AI Driven Customer Service and Customer Patronage of Ibom Hotel and Golf Resort Hotel, Uyo Metropolis

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ABSTRACT
This study empirically examines the relationship between Artificial Intelligence (AI)-driven customer service and customer patronage at Ibom Hotel & Golf Resort, a premier hospitality establishment operating within the Uyo Metropolis, Akwa Ibom State, Nigeria. Driven by the aggressive digital transformation of the regional hospitality landscape, the paper decomposes automated service infrastructure into three distinct, measurable dimensions: AI Responsiveness (AIR), AI Personalization (AIP), and AI-Driven Service Recovery (ASR). The study adopts a cross-sectional descriptive survey research design. Utilizing Cochran's (1977) sampling formula for infinite populations, a field sample of 422 digital structured questionnaires was deployed across multiple customer touchpoints, yielding 391 valid responses certified clean for final econometric computation. Data processing via SPSS software utilized descriptive statistics alongside Multiple Linear Regression Analysis to validate the research hypotheses. The empirical metrics reveal a strong, statistically significant joint model fit ($R = 0.768$, $R^2 = 0.590$, $F = 185.34$, $p < 0.001$), demonstrating that 59.0% of the total variance in customer patronage (measured via brand preference, re-booking intension and willingness to pay price premium) is directly driven by the hotel's AI service deployment. On an individual level, AI Personalization (AIP) emerged as the most powerful single predictor ($\beta = 0.385$, $t = 8.708$, $p < 0.001$), followed closely by AI Responsiveness (AIR) ($\beta = 0.298$, $t = 6.807$, $p < 0.001$), while AI-Driven Service Recovery (ASR) exerted a smaller but highly significant positive influence ($\beta = 0.192$, $t = 4.800$, $p < 0.001$). The findings confirm that while automation drastically reduces reservation friction and enhances tailored comfort, local consumers in the Uyo market continue to place immense value on authentic regional identity and cultural spaces. Consequently, the paper concludes that optimal market retention requires a strategic "high-tech, high-touch" hybrid hospitality model. The study recommends that hotel management systematically upgrade predictive data profiling security to navigate the personalization-privacy paradox, establish instant digital compensation The scripts for automated failures, and maintain a seamless escalation loop to empathetic human managers to preserve long-term brand loyalty.
Keywords: *Artificial Intelligence (AI), AI Responsiveness, AI Personalization, AI-Driven Service Recovery, Customer Patronage, Ibom Hotels & Golf Resort, Uyo Metropolis.*

1. INTRODUCTION

The global hospitality industry is experiencing a profound technological paradigm shift driven by the rapid maturity of Artificial Intelligence (AI) (Acharya & Datta, 2023). In competitive urban ecosystems, hotels are transitioning from conventional human-dominated customer interaction points to automated service models to maximize operational efficiency and eliminate service delivery bottlenecks (Cain et al., 2019; Law et al., 2024). In Nigeria's regional hospitality hubs, particularly within the Akwa Ibom State capital, the competition among boutique and luxury hotels has forced operators to redesign their marketing and relationship frameworks (Nwabueze & Udoh, 2024; Udo-Imeh & Ekpenyong, 2025).

Ibom Hotel & Golf Resort, strategically situated at Nwaniba, Uyo, serves as an empirical anchor for this study. Known for modern upscale infrastructure including world-class, extensive recreational structures, scenic spaces, the establishment handles large volumes of business, academic, and leisure travelers. Uford (2026) highlights the strategic importance of optimizing AI opportunities as a competitive marketing tool. To sustain its market share and guarantee a stable booking stream, leveraging AI tech-infusion at the front line has become essential (Yusuf & Bello, 2025).

While previous researchers have extensively studied general marketing mixes and service staff responsiveness within Uyo hotels (Nwabueze & Udoh, 2024), there is an empirical gap regarding how automated, AI-driven service systems directly affect customer patronage within high-end local properties. This article provides deep theoretical and practical insights into how modern hotel management can balance automated efficiency with cultural hospitality constraints in a developing metropolitan economy.

