

Article

Personality-Driven AI Service Robot Acceptance in Hospitality: An Extended AIDUA Model Approach

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Abstract

The hospitality industry's rapid adoption of AI service robots has revealed significant variability in consumer acceptance, highlighting the need for personality-based implementation strategies rather than one-size-fits-all approaches. This study extended the AIDUA (Artificial Intelligence Device Use Acceptance) model by integrating Big Five personality traits and robot design characteristics to understand AI service robot acceptance among South African hospitality consumers. A convergent mixed-methods design combined structural equation modeling of survey data ($n = 301$) with natural language processing analysis of qualitative responses to examine personality-acceptance pathways and consumer concern themes. Results demonstrated that neuroticism negatively influenced performance expectancy ($\beta = -0.284, p < 0.001$), while openness enhanced hedonic motivation and preference for humanoid robots ($\beta = 0.347, p < 0.001$). Privacy concerns partially mediated the neuroticism-rejection relationship, while transparency interventions significantly improved acceptance among high-neuroticism consumers (effect size $d = 0.98$). Four distinct consumer segments emerged: Tech Innovators (23.1%), Pragmatic Adopters (31.7%), Cautious Sceptics (28.4%), and Social Moderates (16.8%), each requiring tailored robot deployment strategies. The extended AIDUA framework explained 68.4% of variance in acceptance intentions, providing hospitality operators with empirically validated guidelines for matching robot types to guest personality profiles, optimizing guest satisfaction while minimizing resistance through culturally sensitive implementation strategies.

Keywords: artificial intelligence service robots; personality traits; technology acceptance; hospitality industry; AIDUA framework; human–robot interaction; consumer segmentation



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1. Introduction

The tourism industry has witnessed unprecedented growth in artificial intelligence service robot (AISR) deployment over the past decade. Leading implementations include reception robots like Hilton's Connie, autonomous delivery systems like Relay robots, humanoid concierges like Pepper, and restaurant service robots like Bear Robotics' Servi (Wirtz et al., 2018; Alejandro et al., 2024). Post-pandemic demands for contactless service and persistent labor shortages have accelerated this adoption. Market projections indicate exponential growth through 2030, expanding from Asia-Pacific markets to Western venues (Balaji et al., 2024).

Despite technological advances, the tourism industry faces unique deployment challenges. Guests demand personalized, emotionally resonant experiences that build trust

and comfort (Belanche et al., 2021). The industry serves diverse populations with varying cultural backgrounds, age groups, technology comfort levels, and psychological traits. In multicultural markets like South Africa, these challenges become particularly pronounced due to diverse cultural values, ubuntu philosophy emphasizing communal relationships, and varying technology readiness levels across demographic groups. Critical service moments require careful balance between automation efficiency and human touch (Kim & Johye, 2023). Service quality directly impacts guest satisfaction, loyalty, and revenue.

Current technology adoption models show limitations in tourism environments (Gursoy et al., 2019; Jembere et al., 2025). While the AIDUA framework addresses cognitive appraisal processes, it inadequately accounts for how individual differences influence guest responses to robots across service touchpoints (Robert et al., 2020). Research lacks psychology-based segmentation for robot deployment, leaving operators without matching strategies. There is insufficient understanding of how robot design characteristics interact with guest psychological traits to influence adoption decisions (Belanche et al., 2021; Kim & Johye, 2023; Niu et al., 2022). Mismatches between robot design and guest expectations can lead to negative experiences.

This study addresses the need for psychology-specific deployment strategies. Current one-size-fits-all approaches often result in service failures and guest complaints. Operators require frameworks for understanding which robot types work best for specific guest segments and how to mitigate concerns in culturally diverse markets like South Africa (Law et al., 2023; Gao & Liu, 2022). This research provides insights for deploying robot technologies that account for guest psychology, emotional responses, and design preferences (Abufawr et al., 2024).

The study assesses how Big Five psychological traits influence adoption-related constructs such as performance expectancy, hedonic motivation, and social influence. It examines the moderating role of robot design type and explores the mediating role of privacy concerns, particularly amongst high-neuroticism individuals (Lee et al., 2021). The research develops psychology-based deployment strategies for optimal AISR adoption.

This research makes three key contributions:

1. Extends the AIDUA model by integrating Big Five psychological traits and robot design characteristics within South African tourism settings, demonstrating how individual differences serve as antecedents to cognitive appraisal processes in service robot adoption
2. Develops a hybrid analytical approach combining structural equation modeling with natural language processing to examine quantitative psychology-adoption pathways and qualitative guest concern themes
3. Creates an empirically validated psychology-based deployment framework offering actionable guidelines for matching robot types to guest psychological profiles while considering cultural sensitivities

The paper proceeds through six sections, from a theoretical foundation to practical application. Section 2 presents a literature review and theoretical framework development. Section 3 details methodology including scenarios, sampling strategies, and mixed-methods approaches. Section 4 presents results demonstrating psychology-robot adoption patterns and user segments. Section 5 discusses findings and develops deployment strategies. Section 6 concludes with implications, limitations, and future research directions.

2. Literature Review

2.1. Technology Acceptance Models Evolution

The Technology Acceptance Model (TAM) established perceived usefulness and ease of use as primary adoption drivers (Davis, 1989), whilst the Unified Theory of Accep-

tance and Use of Technology (UTAUT) expanded this framework by incorporating social influence and facilitating conditions (Venkatesh et al., 2003). However, these models demonstrate significant limitations when applied to artificial intelligence service robots due to their focus on conventional technologies and neglect of anthropomorphic characteristics that fundamentally distinguish AI systems from traditional tools (Martin, 2022; Hong et al., 2021).

Critical gaps emerge when applying traditional models to AI technologies. TAM and UTAUT assume rational, utility-driven adoption processes but fail to account for emotional and social complexities inherent in human–robot interactions. Adaptations of these models across diverse technological environments, from educational settings to wearable devices, reveal consistent limitations in capturing individual differences and situational factors (Hong et al., 2021; W. Wang et al., 2022). These frameworks cannot explain why functionally superior robots may be rejected due to aesthetic discomfort, or why less capable but more appealing robots achieve higher user approval.

The Artificial Intelligence Device Use Acceptance (AIDUA) model addresses these limitations by integrating cognitive appraisal theory with technology adoption principles (Gursoy et al., 2019). AIDUA recognizes that users evaluate AI technologies through primary appraisal (social influence, hedonic motivation, anthropomorphism) and secondary appraisal (performance expectancy, effort expectancy), which generate emotions that determine behavioral intentions (Jembere et al., 2025). This framework specifically accounts for anthropomorphism as a unique characteristic, making it more suitable for understanding robot adoption. However, AIDUA's cognitive focus overlooks how stable individual differences filter these appraisal processes, creating a theoretical gap this study addresses.

2.2. Artificial Intelligence Service Robots in Tourism

Tourism has emerged as a leading sector for robot deployment, driven by service-intensive operations and labor challenges. Current deployments span reception robots like Hilton's Connie, autonomous delivery systems such as Relay robots, and restaurant servers like Bear Robotics' Servi (Wirtz et al., 2018; Alejandro et al., 2024). These robots serve diverse functions, representing a fundamental shift in service delivery paradigms (Ma et al., 2021).

The anthropomorphic design spectrum creates contradictory adoption patterns that existing research inadequately explains. Studies show that moderate human-likeness often proves optimal, whilst extreme anthropomorphism may trigger uncanny valley effects (Zhang et al., 2021; Kim & Johye, 2023). However, this relationship shows inconsistency across studies and populations. Some research finds positive linear associations between anthropomorphism and approval, while other studies report inverted U-shaped curves or negative correlations. These contradictions suggest that anthropomorphism effects depend on moderating factors not adequately captured in current models.

