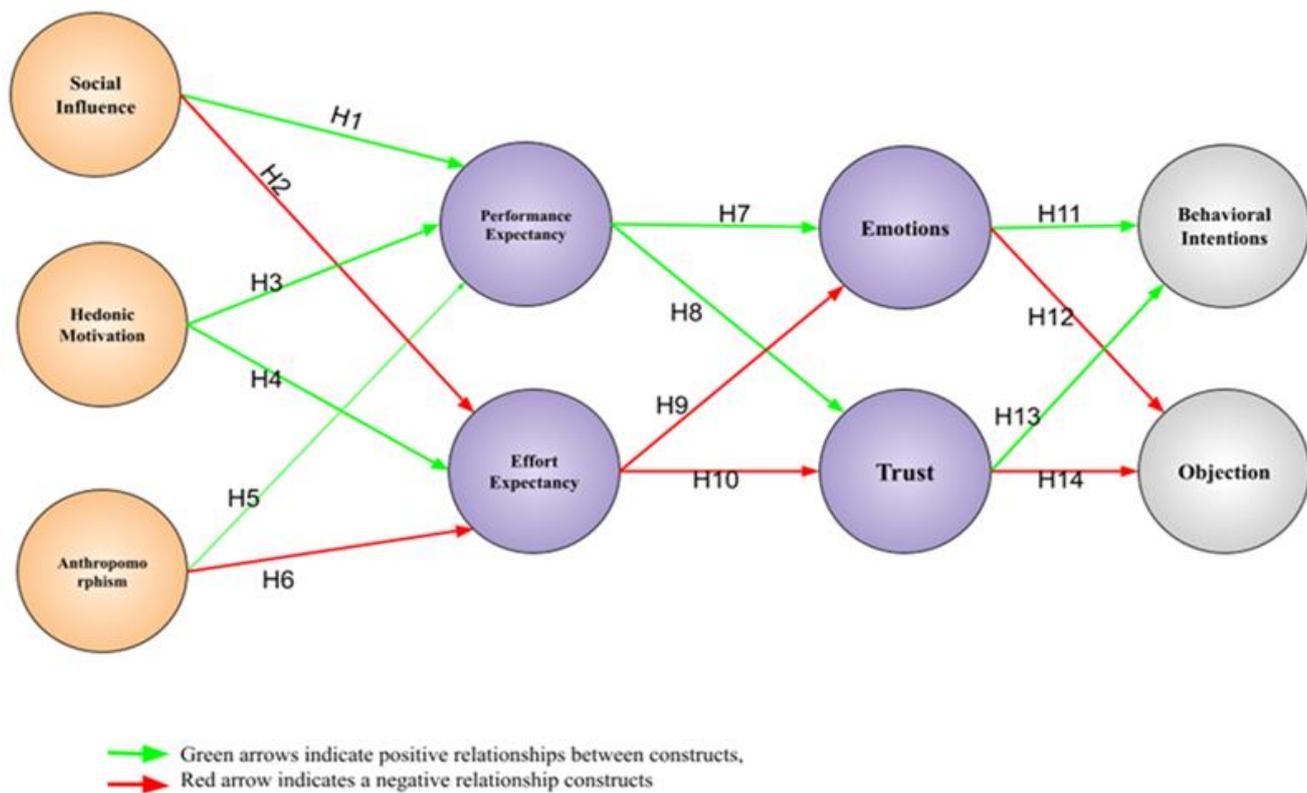
FIGURE 1: PROPOSED AIDUA FRAMEWORK

4. RESEARCH METHODOLOGY

This study adopted a quantitative, cross-sectional survey design. Data were collected through an online self-administered questionnaire targeting South African Hospitality consumers aged eighteen years and older who reside in the country, have used South African hotels within the past year, and have been exposed to AI and AISRs in the industry. Given the nascent stage of AISRs, exposure was not restricted to South Africa, and a multi-stage non-probability sampling approach, combining purposive, convenience, and snowball sampling, was employed. The survey link was disseminated via various social media platforms, including LinkedIn, Instagram, WhatsApp, and Facebook, to ensure diverse participation across age groups and to evaluate exposure to AI and AISRs.

4.1 SAMPLE SIZE AND POWER ANALYSIS

A priori power analysis ($\alpha = 0.05$, power $= 0.80$) indicated a minimum sample n= 117 for medium effects. The final N = 301 achieved powers > 0.99, meeting SEM requirements. Of the 314 collected responses, 13 were removed due to failed attention checks, resulting in a final sample of N=301 (95.9%). The final sample size achieved statistical power greater than 0.99, comfortably exceeding the requirements for PLS-SEM analysis.

4.2 DATA COLLECTION

To mitigate the challenge of limited real-world AISR exposure in South Africa, a scenario-based approach was employed, introducing participants to hypothetical hotel interactions involving various AISR types. All latent constructs were measured using established, multi-item scales rated on 5-point Likert scales. They were pre-tested (n = 50), confirming strong reliability (Cronbach's alpha (α) > 0.80 for most constructs). To ensure validity, the researchers adapted all constructs from Gursoy et al.'s (2019) original AIDUA model and added trust, adapted from Chi *et al.* (2023).

4.3 DATA ANALYSIS

Data was analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis in SPSS 29. PLS-SEM was appropriate because it assessed both the measurement and structural models, as well as the model's hypotheses. Composite reliability (CR) > 0.70 was used to assess internal reliability, and convergent validity was evaluated using average variance extracted (AVE) > 0.50. Discriminant validity, as assessed by heterotrait-monotrait (HTMT) < 0.85, was confirmed. Standard-method bias was assessed using Harman's single-factor test (34.2%). The factor loadings for all constructs except Effort Expectancy were 0.70 and above, making them ideal (Hair *et al.* 2019). Since Effort Expectancy was below 0.7, it was split into two components: time-based effort expectancy and intellectual-based effort expectancy. Participants provided informed consent at the beginning of the survey and were informed of their voluntary participation and the right to withdraw without consequences. Additionally, responses were anonymized and de-identified to ensure anonymity and confidentiality.

