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 examines consumer acceptance of AISRs through the AIDUA framework and tests its validity in a South African context. Data were collected via an online survey from 301 participants using a scenario-based method and analyzed using Structural Equation Modeling (SEM) in AMOS. Trust emerged as the strongest predictor of behavioural intention, while hedonic motivation and social influence significantly shaped performance expectancy. Anthropomorphism increased perceived time-based effort, suggesting that human-like features may signal interaction complexity. The study refines the AIDUA model by separating effort expectancy into time-based and intellect-based dimensions, revealing their distinct roles in shaping emotional responses and trust. In practice, to boost AISR acceptance, hospitality managers and marketers should focus on enhancing enjoyment and trust whilst avoiding over-humanization in the design and deployment of AISR. 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

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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 such as Japan's Henn-na Hotel deployed AISRs in 2015, Africa's first deployment 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 more by crisis than by 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 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 decolonisation 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 on the service frontline to perform tasks that traditionally require 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, particularly in markets such as 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 in its nascent stages 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 (Jembere *et al.* 2025). 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 serve as both a prerequisite and a 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, drawing on 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 PE of AISR, which is viewed as community-endorsed (Gursoy et al. 2019). Thus, this study proposes

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

SI also affects EE, the perceived difficulty associated with engaging with AISRs (Gürsoy et al., 2019). When individuals lack direct experience with AISRs, they often rely on the opinions and experiences of their social networks to judge whether the technology is easy or difficult to use (Venkatesh et al., 2012; Gürsoy et al., 2019). Positive judgments can reduce users' uncertainty arising from concerns such as job displacement or limited digital literacy, making AISRs appear more intuitive and manageable. As SI increases, perceived EE decreases, establishing a negative relationship. Therefore,

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

3.1.2 Hedonic Motivation, Performance Expectancy, and Effort Expectancy

HM, the pleasure, fun, and novelty derived from using AISRs shape instrumental evaluations through the fulfilment of psychological needs (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 EE 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). In collectivist communities, positive shared experiences during engagement with AISRs enable consumers to cope with difficult tasks and reinforce a collective perception that the interaction is less demanding. Consequently, the study hypothesizes

H4: Hedonic motivation is negatively related *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 if AISR are overly humanised (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 AISRs.

The effect of AN on EE is complex, although negative mechanisms often dominate. While human-like cues may initially activate familiar social schemas that facilitate interaction, excessive AN may also violate expectations for natural communication. (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 becomes ambiguous or confusing, consumers expend greater mental effort 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, we hypothesize that:

H6: Anthropomorphism is positively associated with the effort expectancy of AISRs in South Africa's hospitality industry.

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 perceive them as valuable, thereby generating positive emotional states such as excitement and anticipation (Alsaad 2023; Chi et al. 2023).

H7: Performance expectancy positively influences emotions toward AISRs 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 difficult or cognitively demanding to use, they judge the interaction as challenging, leading to a negative response (Ma and Huo 2023). AI identity threats may further intensify this response when highly advanced AISRs appear intimidating, thereby increasing anxiety and frustration (Alsaad, 2023). Therefore,

H8: Effort expectancy negatively impacts emotions toward AISRs 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 AISRs.

Conversely, if consumers perceive AISRs as requiring effort to use (EE), this signals risk and uncertainty, thereby reducing trust. Difficult or cognitively demanding interactions can undermine perceptions of reliability and competence during service encounters (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, EM drives BI through situational evaluations (Heber and Schneider 2020). PE and reduced EE can generate positive emotional reactions such as anticipation and enjoyment, thereby increasing willingness to engage with AISRs (Jameel et al., 2024). Positive EM from SI and HM strengthens AISR acceptance (Vafaei-Zadeh et al. 2024). Therefore,

H11: Positive emotions significantly enhance behavioural intention toward AISRs.

Conversely, consumers may resist AISR adoption due to concerns about reduced human interaction or discomfort with anthropomorphic technologies (Gursoy et al. 2019; Della Corte et al. 2023). However, positive emotional experiences during interaction can reduce such resistance. Consistent with Cognitive Appraisal Theory, when consumers appraise AISRs as beneficial (high PE) and easy to use (low EE), they generate positive emotions that counteract objections to AISR adoption (Gursoy et al., 2019). *Thus,*

H12: Positive emotions negatively influence objections to using AISRs.