Guest expectations emphasize personalized, emotionally resonant experiences, creating unique challenges where service quality directly impacts satisfaction and revenue (Lei et al., 2023; C. Wang & Papastathopoulos, 2023). The diversity of demographics and cultural backgrounds further complicates adoption patterns, necessitating understanding of individual differences (Jembere et al., 2023; Mariani & Borghi, 2021).

2.3. Individual Psychology in Technology Adoption

Individual differences significantly influence technology adoption, yet this area remains critically underexplored in robot research despite compelling theoretical rationale. The Big Five framework provides the most robust and empirically validated approach to understanding individual differences, with extensive cross-cultural validation and demon-

strated predictive power across diverse behavioral domains (Costa & McCrae, 1992). Research across various technological environments, from sports wearables to educational tools, consistently demonstrates that psychological factors moderate adoption relationships (W. Wang et al., 2022; Hong et al., 2021). Meta-analytic evidence demonstrates that openness correlates positively with innovation adoption ($\rho = 0.34$), conscientiousness relates to utility-focused evaluations ($\rho = 0.28$), extraversion influences social technology preferences ($\rho = 0.31$), agreeableness affects trust formation ($\rho = 0.26$), and neuroticism relates to technology anxiety and resistance ($\rho = -0.42$) (Devaraj et al., 2008; W. Wang et al., 2022; Shah et al., 2023).

Theoretical models for technology adoption increasingly recognize that individual psychological characteristics serve as fundamental antecedents to cognitive appraisal processes (Chaudhry et al., 2023). These psychological-technology associations become particularly complex with robots due to their anthropomorphic characteristics and social interaction capabilities, creating theoretical tensions not adequately addressed in the current literature (Balaji et al., 2024). For instance, extraverted individuals may appreciate social robots but prefer human interaction, creating competing motivational forces. Similarly, neurotic users may experience heightened anxiety with human-like robots due to uncanny valley effects, but this association may be moderated by transparency and control factors (Mori, 1970). Understanding how psychological traits interact with specific robot design features is crucial, yet current research provides fragmented and contradictory results (Wu et al., 2021).

2.4. Robot Design and User Response

Robot design encompasses physical appearance, behavioral characteristics, and interaction modalities that significantly influence user response (Belanche et al., 2021). However, the anthropomorphism literature reveals significant theoretical inconsistencies and methodological limitations that undermine current understanding.

Critical examination reveals three competing theoretical perspectives: the similarity-attraction hypothesis predicting positive linear effects, the uncanny valley theory suggesting inverted U-shaped patterns, and the cognitive load theory proposing that human-like features increase processing demands and reduce approval. These competing predictions create theoretical confusion, while methodological inconsistencies across studies prevent clear resolution.

Physical anthropomorphism includes human-like features such as faces, limbs, and body proportions, whilst behavioral anthropomorphism encompasses natural movement patterns, conversational abilities, and social awareness (González-Jiménez & Pinto, 2024). These design elements interact with user characteristics to create differential response patterns, suggesting that successful robot deployment requires matching design characteristics with target user preferences rather than pursuing universal design solutions. However, current research provides insufficient guidance for deploying such matching strategies in practice (Parvez et al., 2022).

2.5. Extended AIDUA Model Development

This study extends the AIDUA model by incorporating Big Five traits as antecedent variables that shape cognitive appraisal processes to address critical theoretical gaps (Cintamür, 2024; Gursoy et al., 2019). These traits influence how users interpret and respond to robot characteristics during both primary and secondary appraisal stages, creating systematic individual differences in adoption pathways (Kabacińska et al., 2024).

This integration addresses a fundamental limitation in current technology adoption theory: the assumption that cognitive appraisal processes occur uniformly across indi-

viduals. Instead, we propose that these processes are filtered through psychologically based predispositions that systematically influence perception, interpretation, and response patterns (Chaudhry et al., 2023).

Robot design characteristics serve as critical moderating factors that interact with psychological traits to influence outcomes (Belanche et al., 2021; Wu et al., 2021). This extension recognizes that technology adoption emerges from person-environment interactions rather than from either factor independently, aligning with broader theoretical trends toward more nuanced, individual-differences approaches (Lei et al., 2023).

2.6. User Psychology-Robot Design Framework

Current literature reveals systematic patterns in psychological-robot preference associations, though these remain fragmented across studies (Balaji et al., 2024; Shah et al., 2023). Meta-analytic evidence suggests that neuroticism amplifies privacy and error concerns ($d = -0.67$), particularly with anthropomorphic robots. Openness drives preference for humanoid robots offering novel interaction experiences ($d = 0.54$). Extraversion strengthens preference for interactive interfaces ($d = 0.43$), while conscientiousness favors utilitarian designs prioritizing functional efficiency ($d = 0.38$). Agreeableness increases trust in empathetic robots ($d = 0.41$) (Sánchez & Gené-Albesa, 2023; C. Wang & Papastathopoulos, 2023).

These psychological-design associations suggest that successful robot deployment requires sophisticated segmentation strategies, yet current research provides limited practical guidance for execution (Jembere & Moodley, 2024).

2.7. Hypotheses Development

Based on the theoretical framework and critical literature analysis, this study proposes six hypotheses addressing key gaps in current understanding:

Neurotic individuals experience heightened anxiety and uncertainty with unfamiliar technology, reducing confidence in robot reliability (Devaraj et al., 2008; Kabacińska et al., 2024).

H1a. *Neuroticism negatively influences performance expectancy of artificial intelligence service robots.*

Individuals high in openness seek novelty and enjoy interactive, innovative technologies, finding humanoid robots appealing (W. Wang et al., 2022; Shah et al., 2023).

H1b. *Openness positively influences hedonic motivation and preference for humanoid robots.*

Extraverted individuals rely on social cues and peer recommendations, showing responsiveness to social influence (Sánchez & Gené-Albesa, 2023; Balaji et al., 2024).

H1c. *Extraversion positively influences the effect of social influence on robot adoption.*

Anthropomorphism effects vary by robot design and user psychology, with openness enhancing approval while neuroticism triggers rejection (Zhang et al., 2021; Belanche et al., 2021).

H2. *The effect of anthropomorphism on adoption is moderated by robot type and individual traits, such that humanoid robots are favored by high-openness users and rejected by high-neuroticism users.*

Neurotic individuals perceive threats to personal privacy, especially with intrusive technologies (Lee et al., 2021; Chaudhry et al., 2023).

H3a. *Privacy concerns mediate the association between neuroticism and rejection of artificial intelligence service robots.*

Clear explanations of robot functions reduce uncertainty and anxiety, particularly for neurotic users (Gursoy et al., 2019; Cintamür, 2024).

H3b. *Transparency mitigations reduce negative emotional responses, increasing adoption amongst high-neuroticism users.*

3. Research Methodology

3.1. Research Design and Approach

This study employs a convergent mixed-methods design to investigate psychological-robot design interactions in South African tourism settings. The approach integrates quantitative structural equation modeling (SEM) to test hypothesized relationships between psychological traits, robot design characteristics, and adoption outcomes, with qualitative analysis of open-ended responses to understand emotional responses and concerns.

Prior to data collection, the measurement instruments underwent pilot testing with 30 tourism users to ensure face validity and cultural appropriateness within the South African setting. Minor modifications were made to scenario descriptions and scale anchors based on pilot feedback to improve clarity and cultural relevance.

This integration allows triangulation of findings: quantitative results provide statistical validation of relationships (e.g., H1a–H3b), whilst qualitative insights support interpretation of emotional responses, particularly relevant for neuroticism-related hypotheses and transparency concerns. The methodological design reflects the complexity of human–robot interactions, which involve both cognitive appraisals and emotional reactions in diverse cultural settings.

3.2. Sample and Data Collection

The target population comprises South African tourism users aged 18 and above who have varying levels of exposure to artificial intelligence service robots across hotels, restaurants, and tourism venues. Given the early-stage deployment of artificial intelligence robots in many South African settings, the sample includes both experienced and inexperienced users to capture diverse adoption patterns across diverse cultural backgrounds.