5. RESULTS

The initial evaluation of the measurement model, which treated Effort Expectancy as a single construct, revealed psychometric limitations. Specifically, the analysis indicated significant cross-loadings amongst several items and a Cronbach's alpha below the acceptable threshold of 0.7, suggesting issues with reliability and discriminant validity.

To resolve this, the Effort Expectancy construct was refined as shown in Table 1, based on an examination of factor loadings and item themes. This indicated that Effort Expectancy was multidimensional within the context of AISRs in South Africa. The items naturally separated into two distinct constructs, namely: 1. Time-Based Effort Expectancy (EFt) and 2. Intellect-Based Effort Expectancy (EF). This conceptual distinction aligns with established human-computer interaction literature on temporal versus mental demand.

This refinement successfully resolved the initial issues. The purified measurement model demonstrated all factor loadings above 0.7 with no significant cross-loadings. The factor loading for the time-based Effort Expectancy ranged from 0.786 to 0.855, whilst the factor loading for Intellect-Based Effort Expectancy ranged from 0.770 to 0.867. Furthermore, both new constructs exhibited strong reliability, confirming the robustness of the refined model.

TABLE 1: ORIGINAL HYPOTHESES AND REVISED HYPOTHESES FOR EFFORT EXPECTANCY

Original Hypotheses	Revised Hypotheses & Number
H2: EE <--- SI	H2a: EFt <--- SI
	H2b: EF <--- SI
H4: EE <--- HM	H4a: EFt <--- HM
	H4b: EF <--- HM
H6: EE <--- AN	H6a: EFt <--- AN
	H6b: EF <--- AN
H8: EM<--- EE	H8a: EM <--- EFt
	H8b: EM <--- EF
H10: T <--- EE	H10a: T <--- EFt
	H10b: T<--- EF

Note: SI=Social Influence, HM=Hedonic Motivation, AN= Anthropomorphism, PE=Performance Expectancy, EFt=Time-Based Effort Expectancy, EF=Intellect-Based Effort Expectancy, EM=Emotions, T=Trust, BI=Behavioral Intention, OB=Objection

Source(s): Authors' Analysis

Table 2 below shows the exploratory factor loadings, means, Cronbach's alpha, AVE and CR scores for the ten constructs in the measurement model. All constructs demonstrated acceptable to good reliability (α = 0.762–0.898) and strong factor loadings. The Kaiser-Meyer-Olkin value (0.885) and Bartlett's Test of Sphericity ($p < 0.001$) confirmed the data's suitability for factor analysis, explaining 72.69% of the total variance. All constructs were valid as their AVE values exceeded 0.05, indicating convergent validity.

Confirmatory Factor Analysis assessed the validity of extracted factors within the AIDUA model for South African consumers' AISR acceptance. The measurement model demonstrated good fit: χ^2 = 1200.419, df = 653, $p < 0.001$, χ^2/df = 1.838, CFI = 0.924, IFI = 0.925, TLI = 0.914, RMSEA = 0.053, RMR = 0.060. Incremental indices (CFI, IFI, TLI) exceeded the 0.9 threshold, whilst absolute indices (RMSEA, RMR) fell within acceptable ranges, confirming model adequacy and empirical support for the hypothesized AIDUA relationship.

Descriptive statistics revealed notably low perceptions of AI's human-like qualities (Anthropomorphism), in contrast to the high enjoyment of AI (Hedonic Motivation) and positive emotional attachments. Participants expressed moderate behavioral intentions to use AISR, alongside significant concerns about its potential adverse outcomes (Objection), particularly regarding job displacement.

The constructs demonstrated strong internal consistency, with CR values all exceeding 0.7 (range: 0.742–0.924). Convergent validity was established, as AVEs were above 0.5 for all constructs. Furthermore, discriminant validity was confirmed, as each construct's AVE was greater than its Maximum Shared Variance (MSV), as shown in Table 3 below.

5.1 STRUCTURAL RESULTS

The structural model was assessed to evaluate the hypothesised relationships presented in Figure 1, and the results are shown in Table 4. Findings indicate a nuanced role for SI as a significant positive predictor of PE (H1: β = 0.302, $p < 0.001$). However, its effect on EE was mixed. SI did not have a significant effect on EFt (H2a: β = 0.039, $p = 0.628$), but it positively predicted EF (H2b: β = 0.188, $p = 0.007$). Results for HM were that HM was a strong positive predictor of PE (H3: β = 0.335, $p < 0.001$) and EF (H4b: β = 0.180, $p = 0.006$). Its effect on EFt was not significant (H4a: β = -0.048, $p = 0.533$). Furthermore, AN revealed a distinct pattern. Its relationship with PE was not significant (H5: β = 0.009, $p = 0.874$). Contrary to expectations, AN had a significant positive relationship with EFt (H6a: β = 0.213, $p = 0.004$), whilst its relationship with EF was not significant (H6b: β = -0.053, p = 0.378).

Both performance and effort perceptions were significant antecedents to emotional and trust responses. PE was a significant positive predictor of Positive EM (H7: β = 0.307, $p < 0.001$) and T (H9: β = 0.508, $p < 0.001$). EFt had a significant negative relationship with both EM (H8a: β = -0.327, $p < 0.001$) and T (H10a: β = -0.129, $p = 0.02$). Conversely, EF was a significant positive predictor of both EM (H8b: β = 0.180, p = 0.006) and T (H10b: β = 0.383, $p < 0.001$). Finally, both EM and T were confirmed as direct antecedents of BI and negative predictors of OB. Additionally, EM positively influenced BI (H11: β = 0.185, p < 0.001) and reduced OB (H12: β = -0.434, p < 0.001). Trust was a powerful positive predictor of BI (H13: β = 0.636, p < 0.001) and significantly reduced OB (H14: β = -0.302, p < 0.001).

