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Assessing the Communicative Effectiveness of Customised AI Chatbots in Nigeria's Banking Sector: Evidence from Undergraduate Users

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Abstract

The integration of Artificial Intelligence (AI) chatbots in Nigerian banking has transformed customer service delivery, yet rigorous empirical assessments of their communicative effectiveness remain scarce. This study examined the usage patterns of customised AI chatbots of Sterling Bank (Naya) and United Bank for Africa (Leo) by undergraduates at Bowen University, Iwo, Osun State; evaluated the operational/communicative performance of these chatbots; identified common issues encountered using them; and assessed their influence on customers' perceptions of service quality. Anchored on the Uses and Gratifications Theory and Technology Acceptance Model, the study employed a mixed-methods design combining a survey among purposively selected 344 undergraduates and in-depth interviews with customer service officials of the selected banks. Findings reveal that information retrieval was the dominant purpose of chatbot use (47.1%). Misunderstanding or misinterpretation of queries accounted for 36.87% of all reported issues. However, response accuracy (27.1%) and contextual understanding (31.2%) emerged as critical weaknesses. Overall, 41.3% of respondents were often satisfied, 42.2% sometimes satisfied, and 11.7% expressed rare or no satisfaction. The researchers conclude that customised AI chatbots in Nigerian banking have established a functional but communicatively limited presence, requiring urgent improvements in natural language processing accuracy, contextual intelligence, and linguistic adaptability to Nigeria's multilingual environment. Nigerian banks should institute periodic independent audits of chatbot communicative accuracy, build continuous feedback mechanisms for real-



time learning, and invest in NLP models trained on Nigerian language data, including Pidgin English and indigenous language-influenced varieties.

Keywords: Artificial Intelligence, Chatbot communication, Customer service, Natural language processing, Service quality, Nigerian banking sector

Introduction

Communication is the lifeblood of banking. Every product recommendation, such as transaction confirmation, complaint resolution, and service enquiry, passes through communicative exchanges that shape customer trust, satisfaction, and long-term loyalty. Shannon and Weaver's (1949) foundational model of communication frames this process as the transmission of information from a sender to a receiver through a channel, with noise that can disrupt faithful delivery at any stage. In banking, that noise, whether linguistic, technical, or cultural, has historically been managed by human agents trained to interpret customer needs contextually. The emergence of AI-powered chatbots as frontline communicative agents fundamentally disrupts this dynamic, replacing human interpretive judgment with algorithmic pattern matching.

The history of conversational AI in human-computer interaction traces to Weizenbaum's (1966) ELIZA, a programme that simulated psychotherapeutic dialogue through scripted pattern matching. From these rudimentary beginnings, chatbot technology has evolved from rule-based systems and retrieval-based architectures to Large Language Model (LLM)-powered conversational agents capable of sustaining multi-turn dialogue across diverse domains (Adamopoulou & Moussiades, 2020). Brandtzaeg and Følstad (2017), in a study of why people use chatbots, identified three primary motivational clusters: productivity and efficiency (information retrieval), entertainment and curiosity, and social interaction.

In the financial services sector, AI chatbot deployment has accelerated dramatically. A report by McKinsey and Company (2023) estimates that generative AI could add between 2.6 and 4.4 trillion USD annually to the global economy, with financial services among the highest-impact sectors. Adamet *al.* (2020) found that AI-powered customer service chatbots measurably improve response times and customer engagement satisfaction when deployed effectively. Xu et *al.* (2017) demonstrated in a CHI study that chatbots handling customer service queries on social media platforms showed significant potential but also systematic failures when user inputs deviated from anticipated patterns, a finding with direct relevance to the Nigerian banking context examined in this study. Nicolescu and Măriuța-Teodora (2022) further documented that chatbots in customer service improve perceived service quality primarily along the dimensions of responsiveness and availability, but struggle with personalisation and complex issue resolution.

Nigeria's banking sector occupies a distinctive position in sub-Saharan Africa's financial landscape. The World Bank's Global Findex Database (2021) reports that while account ownership in sub-Saharan Africa has risen sharply, reaching 55% of adults, Nigeria's financial inclusion trajectory is shaped by high mobile phone penetration juxtaposed with persistent access barriers. The Enhancing Financial Innovation and Access survey (EFInA, 2023) found that 56% of Nigerian adults now have access to formal financial services, but that digital banking adoption remains concentrated among urban, educated youth. It is this population, represented in this study by undergraduates at Bowen University, who are the most active users of AI chatbot-enabled banking services. The Central Bank of Nigeria (CBN, 2022) has actively promoted digital banking innovation through its regulatory sandbox framework, and major commercial banks have responded by deploying customised conversational AI systems. United Bank for Africa's (UBA) Leo chatbot and Sterling Bank's Naya chatbot represent two of the most prominent deployments



in Nigerian retail banking, both capable of handling balance enquiries, fund transfers, bill payments, and customer support through natural language interfaces.