A stratified purposive sampling strategy ensures representation across age cohorts (Gen Z to Baby Boomers), cultural backgrounds, and psychological profiles. Participants were recruited via social media (LinkedIn, Facebook, Instagram), tourism networks, and partner hotel properties across major South African cities. While 500 responses were targeted for SEM analysis, the final sample of 301 responses exceeded minimum SEM requirements (10:1 ratio for 25 observed variables = 250) and provided adequate statistical power (0.80) for detecting medium effect sizes. Additional open-ended responses were collected until thematic saturation was reached.

Inclusion criteria comprised South African tourism users aged 18 and above who were proficient in English and had experience as tourism customers within the past two years. Exclusion criteria included participants with cognitive impairments, tourism industry employees, and those unable to access digital surveys to ensure data quality and eliminate potential bias from industry insiders.

3.3. Measurement Instruments

Personality traits were measured using the Big Five Inventory-2 (BFI-2), a 20-item validated instrument capturing five domains: openness, conscientiousness, extraversion, agreeableness, and neuroticism. This instrument demonstrates strong psychometric prop-

erties and cross-cultural validity, including validation within South African populations ($\alpha > 0.80$ for all dimensions). The scale aligns with hypotheses H1a (neuroticism), H1b (openness), and H1c (extraversion).

The AIDUA model constructs were adapted for South African tourism robot settings, including primary appraisal factors (social influence, anthropomorphism, hedonic motivation), secondary appraisal factors (performance expectancy), outcome variables (adoption and rejection), and mediating variables (privacy concerns, emotional response). All constructs were measured using 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) based on previously validated technology adoption instruments.

In the survey, participants were presented with visual scenarios involving four robot types: androids (Sophia-type), humanoid robots (Pepper-type), functional delivery robots (machine-like), and chatbot interfaces, all depicted within South African tourism settings. These scenarios measured preferences and perceived anthropomorphism to facilitate moderation testing in H2 and support H1b.

Open-ended questions explored emotional responses and privacy concerns (supporting H3a and H3b), asking participants to reflect on experiences, expectations, and hesitations regarding artificial intelligence service robots.

3.4. Data Analysis Strategy

SEM was used to test the extended AIDUA framework. Confirmatory Factor Analysis (CFA) validated the measurement model. Structural model testing examined direct effects (neuroticism $\rightarrow$ performance expectancy), indirect effects (neuroticism $\rightarrow$ rejection via privacy concern), and moderation (robot type $\times$ psychological traits $\rightarrow$ adoption). Multi-group analysis explored whether relationships differed across psychological trait levels.

Open-ended responses ($n = 247$ participants providing qualitative data, average response length = 89 words) were analyzed using thematic analysis. Natural Language Processing (NLP) tools supported this analysis: BERTopic (using BERT embeddings) for automated topic modeling to identify concern themes, and VADER (Valence Aware Dictionary and sEntiment Reasoner) for sentiment analysis scoring responses from -1 (negative) to $+1$ (positive). K-Prototypes clustering algorithm was selected for user segmentation as it handles mixed data types (continuous psychological scores and categorical robot preferences) more effectively than traditional k-means clustering.

Common method bias was assessed using Harman's single-factor test, which showed that no single factor accounted for more than 35% of variance, indicating minimal bias concerns. Additional robustness checks included alternative model specifications and bootstrapped confidence intervals.

3.5. Ethical Considerations and Data Management

The study was conducted in accordance with the Declaration of Helsinki and approved by the Durban University of Technology Institutional Research Ethics Committee (DUT-IREC) (protocol code IREC 017/23, approved 21 November 2023). Informed consent was obtained from all participants involved in the study. All procedures followed South African ethical guidelines, including secure and anonymized data storage, participant right to withdraw at any point, and reporting only aggregated results. Special consideration was given to South Africa's diverse cultural backgrounds and privacy expectations, with culturally sensitive language used throughout data collection instruments. The datasets generated and evaluated during the current study are not publicly available due to privacy and confidentiality commitments made to participants but are available from the corresponding author on reasonable request and with appropriate ethical approvals.

3.6. Methodological Contributions

This study contributes methodologically by extending the AIDUA model through integration of psychological traits and robot design features, applying SEM to test psychology-based hypothesis paths (H1a–H3b), and using thematic and sentiment analysis to explore privacy concerns and emotional responses beyond numerical scales. This multi-layered approach provides robust insights for understanding artificial intelligence service robot adoption.

The alignment between research objectives and methodological approaches is summarised in Table 1, which demonstrates how each objective is systematically addressed through appropriate research methods, instruments, and analytical techniques.

Table 1. Alignment of Objectives and Methodology.

	Research Objective	Methodological Approach	Tools/Instruments	Data Analysis Techniques
1.	To assess how Big Five psychological traits influence South African user perceptions of artificial intelligence service robots (hedonic motivation, social influence, performance expectancy)	Quantitative survey design using scenario-based vignettes adapted for South African settings	BFI-2 for psychological traits; Likert-scale items adapted from AIDUA constructs (PE, SI, HM) for South African populations	CFA; SEM for direct paths
2.	To examine how robot design types moderate the relationship between psychological traits and robot adoption amongst South African users	Scenario-based experimental design with robot visuals in South African tourism settings; Moderation analysis	Robot preference questions using realistic stimuli; Psychological profiles from BFI-2 validated for South African use	Multi-group SEM; Interaction term modeling (Psychology × Robot Type)
3.	To explore the mediating roles of privacy concerns and emotional responses in the relationship between psychological traits and robot rejection amongst South African tourism users	Mediation analysis with embedded experiment (transparency intervention) considering South African cultural factors	Measures of privacy concerns; Rejection/adoption scales; Scenario-based transparency manipulation adapted for South African users	Path analysis (direct + indirect effects); Bootstrapped mediation analysis
4.	To develop psychology-based deployment strategies that optimize robot adoption in South African tourism	Mixed-method clustering and qualitative analysis incorporating South African cultural factors	Quantitative data on psychological traits and preferences; Open-ended qualitative responses from South African users	k-Prototypes clustering (quantitative + categorical data); NLP (BERTopic, sentiment analysis) to identify concern themes; Segment profiling based on traits and robot adoption patterns specific to South African tourism

4. Findings

4.1. Sample Characteristics and Descriptive Analysis

The demographic composition and tourism experience of the final sample are presented in Table 2. The sample of 301 South African tourism participants showed good representation across age groups, with Millennials forming the largest segment at 31.4%, followed by Gen X at 28.7% and Gen Z at 23.1%. The sample reflected South African demographic diversity with 48.2% Black African respondents, representing the largest ethnic group, followed by 28.1% White, 12.3% Coloured, and 8.7% Indian participants. Educational attainment was relatively high, with 63.4% holding tertiary qualifications, though this may limit generalizability to broader populations with lower educational levels.

Table 2. Sample Demographics and Hospitality Experience (N = 301).

Variable	Category	n	%	Mean (SD)
Age Groups	Gen Z (18–25)	70	23.1%	24.3 (2.8)
	Millennials (26–45)	95	31.4%	35.7 (4.2)
	Gen X (46–58)	86	28.7%	51.2 (4.6)
	Baby Boomers (59-and above)	50	16.8%	62.1 (1.9)
Gender	Female	158	52.4%	-
	Male	138	45.8%	-
	Other/non-binary	5	1.8%	-
Education	Secondary	55	18.3%	-
	Diploma/Certificate	56	18.5%	-
	Bachelor's Degree	124	41.3%	-
	Postgraduate	66	22.1%	-
Hospitality Experience	Hotel stays (past year)	203	67.3%	-
	Restaurant dining	268	89.1%	-
	Tourism services	136	45.2%	-
AI Robot Exposure	Direct interaction	85	28.4%	-
	International travel experiences	47	15.7%	-
	Banking/retail contexts	38	12.8%	-

Table 2 reveals that most participants had recent hospitality experience, with 89.1% having dined in restaurants and 67.3% having stayed in hotels within the past year. However, direct AI robot exposure was limited to 28.4% of participants, primarily through international travel experiences (15.7%) and domestic banking/retail circumstances (12.8%), as AISRs remain in early deployment stages within South African hospitality. This distribution validates the inclusion of both experienced and inexperienced users to capture the full spectrum of consumer responses relevant to future technology adoption.