TABLE 2: CONSTRUCT MEASUREMENTS

CONSTRUCT		Measured variables	Factor Loadings	Mean	(SD)	Cronbach's Alpha	CR	AVE
Social Influence	SI1	People's Opinion	0,734	3.16	(1.065)	0.846	0,851	0,537
	SI2	Family's Influence	0,575	2.90	(0.985)			
	SI3	People's influence on behaviour	0,864	3.12	(1.177)			
	SI4	Influence of social media	0,799	2.97	(1.154)			
	SI5	People's perception of my value	0,662	2.91	(1.074)			
Hedonic motivation	HM1	Interaction is Fun	0,856	3.28	(1.099)	0.762	0,924	0,754
	HM2	Interaction is Entertaining	0,835	3.36	(1.079)			
	HM3	Interaction is Enjoyable	0,804	3.26	(1.083)			
	HM4	Interaction is Interesting	0,711	3.61	(1.028)			
Anthropomorphism	AN1	Mind of their Own	0,796	2.61	(1.122)	0.886	0,888	0,665
	AN2	Consciousness	0,852	2.28	(1.074)			
	AN3	Free Will	0,887	2.18	(1.020)			
	AN4	Emotions	0,866	2.10	(1.077)			
Performance Expectancy	PE1	Efficient	0,763	2.94	(1.096)	0.867	0,87	0,628
	PE2	Accurate	0,754	3.26	(1.086)			
	PE2	More Consistent than Humans	0,814	3.35	(1.099)			
	PE4	Consistent	0,784	3.40	(1.068)			
Time-Based Effort Expectancy	EE1	Time-consuming	0,855	2.39	(0.982)	0.733	0,742	0,593
	EE2	Learning Time	0,786	2.63	(1.052)			
Intellect-Based Effort Expectancy	EE3	Intellectual Effort	0,867	3.51	(1.109)	0.800	0,82	0,699
	EE4	Effort consuming	0,77	3.38	(1.109)			
Emotions	E1	Hopeful	0,747	3.56	(0.997)	0.886	0,873	0,539
	E2	Pleased	0,791	3.52	(1.047)			
	E3	Satisfied	0,772	3.57	(1.000)			

CONSTRUCT		Measured variables	Factor Loadings	Mean	(SD)	Cronbach's Alpha	CR	AVE
	E4	Calm	0,732	3.60	(1.114)			
	E5	Contented	0,756	3.50	(0.954)			
	E6	Relaxed	0,743	3.58	(1.076)			
Trusts	T1	General Trust	0,635	3.31	(1.007)	0.889	0,887	0,613
	T2	Willingness to Use AISR	0,639	3.62	(0.903)			
	T3	Perceived Trustworthiness	0,737	3.32	(0.982)			
	T4	Best Interest in Mind	0,726	3.16	(1.028)			
	T5	Keeps Promises	0,69	3.21	(1.037)			
Behavioral intention	BI1	Future Use	0,745	3.37	(0.977)	0.898	0,899	0,748
	BI2	Frequency of Use	0,693	3.36	(0.998)			
	BI2	Positive Emotions	0,711	3.36	(1.025)			
Objections	OB1	Preference for Human Contact	0,811	3.60	(1.055)	0.803	0,828	0,548
	OB2	Need for Emotional Exchange	0,773	3.47	(1.147)			
	OB3	Lack of Social Contact	0,786	3.71	(1.132)			
	OB4	Technological Difficulty	0,518	2.67	(1.219)			
	OB5	Job Displacement Concerns	0,753	3.81	(1.098)			

Variance=72.69%
Kaiser-Meyer-Olkin Measure of Sampling Adequacy=,885
Bartlett's Test of Sphericity= (p<0.001; X^2=7726,517; df=780)
Note: SI=Social Influence, HM=Hedonic Motivation, AN= Anthropomorphism, PE=Performance Expectancy, EFt=Time-Based Effort Expectancy, EF=Intellect-Based Effort Expectancy, EM=Emotions, T=Trust, BI=Behavioral Intention, OB=Objection
Source(s): Authors' Analysis

TABLE 3: MAXIMUM SHARED SQUARE VALUES

	MSV	MaxR(H)	SI	HM	AN	PE	EFt	EF	EM	T	BI	OB
SI	0,299	0,878	**0,733**									
HM	0,412	0,936	0,437	**0,868**								
AN	0,061	0,895	0,179	0,133	**0,816**							
PE	0,352	0,895	0,412	0,419	0,075	**0,793**						
EFt	0,172	0,774	0,091	0,058	0,243	0,122	**0,77**					
EF	0,243	0,917	0,294	0,45	0,003	0,421	-0,134	**0,836**				
EM	276	0,893	0,294	0,458	0,096	0,307	-0,267	0,261	**0,734**			
T	0,494	0,899	0,547	0,642	0,247	0,593	-0,053	0,488	0,525	**0,783**		
BI	0,494	0,9	0,536	0,596	0,13	0,46	-0,127	0,493	0,482	0,703	**0,865**	
OB	0,172	0,844	0,038	0,028	0,001	0,21	0,415	0,08	-0,274	0,087	0,035	**0,74**

Note: SI=Social Influence, HM=Hedonic Motivation, AN= Anthropomorphism, PE=Performance Expectancy, EFt=Time-Based Effort Expectancy, EF=Intellect-Based Effort Expectancy, EM=Emotions, T=Trust, BI=Behavioral Intention, OB=Objection