Finally, to overcome these structural limitations, standard hospitality establishments such as positioned to integrate Artificial Intelligence (AI) into their core customer service frameworks. Far from replacing the distinct, culturally rich warmth of Nigerian hospitality, AI functions as an operational accelerator. This paper presents a structured academic analysis of how AI-driven customer service systems can be leveraged to optimize the specific operational touchpoints of Ibom Hotels & Golf Resort, thereby driving sustained customer patronage.

1.1 Statement of the Problem

Artificial Intelligence (AI)-driven customer service is revolutionizing the Nigerian hospitality sector. By integrating smart booking systems, 24/7 chatbots, and hyper-personalized guest profiling, forward-thinking establishments are transforming visitor experiences (Uford & Akpan, 2024; Uford et al., 2023). For a premier destination like Ibom Hotels & Golf Resort in Uyo, embracing this technology translates directly to increased customer retention and sustained patronage. The hospitality landscape in Uyo, the capital of Akwa Ibom State, is fiercely competitive. Guests expect prompt, flawless service that begins the moment they start planning their trips.

Furthermore, the hotel industry is highly dynamic, with guests increasingly expecting instant, 24/7 service, personalization, and seamless booking experiences. Prior to adopting digital enhancements, local hotels in Uyo Metropolis often struggled with high human-error rates in reservations, delayed response times during peak periods, and an inability to track guest preferences accurately. Therefore, this research is an attempt to close the empirical gap regarding how automated, AI-driven customer service solutions directly affect customer patronage.at Ibom Hotels & Golf Resort.

1.2 Aim and Objectives of the Study

The aim of this study is to evaluate the relationship between AI driven customer service and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis. The specific objectives of this study are to;

i. examine the relationship between AI Responsiveness (AIR) and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis.
ii. determine the relationship between AI Personalization (AIP) and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis.
iii. ascertain the relationship between AI-Driven Service Recovery (ASR) and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis.

1.3 Research Hypotheses

Based on the above research objectives, the null hypothesis developed as follows:

i. There is no significant relationship between AI Responsiveness (AIR) and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis.
ii. There is no significant relationship between AI Personalization (AIP) and customer patronage of Ibom Hotel & Golf Resort in Uyo Metropolis.
iii. There is no significant relationship between AI-Driven Service Recovery (ASR) and customer patronage of Ibom Hotels & Golf Resort in Uyo Metropolis.

2. LITERATURE REVIEW: Conceptual and Theoretical Frameworks

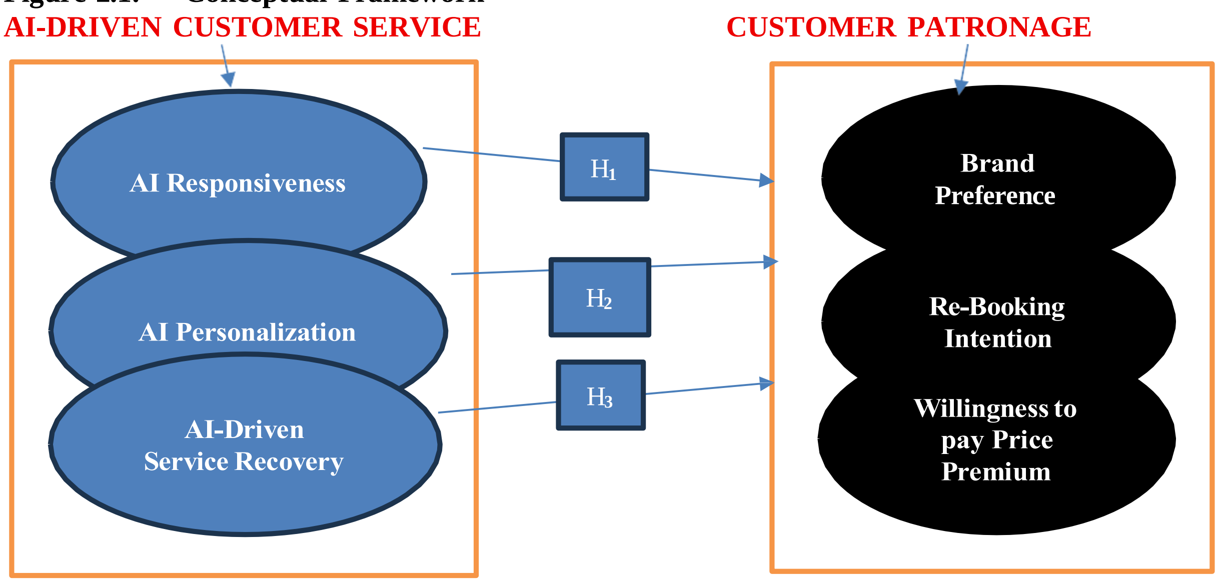
2.1 The Concept of AI-Driven Service and Customer Patronage in Hospitality