However, the communicative effectiveness of these systems in Nigeria's uniquely complex sociolinguistic environment poses profound challenges that generic NLP architectures are ill-equipped to address. Nigeria hosts over 500 languages (Blench, 2012), with Yoruba, Igbo, and Hausa serving as major regional languages and Nigerian Pidgin English functioning as a widely spoken lingua franca across ethnic and demographic groups. Bender *et al.* (2021), in their influential critique of large language models, demonstrate that systems trained on predominantly Western English corpora fail systematically when deployed in communities whose communicative norms, code-switching patterns, and lexical inventories are absent from training data. Adelani *et al.* (2021), in the MasakhaNER project on named entity recognition for African languages, confirmed that African language data remains critically underrepresented in major NLP training corpora, a structural deficit that cascades into poor performance when AI systems encounter Nigerian language-influenced English in real banking interactions.

The mismatch between the linguistic profiles of Nigerian bank customers and the training data of deployed NLP systems represents a structurally embedded communication problem. Most commercial chatbots deployed in Nigerian banking are built on NLP architectures developed and trained on standardised British or American English corpora. Yet Nigerian bank customers, particularly mobile-first youth populations, communicate in Nigerian Pidgin English, Yoruba-inflected English, Igbo-patterned constructions, and informal abbreviated forms that differ substantially from the language patterns these systems were designed to process (Bender *et al.*, 2021; Adelani *et al.*, 2021). When a customer types “*abeg show me my balance*” or “*how much remain for my acct.*,” the chatbot's capacity to correctly interpret the pragmatic intent and respond appropriately becomes a direct test of its communicative competence, a test that generic English-trained NLP systems routinely fail.

From a service quality perspective, communicative failure in AI chatbot interactions carries consequences beyond mere technical inconvenience. Haugeland *et al.* (2022) demonstrated that the user experience of chatbot interactions is fundamentally shaped by perceived communicative competence, the sense that the system understands what the customer means, not merely what the customer says. When chatbots fail this test, they erode customer trust, damage brand perception, and potentially drive customers toward competitors or away from digital banking channels altogether. Gefen *et al.* (2003) established that perceived usefulness and trust are the critical antecedents of continued technology adoption, suggesting that communicative failures directly threaten the long-term viability of AI chatbot programmes in Nigerian banking.

Despite these stakes, systematic empirical assessment of AI chatbot communicative effectiveness in the Nigerian banking context is conspicuously absent from the academic literature. Følstad and Brandtzaeg (2017) note that chatbot research has overwhelmingly focused on developed-country contexts, treating effectiveness as a technical measurement while neglecting the communicative and sociolinguistic dimensions that determine real-world user outcomes. This study addresses that gap.

Generally, this study examines the communicative effectiveness of the Naya and Leo chatbots of Sterling Bank and UBA, respectively, among undergraduates of Bowen University, Iwo, Osun State. Specifically, this study aims to:

1. examine patterns of AI chatbot usage among undergraduate bank customers, including frequency, duration, and purposes of engagement;
2. evaluate the operational performance of these chatbots across key effectiveness dimensions in addressing customer inquiries;



3. assess how chatbot communication influences customers' perceptions of service quality; and
4. identify common issues encountered by customers during AI chatbot interactions.

Theoretical Framework

This study is anchored on a theory and model – the Uses and Gratifications Theory (UGT) and Technology Acceptance Model (TAM), respectively. First articulated by Katz, Blumler, and Gurevitch (1974) in the context of mass media, the UGT positions audiences as active agents who deliberately select media to fulfil specific psychological and social needs. The theory has been productively adapted to digital media and AI communication contexts, where users interact with platforms to satisfy informational, transactional, relational, and entertainment-related needs (Adam *et al.*, 2020). In the banking context, UGT explains why customers choose AI chatbot interfaces over human agents or branch visits: they seek the gratifications of immediacy, convenience, and 24/7 availability. In the Nigerian context, where mobile banking uptake has accelerated rapidly (Ejiobih *et al.*, 2019), users' chatbot gratifications are shaped by both access convenience and the perceived communicative competence of the AI interface. When chatbots successfully satisfy these motivations, users report positive service quality perceptions and maintain continued engagement (Gefen *et al.*, 2003). When they fail, through misinterpretation, vague responses, or inability to handle complex queries, users are gratificationally frustrated, producing negative service quality assessments and reduced adoption intention.

Also, the TAM, developed by Davis (1989), posits that an individual's decision to use a given technology is determined primarily by two perceptual constructs: perceived usefulness, the degree to which the user believes the technology enhances their performance, and perceived ease of use, the degree to which engaging the system is free of effort. Venkatesh and Davis (2000) extended TAM to demonstrate that social influence and cognitive instrumental processes also shape technology adoption across diverse cultural and organisational settings. In this study, TAM informs analysis of how students' perceptions of chatbot usefulness and ease of use predict their satisfaction levels, frequency of interaction, and continued engagement. Chatbots perceived as genuinely helpful and navigationally simple are more likely to be adopted; those that generate confusion or inaccurate responses face behavioural resistance regardless of their technical sophistication.