Source(s): Authors' Analysis

TABLE 4: RESULTS OF THE HYPOTHESES TESTING

Hypotheses	Independent		Dependent	Standardized coefficient β	S.E.	Critical ratio (CR)	P	Decision
H1	PE	<---	SI	0,302	0,075	4,211	***	Accepted
H2a	EFt	<---	SI	0,039	0,091	0,485	0,628	Rejected
H2b	EF	<---	SI	0,188	0,1	2,693	0,007	Accepted
H3	PE	<---	HM	0,335	0,061	4,891	***	Accepted
H4a	EFt	<---	HM	-0,048	0,075	-0,623	0,533	Rejected
H4b	EF	<---	HM	0,447	0,085	6,365	***	Accepted
H5	PE	<---	AN	0,009	0,045	0,159	0,874	Rejected
H6a	EFt	<---	AN	0,213	0,063	2,85	0,004	Accepted
H6b	EF	<---	AN	-0,053	0,065	-0,882	0,378	Rejected
H7	EM	<---	PE	0,307	0,077	4,6	***	Accepted
H8a	EM	<---	EFt	-0,327	0,075	-4,607	***	Accepted
H8b	EM	<---	EF	0,18	0,056	2,74	0,006	Accepted
H9	T	<---	PE	0,508	0,067	6,929	***	Accepted
H10a	T	<---	EFt	-0,129	0,047	-2,324	0,02	Accepted
H10b	T	<---	EF	0,383	0,045	5,804	***	Accepted
H11	BI	<---	EM	0,185	0,055	3,449	***	Accepted
H12	OB	<---	EM	-0,434	0,081	-6,254	***	Accepted
H13	BI	<---	T	0,636	0,093	8,729	***	Accepted
H14	OB	<---	T	0,302	0,101	4,344	***	Accepted

Note: SI=Social Influence, HM=Hedonic Motivation, AN= Anthropomorphism, PE=Performance Expectancy, EFt=Time-Based Effort Expectancy, EF=Intellect-Based Effort Expectancy, EM=Emotions, T=Trust, BI=Behavioral Intention, OB=Objection
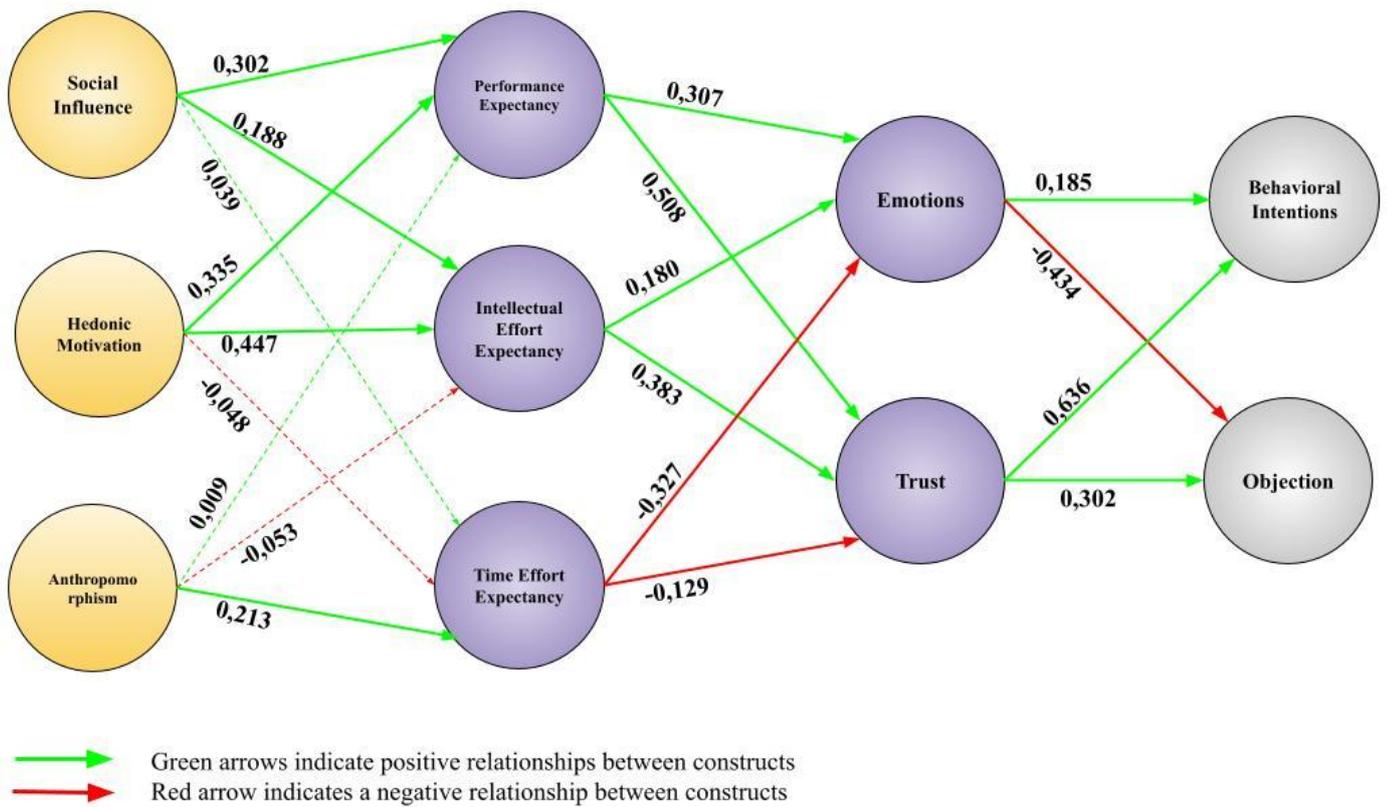
Source(s): Authors' Analysis

FIGURE 2: EXTENDED AIDUA MODEL

6. DISCUSSION, RECOMMENDATIONS, AND CONCLUSION

This study improves the AIDUA model by exploring the factors influencing South African Hospitality consumers' acceptance of AISRs. It explains 72.69% of the variance in AISR adoption, surpassing 60%, confirming the three-stage cognitive process (Hair *et al.* 2019). It validates the original AIDUA constructs in South Africa and adds trust, reflecting communal decision-making. The model illustrates how social, experiential and cognitive factors interact within South Africa's socio-economic and cultural context to influence adoption.

Additionally, SI influences PE, confirming that communal approval shapes the PE of AISRs in South Africa's collective community (Ngubelanga and Duffett 2021; Mogaji *et al.* 2024). However, SI does not decrease concerns about time-based effort expectancy (EFt), contradicting the idea that social endorsement lessens perceived effort (Mutlu 2024). Similarly, HM positively impacts PE and EF, highlighting that in South Africa where AISRs' exposure is limited, novelty, enjoyment and engagement enhance PE and effort expectancy.