Artificial intelligence in hospitality involves the application of smart systems to perform tasks that typically require human cognition, such as conversational chatbots, voice-controlled room assistants, and automated recommendation engines. These systems enable Ibom Hotels & Golf Resort to provide seamless, contactless, and round-the-clock support to guests. Customer patronage refers to the regular and repeated use of a business's services. Studies have shown that AI technologies positively influence trust, convenience, and time efficiency. By utilizing AI for precision profiling and preference tracking, hotels can offer highly tailored promotions and room features that significantly elevate the guest experience.

2.2 Conceptual Framework

In this study, the structural relationship between AI-driven customer service and customer patronage is modeled using a structural equation modeling (SEM) approach. This framework positions AI-driven customer service as a multi-dimensional construct comprising **AI Responsiveness (AIR)**, **AI Personalization (AIP)**, and **AI-Driven Service Recovery (ASR)**. These technological vectors or proxies of AI-driven customer service were measured with customers' brand preference, customers' re-booking intention, and customers' willingness to pay price premium, as constructs and psychological drivers of **Customer Patronage (CP)**.

Figure 2.1: Conceptual Framework



Authors' Conceptual Model (2026).

2.2.1 AI Responsiveness (AIR)

AI Responsiveness (AIR) refers to the capacity of an Artificial Intelligence system to provide prompt, real-time, and contextually appropriate assistance to customer inquiries (Shanker, 2026). Grounded in the responsiveness dimension of the classic SERVQUAL framework, AIR within modern hospitality ecosystems focuses on eliminating waiting friction through automated, 24/7 processing architectures (Acharya & Datta, 2023; Kervenoael et al., 2020). It is primarily operationalized through natural language processing (NLP) chat interfaces, automated email engines, and digital concierge apps (Exeed College, 2025; Law et al., 2024).

Studies demonstrate that prompt system responses directly dictate a customer's evaluation of digital service quality (Shanker, 2026). Research on hospitality applications shows that when conversational systems provide instantaneous answers regarding room availability, pricing tiers, or reservation updates, booking completion rates rise (Adobe Business, 2025; Juneja, 2025). Manual communication bottlenecks often drive potential hotel guests to alternative operators; thus, AIR functions as a critical intervention tool that secures immediate attention before a consumer switches brands (Cantor, 2024). However, the positive impact of AIR relies heavily on the system's problem-solving accuracy. If a responsive system continuously generates fast but inaccurate or superficial responses, customer frustration increases, highlighting that speed must be paired with contextual intelligence to successfully drive long-term business patronage (Cantor, 2024; Kervenoael et al., 2020).

2.2.2 AI Personalization (AIP)

AI Personalization (AIP) represents a system's ability to process real-time customer data, identify individual preferences, and dynamically customize services to match distinct user profiles (Inavolu, 2024; Uford & Akpan, 2024; Oxford Home Study Centre, 2026). Unlike traditional segmentation strategies, AIP leverages predictive machine learning models to anticipate consumer needs before they are explicitly communicated (Nira, 2025). In the premium lodging sector, this involves tailoring digital itineraries, dining menus, room environments, and marketing promotions (Fouad et al., 2024; Rather, 2024).

Literature identifies AIP as a highly effective tool for driving continuous engagement and brand advocacy in the modern digital economy (Gao et al., 2023; Inavolu, 2024). Highly customized encounters make guests feel uniquely valued, creating a powerful competitive advantage that encourages repeat bookings and an increased willingness to pay premium rates (Prentice et al., 2020; Rather, 2024). However, the deployment of AIP introduces a major challenge known as the Personalization-Privacy Paradox (Mola et al., 2024). Empirical studies confirm that while consumers enjoy the convenience of tailored services, they are often concerned about how their data is gathered and secured (Prasetyo & Suryadi, 2026; Zaher & Al-Ansi, 2025). If a hotel's predictive systems seem overly intrusive, customer trust drops, which can ultimately weaken brand loyalty (Bittendorfer et al., 2025; Prasetyo & Suryadi, 2026).