Both UGT and TAM offer a robust and mutually reinforcing theoretical foundation for this study. While UGT illuminates the motivational landscape that draws undergraduate banking customers to AI chatbot interfaces, specifically the gratifications of immediacy, convenience, and 24/7 accessibility, TAM explains the cognitive evaluative processes through which users assess whether those chatbots deliver sufficient utility to warrant continued engagement. Their complementarity is particularly apt in the Nigerian banking context, where chatbot adoption is simultaneously driven by pragmatic gratification motives and constrained by perceived usefulness limitations arising from NLP inaccuracies and sociolinguistic mismatches. Together, they enable a holistic assessment of communicative effectiveness that neither framework could achieve independently, making them the ideal dual-lens through which to examine the behaviour, expectations, and satisfaction of undergraduate chatbot users in this study.

Method

A mixed-methods research design was adopted in this study, comprising quantitative and qualitative approaches. These involved the use of a survey, which enabled the measurement of undergraduates' perceptions of the chatbots' effectiveness, their usage patterns, and satisfaction levels; and in-depth interviews with banking officials, which provided institutional perspectives.

The study population comprised undergraduates of Bowen University, Iwo, Osun State, who held active accounts with either Sterling Bank or UBA and had prior experience using the Naya or Leo AI chatbots,



respectively. The university had approximately 5,000 registered undergraduates at the time of the study. Therefore, the study used Yamane's (1967) formula for finite population sample size determination, $n = N/(1 + N \cdot e^2)$; the minimum required sample for $N = 5,000$ at a 95% confidence level and 5% margin of error is $n = 5,000/(1 + 5,000 \times 0.0025) = 5,000/13.5 \approx 371$. A target of 371 respondents was therefore pursued. To account for retrieval attrition and data quality margins inherent in survey research, the sample size for this study was rounded up to 400; hence, 400 questionnaire copies were administered. However, based on purposive identification of eligible chatbot users across the seven colleges, 344 were returned, and completely filled, and this was considered usable representing an 86.0% retrieval rate.

Then, multi-stage sampling was employed. For the survey, stratified sampling was first used to divide the undergraduate population into the seven constituent colleges of Bowen University: College of Agriculture, Engineering and Science (COAES); College of Management and Social Sciences (COMSS); College of Computing Studies (COCS); College of Health Sciences (COHES); College of Law (COLAW); College of Environmental Sciences (COEVS); and College of Liberal Studies (COLBS). Purposive sampling was then applied within each stratum to select respondents with documented prior experience using the Naya or Leo chatbots. For in-depth interviews, purposive sampling was used to select customer service officials from each bank on account of their specialised knowledge of chatbot deployment and performance. A total of six (6) in-depth interviews were conducted, three (3) with senior customer service officials of Sterling Bank and three (3) with their counterparts at UBA, each lasting between 30 and 40 minutes.

Consequently, two instruments were used to collect data in this study – a questionnaire and a structured interview guide. The questionnaire comprised 30 items, while the interview guide was designed to elicit qualitative insights on chatbot functionality, customer feedback, and institutional perspectives on communicative performance.

The validity of the research instruments was done systematically. Content validity approach was used for the questionnaire, where it was reviewed by three experts in Mass Communication and survey research at Bowen University, Precious Cornerstone University and University of Ibadan. Their observations informed revisions to item wording, response scaling, and thematic coverage.

To establish reliability, the questionnaire was pilot-tested on 30 undergraduates outside the main sample who had prior experience with either chatbots, and the resulting responses were subjected to Cronbach's alpha reliability analysis, yielding a coefficient of 0.81, above the 0.70 threshold conventionally regarded as acceptable for social science instruments (Nunnally, 1978). For the interview guide, dependability was established through an audit trail: interview recordings, transcripts, and coding decisions were retained and cross-checked independently by two of the researchers to confirm the consistency and trustworthiness of the qualitative data.

The questionnaire was physically self-administered with the help of trained research assistants to ensure completion integrity. The interview guide was administered face-to-face by the researchers in the offices of the respective banks' customer service units, with each session audio-recorded with the participant's consent and later transcribed verbatim for analysis.

Quantitative data, from the questionnaire, were analysed using frequency counts and simple percentages, computed with the Statistical Package for the Social Sciences (SPSS), and presented in tables and charts. Qualitative data from the interviews were analysed using Braun and Clarke's (2006) thematic analysis approach, involving transcription, familiarisation, coding, theme generation, and thematic reporting, to draw out institutional perspectives that complemented and contextualised the quantitative findings.



Importantly also, ethical consideration was strictly observed. The consents of the respondents and interviewees were sought prior to their participation in the study. They were informed with the purpose of the study, the voluntariness to participate, and the assurance of confidentiality and anonymity.

Findings

Objective 1: Undergraduates' Chatbot Usage Patterns: frequency, duration and purposes of Use

The study assessed the pattern of chatbot use among the undergraduates across three different levels, which are frequency of use, duration of use and purpose of use. The findings are presented in Table 1.