3.1.7 Trust, Behavioural Intention and Objection

Trust influences AISR behavioural intentions by reducing uncertainty and fostering positive attitudes through assessments of reliability, competence, and benefits, particularly in emerging service environments where technological uncertainty remains salient (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.

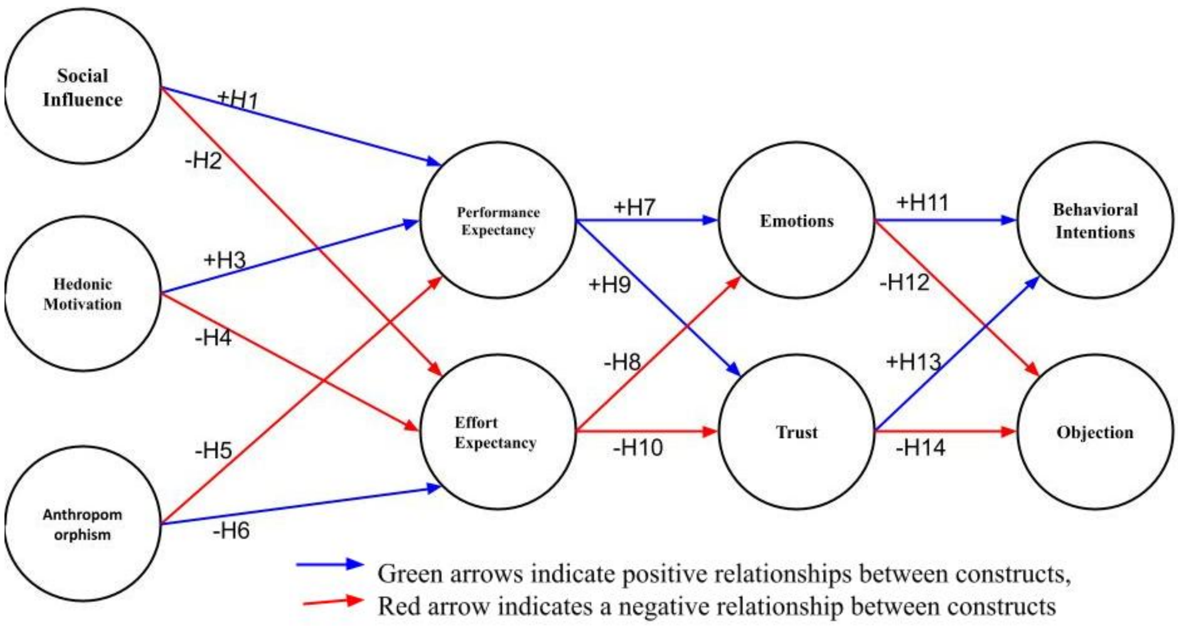

FIGURE 1: PROPOSED AIDUA FRAMEWORK

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. A purposive sampling strategy targeted individuals with hotel experience and exposure to AI technologies. Convenience and snowball techniques were subsequently used to increase participation. The survey link was disseminated via various social media platforms, including LinkedIn, Instagram, WhatsApp, and Facebook, to ensure diverse participation across age groups and broader exposure to AI technologies and AISRs.

4.1 SAMPLE SIZE AND POWER ANALYSIS

A priori power analysis ($\alpha = 0.05$, power = 0.80) indicated a minimum sample size of n = 117 for medium effects. The final N = 301 achieved powers > 0.99, exceeding 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 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 that described a hotel service interaction involving delivery robots, thereby introducing participants to hypothetical AISR interactions. All latent constructs were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A pilot study with 50 participants was conducted to assess the clarity and reliability of the measurement items. This confirmed 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 were analysed using the Structural Equation Modelling (SEM) in AMOS. 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 was assessed using the heterotrait–monotrait ratio (HTMT < 0.85). Standard-method bias was assessed using Harman's single-factor test (34.2%). Exploratory analysis revealed that effort expectancy consisted of two distinct dimensions; therefore, the construct was modelled as time-based effort (EFt) and intellectual effort (EF). 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, with 72.69% of the total variance explained. 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, AN, in contrast to the high enjoyment of AISR's HM and positive emotional attachments. Participants expressed moderate behavioral intentions to use AISR, alongside significant concerns about its potential adverse outcomes, OB, 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: $\beta = 0.302$, $p < 0.001$). However, its effect on EE was mixed. SI did not have a significant effect on EFt (H2a: $\beta = 0.039$, $p = 0.628$) but showed a significant positive relationship with EF (H2b: $\beta = 0.188$, $p = 0.007$), contrary to expectations. HM was a strong positive predictor of PE. (H3: $\beta = 0.335$, $p < 0.001$) and EF (H4b: $\beta = 0.447$, $p < 0.001$). Its effect on EFt was not significant (H4a: $\beta = -0.048$, $p = 0.533$), and AN revealed a distinct pattern. Its relationship with PE was not significant (H5: $\beta = 0.009$, $p = 0.874$). Contrary to expectations, AN had a significant positive relationship with EFt (H6a: $\beta = 0.213$, $p = 0.004$), whilst its relationship with EF was not significant (H6b: $\beta = -0.053$, $p = 0.378$).