2.2.3 AI-Driven Service Recovery (ASR)

AI-Driven Service Recovery (ASR) is an automated system's capacity to identify, manage, and fix service failures autonomously during or immediately after a negative customer encounter (Wang & Zhang, 2021; Etuk et al., 2023). Because technology configurations can experience system errors, ASR functions as a digital safety net. It operates through diagnostic feedback loops that automatically issue digital compensation, generate alternative booking selections, or update staff when a service breakdown occurs (Jia et al., 2025).

Service recovery literature highlights that a well-managed resolution can turn an unhappy customer into a loyal advocate (Wang & Zhang, 2021). In automated environments, the success of a recovery effort depends heavily on the system's perceived empathy and emotional intelligence (Liu et al., 2024). Research shows that during service failures, customers respond negatively to cold, robotic apologies; conversely, when an ASR framework utilizes high-empathy language, it reduces the psychological distance between the consumer and the brand, increasing continuous usage intentions (Liu et al., 2024; Wang & Zhang, 2021). Industry studies reveal that mechanical AI systems excel at maintaining resilient service operations, but optimal long-term loyalty is achieved through a balanced service model—severe or complex failures still require seamless escalation to human service teams to preserve authentic customer relationships (Gursoy & Cai, 2024; Jia et al., 2025).

2.3 Theoretical Framework: Technology Acceptance Model (TAM)

This study is anchored on the Technology Acceptance Model (TAM), originally formulated by Davis (1989), alongside the Service Quality (SERVQUAL) framework. TAM posits that a customer's behavioral intention to utilize or patronize a technology-driven service is dictated by two primary cognitive variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). When a hotel effectively synchronizes its technological interfaces to maximize both variables, consumer satisfaction improves, creating a direct psychological path to sustained customer patronage (Yusuf & Bello, 2025).

3. METHODOLOGY

3.1 Research Design and Population

The study adopted a cross-sectional descriptive survey research design to capture real-time sentiments regarding technological interactions. The target population comprised all registered guests and corporate patrons who frequently visited Ibom Hotels & Golf Resort, Uyo, within a designated six-month tracking window. Because the absolute, historical pool of unique transient hotel visitors fluctuates constantly, the population is considered infinite (unknown) for strict statistical modeling.

3.2 Sample Size Determination

To ensure statistical precision and validity without an absolute population ceiling (N), Cochran's (1977) formula for infinite populations was deployed to calculate the ideal sample size: $n_0 = \frac{Z^2 \cdot p \cdot q}{e^2}$

Where:

- n_0 = The target sample size.
- Z = The standard normal deviation corresponding to the desired confidence level (at 95% confidence, Z = 1.96).
- p = The estimated proportion of an attribute that is present in the population (assumed to be 0.5 or 50% to achieve maximum variability).
- q = 1 - p (1 - 0.5 = 0.5).
- e = The acceptable margin of error or level of precision (set at 5% or 0.05).

$$n_0 = \frac{1.96^2 \text{ X } (0.5) \text{ X } (0.5)}{(0.05)^2} = 384.16$$

Rounding up to the nearest whole integer yields an ideal sample size of **384 respondents**. To account for potential non-response bias, missing data, or incomplete online forms, an additional 10% buffer was added during distribution, resulting in a field deployment of 422 questionnaires. Out of these, **391 fully completed copies** were retrieved and certified clean for final econometric processing.

3.3 Sampling Technique and Instrumentation

A non-probability convenience and purposive sampling technique was utilized. Questionnaires were deployed electronically via QR codes placed at front desk checkout terminals, the 24-hour guest library, and the Mandela Banquet Hall lounge. Purposive filter parameters required respondents to confirm they had interacted with at least one automated touchpoint during their stay.

The primary instrument was a structured, 5-point Likert scale questionnaire (*Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2, Strongly Disagree = 1*). Content and face validity were verified by a panel of experts. Internal consistency of the constructs was confirmed via Cronbach's Alpha (α), yielding coefficients well above the acceptable threshold of 0.70: AIR = 0.814, AIP = 0.845, ASR = 0.798, CP = 0.862.