Table 1: Undergraduates' Chatbot Usage Patterns

Usage Patterns	Pattern Variables	No. of Respondents (f)	Percentage (%)
Frequency of Use	Daily	35	10.2
	Weekly	138	40.1
	Monthly	141	41.0
	Rarely	21	6.1
	Never	9	2.6
	Total	344	100.0
Duration of Use	Under 5 minutes	109	31.7
	5–10 minutes	128	37.2
	10–20 minutes	78	22.7
	Over 20 minutes	29	8.4
	Total	344	100.0
Purpose of Use	Information Retrieval	162	47.1
	Transaction Assistance	97	28.2
	Complaint Lodgment	49	14.2
	Account Management	24	7.0
	Other Purposes	12	3.5
	Total	344	100.0

Trend-wise, this pattern signals a maturing but narrow relationship between undergraduates and their banks' AI chatbots: usage has moved beyond novelty into routine, yet it remains confined to low-stakes, transactional purposes. The practical implication is that these chatbots have secured a foothold as convenience tools but have not yet been trusted with more complex banking needs, suggesting that expanding their communicative competence could unlock deeper engagement rather than merely wider usage. A UBA official responsible for Leo's deployment similarly indicated that transaction-related queries account for the bulk of chatbot interactions, particularly late evenings and weekends, underscoring the 24/7 availability gratification that UGT theory identifies as the core driver of chatbot adoption among mobile-first banking users.

Objective 2: Chatbot Operational/Communicative Effectiveness

Across six dimensions of operational effectiveness, the data reveal a pattern of asymmetric performance: chatbots perform robustly on speed but fall significantly short on accuracy and contextual interpretation.

Figure 1 presents the full distribution of respondent ratings across all six dimensions.

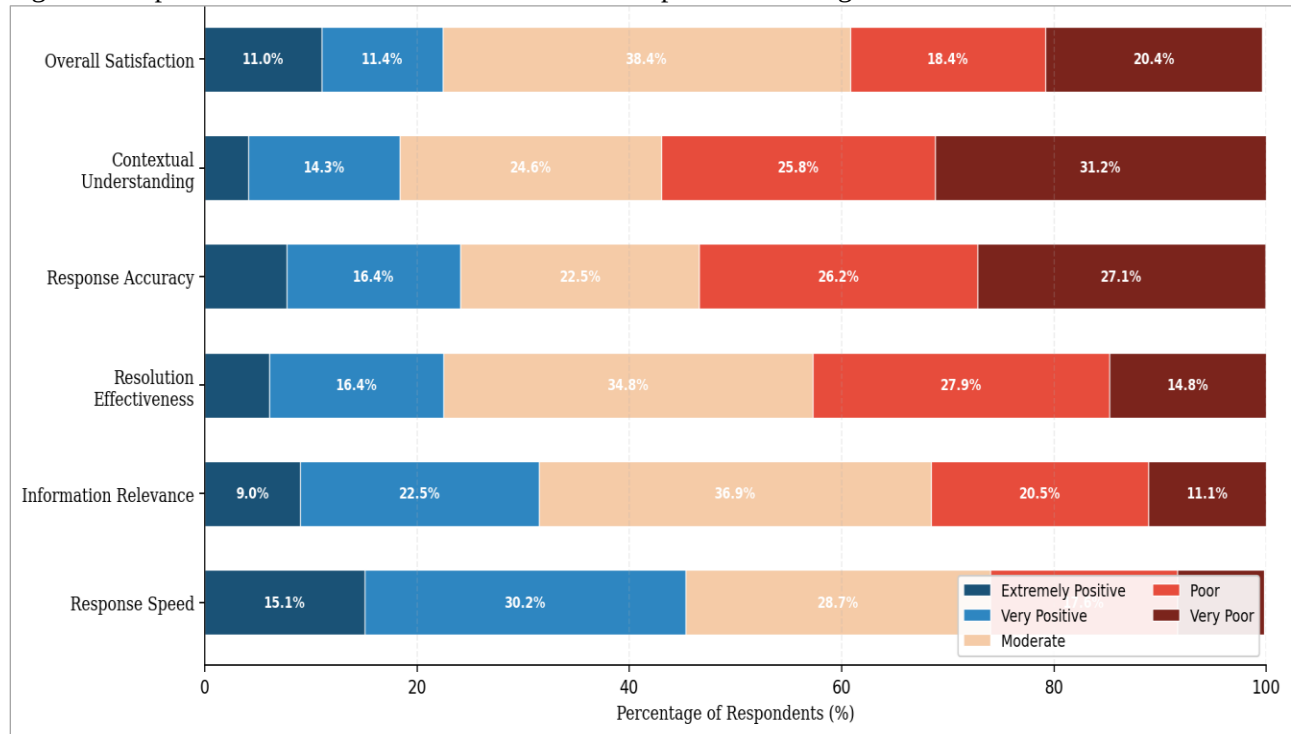


Figure 1: Distribution of Ratings Across Six Chatbot Operational Effectiveness Dimensions

Findings in Figure 1 implicate that speed alone cannot sustain the value proposition of banking chatbots; where accuracy and contextual understanding lag, users experience the interaction as fast but hollow, a combination that erodes confidence in the system's competence even as it satisfies expectations of immediacy. This asymmetry signals that future investment should prioritise linguistic and contextual intelligence over further gains in response latency, which has already reached a ceiling of user satisfaction.