Contrary to Western research (Gursoy *et al.* 2019; Della Corte *et al.* 2023) which views AN as an adoption driver, this study finds that human-like features boost EFt but not PE or EF. This suggests that South African consumers value functionality and trust over human-like appearance and abilities. Human traits may signal complexity or inefficiency as they require more time. Hence, this expands the Uncanny Valley Theory beyond affective discomfort to include time-based concerns.

This study uniquely splits EE into intellectual-based (EF) and time-based effort expectancy (EFt), a distinction missing in prior AIDUA research (Gursoy *et al.* 2019; Lin *et al.* 2020). EF boosts emotional response, while EFt negatively influences adoption by signalling perceived time wastage. This shows a trade-off: AISRs can be intellectually easy to use but still rejected if perceived as slow. This is especially important in Hospitality, were time efficiency impacts guest satisfaction. Despite positive perceptions (PE and EF), perceived slowness hinders adoption. This challenges the unitary view of EE in TAM, UTAUT and AIDUA, implying that models should account for both intellectual and time-based dimensions.

A key and surprising finding from the current study is the simultaneous positive effects of T on BI and OBJ, contradicting H14 and differing from previous AIDUA, which only considers trust as resistance reduction (Della Corte *et al.* 2023; Cintamür 2024). Trust stands out as the strongest predictor of BI, underscoring its vital role in markets sceptical of institutions (Abdul-Hamid *et al.* 2019). However, paradoxically, trust also increases objection, a phenomenon understood through Behavioral Reasoning Theory (BRT), which suggests that individuals hold both "reasons for" and "reasons against" a behavior simultaneously (Westaby 2005). In a market like South Africa, which values community well-being and faces institutional mistrust, high unemployment, and socio-economic challenges, consumers who see an AISR as trustworthy may also become more alert to its societal impacts. For example, they may worry more about AISRs' effects on job loss or social decline even whilst trusting them for the benefits they offer to the community (Mangaroo-Pillay *et al.* 2023; Jembere *et al.* 2023). Trust functions as a double-edged sword, helping adoption by reducing uncertainty and signalling reliability, yet also possibly increasing the scrutiny of broader effects where technology use intersects with fragile labour markets and past injustices.

Consistent with prior AIDUA research (Gursoy *et al.* 2019; Ma and Huo 2023), emotional response (EM) negatively relates to OBJ, confirming that enjoyable, engaging experiences reduce resistance. Critically, this effect serves as a counterbalance to the trust-objection paradox. In contrast, trust may heighten the awareness of adverse outcomes, and positive emotions foster affective bonds that shield against resistance. This suggests that emotionally engaging AISR designs that incorporate personalization, empathy, and social presence can mitigate socioeconomic concerns. Eventually, this will facilitate acceptance, even in contexts where cognitive trust unexpectedly increases objections (Zhang *et al.* 2025).

Theoretically, this study advances the literature by validating the AIDUA model in an understudied African context and evaluating its boundary conditions in a culturally distinct setting with structural and socioeconomic challenges. This research provides rigorous full-scale psychometric validation of the core AIDUA framework, confirming its robustness. The researchers contribute to refining the AIDUA by splitting EE into time-related and intellect-related dimensions, revealing their roles in shaping emotions and trust. The study positions T as a central driver of AISRs' acceptance and reveals its co-existence with OB and BI. By contextualizing the AIDUA model with local norms, the researchers move beyond mere replication toward offering decolonized, context-sensitive approaches to increase AISRs' adoption in the Global South.

In practice, these findings guide hotel and marketing managers to strategically prioritize trust-building and positive emotional experiences, as these are key predictors of AISR acceptance. Moreover, AISRs' developers and designers should consider optimizing AISRs' functionality and reducing perceptions of time-related and intellectual burdens, rather than relying on anthropomorphic features. For marketers, educational campaigns that train concerned stakeholders and enhance digital literacy are recommended to increase AISR acceptance. By presenting AISRs as both valuable and enjoyable, Hospitality firms can address communal concerns and bolster customer confidence.

The limitations of this study are that data were collected from digital platforms, which may exclude digitally illiterate and offline consumers, thereby limiting its generalisability to other contexts. Additionally, because AISRs were still in their infancy, some participants lacked direct experience with AISRs in the South African Hospitality industry. Future studies should therefore conduct a longitudinal study to examine changes in consumer perceptions and expectations as AISR evolves in the industry.

This study provides the first full-scale psychometric validation of the original constructs of the AIDUA model, confirming its robustness in South Africa's Hospitality industry. Results demonstrate that HM, SI, PE, T and EM influence consumers' acceptance of AISRs, whereas AN has a limited impact. Notably, the study positions T as a central driver of AISRs' acceptance in collectivist contexts and reveal its co-existence with OB and BI. Theoretically, the study validates the AIDUA model by contextualizing it, splitting effort expectancy into two aspects: time-related and intellect-related, highlighting a dual influence of effort in emerging markets. In practice, it guides Marketing and Hospitality managers in deploying AISRs by strategically building trust, reducing intellectual strain and emphasising functionality through culturally grounded marketing campaigns. It highlights the need to contextualise AI adoption models for African markets. Thus, moving beyond Western-centric frameworks to contribute to the decolonisation of AISRs adoption research and to support culturally responsive service robot implementation strategies. Further studies should assess the emerging EFt and EF using consumers with actual experience to generalise the AIDUA.

REFERENCES

Abdul-Hamid I.K., Shaikh A.A., Boateng H. and Hinson R.E. (2019). "Customers' perceived risk and trust in using mobile money services: an empirical study of Ghana." *International Journal of E-Business Research (IJEBR)*, 15(1), pp.1–19. Available at: https://doi.org/10.4018/IJEBR.2019010101 [accessed 24 November 2024].