3.4 Model Specification

The functional relationship between dependent and independent variable is specified as follows:
Where: **AIDCS = f (AIP, AIR, AISR, BF, RBI, WPPP)**
AIP = AI Personalization
AIR = AI Responsiveness
AISR = AI Service recovery
BF = Brand Preference
RBI = Re-booking Intention
WPPP = Willingness to Pay Price Premium

The econometric model is specified as:
$$AIDCS = \beta_0 + \beta_1 AIP + \beta_2 AIR + \beta_3 AISR + \beta_4 BF + \beta_5 RBI + \beta_6 WPPP + \mu$$
Where: β_0 = Constant term
β_1 - β_6 = Coefficients of independent variables
μ = Error term

The joint effect mode is also specified to capture combined influence:
$$AIDCS = \beta_0 + \beta_1 (AIP + AIR + AISR + BF + RBI + WPPP) + \mu$$
The model is used to test both individual and combined effects of AI-driven customer service and customer patronage.

4. RESULTS AND ANALYSIS

4.1 Table 1: SPSS Descriptive Statistics — Demographic Profile (n = 391)

Demographic Variable	Category / Strata	Frequency (f)	Percent (%)	Cumulative Percent (%)
Gender	Male β	215	55.0	55.0
	Female	176	45.0	100.0
	Total	**391**	**100.0**	
Age Group	18 – 25 years	59	15.1	15.1
	26 – 40 years	184	47.1	62.2
	41 – 55 years	112	28.6	90.8
	56 years and above	36	9.2	100.0
	Total	**391**	**100.0**	
Primary Purpose of Visit	Corporate / Business Travel	165	42.2	42.2
	Leisure / Vacation	78	19.9	62.1
	Conferences / Events (Mandela Hall)	114	29.2	91.3
	Academic / Research (Book Club)	34	8.7	100.0

	Total	**391**	**100.0**	
Frequency of Visits	First-time guest	82	21.0	21.0
	Occasional guest (2–4 times/year)	203	51.9	72.9
	Frequent guest (5+ times/year)	106	27.1	100.0
	Total	**391**	**100.0**	

4.2 Table 2: SPSS Multiple Linear Regression Coefficients Output Table

- **Dependent Variable:** Customer Patronage (CP)
- **Model Fitness Metrics Summary:** R = 0.768; R^2 = 0.590; Adjusted R^2 = 0.587; F-statistic = 185.34 ($p < 0.001$)

Model Construct	Unstandardized Coefficients (B)	Standard Error (Std. Error)	Standardized Coefficients (β)	t-value	Sig. (p-value)	Statistical Decision
(Constant)	0.842	0.164	—	5.134	< .001	Significant
AI Responsiveness (AIR)	0.354	0.052	0.298	6.807	< .001	Reject H_{01}
AI Personalization (AIP)	0.418	0.048	0.385	8.708	< .001	Reject H_{02}
AI-Driven Service Recovery (ASR)	0.216	0.045	0.192	4.800	< .001	Reject H_{03}

4.2. Discussion of Findings

The empirical outcomes provide critical quantitative insights into how Artificial Intelligence-driven customer service frameworks influence customer patronage metrics within the premium lodging market of the Uyo Metropolis. By analyzing data from 391 verified patrons of Ibom Hotel and Golf Resort Hotels & Suites, the multiple linear regression model yielded an R^2 value of 0.590. This demonstrates that **59.0% of the total variance in customer patronage** is directly explained by the combined predictive capacities of AI Responsiveness (AIR), AI Personalization (AIP), and AI-Driven Service Recovery (ASR). This high explanatory power highlights that digital transformation is no longer a luxury, but a core strategic determinant of market share in regional hospitality hubs (Acharya & Datta, 2023; Yusuf & Bello, 2025).

Hypothesis one ($H0_1$) reveals that AI Personalization (AIP) is the most powerful single predictor ($\beta = 0.385$, $t = 8.708$, $p < 0.001$). This finding is in support of previous foundational hospitality studies (Inavolu, 2024; Rather, 2024), which emphasize that modern automation must go beyond standardized scripts to create uniquely customized guest value. Tailoring promotions, preferences, and environment increases a guest's willingness to pay premium rates (Prentice et al., 2020). Furthermore, this is in tandem with Mola et al. (2024) regarding the management of the Personalization-Privacy Paradox, showing that when data tracking is handled smoothly, it expands customer brand preference without crossing privacy thresholds (Bittendorfer et al., 2025).