Qualitative insights from bank officials corroborated these patterns: a Sterling Bank official described Naya as 'very effective for routine queries' but acknowledged that it 'sometimes misses the point' when customers phrase requests informally or mix languages. A UBA official similarly described Leo as performing reliably within scripted parameters, particularly for balance enquiries and fund transfer confirmations, while candidly acknowledging persistent communicative challenges when customers employ informal registers, Pidgin English, or code-switched constructions that deviate from the chatbot's standard English training inputs.

Objective 3: Influence of Chatbot Interaction on Customer Perception of Service Quality

Customer perceptions of AI chatbot service quality were assessed across three measures: overall satisfaction with chatbot interactions, the degree to which chatbot responses met respondents' expectations, and perceived user-friendliness of the chatbot interface. Figure 3 presents a comparative overview across all three measures, and Figure 4 provides a distributional breakdown of overall satisfaction.

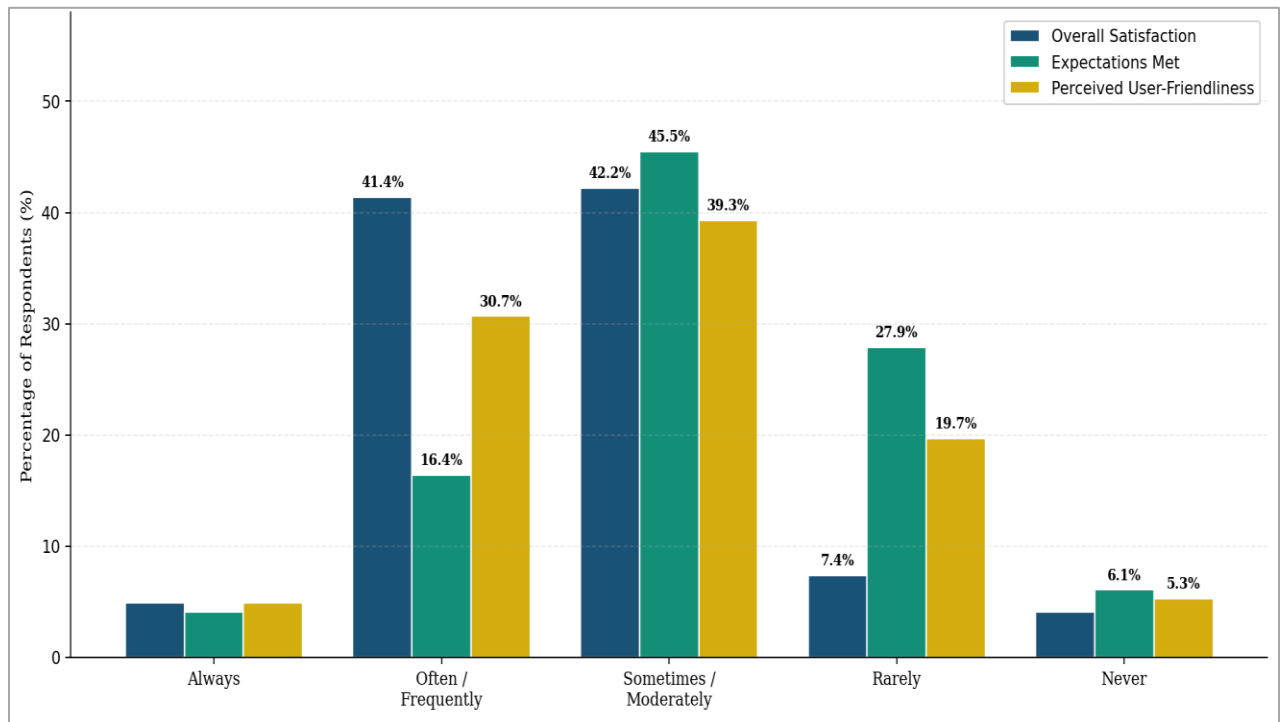


Figure 2: Customer Perception of AI Chatbot Service Quality Across Three Measures