Both performance and effort perceptions were significant antecedents to emotional and trust responses. PE positive predicted EM (H7: $\beta = 0.307$, $p < 0.001$) and T (H9: $\beta = 0.508$, $p < 0.001$). EFt showed a significant negative relationship with both EM (H8a: $\beta = -0.327$, $p < 0.001$) and T (H10a: $\beta = -0.129$, $p = 0.020$). Conversely, EF positively predicted EM (H8b: $\beta = 0.180$, $p = 0.006$) and T (H10b: $\beta = 0.383$, $p < 0.001$), contrary to expectations. Finally, both EM and T were significant predictors of BI. EM positively influenced BI (H11: $\beta = 0.185$, $p < 0.001$) and reduced OB (H12: $\beta = -0.434$, $p < 0.001$). T was a powerful positive predictor of BI (H13: $\beta = 0.636$, $p < 0.001$) but showed a positive relationship with OB (H14: $\beta = 0.302$, $p < 0.001$), contrary to expectations.

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

Hypothesis	Path	β	S.E.	C.R	p	Decision
H1	SI → PE	0.302	0.075	4.211	***	Supported
H2a	SI → EFt	0.039	0.091	0.485	0.628	Not Supported
H2b	SI → EF	0.188	0.100	2.693	0.007	Not Supported
H3	HM → PE	0.335	0.061	4.891	***	Supported
H4a	HM → EFt	-0.048	0.075	-0.623	0.533	Not Supported
H4b	HM → EF	0.447	0.085	6.365	***	Not Supported
H5	AN → PE	0.009	0.045	0.159	0.874	Not Supported
H6a	AN → EFt	0.213	0.063	2.850	0.004	Supported
H6b	AN → EF	-0.053	0.065	-0.882	0.378	Not Supported
H7	PE → EM	0.307	0.077	4.600	***	Supported
H8a	EFt → EM	-0.327	0.075	-4.607	***	Supported
H8b	EF → EM	0.180	0.056	2.740	0.006	Not Supported
H9	PE → T	0.508	0.067	6.929	***	Supported
H10a	EFt → T	-0.129	0.047	-2.324	0.020	Supported
H10b	EF → T	0.383	0.045	5.804	***	Not Supported
H11	EM → BI	0.185	0.055	3.449	***	Supported
H12	EM → OB	-0.434	0.081	-6.254	***	Supported
H13	T → BI	0.636	0.093	8.729	***	Supported
H14	T → OB	0.302	0.101	4.344	***	Not Supported

Notes
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 = Behavioural Intention; OB = Objection; β = Standardized coefficient; *** $p < 0.001$