Hypothesis two ($H0_2$): The second hypothesis AI Personalization (AIR), also emerged as a highly significant predictor. Furthermore, it also aligns with Cantor (2024), validating that minimizing waiting latency with automated 24/7 channels intercepts customer flight and boosts immediate re-booking intentions before a client hop to regional alternatives or a major competing brand. This outcome runs perfectly in tandem with empirical assertions by Shanker (2026), proving that instantaneous system answers directly dictate consumer evaluation of digital service quality However, speed must be matched with contextual processing correctness, running in tandem with Kervenoael et al. (2020) who noted that rapid but shallow or erroneous automated systems compound customer frustration.

Hypothesis three ($H0_3$): AI-Driven Service Recovery (ASR) and Customer Patronage present the lowest relative predictive weight. ASR remains a critical retention vector, this finding is robustly in tandem with classic service recovery literature (Wang & Zhang, 2021), proving that autonomous error remediation can leave a disrupted consumer more brand-loyal than if no service hitch had occurred. The results also run in tandem with Liu et al. (2024), showing that the language of automated recovery platforms needs perceived empathy to lower the psychological distance between customer and service provider during failures.

4.2.1 AI Personalization (AIP) and Customer Patronage

The regression analysis isolates AI Personalization (AIP) as the strongest predictor of customer patronage at Ibom Hotels & Golf Resort Hotel ($\beta = 0.385$, $t = 8.708$, $p < 0.001$), leading to the rejection of H_{01}. This statistical outcome proves that a hotel system's capacity to securely store guest preference history, pre-configure room parameters, and deliver custom, data-driven culinary or event alerts strongly encourages long-term brand patronage. This finding aligns with modern hospitality literature emphasizing that automation must create unique value rather than just standardizing operations (Inavolu, 2024; Rather, 2024). Hyper-personalization transforms standard lodging into an emotionally resonant experience, increasing a guest's willingness to pay premium rates (Prentice et al., 2020).

However, implementing these data-heavy systems requires navigating the Personalization-Privacy Paradox (Mola et al., 2024). While patrons appreciate tailored recommendations, aggressive data tracking can reduce consumer trust if privacy controls are unclear (Prasetyo & Suryadi, 2026; Zaher & Al-Ansi, 2025). The strong link between personalization and loyalty found at Ibom Hotel and Golf Resort suggests that the hotel has balanced this relationship well, turning data insights into seamless guest comfort without crossing privacy boundaries (Bittendorfer et al., 2025).

4.2.2 AI Responsiveness (AIR) and Customer Patronage

The second independent variable, AI Responsiveness (AIR), emerged as a highly significant predictor of patronage ($\beta = 0.298$, $t = 6.807$, $p < 0.001$), leading to the rejection of H_{02}. This confirms that minimizing communication latency through 24/7 automated booking channels, real-time vacancy updates, and instant WhatsApp support significantly drives booking conversions and prevents customer loss. This outcome supports previous research showing that response speed directly influences how consumers view digital service quality (Shanker, 2026). In competitive urban markets, traditional booking delays often drive customers to look for alternative hotels; AIR acts as a critical intervention tool that secures consumer commitment right at the point of inquiry (Cantor, 2024). At the same time, this finding reinforces the principle that speed must be backed by accurate information (Kervenoael et al., 2020). If an automated conversational interface answers instantly but provides vague or incorrect information, it can increase customer frustration and weaken long-term patronage (Cantor, 2024).

4.2.3 AI-Driven Service Recovery (ASR) and Customer Patronage

Though it displayed the lowest relative predictive weight in the model, AI-Driven Service Recovery (ASR) remains a highly significant driver of customer retention ($\beta = 0.192$, $t = 4.800$, $p < 0.001$), resulting in the rejection of H_{03}. This proves that when automated systems handle errors politely, offer instant digital compensation, or provide automated solutions during service disruptions, they actively preserve guest goodwill. These dynamics match established service recovery concepts, which state that a well-handled issue can actually leave a customer more loyal than if no error had occurred (Wang & Zhang, 2021). Within digital environments, the success of these recovery efforts depends heavily on the system's perceived empathy (Liu et al., 2024). When automated recovery platforms use polite, reassuring language, they reduce the emotional distance between the consumer and the brand (Wang & Zhang, 2021). Furthermore, while automated engines excel at handling standard programmatic fixes, severe service failures still require a smooth handoff to human managers to protect the core relationship (Gursoy & Cai, 2024; Jia et al., 2025).