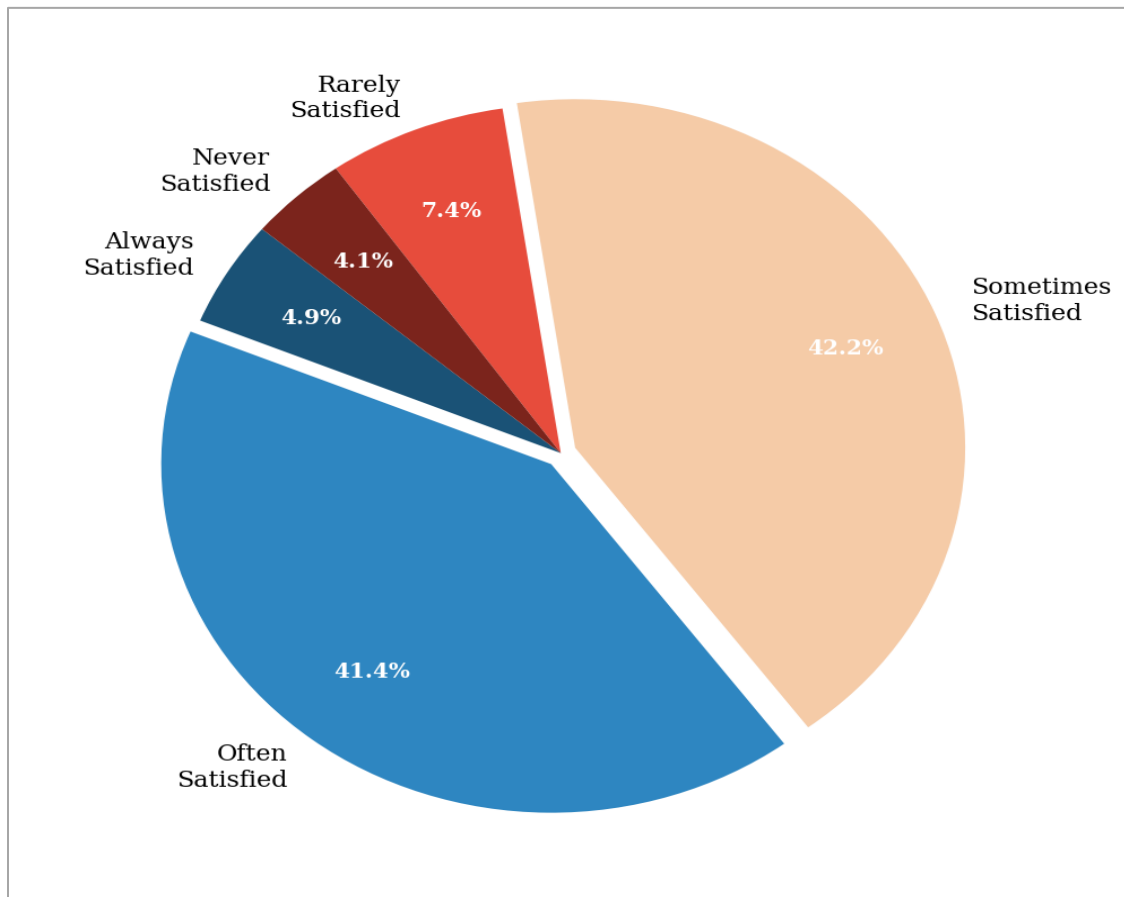


Figure 3: Overall Satisfaction with AI Chatbot Interactions

Findings in Figures 3 and 4, read together, point to a widening gap between what chatbots deliver and what users expect of them the longer they use these systems, a trend that, left unaddressed, risks converting habitual use into habitual tolerance rather than genuine satisfaction, with implications for long-term customer retention on digital banking channels. Institutional perspectives from bank officials corroborate the service quality findings. A UBA official noted that internal customer satisfaction data for Leo broadly mirror the ‘often’ and ‘sometimes’ satisfied distribution recorded in the survey, and acknowledged that satisfaction scores improve markedly when queries are formulated in standard English but deteriorate with informal or code-switched inputs. A Sterling Bank representative confirmed that Naya’s complaint logs similarly reflect unmet expectations around contextual accuracy, and indicated that the bank is actively investing in interface redesign and NLP model upgrades specifically targeting Nigerian language variety inputs, with a view to closing the expectation–fulfilment gap identified by users.

Objective 4: Common Issues Encountered During Chatbot Interactions

Respondents reported a total of 575 issues across six categories, with multiple selections permitted. Figure 2 presents these issues in descending order of frequency, revealing a clear concentration of problems around the chatbot’s capacity to correctly interpret and respond to queries.