Al-Mawali H., Allozi Y., Nawaiseh A., Zaidan H., Al Natour, A.R. and Alshurideh M., (2025). AI-based audit acceptance and auditors' technology readiness, *International Journal of Data and Network Science*, 9(3), pp. 525–540. Available at: https://doi.org/10.5267/j.ijdns.2024.8.013 [accessed 5 May 2025].

Alsaad, A. (2023). The dual effect of anthropomorphism on customers' decisions to use artificial intelligence devices in hotel services, *Journal of Hospitality Marketing and Management*, 32(8), pp. 1048–1076. Available at: https://doi.org/10.1080/19368623.2023.2223584 [accessed 4 November 2025].

Bandura, A. (1969). *Social learning theory of identificatory processes*. In handbook of socialisation theory and research (pp. 213-262). Chicago, IL: Rand McNally and Company.

Barrett M., Davidson E., Prabhu J., and Vargo S. L. (2024). Customer engagement in utilitarian vs. hedonic service contexts. *Journal of Service Research*, 27(2), pp 183–201. Available at: https://doi.org/10.1177/10946705241242901 [accessed 14 September 2025].

Belanche D., Casaló L.V., and Flavián C. (2021). Frontline robots in tourism and hospitality: service enhancement or cost reduction? *Electronic Markets*, 31(3), pp. 477–492. Available at: https://doi.org/10.1007/s12525-020-00432-5 [accessed 4 November 2024].

Cai D., Li H., and Law R. (2022). Anthropomorphism and OTA chatbot adoption: a mixed methods study, *Journal of Travel and Tourism Marketing*, 39(2), pp. 228–255. https://doi.org/10.1080/10548408.2022.2061672 [accessed 14 November 2025].

Chen G., Fan J., and Azam M. (2024). Exploring artificial intelligence (AI) chatbots adoption among research
    scholars using unified theory of acceptance and use of technology (UTAUT), *Journal of Librarianship and
    Information Science*, p. 09610006241269189. Available at: https://doi.org/10.1177/09610006241269189.
    [accessed 14 November 2025].

Chen Q., Gong Y., Lu Y. and Luo. X (2025). The golden zone of AI's emotional expression in frontline chatbot service
    failures, *Internet Research*, 35(3), pp. 1065–1103. Available at: https://doi.org/10.1108/INTR-07-2023-0551.
    [accessed 5 December 2025].

Chi O.H., Chi C.G., Gursoy D. and Nunkoo R. (2023). Customers' acceptance of artificially intelligent service robots:
    the influence of trust and culture, *International Journal of Information Management*, Vol. 70, p. 102623. Available
    at: https://doi.org/10.1016/j.ijinfomgt.2023.102623 [accessed 4 May 2024].

Christou P., Simillidou A. and Stylianou M. C. (2020). Tourists' perceptions regarding the use of anthropomorphic
    robots in tourism and hospitality. International Journal of Contemporary Hospitality Management, 32(11), pp
    3665–3683. Available at: https://doi.org/10.1108/IJCHM-05-2020-0423 [accessed 6 May 2024].

Cintamür, İ.G. (2024). Acceptance of artificial intelligence devices in banking services: moderation role of technology
    anxiety and risk aversion, *International Journal of Bank Marketing,* 42(7), pp. 2143–2176. Available at:
    https://doi.org/10.1108/IJBM-10-2023-0563 [accessed 4 November 2025].

Davis, F.D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology,
    MIS Quarterly, 13(3), p. 319. Available at: https://doi.org/10.2307/249008 [accessed 14 November 2024].

Della Corte. V., Sepe F., Gursoy D. and Prisco A. (2023). Role of Trust in customer attitude and behaviour formation
    towards social service robots*, International Journal of Hospitality Management*, Vol. 114, p.103587.
    https://doi.org/10.1016/j.ijhm.2023.103587 [accessed 4 November 2025].

Dube, K. (2024). The state of technology deployment in South Africa's tourism and hospitality industry, in Tourism
    and Hospitality for Sustainable Development: Volume Two: *Emerging Trends and Global Issues. Springer*, pp.
    149–161. Available at: https://doi.org/10.1007/978-3-031-63073-6_9 [accessed 4 May 2025].

Eke D.O., Chintu S.S., and Wakunuma K. (2023). Towards Shaping the Future of Responsible AI in Africa, in D.O.
    Eke, K. Wakunuma, and S. Akintoye (eds.) Responsible AI in Africa. Cham: Springer International Publishing
    (*Social and Cultural Studies of Robots and AI),* pp. 169–193. Available at: https://doi.org/10.1007/978-3-031-
    08215-3_8 [accessed 4 November 2025].

Espinoza-Bravo M.G., Cabezas-Cabezas R., Pérez-Cepeda M., Carvache-Franco O. and Carvache-Franco W.
    (2025). AIDUA (artificial intelligence device use and acceptance) model to assess the acceptance of AI in the
    learning practices of higher education students, *Cogent Education*, 12(1). Available at:
    https://doi.org/10.1080/2331186X.2025.2560618 [accessed 4 November 2025].

Fuentes-Moraleda L., Díaz-Ocejo J., Muñoz-Mazón A. and Orea-Giner A. (2020). Interaction between hotel service
    robots and humans: A hotel-specific Service Robot Acceptance Model (sRAM), *Tourism Management
    Perspectives,* 36, p. 100751. Available at: https://doi.org/10.1016/j.tmp.2020.100751 [accessed 16 September
    2024].

Grazzini L., Viglia G. and Nunan D. (2023). Dashed expectations in service experiences: Effects of robots' human-likeness on customers' responses. *European Journal of Marketing,* 57(3), pp 582–607. Available at: https://doi.org/10.1108/EJM-03-2021-0220 [accessed 16 September 2024].

Hair J. F., Risher J. J., Sarstedt M. and Ringle C. M. (2019). When to use and how to report the results of PLS-SEM, *European Business Review*, Vol. 31 No. 1, pp. 2-24. https://doi.org/10.1108/EBR-11-2018-0203 [accessed 16 May 2024].