Source(s): Authors' Analysis

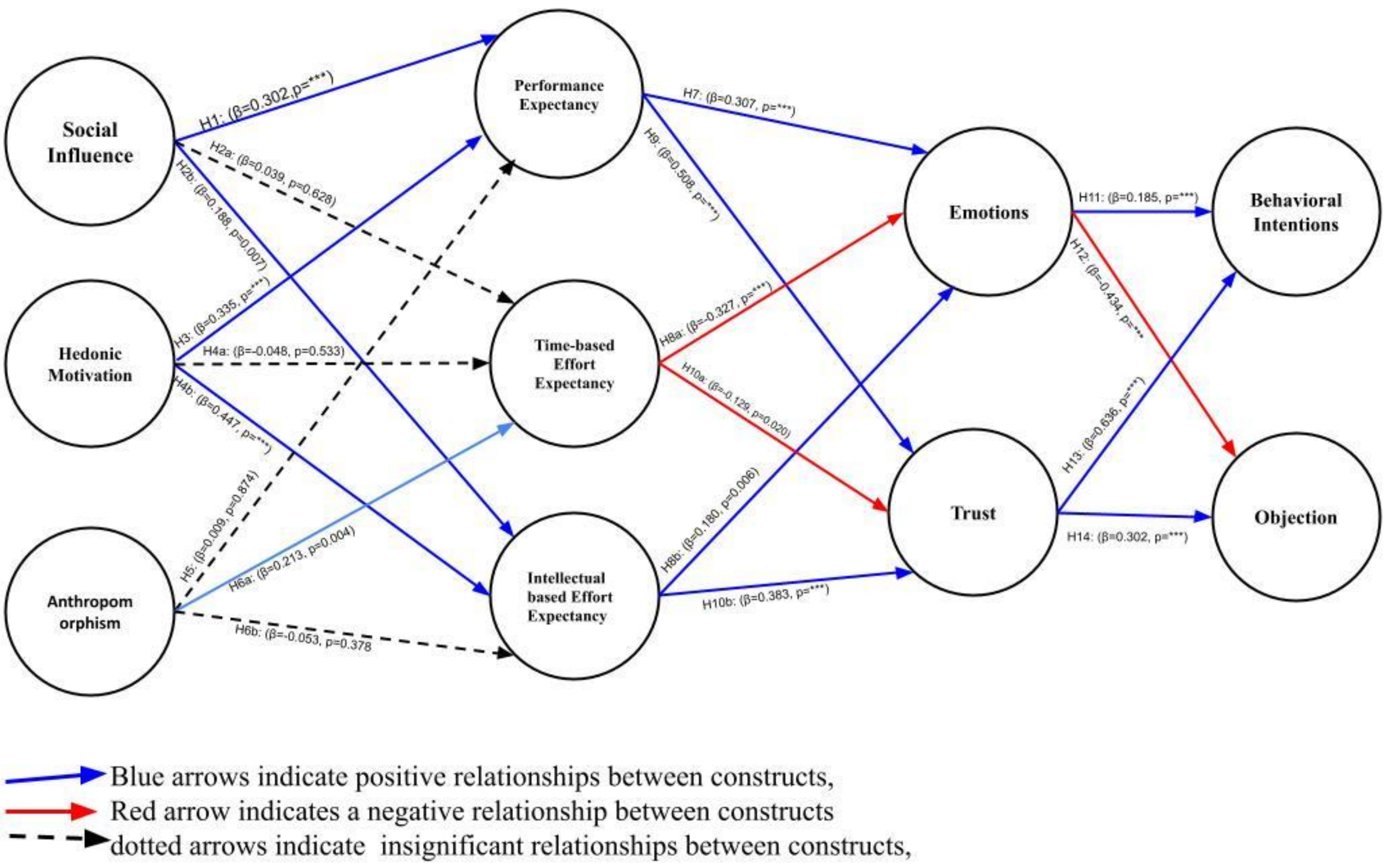

FIGURE 2: EXTENDED AIDUA MODEL

6. DISCUSSION, RECOMMENDATIONS, AND CONCLUSION

This study improves the AIDUA model by examining the factors that influence South African Hospitality consumers' acceptance of AISRs. The model explains 72.69% of the variance in behavioural intention, confirming the explanatory power of the AIDUA framework. 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 AISRs' PE within 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). HM positively influenced EF, contrary to expectations, suggesting that enjoyable interactions with AISRs may encourage consumers to engage with the cognitive effort required to understand the technology.

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. These findings suggest that anthropomorphic features may introduce perceived complexity of interaction rather than enhance functional evaluations. 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). Contrary to expectations, EF positively predicted EM, suggesting that cognitive engagement with AISRs may generate curiosity and interest rather than frustration. EFt was found to negatively influence 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 studies, which consider trust only as a reduction in resistance (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 showed a significant positive relationship with objection, contradicting H14. This phenomenon is understood through Behavioral Reasoning Theory (BRT), which posits that individuals simultaneously hold both "reasons for" and "reasons against" a behavior (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 within local norms, the researchers move beyond mere replication to offer 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. To strengthen the robustness of future research, combining digital surveys with offline Data collection could provide a more comprehensive understanding of consumer perceptions, especially in regions with lower digital literacy.

This study provides one of the first validations of the AIDUA model in an African hospitality context, 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 reveals 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.

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