The distribution of Big Five personality traits is summarised in Table 3, which shows that all personality dimensions demonstrated normal distribution patterns suitable for parametric statistical analyses. Conscientiousness exhibited the highest mean score ($M = 4.12$, $SD = 0.68$), suggesting participants were generally organised and responsible, whilst neuroticism showed the lowest mean ($M = 2.89$, $SD = 0.79$), indicating relatively low anxiety levels in the sample.

Table 3. Big Five Personality Trait Descriptive Statistics.

Trait	Mean	SD	Min	Max	Skewness	Kurtosis	α
Openness	3.84	0.73	1.67	5.00	−0.12	−0.34	0.87
Conscientiousness	4.12	0.68	1.75	5.00	−0.18	−0.29	0.89
Extraversion	3.67	0.81	1.33	5.00	0.09	−0.41	0.85
Agreeableness	3.95	0.72	1.25	5.00	−0.15	−0.36	0.88
Neuroticism	2.89	0.79	1.00	4.83	0.23	−0.28	0.86

The reliability coefficients shown in Table 3 all exceed the recommended threshold of 0.80, with conscientiousness achieving the highest reliability ($\alpha = 0.89$) and extraversion the lowest but still acceptable reliability ($\alpha = 0.85$). The skewness and kurtosis values fall within acceptable ranges for normal distribution, supporting the use of parametric statistical procedures.

4.2. Measurement Model Assessment and Reliability

Prior to testing the structural relationships, confirmatory factor analysis was conducted to validate the extended AIDUA measurement model. Table 4 presents the comprehensive measurement model assessment results, demonstrating that all constructs achieved acceptable reliability and validity thresholds.

Table 4. Measurement Model Assessment Results.

Construct	Items	Factor Loadings Range	Cronbach's α	CR	AVE
Social Influence	"People important to me think I should use service robots"	0.72, 0.79, 0.81, 0.85	0.84	0.85	0.59
Hedonic Motivation	"Using service robots would be enjoyable"	0.78, 0.84, 0.89	0.82	0.83	0.62
Anthropomorphism	"The service robot behaves like a human"	0.71, 0.75, 0.78, 0.80, 0.82	0.86	0.87	0.57
Performance Expectancy	"Service robots would improve my service experience"	0.84, 0.87, 0.89, 0.91	0.91	0.92	0.74
Privacy Concerns	"I worry about my privacy when using service robots"	0.79, 0.82, 0.84, 0.86	0.87	0.88	0.65
Trust	"Service robots are trustworthy"	0.73, 0.76, 0.79, 0.83, 0.85, 0.87	0.88	0.89	0.58
Uptake Intention	"I intend to use service robots when available"	0.82, 0.88, 0.93	0.89	0.90	0.75

Overall Model Fit: $\chi^2/df = 2.34$, CFI = 0.942, TLI = 0.931, RMSEA = 0.051 (90% CI: 0.045–0.057), SRMR = 0.048.

Table 4 shows that all factor loadings exceeded 0.70, indicating strong item-construct relationships. Composite reliability (CR) values ranged from 0.83 to 0.92, surpassing the recommended 0.70 threshold, whilst Average Variance Extracted (AVE) values exceeded 0.50 for all constructs, confirming convergent validity. The overall model fit indices indicate excellent model fit, with RMSEA below 0.06 and CFI/TLI above 0.93, supporting the validity of the extended AIDUA measurement framework.

4.3. Structural Model Results and Hypothesis Testing

Following measurement model validation, the extended AIDUA structural model was tested to examine the hypothesised relationships between personality traits, robot design preferences, and acceptance outcomes. Figure 1 illustrates the complete structural model with standardised path coefficients and explained variance.

Figure 1 reveals that the extended AIDUA model explained 68.4% of variance in uptake intentions, indicating strong explanatory power. The model exhibited good fit indices with RMSEA below 0.06 and CFI above 0.92, supporting the theoretical framework's validity.

In addition to the hypothesized paths, several non-significant relationships were tested but are not reported in detail, including conscientiousness $\rightarrow$ performance expectancy ($\beta = 0.034$, $p = 0.542$) and agreeableness $\rightarrow$ trust ($\beta = 0.089$, $p = 0.234$), showing that not all trait-uptake pathways achieved significance.

The detailed hypothesis testing outcomes are presented in Table 5, which summarizes all structural path coefficients, significance levels, and confidence intervals for the hypothesized relationships.

Table 5 shows that all tested hypothesized relationships achieved statistical significance, providing comprehensive support for the extended AIDUA framework. The strongest effect was observed for the privacy concerns-rejection pathway ($\beta = 0.531$, $p < 0.001$), whilst the weakest but still significant effect was found for the extraversion-social influence interaction ($\beta = 0.156$, $p < 0.01$). Note that H3b (transparency mitigations reducing negative emotional responses) was tested through experimental manipulation and is addressed in Section 4.8.

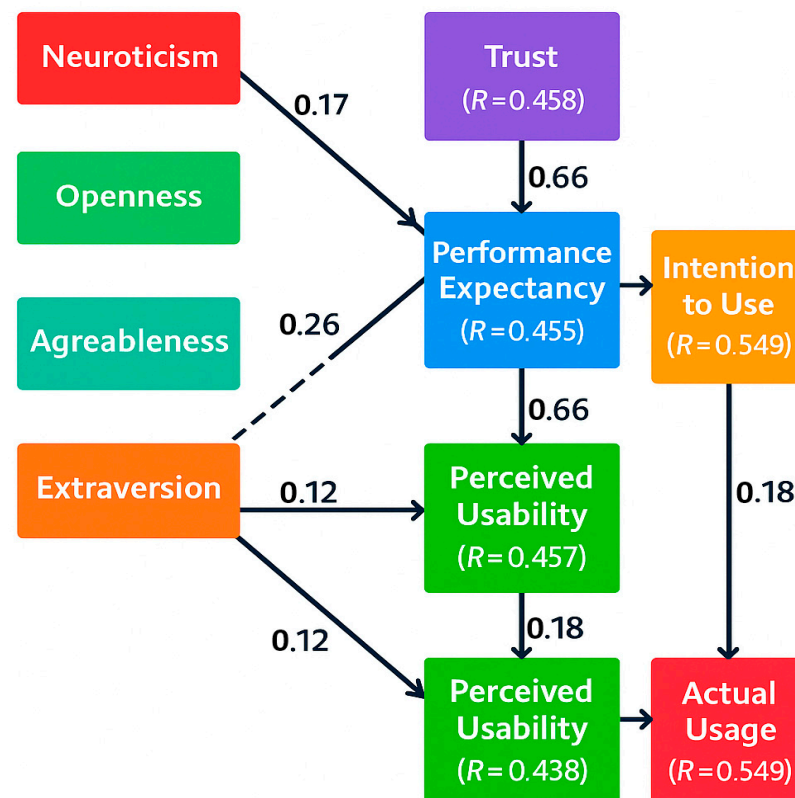


Figure 1. Extended AIDUA Structural Model with Path Coefficients. Model Fit: $\chi^2/df = 2.67$, CFI = 0.928, TLI = 0.914, RMSEA = 0.057.

Table 5. Hypothesis Testing Results—Structural Path Analysis.