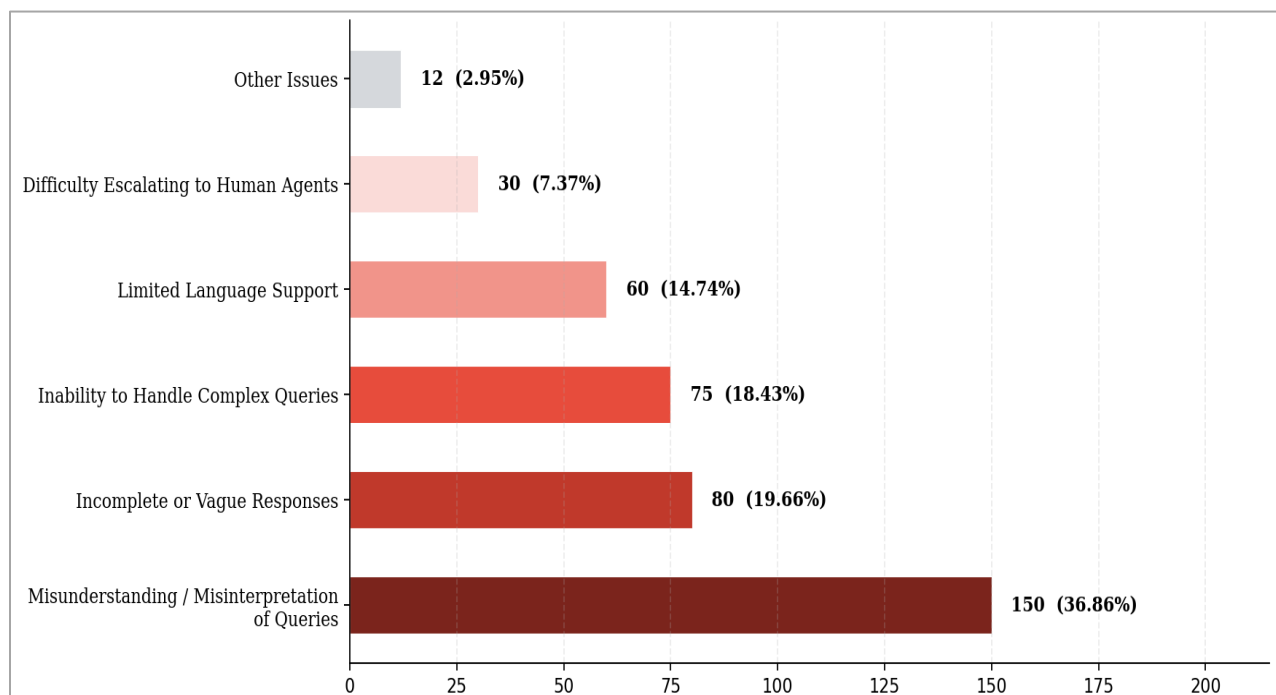


Figure 4: Common Issues Encountered During AI Chatbot Interactions

The clustering of issues around interpretation and complexity, rather than around speed or availability, signals where remedial investment will yield the greatest returns: not in infrastructure or interface redesign, but in the underlying language models’ capacity to parse Nigerian communicative norms, a targeted intervention with more direct payoff than broader technical upgrades. Limited language support was the fourth most reported issue (85 instances, 14.78%). The difficulty in escalating to human agents (42 instances, 7.30%) represents a secondary but significant finding: when chatbots fail, the inability to reach a human agent compounds the communicative failure, leaving customers stranded without resolution.



Discussion

The findings from Objective 1 establish that AI chatbot use has achieved a meaningful level of habitual integration into the banking routines of undergraduate users at Bowen University. The dominance of weekly and monthly engagement (combined 81.1%), alongside the brevity of most sessions (68.9% under ten minutes), confirms that students are deploying chatbots as efficient transactional touchpoints rather than as rich communicative interfaces. Information retrieval (47.1%) and transaction assistance (28.2%) together account for over three-quarters of stated usage purposes, reflecting the productivity gratification motive that UGT theory predicts will dominate in contexts where immediacy and convenience are prioritised (Brandtzaeg & Følstad, 2017; Adam *et al.*, 2020). Bank officials from both Sterling Bank and UBA corroborated this picture: interviewed officials confirmed that mobile-first undergraduate customers overwhelmingly engage their respective chatbots for routine, time-sensitive queries outside branch hours, indicating that 24/7 availability is the primary adoption driver and that communicative sophistication is a secondary consideration for this user segment.

With respect to Objective 2, the findings expose a structural performance asymmetry at the core of these chatbots' communicative profiles. Response speed, rated positively by a combined 45.3% of respondents, represents the unambiguous operational strength, consistent with the structural advantage of AI systems in delivering instantaneous, round-the-clock responses without queuing (Oracle, 2020). However, this speed advantage is critically undermined by poor response accuracy (53.3% rated it poor or very poor) and deficient contextual understanding (57.0% rated it poor or very poor), the two dimensions most central to communicative effectiveness. From a TAM perspective, this constitutes a strategic paradox: perceived ease of use is broadly acceptable, as reflected in comparatively positive user-friendliness ratings, but perceived usefulness is critically compromised by accuracy failures (Davis, 1989; Venkatesh & Davis, 2000). Since Davis (1989) established that perceived usefulness is the stronger predictor of sustained adoption intention, the accuracy deficit documented here represents the more strategically decisive vulnerability, regardless of the chatbots' navigational simplicity (Venkatesh & Davis, 2000). A Sterling Bank official acknowledged that Naya 'sometimes misses the point' with informally phrased queries, while a UBA official described Leo as reliable within scripted parameters but challenged by multilingual and non-standard inputs, institutional admissions that directly corroborate the quantitative findings.

The third objective reveals that the dominant source of chatbot failure is pragmatic rather than technical in nature. Misunderstanding or misinterpretation of user queries accounted for 36.87% of all 575 reported issues, confirming Thomas's (1983) framework of cross-cultural pragmatic failure as directly applicable to AI-mediated banking communication in Nigeria's multilingual environment. Nigeria's estimated 500-plus languages (Blench, 2012) and the pervasive use of Pidgin English and vernacular-influenced code-switching create a communicative context that NLP architectures trained on standardised Western English corpora are structurally ill-equipped to handle, directly affirming Bender *et al.*'s (2021) critique of language models trained on unrepresentative corpora. Incomplete or vague responses (19.65%) and inability to handle complex queries (18.43%) compound this pragmatic deficit, with these three categories collectively accounting for 75.0% of all reported problems. The difficulty of escalation to human agents (7.30%) represents a secondary but significant finding: when chatbots fail communicatively, the absence of clear escalation pathways compounds the breakdown, leaving customers without resolution pathways and further eroding service quality perceptions (Haugeland *et al.*, 2022). Sterling Bank and UBA officials candidly confirmed that informal and code-switched queries consistently generate the highest rates of misinterpretation-related escalations, and that this pattern is recognised institutionally even where remediation remains incomplete.

