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Service Quality and Customer Satisfaction in AI-Driven versus Human Banking Support

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Abstract

Background: The integration of artificial intelligence (AI) into retail banking has transformed frontline service delivery, prompting financial institutions to substitute human personnel with automated virtual assistants. While conversational agents offer scalable operational speed, their comparative performance against human representatives across core service quality dimensions remains contested.

Objective: This study evaluated customer-perceived service quality dimensions (responsiveness, reliability, assurance, and empathy), customer satisfaction, and service continuance intention across AI-driven and human banking support channels, while examining the moderating influence of query complexity.

Methodology: A cross-sectional comparative survey was conducted among 384 verified commercial retail bank customers who had interacted with both automated virtual assistants and human support personnel within the preceding twelve months. Data were collected using structured instruments developed for the study. Hypotheses were tested using paired-samples t-tests, two-way repeated-measures Analysis of Variance (ANOVA), and Partial Least Squares Structural Equation Modelling (PLS-SEM).

Result: AI virtual assistants achieved significantly higher perceived responsiveness than human personnel, while both channels demonstrated equivalent transactional reliability. Conversely, human representatives achieved significantly higher ratings in empathy and assurance. The structural model demonstrated that perceived empathy significantly predicted customer satisfaction in human encounters but failed to predict satisfaction in AI interactions. Furthermore, query complexity significantly moderated satisfaction: AI support generated higher satisfaction for routine transactions, whereas human support produced markedly superior satisfaction for

complex, disputed, or emotionally sensitive issues. Service quality dimensions collectively mediated the relationship between support modality and customer satisfaction.

Conclusion: Conversational AI cannot completely replace human professionals in retail banking. Financial institutions must adopt hybrid service delivery models that leverage AI for rapid routine triage while maintaining seamless escalation pathways to human specialists for complex grievances.

Keywords: Artificial intelligence; retail banking; service quality; customer satisfaction; virtual assistants; human customer service; query complexity; PLS-SEM.

Introduction

The rapid acceleration of financial technology has reshaped the landscape of retail banking, prompting financial institutions globally to transition from traditional counter services to automated, digital touchpoints (Abdeljawad et al., 2025; Shaikh et al., 2024). At the core of this transformation is the deployment of artificial intelligence (AI), particularly conversational agents, natural language processing tools, and intelligent virtual assistants designed to automate front-line customer engagement (Hossain et al., 2025; Junaedi et al., 2024). In an operational environment defined by round-the-clock consumer demands, commercial retail banks are investing heavily in automated service platforms to streamline query triage, minimise operational overheads, and deliver instant, real-time responses to routine inquiries (Gopinathan, 2024; Ikbali, 2026).

Despite extensive institutional investments, the widespread substitution of human service personnel with AI-driven interfaces has created notable operational and relational tensions (Mahmud, 2025). While AI interfaces excel at standard computational tasks, transaction tracking, and immediate retrieval of account balances, their capacity to deliver comprehensive service quality remains contested (Hasan et al., 2026; Sheth et al., 2022). Consumer satisfaction within retail banking is fundamentally rooted in relational attributes: empathy, conversational understanding, perceived assurance, and situational sensitivity (Hui et al., 2024; Patil et al., 2025). When clients encounter technical errors, fraudulent transactions, or complex credit arrangements, automated bots often struggle to interpret affective nuances or handle unstructured conversational inputs (Ibidunmoye & Ekeh, 2026; Wahyuni et al., 2025). This communicative rigidity risks frustrating users, degrading perceived institutional reliability, and accelerating customer churn (Joseph et al., 2026; Wu & Sun, 2026).

Consequently, the retail banking sector faces a strategic dilemma: balancing the transactional efficiency and scalability of conversational AI against the interpersonal trust, nuanced problem-solving, and emotional assurance delivered by human service representatives (Mahmud, 2025; Sheth et al., 2022). While several empirical inquiries have examined AI adoption as an isolated technological intervention within specific national contexts (Hossain et al., 2025; Shaikh et al., 2024), there is a distinct shortage of empirical research directly comparing customer-evaluated

service quality dimensions between AI virtual assistants and human support personnel across differing levels of query complexity.