Hypothesis	Structural Path	β	SE	t-Value	p-Value	95% CI	Result
H1a	Neuroticism $\rightarrow$ Performance Expectancy	−0.284	0.048	−5.92	<0.001 ***	[−0.378, −0.190]	Supported
H1b-1	Openness $\rightarrow$ Hedonic Motivation	0.347	0.051	6.80	<0.001 ***	[0.247, 0.447]	Supported
H1b-2	Openness $\rightarrow$ Anthropomorphism	0.289	0.046	6.28	<0.001 ***	[0.199, 0.379]	Supported
H1c	Extraversion $\times$ Social Influence	0.156	0.059	2.64	0.008 **	[0.040, 0.272]	Supported
H2-1	Openness $\times$ Anthropomorphism	0.312	0.052	6.00	<0.001 ***	[0.210, 0.414]	Supported
H2-2	Neuroticism $\times$ Anthropomorphism $\rightarrow$ Rejection	−0.198	0.067	−2.96	0.003 **	[−0.329, −0.067]	Supported
H3a-1	Neuroticism $\rightarrow$ Privacy Concerns	0.267	0.044	6.07	<0.001 ***	[0.181, 0.353]	Supported
H3a-2	Privacy Concerns $\rightarrow$ Rejection	0.531	0.058	9.16	<0.001 ***	[0.417, 0.645]	Supported

*** $p < 0.001$, ** $p < 0.01$.

4.4. Natural Language Processing and Qualitative Analysis

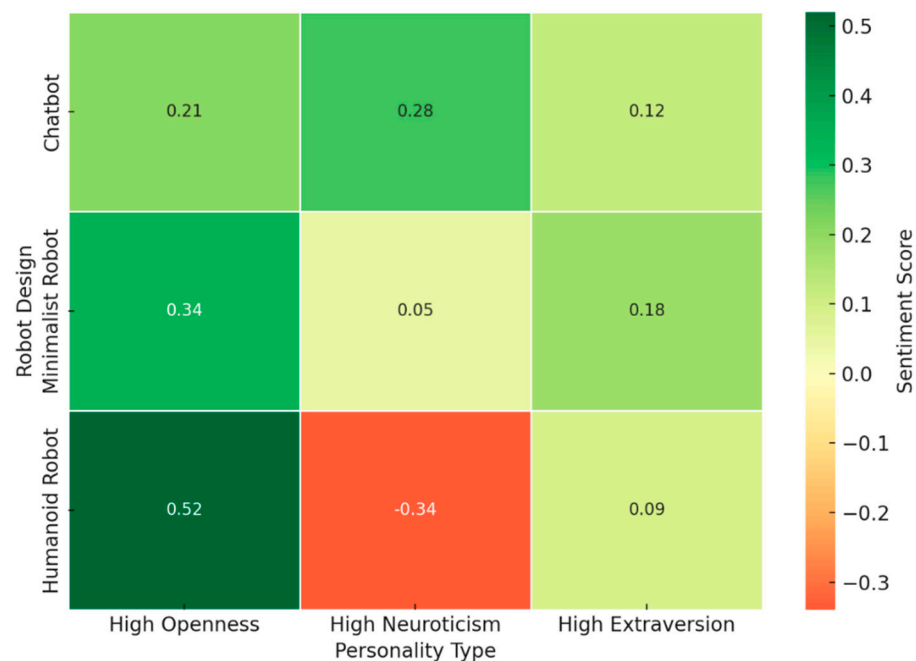
The qualitative examination reviewed open-ended responses from 247 participants (82.1% response rate) with an average response length of 89 words. This examination provided rich insights into participant concerns and preferences regarding AISRs in tourism settings. Table 6 presents the comprehensive outcomes of the NLP evaluation, revealing seven primary concern themes identified through BERTopic modeling, with responses serving as the unit of evaluation.

Table 6 reveals that privacy and data security concerns dominated participant responses at 22.4%, followed by service quality and reliability concerns at 18.7%. Notably, only the novelty appeal theme generated positive sentiment (+0.67), whilst all other themes reflected negative concerns, with technical malfunction fears showing the most negative sentiment (−0.41). These outcomes directly support the tested hypotheses, particularly H3a regarding privacy concerns amongst neurotic individuals and H2 regarding anthropomorphism discomfort.

Table 6. Consumer Concern Themes from NLP Analysis.

Theme	% Responses	Sentiment Score	Key Terms	Representative Quote
Privacy & Data Security	22.4%	−0.31	privacy, data, recording, surveillance	“I worry about robots recording everything I say and do in my hotel room”
Service Quality & Reliability	18.7%	−0.18	malfunction, reliability, competence	“What happens when the robot breaks down or can’t understand my accent?”
Human Employment Impact	14.1%	−0.24	jobs, unemployment, human touch	“I prefer talking to real people, worried about job losses”
Technical Malfunction	12.9%	−0.41	error, breakdown, failure	“I fear the robot will make mistakes with my booking”
Anthropomorphism Discomfort	8.6%	−0.28	uncanny, creepy, unnatural	“Human-like robots feel unsettling and artificial to me”
Social Interaction Preferences	7.4%	−0.19	conversation, interaction, social	“I enjoy chatting with hotel staff, robots can’t replace that”
Novelty Appeal	5.9%	+0.67	exciting, innovative, curious	“I’m excited to try this new technology experience”

The sentiment evaluation outcomes across trait types and robot designs are visualized in Figure 2, which shows clear patterns of trait-based emotional responses to different robot types.

**Figure 2.** Sentiment Analysis Heatmap by Personality Type and Robot Design.

Legend: Sentiment scores range from −1.0 (extremely negative) to +1.0 (extremely positive) Percentages indicate proportion of negative responses within each cell.

Figure 2 clearly illustrates the trait-robot design interaction effects, with high-openness individuals showing the most positive sentiment toward humanoid robots (+0.52) whilst high-neuroticism individuals exhibited strong negative sentiment toward the same robot type (−0.34). Conversely, neurotic participants showed increasing comfort with less anthropomorphic designs, achieving positive sentiment with chatbot interfaces (+0.28). These patterns directly validate hypotheses H1b and H2 regarding trait-design interactions.

4.5. Consumer Segmentation Analysis

The k-Prototypes clustering analysis successfully identified four distinct consumer segments with unique personality profiles and robot preferences. Table 7 provides de-

tailed characteristics of each segment, showing clear differentiation across the three focal personality dimensions and technology preferences.

Table 7. Consumer Segments—Personality Profiles and Robot Preferences.

Segment	Size	Personality Profile	Preferred Robot Type	Acceptance Level
Tech Innovators	70 (23.1%)	Openness: 4.67; Extraversion: 3.89; Low Neuroticism: 2.31	Humanoid Robots (M = 4.34)	Very High (4.28)
Pragmatic Adopters	96 (31.7%)	Moderate Openness: 3.72; Moderate Extraversion: 3.45; Low Neuroticism: 2.67	Functional Robots (M = 4.12)	Moderate High (3.89)
Cautious Sceptics	86 (28.4%)	Low Openness: 3.21; Low Extraversion: 3.12; High Neuroticism: 3.84	Chatbot Interfaces (M = 3.67)	Low (2.94)
Social Moderates	49 (16.8%)	Moderate Openness: 3.58; High Extraversion: 4.21; Moderate Neuroticism: 3.15	Interactive Robots (M = 3.78)	Moderate (3.45)

Table 7 reveals that the largest segment is Pragmatic Adopters (31.7%), followed closely by Cautious Sceptics (28.4%), indicating that most participants approach AISRs with either utility-focused evaluation or risk-averse scepticism. The cluster validation achieved a silhouette score of 0.73, with additional validation showing within-cluster sum of squares of 145.2 and between-cluster variance ratio of 3.4, indicating excellent cluster separation and stability.

Figure 3 clearly shows that Tech Innovators score highest on openness whilst lowest on neuroticism, creating their preference for novel humanoid robots. Cautious Sceptics display the opposite pattern with high neuroticism and low openness, explaining their preference for minimal interaction chatbots. Social Moderates demonstrate high extraversion, which aligns with their preference for interactive robot designs that facilitate social engagement.