Heber M., and Schneider S. (2020). Cannot stop the feeling: influence of incidental emotions on manager's willingness to delegate to AI, *Academy of Management Proceedings*, Vol. 1 https://doi.org/10.5465/AMBPP.2020.19462abstract [accessed 26 May 2024].

Ivanov S., Gretzel U., Berezina K., Sigala M., and Webster C. (2019). Progress on robotics in hospitality and tourism: a review of the literature, *Journal of Hospitality and Tourism Technology*, Vol. 10 No. 4, pp. 489–521. https://doi.org/10.1108/JHTT-08-2018-0087 [accessed 10 April 2024].

Jameel A. S., Abdulnabi S. M., Thabit T. H., and Alheety A. S. (2024). Examining the intentions and behaviours of using e-wallets, *2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA)*, https://doi.org/10.1109/eSmarTA62850.2024.10638887 [accessed 16 May 2025].

Jembere S.T., Moodley P., and Kiliswa N. (2023). Acceptance of Professional Service Robots: A Cross-Cultural Study, *African Journal of Inter/Multidisciplinary Studies*, 5(1), pp. 1–11. Available at: https://doi.org/10.51415/ajims.v5i1.1162. [accessed 16 May 2025].

Jembere S.T., and Moodley P. (2024). Consumer Concerns on Adopting AI Service Robots in the South African Hospitality Industry, *Interdisciplinary Journal of Economics and Business Law*, 13 (Special Issue), pp. 329–353. Available at: https://www.researchgate.net/publication/396677316_Consumer_Concerns_on_Adopting_AI_Service_Robots_in_the_South_African_Hospitality_Industry. [accessed 16 December 2025].

Jembere S.T. and Revesai Z. (2025). Personality-Driven AI Service Robot Acceptance in Hospitality: An Extended AIDUA Model Approach. Tourism and Hospitality, 6(4), p.214. Available at: https://doi.org/10.3390/tourhosp6040214 [accessed 13 November 2025].

Khan S. and Khan S. U. (2024). Tourist motivation to adopt smart hospitality: the impact of smartness and technology readiness. *Journal of Hospitality and Tourism Insights*. Available at: https://doi.org/10.1108/jhti-04-2024-0335 [accessed 16 December 2025].

Kondo T.S. and Diwani S.A. (2023). Artificial intelligence in Africa: a bibliometric analysis from 2013 to 2022. *Discover Artificial Intelligence,* 3(34). Available at: https://doi.org/10.1007/s44163-023-00084-2 [accessed 16 December 2025].

Kwinda H.Q. and Wakelin-Theron N. (2025). Customers' satisfaction and adaptations to service robots in a hotel environment, *Tourism and Hospitality Management*, 31(2), pp. 293–306. Available at: https://doi.org/10.20867/thm.31.2.10 [accessed 16 December 2025].

Ladeira W., Perin, M.G. and Santini F. (2023). Acceptance of service robots: a meta-analysis in the hospitality and tourism industry, *Journal of Hospitality Marketing and Management,* 32(6), pp. 694–716. Available at: https://doi.org/10.1080/19368623.2023.2202168 [accessed 16 December 2025].

Lazarus, R. S. (1991). *Emotion and adaptation.* New York: Oxford University Press.

Lu Q., Rong B., Men, X., Luo X. and Chang Q. (2024). WeChat adoption among older adults and urban-rural differences in China. *International Journal of Human-Computer Interaction.* Available at: https://doi.org/10.1080/10447318.2024.2364475 [accessed 16 December 2025].

Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A., & Patterson, P. G. (2020). Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps? Journal of Service Theory and Practice, 30(3), 361–391. Available at: https://doi.org/10.1108/JSTP-04-2019-0088 [accessed 27 January 2026].

Ma X., and Huo Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of the AIDUA framework. *Technology in Society*, Vol. 75, p. 102362. https://doi.org/10.1016/j.techsoc.2023.102362 [accessed 16 December 2025].

Maimela C. and Mbonde P. (2025). Artificial intelligence in South African universities: curriculum transformation and decolonisation—aid or obstacle? *Frontiers in Sociology,* 10. Available at: https://doi.org/10.3389/fsoc.2025.1543471 [accessed 26 December 2025].

Mangaroo-Pillay M., Roopa M. and Maisiri W. (2023). Could digital Ubuntu be the South African version of Industry 4.0? *South African Journal of Industrial Engineering*, 34(1), pp.1–12. Available at: https://hdl.handle.net/10520/ejc-indeng_v34_n1_a2 [accessed 16 May 2025].

May W., Conradie N., and Van Zyl C. (2024). Testing the relationships regarding hotel guests' perception of robots in 4- and 5-star hotels, South Africa, in V. Katsoni and G. Cassar (eds.) Recent Advancements in Tourism Business, Technology and Social Sciences. Cham: *Springer Nature Switzerland (Springer Proceedings in Business and Economics)*, pp. 431–445. Available at: https://doi.org/10.1007/978-3-031-54338-8_24 [accessed 16 November 2025].

Mei H., Bodog S.-A. and Badulescu D. (2024). Artificial intelligence adoption in sustainable banking services: the critical role of technological literacy, *Sustainability* (Switzerland), 16(20). Available at: https://doi.org/10.3390/su16208934 [accessed 11 June 2025].

Mogaji E., Viglia G., Srivastava P., and Dwivedi Y.K. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence? *International Journal of Contemporary Hospitality Management*, 36(10), pp. 3324–3339. Available at: https://doi.org/10.1108/IJCHM-08-2023-1271 [accessed 11 May 2025].

Mohammed F. and Seymour L.F. (2023). The decision criteria used by large organisations in South Africa for adopting artificial intelligence. In: Pillay, A., Jembere, E., J. Gerber, A. (eds) Artificial Intelligence Research. SACAIR 2023. Communications in Computer and Information Science, vol 1976. Springer, Cham. https://doi.org/10.1007/978-3-031-49002-6_6 [accessed 11 May 2025].