Regarding Objective 4, the distribution of overall satisfaction, concentrated in the 'often' (41.3%) and 'sometimes' (42.2%) satisfied bands, with only 4.9% always satisfied, describes a condition of conditional, functional adequacy rather than communicative excellence. This pattern is consistent with



Madsen and Gregor's (2000) framework: where system performance consistently falls short of user expectations, satisfaction remains variable and structurally fragile. The expectations dimension is especially revealing: a combined 34.0% of respondents reported that chatbot responses 'rarely' or 'never' met their expectations, compared to only 20.5% reporting expectations being 'often' or 'always' met. From a UGT perspective, this chronic divergence between gratification sought and gratification obtained reflects a fundamental communicative utility problem: users engage chatbots in pursuit of accurate, contextually appropriate responses, but systematically obtain something less (Katz *et al.*, 1974; Adam *et al.*, 2020). User-friendliness fared somewhat better (35.6% rated it 'often' or 'always' user-friendly), suggesting that interface design is less problematic than NLP capability, a finding that pinpoints communicative deficiency, not interaction design, as the primary area requiring intervention. Bank officials from both institutions corroborated this service quality picture: a UBA official noted that satisfaction with Leo improves markedly when queries are formulated in standard English but deteriorates with informal or code-switched inputs, while a Sterling Bank representative confirmed that Naya's internal complaint logs reflect unmet accuracy expectations and that NLP upgrade investments targeting Nigerian language varieties are underway.

Conclusion and Recommendation

This study assessed the communicative effectiveness of UBA's Leo and Sterling Bank's Naya AI chatbots among 344 undergraduate users at Bowen University, anchored on UGT and TAM. The findings converge on a coherent picture of functional but communicatively limited performance: chatbot engagement is habitual and purposeful, driven primarily by information retrieval (47.1%) and completed within brief, transactional sessions, consistent with UGT's informational gratification motive. Response speed is the clear operational strength (45.3% positive ratings), while accuracy (53.3% poor or very poor) and contextual understanding (57.0% poor or very poor) constitute critical weaknesses that directly undermine TAM's perceived usefulness threshold for sustained adoption. Misunderstanding and misinterpretation of queries, accounting for 36.87% of 575 reported issues, represent the dominant communicative failure, rooted in the structural mismatch between Nigeria's multilingual sociolinguistic environment and NLP systems trained on standardised Western English corpora.

Overall satisfaction is variable and conditional, concentrated in the 'often' and 'sometimes' bands, with user expectations chronically undermet and service quality perceptions correspondingly modest. These chatbots have succeeded in establishing a fast, accessible, and broadly adopted customer service interface, but have not yet achieved the communicative quality, the accuracy, contextual intelligence, and linguistic adaptability required to function as dependable communicators in Nigeria's complex linguistic environment. Substantial investment in Nigerian-language NLP training data, continuous feedback loops, and robust escalation protocols is urgently needed if these systems are to transition from functional tools to genuinely effective communicative agents in the country's rapidly digitising banking sector.

Limitations and Practical Implications of the Study

This study is not without limitations. The sample, drawn exclusively from undergraduates of a single private university, and the focused on only two bank chatbots, Naya and Leo, constrains the generalisability of the findings to Nigeria's broader and more socioeconomically diverse banking population. Practically, the findings offer Nigerian banks a clear roadmap: communicative accuracy and contextual understanding, rather than speed or interface design, are the binding constraints on chatbot effectiveness, and resources directed at Nigerian-language NLP training, continuous feedback mechanisms, and seamless human escalation pathways are likely to yield the greatest improvements in customer satisfaction and digital banking adoption.

Based on the findings, the following recommendations are offered:



1. Periodic independent audits of chatbot communicative accuracy and contextual understanding should be institutionalised, using a combination of quantitative interaction metrics and qualitative user feedback panels that include linguistically diverse participants.
2. Nigerian banks should invest in NLP models trained specifically on Nigerian language data, including Nigerian Pidgin English, Yoruba-, Igbo-, and Hausa-influenced English patterns, and informal abbreviated digital communication styles, to address the dominant problem of query misunderstanding and misinterpretation.
3. Continuous feedback loops should be built into chatbot systems, enabling real-time learning from mishandled interactions and rapid correction of recurring communicative errors.
4. Escalation protocols to human agents should be clearly integrated into chatbot interaction flows, ensuring that queries beyond the chatbot's competence are smoothly redirected without frustrating the customer.

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