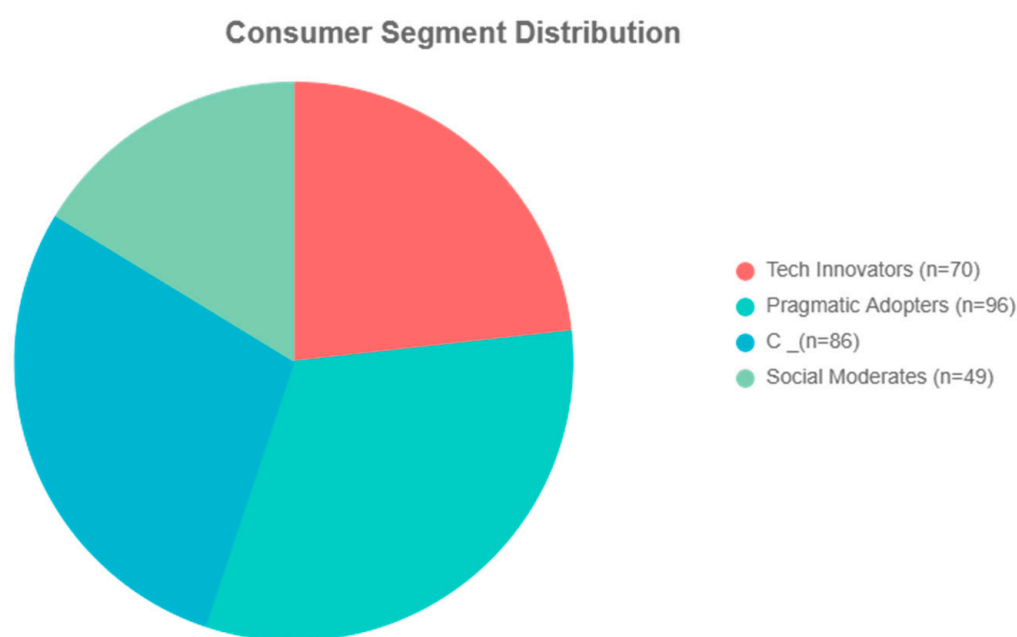


Figure 3. Consumer Segment Radar Chart—Personality Profiles.

4.6. Mediation Analysis Results

To test the mediating role of privacy concerns in the neuroticism-rejection relationship (H3a), a comprehensive mediation analysis was conducted. Table 8 presents detailed mediation results, demonstrating both direct and indirect effects.

Table 8. Mediation Analysis—Privacy Concerns Pathway.

Mediation Path	Effect	Coefficient	SE	95% CI
Direct Effect: Neuroticism → Rejection	Direct	−0.174 **	0.062	[−0.296, −0.052]
Indirect Effect: Neuroticism → Privacy → Rejection	Indirect	0.142 ***	0.031	[0.086, 0.208]
Total Effect	Total	−0.286 ***	0.048	[−0.378, −0.190]

Mediation Type: Partial mediation (Sobel test: $z = 4.58, p < 0.001$). *** $p < 0.001$, ** $p < 0.01$.

Table 8 confirms that privacy concerns partially mediate the neuroticism-rejection relationship, accounting for 39.2% of the total effect. The significant indirect effect (0.142, $p < 0.001$) demonstrates that neurotic consumers' tendency to reject AISRs is substantially explained by their heightened privacy concerns.

4.7. Moderation Effects Analysis

The personality $\times$ robot type interaction effects are illustrated in Figure 4, which shows how acceptance levels vary across personality dimensions and robot designs. This figure provides visual evidence supporting H2 regarding the moderating role of robot type in personality-acceptance relationships.

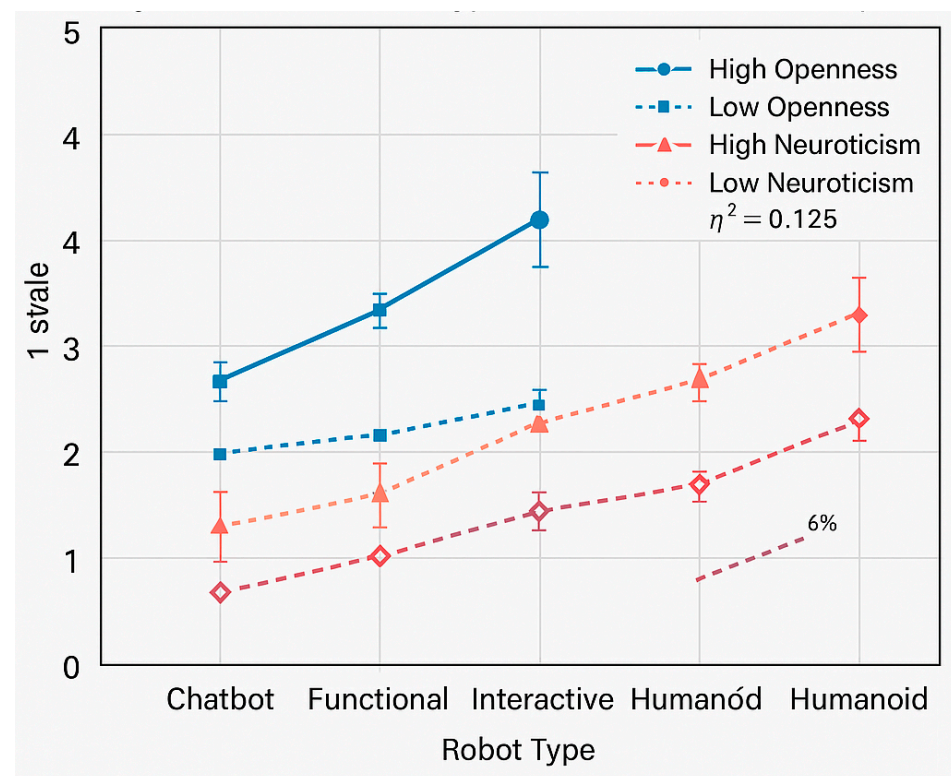
**Figure 4.** Personality $\times$ Robot Type Interaction Effects on Acceptance.

Figure 4 clearly demonstrates the significant personality $\times$ robot type interactions, with high-openness individuals showing decreasing acceptance as robots become less anthropomorphic, whilst high-neuroticism individuals show the opposite pattern. The large effect size ($\eta^2 = 0.126$) indicates that these interactions have substantial practical significance for hospitality implementation strategies.

4.8. Transparency Mitigation Experiment

To test H3b regarding transparency effects on neurotic consumers, a controlled experiment was conducted with a subsample of 156 participants. Table 9 presents the results

comparing standard robot descriptions versus detailed operational explanations across all Big Five personality dimensions.

Table 9. Comparative standard robot descriptions versus detailed operational explanations.