Munoriyarwa A., Chiumbu S. and Motsaathebe G. (2023). Artificial intelligence practices in everyday news production: the case of South Africa's mainstream newsrooms, *Journalism Practice*, 17(7), pp. 1374–1392. Available at: https://doi.org/10.1080/17512786.2021.1984976 [accessed 11 May 2025].

Musakuro R. and Gie L. (2024). University staff's intentions to adopt e-health tools for digital mental health services in post-pandemic South Africa. *Sa Journal of Information Management,* 26(1). Available at: https://doi.org/10.4102/sajim.v26i1.1897 [accessed 11 May 2025].

Mutlu, A.Y. (2024). Users' acceptance of generative artificial intelligence based on chatbot use, in. *UBMK 2024 - Proceedings: 9th International Conference on Computer Science and Engineering*, pp. 343–348. Available at: https://doi.org/10.1109/UBMK63289.2024.10773553 [accessed 13 June 2025].

Ngubelanga A. and Duffett R. (2021). Modelling mobile commerce applications' antecedents of customer satisfaction among millennials: an extended TAM perspective," *Sustainability*, 13(11), p. 5973. Available at: https://doi.org/10.3390/su13115973 [accessed 13 June 2025].

Oliver, R.L., 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research,* 17(4), pp.460–469. Available at https://doi.org/10.2307/3150499 [accessed 26 January 2026].

Pitardi V., Wirtz J., Paluch S. and Kunz W.H. (2022). Service robots, agency, and embarrassing service encounters. *Journal of Service Management*, 33(2), 389–414. Available at: https://doi.org/10.1108/JOSM-12-2020-0435 [accessed 13 June 2025].

Qian Y. and Wan X. (2024). Influence of robot anthropomorphism on consumer attitudes toward restaurants and service providers*, International Journal of Hospitality Management*, Vol. 123, p. 103939. Available at: https://doi.org/10.1016/j.ijhm.2024.103939 [accessed 11 May 2025].

Rasheed H. M. W., Chen Y., Khizar H. M. U. and Safeer A. A. (2023). Understanding the factors affecting AI services adoption in hospitality: The role of behavioral reasons and emotional intelligence. *Heliyon*, Vol. 9 No. 6. Available at: https://doi.org/10.1016/j.heliyon.2023.e16968 [accessed 12 May 2025].

Reid S. A., Vetter G., Lackes R. and Sieperman M. (2024). Is it all about fun? Self-service technology acceptance in Germany. *The International Review of Retail, Distribution and Consumer Research*. Available at: https://doi.org/10.1080/09593969.2024.2342795 [accessed 18 May 2025].

Roy P., Ramaprasad B.S., Chakraborty M., Prabhu N. and Rao S. (2024). Customer acceptance of use of artificial intelligence in hospitality services: An Indian hospitality sector perspective. *Global Business Review*, 25(3), pp.832-851. Available at: https://doi.org/10.1177/0972150920939753 [accessed 11 May 2025].

Sarfo J.O., Tachie-Donkor G., Aggrey E.K. and Mordi P., (2024). Attitudes, perceptions, and challenges towards artificial intelligence adoption in Ghana and Nigeria: a systematic review with a narrative synthesis attitudes, perceptions, and challenges towards artificial intelligence." *International Journal of Media and Information Literacy*, 9(2), pp.437-452. Available at: https://doi.org/10.13187/ijmil.2024.2.437 [accessed 11 May 2025].

Schoeman F. and Seymour L.F. (2022). "Understanding the low adoption of AI in South African medium-sized organisations." *In Proceedings of 43rd Conference of the South African Institute* (Vol. 85, pp. 257–269). Available at: https://doi.org/10.29007/c4rr [accessed 20 May 2025].

Shum C., Kim H. J., Calhoun J. R. and Putra E. D. (2024). "Uncanny valley effects on employee fear and industry turnover intentions". *International Journal of Hospitality Management*, 119, Article 103762. Available at: https://doi.org/10.1016/j.ijhm.2024.103762 [accessed 21 May 2025].

Vafaei-Zadeh A., Nikbin D., Loo J. and Hanifah H. (2024). Unlocking Generation Y's continuance intentions in personal cloud storage services: an extended expectation confirmation model analysis, *The Electronic Library*, Vol. 42 No. 5, pp. 827–847. Available at: https://doi.org/10.1108/EL-03-2024-0097 [accessed 11 May 2025].

Venkatesh V., Thong J.Y. and Xu X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, Vol. 36 No, 1, pp.157-178. Available at: https://doi.org/10.2307/41410412 [accessed 17 May 2025].

Venkatesh V., Morris M.G., Davis G.B. and Davis F.D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, pp.425–478. Available at: https://doi.org/10.2307/30036540 [accessed 17 May 2025].

Vitezić V. and Perić M. (2021). Artificial intelligence acceptance in services: connecting with Generation Z. *The Service Industries Journal*, 41(13-14), pp.926–946. Available at: https://doi.org/10.1080/02642069.2021.1974406 [accessed 11 June 2025].

Wang G., Obrenovic B., Gu X. and Godinic D., (2025). Fear of the new technology: Investigating the factors that influence individual attitudes toward generative Artificial Intelligence (AI). Current psychology, pp.1–18. Available at: https://doi.org/10.1007/s12144-025-07357-2 [accessed 11 December 2025].

Westaby, J.D. (2005). Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior. *Organizational Behavior and Human Decision Processes*, 98(2), pp.97–120. Available at: https://doi.org/10.1016/j.obhdp.2005.07.003 [accessed 26 January 2026].

Zhang H., Li F., and Chen X. (2025). Implicit expectations and cognitive construction: dual pathways shaping graduate students' sustained engagement with generative AI, *Journal of Educational Computing Research*, 63(4), pp. 1024–1054. Available at: https://doi.org/10.1177/07356331251335185 [accessed 11 December 2025].