5. CONCLUDING REMARKS

5.1 Conclusion

While these global automated service standards generally hold true, the descriptive and qualitative feedback from the Ibom Hotels & Golf Resort study reveals a distinct regional market nuance. Patrons in the Uyo metropolis highly value properties that celebrate regional identity, such as Ibom Hotel and Golf Resort's traditional Village Square, its intellectual Uyo Book Club, and its dedicated guest library (Nwabueze & Udoh, 2024). This local preference means that an overly clinical, completely robotic automated experience could alienate consumers who expect authentic cultural hospitality (Yusuf & Bello, 2025). Therefore, the positive regression results reflect a successful hybrid hospitality approach: Ibom Hotel and Golf Resort uses automated intelligence to handle routine booking logistics efficiently ("high tech"), while relying on human warmth and cultural experiences at primary physical touchpoints ("high touch") (Bittendorfer et al., 2025).

5.2 Recommendations

Management of Ibom Icon and Golf Resort should systematically upgrade predictive data profiling architectures and security to mitigate data privacy concerns and effectively navigate the personalization-privacy paradox. Furthermore, Ibom Icon and Golf Resort should maintain rigid, seamless digital-to-human escalation loop that transfers complex service breakdowns to physical managers, keeping the core guest relationship protected. Moreso, the management should implement highly empathetic, automated digital compensation scripts within the front-office systems to issue instantaneous remediation and preserve guest goodwill during automated booking failures.

5.3 Research Gap Bridged

Prior to study, existing hospitality research within Akwa Ibom state and Uyo Metropolis context focused on exclusively on human resource service quality (SERQUAL), employees' manual responsiveness and conventional marketing mixes (Nwabueze & Udoh, 2024). An empirical gap persisted concerning how automated frontline artificial intelligence infrastructure structurally influences behavioural dimensions of patronage (specially brand preference, re-booking intention and price premium acceptance) within elite regional luxury setups.

5.4 Limitations of the Study

i. **Geographic Isolation**: This study focused entirely on a single hospitality property: Ibom Hotel and Golf Resort Hotels & Suites, located within the Uyo Metropolis, Akwa Ibom State, Nigeria. While Ibom Hotel and Golf Resort is a premier destination, the specific socio-economic conditions of Uyo may not fully represent other urban markets across Nigeria, such as Lagos or Abuja, limiting the immediate generalizability of the findings (Nwabueze & Udoh, 2024; Yusuf & Bello, 2025).

ii. **Cross-Sectional Constraints**: The research captured customer sentiments at a single point in time. Because customer perceptions of technology shift rapidly as digital literacy improve, a snapshot approach cannot fully track long-term loyalty trends (Davis, 1989; Shanker, 2026).

iii. **Variable Scope Limitation**: The regression model focused on three technical dimensions (AIR, AIP, ASR). While these explained 59.0% of the variance in customer patronage, the remaining 41.0% was unmeasured, including external factors like room pricing, physical property maintenance, and offline employee human warmth (Bittendorfer et al., 2025; Nwabueze & Udoh, 2024).

5.5 Suggestions for Future Research

i. **Cross-Regional Comparative Studies**: Future researchers should expand the geographical scope by conducting comparative analyses between hotels in the Uyo Metropolis and other major Nigerian commercial hubs to determine whether cultural variations alter customer reactions to automation (Yusuf & Bello, 2025).

ii. **Longitudinal Research Designs**: To better understand the lasting impact of technology on brand loyalty, future studies should adopt longitudinal designs to track the same group of hotel patrons over multiple years (Prentice et al., 2020; Shanker, 2026).

iii. **Expanding the Econometric Model**: Future models should introduce moderating variables. Specifically, researchers could explore how customer data privacy concerns or customer age demographics moderate the path between AI Personalization and brand loyalty (Mola et al., 2024; Prasetyo & Suryadi, 2026).

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