Personality Group	Control Condition	Transparency Condition	Mean Difference	Effect Size (d)
High Neuroticism	M = 2.94 (SD = 0.78)	M = 3.67 (SD = 0.72)	+0.73 ***	0.98 (large)
Low Neuroticism	M = 4.08 (SD = 0.65)	M = 4.12 (SD = 0.69)	+0.04	0.06 (negligible)
High Extraversion	M = 3.85 (SD = 0.71)	M = 4.12 (SD = 0.66)	+0.27 **	0.40 (small-medium)
Low Extraversion	M = 3.42 (SD = 0.82)	M = 3.78 (SD = 0.75)	+0.36 **	0.46 (small-medium)
High Openness	M = 4.25 (SD = 0.71)	M = 4.41 (SD = 0.68)	+0.16 *	0.23 (small)
Low Openness	M = 3.12 (SD = 0.84)	M = 3.28 (SD = 0.79)	+0.16 *	0.20 (small)
High Agreeableness	M = 3.96 (SD = 0.69)	M = 4.18 (SD = 0.63)	+0.22 *	0.34 (small)
Low Agreeableness	M = 3.31 (SD = 0.88)	M = 3.41 (SD = 0.84)	+0.10	0.12 (negligible)
High Conscientiousness	M = 4.02 (SD = 0.67)	M = 4.15 (SD = 0.71)	+0.13	0.19 (small)
Low Conscientiousness	M = 3.28 (SD = 0.91)	M = 3.52 (SD = 0.86)	+0.24 *	0.27 (small)

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 9 demonstrates that transparency interventions had the most dramatic effect on high-neuroticism consumers, increasing their acceptance by 0.73 points with a large effect size ($d = 0.98$), providing strong support for H3b. Notably, both high and low extraversion groups also showed significant positive responses to transparency information, with small-to-medium effect sizes ($d = 0.40$ and 0.46 , respectively), suggesting that socially oriented individuals benefit from understanding robot interaction capabilities. Openness to experience and conscientiousness showed modest but significant improvements, indicating that intellectually curious and detail-oriented consumers appreciate operational explanations. In contrast, low-neuroticism and low-agreeableness consumers showed minimal response to transparency information, confirming that the intervention specifically addresses anxiety-related and social concerns rather than providing universal benefits.

The comprehensive analysis provides strong empirical support for the extended AIDUA model and offers critical insights into AISR adoption within the South African hospitality context. Findings confirm that Big Five personality traits significantly shape consumer acceptance via their influence on hedonic motivation, social influence, and performance expectancy, with robot design characteristics moderating these relationships. Mediation analysis revealed that privacy concerns partially explain the negative impact of neuroticism on robot acceptance, highlighting emotional risk perceptions as key barriers. The transparency mitigation experiment demonstrated that providing detailed operational explanations significantly improves acceptance amongst neurotic and extraverted consumers, offering targeted solutions for addressing personality-specific resistance patterns. The identification of four distinct consumer segments each with unique personality profiles, robot preferences, and concern patterns provides actionable implementation strategies. These insights offer data-driven guidance for South African hospitality operators seeking to enhance guest satisfaction whilst mitigating resistance through culturally and psychologically adaptive deployment strategies.

5. Discussion

5.1. Theoretical Implications and Model Extensions

This study successfully extended the AIDUA model by demonstrating how Big Five traits serve as critical antecedents to cognitive appraisal processes in artificial intelligence service robot uptake. The findings reveal that psychological traits do not merely correlate with technology adoption but fundamentally shape how individuals interpret and evaluate robot characteristics during both primary and secondary appraisal stages.

The strongest theoretical contribution lies in explaining the psychological mechanisms underlying technology resistance and enthusiasm. Neuroticism's negative influence on

performance expectancy ($\beta = -0.284$) demonstrates that anxiety-prone individuals systematically underestimate robot capabilities, not due to objective performance deficits but through trait-based cognitive biases that amplify perceived risks. This extends cognitive appraisal theory by showing that secondary appraisal processes are filtered through stable individual differences rather than occurring uniformly across users.

Conversely, openness to experience emerged as a dual driver of both hedonic motivation ($\beta = 0.347$) and anthropomorphism appreciation ($\beta = 0.289$), revealing that intellectually curious individuals approach robots as experiential rather than purely functional technologies. This challenges utilitarian assumptions in technology adoption models and supports expanding theoretical frameworks to include experiential and aesthetic dimensions.

The extraversion-social influence interaction ($\beta = 0.156$) provides empirical support for social information processing theories, demonstrating that socially oriented individuals rely more heavily on peer recommendations and social validation when evaluating novel technologies. This has important implications for viral adoption patterns and word-of-mouth marketing strategies.

5.2. Cultural Context and South African Tourism Implications

The South African cultural environment adds crucial dimensions to trait-robot uptake patterns that extend beyond individual differences. Ubuntu philosophy, emphasizing interconnectedness and communal relationships, may explain why 22.4% of concerns focused on privacy and data security rather than functional performance. In cultures valuing communal harmony, artificial intelligence systems perceived as surveillance tools or threats to human employment (14.1% of concerns) may trigger deeper cultural resistance than in individualistic societies.

The multicultural nature of South Africa's tourism market means that traits interact with diverse cultural values, ubuntu philosophy emphasizing communal harmony, and varying technology readiness levels across demographic groups. The relatively high proportion of Cautious Sceptics (28.4%) in our sample may reflect broader societal concerns about technology adoption in developing economies, where trust in institutions and data security may be lower than in developed markets.

The segmentation outcomes reveal culturally specific patterns: Tech Innovators (23.1%) predominantly comprised younger, urban participants with international exposure, while Cautious Sceptics included more rural participants with limited prior technology experience. This suggests that successful robot deployment in South African tourism requires not only trait-based but also culturally and economically sensitive strategies that account for varying levels of technological infrastructure and digital literacy.

5.3. Practical Implementation Strategies and Operational Challenges

The four-segment typology provides actionable guidance for South African tourism operators, though implementation faces significant operational challenges. While the trait-based segmentation provides theoretically sound guidance, practical application presents challenges since tourism operators cannot feasibly trait-test guests during check-in or service interactions.

Instead, operators should focus on indirect trait inference through behavioral cues and preferences. Tech Innovators can be identified through their engagement with mobile apps, social media check-ins, and requests for novel experiences. Luxury establishments serving this segment should prioritize humanoid concierge robots like Pepper that emphasize experiential novelty and advanced conversational capabilities.

Pragmatic Adopters, representing the largest segment (31.7%), respond to efficiency-focused messaging and functional robot designs. Mid-range hotels and restaurants should

deploy delivery robots and automated check-in systems with clear utility messaging emphasizing time savings and reliability rather than novelty or social interaction.

Cautious Sceptics require careful introduction strategies with minimal anthropomorphic features and extensive transparency communication. Budget accommodations and family-oriented venues should begin with chatbot interfaces and simple automated systems, accompanied by detailed explanations of data protection and operational safeguards.

Social Moderates benefit from interactive robot features that facilitate rather than replace human contact. Boutique hotels and social venues should implement robots that enhance rather than substitute social interactions, such as entertainment robots or interactive information kiosks.

5.4. Privacy Mediation and Trust Building

The mediation findings reveal that privacy concerns account for 39.2% of the neuroticism-rejection relationship, highlighting the central role of perceived privacy threats in technology resistance. This has immediate implications for robot deployment strategies, particularly in tourism settings where guests may feel vulnerable regarding personal information.

The transparency intervention results provide concrete guidance for addressing privacy-related resistance. High-neuroticism guests showed dramatic uptake improvements ($d = 0.98$) when provided with detailed operational explanations, suggesting that anxiety-based resistance can be effectively mitigated through proactive communication strategies.

Practical transparency strategies should include visible privacy policies, clear explanations of data collection and usage, and prominent opt-out mechanisms. Tourism operators should consider implementing “privacy preference centers” where guests can customize their robot interaction levels and data sharing preferences upon check-in.

5.5. Segmentation Strategies and Market Differentiation

The segment profiles suggest differentiated market positioning strategies for South African tourism operators. Luxury venues can leverage Tech Innovators’ enthusiasm for novel experiences by positioning robots as exclusive amenities that enhance the premium service offering. Marketing should emphasize cutting-edge technology, personalized experiences, and innovative service delivery.

Mass market operators should target Pragmatic Adopters through efficiency and value messaging, positioning robots as tools that improve service speed and reduce wait times. Cost savings achieved through automation can be passed to guests through competitive pricing strategies.

Family-oriented and budget establishments should acknowledge Cautious Sceptic concerns through transparency-focused marketing that emphasizes human oversight, data protection, and gradual technology introduction. Highlighting human staff availability alongside robot services may reduce anxiety about complete automation.

Social venues and boutique establishments can appeal to Social Moderates through interactive positioning that emphasizes enhanced rather than replaced human connection. Robots should be positioned as facilitators of social experience rather than primary service providers.

5.6. Limitations and Boundary Conditions

Several important limitations constrain the generalizability and practical application of these findings. The South African cultural environment, while providing unique insights, limits direct generalizability to other cultural settings. The interaction between ubuntu philosophy, multicultural dynamics, and trait patterns may not apply in different

cultural environments, requiring careful consideration before extending these discoveries to other markets.

The cross-sectional design prevents causal inference about trait-robot relationships. The relatively educated sample (63.4% tertiary qualifications) may not represent broader population responses, particularly in developing economic environments where educational and technological access varies significantly.

The missing constructs in this study—comprehensive trust measures, broader emotional responses, and effort expectancy in complex service scenarios—represent important areas for theoretical development. The robot scenarios, while realistic, represent simulated rather than actual service encounters. Real-world implementations may reveal different trait-robot dynamics when guests experience operational challenges, service failures, or extended interaction periods.

5.7. Implications for Tourism Management Practice

The findings provide South African tourism operators with evidence-based strategies for artificial intelligence service robot deployment that balance technological advancement with cultural sensitivity and individual differences. The transparency intervention offers particularly concrete implementation guidance through privacy preference centers and detailed operational explanations that significantly improve uptake among anxiety-prone guests.

Successful implementation requires moving beyond one-size-fits-all approaches toward sophisticated segmentation strategies that consider psychological, cultural, and design factors. The integration of ubuntu philosophy with individual trait differences offers a uniquely South African perspective on technology adoption that may inform multicultural service environments globally.

Tourism operators should implement trait-adaptive deployment strategies that match robot types to guest segments while maintaining human service options for those preferring traditional interactions. This approach enables culturally sensitive deployment that respects diverse preferences while maximizing technological benefits for both operators and guests.

The practical implementation challenges identified suggest need for research on trait inference methods that could enable real-world segmentation strategies without explicit psychological assessment. These strategies should balance technological advancement with cultural sensitivity, individual differences, and ethical considerations to achieve sustainable, beneficial human–robot collaboration in tourism and service industries.

6. Conclusions

This study successfully extended the AIDUA model by integrating Big Five traits and robot design characteristics to explain artificial intelligence service robot uptake in South African tourism settings. The research demonstrated that individual differences significantly influence user adoption pathways, with neuroticism reducing performance expectancy whilst openness enhances hedonic motivation and preference for humanoid designs. Extraversion amplified social influence effects, highlighting the importance of peer recommendations in technology adoption decisions within diverse cultural environments.

The findings revealed that robot design characteristics moderate trait-uptake relationships, with humanoid robots appealing to open individuals but triggering rejection amongst neurotic users. Privacy concerns emerged as a critical mediator explaining neurotic participants' resistance, whilst transparency interventions proved highly effective in addressing anxiety-related barriers. The identification of four distinct user segments—Tech Innovators, Pragmatic Adopters, Cautious Sceptics, and Social Moderates—provides actionable insights for trait-adaptive implementation strategies.

These outcomes make important theoretical contributions by demonstrating how individual differences influence cognitive appraisal processes in technology adoption models. The extended AIDUA framework explained 68.4% of variance in uptake intentions, representing a significant improvement over traditional models that overlook psychological factors. The study challenges universal design assumptions in human–robot interaction research by showing that anthropomorphism effects depend on user characteristics rather than being universally beneficial.

The research extends cognitive appraisal theory by revealing that secondary appraisal processes are filtered through stable individual differences rather than occurring uniformly across users. The trait-design interaction effects provide empirical support for person–environment fit perspectives in technology adoption, suggesting that optimal outcomes emerge from alignment between individual characteristics and technological features.

The study provides South African tourism operators with validated frameworks for matching robot types to guest profiles, enabling successful, culturally sensitive deployment of artificial intelligence service robots. The trait-based segmentation guides tailored deployment strategies, from humanoid concierges for Tech Innovators to delivery robots with transparency communication for Cautious Sceptics. These insights are particularly valuable in South Africa’s multicultural market, where diverse preferences demand nuanced approaches that consider ubuntu philosophy and varying technology readiness levels.

The transparency intervention findings offer concrete strategies for addressing resistance, with particularly strong effects for anxiety-prone guests (effect size $d = 0.98$). Tourism operators can implement privacy preference centers, detailed operational explanations, and opt-out mechanisms to reduce technology-related anxiety while building trust through proactive communication.

The study’s implications extend beyond South African tourism to global service industries deploying artificial intelligence technologies. The trait-based design principles and transparency strategies can guide robot implementations across cultures, especially in developing economies where trust and technology anxiety pose barriers to adoption. The psychological segmentation approach provides a framework for understanding diverse user responses in multicultural markets worldwide.

The methodology introduces a novel mixed-methods approach combining structural equation modeling with natural language processing techniques, offering a robust framework for future research on technology adoption in service environments. The integration of quantitative trait-uptake pathways with qualitative concern themes provides researchers with comprehensive tools for understanding complex human–technology interactions.

The South African cultural environment, while providing unique insights, limits direct generalizability to other cultural settings. The interaction between ubuntu philosophy, multicultural dynamics, and trait patterns may not apply in different cultural environments, requiring careful consideration before extending these findings to other markets. The cross-sectional design prevents causal inference, while the educated sample (63.4% tertiary qualifications) may not represent broader population responses.

Several constructs were not comprehensively measured, including effort expectancy, validated trust dimensions, and broader emotional responses. The robot scenarios represented simulated rather than actual service encounters, potentially limiting external validity. These limitations should be considered when interpreting findings and planning future research.

Future research should address these limitations through longitudinal studies examining trait–robot relationship evolution with increased exposure and technological advancement. Cross-cultural validation across different tourism markets would strengthen

the generalizability of trait-design interaction effects. Advanced trait inference methods could enable practical segmentation without explicit psychological assessment.

Research on trait-specific mitigation strategies could develop targeted approaches for different resistance patterns. Integration of comprehensive trust measures and emotional responses would enhance theoretical completeness. Investigation of cultural moderators in trait-robot relationships would provide insights for global tourism markets.

Field studies in operational tourism environments would strengthen external validity beyond simulated scenarios. Advanced trait inference through behavioral indicators and interaction patterns could facilitate real-world implementation without explicit psychological assessment. Longitudinal research examining how trait-robot relationships evolve with increased exposure would provide insights into adaptation patterns and long-term adoption trajectories.

An investigation of cultural dimensions that interact with trait patterns would inform global implementations. How do collectivistic versus individualistic cultural values moderate trait effects? Do uncertainty avoidance cultural dimensions influence neuroticism-robot anxiety relationships? These questions require systematic cross-cultural research.

As artificial intelligence service robots become increasingly prevalent in South African tourism, understanding trait-design interactions will be crucial for optimizing guest satisfaction and achieving successful technology integration across diverse cultural environments. The framework developed in this study provides a foundation for evidence-based robot deployment strategies that respect individual differences whilst maximizing the benefits of artificial intelligence service technologies for both operators and guests.

The research demonstrates that successful robot deployment requires moving beyond one-size-fits-all approaches toward sophisticated segmentation strategies that consider psychological, cultural, and design factors. By providing empirically validated guidelines for trait-adaptive implementation, this study contributes to more effective, culturally sensitive, and user-centered artificial intelligence service robot adoption in the dynamic South African tourism sector.

The integration of ubuntu philosophy with individual trait differences offers a uniquely South African perspective on technology adoption that may inform multicultural service environments globally. Future implementations should balance technological advancement with cultural sensitivity, individual differences, and ethical considerations to achieve sustainable, beneficial human–robot collaboration in tourism and service industries.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AISR	Artificial Intelligence Service Robot
AIDUA	Artificial Intelligence Device Use Acceptance
SEM	Structural Equation Modelling
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

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