This study addresses this gap by comparing customer satisfaction and perceived service quality in AI-driven versus human banking support. Drawing upon established service quality frameworks, the investigation evaluates how responsiveness, reliability, assurance, and empathy vary between these two service channels, establishing the operational conditions under which automated support succeeds or requires human intervention.

Literature Review

Theoretical Foundations: Service Quality in the Era of Algorithmic Service Delivery

The conceptualisation of service quality within commercial banking has traditionally been anchored in the SERVQUAL paradigm, which posits that customer evaluations reflect discrepancies between prior service expectations and actual performance across five dimensions: reliability, responsiveness, assurance, empathy, and tangibles (Hasan et al., 2026; Patil et al., 2025). In digital financial environments, these dimensions require re-evaluation. Automated virtual assistants have fundamentally disrupted traditional notions of responsiveness and tangibility by replacing physical bank premises with responsive, mobile-integrated conversational interfaces capable of instantaneous response times (Gopinathan, 2024; Ikbal, 2026).

Nevertheless, the integration of algorithmic agents challenges the affective dimensions of service quality: assurance and empathy (Hui et al., 2024). While modern generative and retrieval-based chatbots are programmed with anthropomorphic features, conversational politeness, and simulated attunement to replicate interpersonal rapport (Patil et al., 2025), they operate without subjective consciousness or authentic intersubjective understanding. As Wu and Sun (2026) illustrate using hybrid analytical approaches, customer satisfaction in automated banking is asymmetric; technical accuracy and operational speed do not automatically compensate for failures in emotional validation or perceived security. Consequently, evaluating AI service quality requires assessing not merely computational speed, but how automated systems navigate relational and problem-solving boundaries compared to human practitioners (Abdeljawad et al., 2025; Mahmud, 2025).

Operational Capabilities and Efficiency of AI-Driven Banking Support

A substantial body of empirical literature documents the operational dividends realised by financial institutions adopting AI customer support architectures (Hossain et al., 2025; Ikbal, 2026; Junaedi et al., 2024). In their analysis of Indian banking consumers, Shaikh et al. (2024) observed that the perceived reliability and operational efficiency of AI platforms significantly influenced customer satisfaction, primarily by cutting queue durations and eliminating temporal barriers to account administration. Similarly, Hossain et al. (2025) identified AI chatbots as pivotal drivers of service efficiency and institutional marketing in the United States, showing that virtual assistants

reduce resolution latency for standardised queries such as balance checks, recent transaction audits, and card activation.

The capacity of AI tools to deliver ubiquitous, real-time access is central to customer retention across emerging and developed markets alike (Ikbal, 2026; Sheth et al., 2022). In specialised banking domains, such as Islamic financial institutions, Wahyuni et al. (2025) reported that AI chatbots effectively streamlined client communication by offering direct, policy-compliant answers to routine inquiries. Furthermore, when conversational bots incorporate humanoid or anthropomorphic design cues, users tend to perceive them as more responsive, fostering initial cognitive trust and encouraging digital self-service adoption (Hui et al., 2024; Patil et al., 2025).

Relational Boundaries, Failure Modes, and the Primacy of Human Intervention

Despite the operational strengths of conversational software, empirical investigations highlight persistent relational constraints when bots operate without human oversight (Gopinathan, 2024; Mahmud, 2025). Sheth et al. (2022) caution that while AI offers a powerful frontier for service personalisation in emerging markets, automated ecosystems frequently underperform due to infrastructure bottlenecks, algorithmic rigidity, and an inability to resolve nuanced customer grievances that demand human intervention. When financial clients face distressing, non-standard dilemmas—such as unauthorised debits, complex loan restructuring, or disputed payments—the inability of automated chatbots to exercise situational flexibility or demonstrate authentic empathy frequently leads to customer alienation (Ibidunmoye & Ekeh, 2026; Joseph et al., 2026).

In an empirical assessment of retail banking in Nigeria, Ibidunmoye and Ekeh (2026) established that while AI-driven client services positively correlate with customer satisfaction, this relationship degrades when system responses become repetitive or fail to resolve core complaints. Similar dynamics were documented by Joseph et al. (2026) among mobile fintech users, where service interruptions, algorithmic failures, and unhelpful automated dialogues negatively affected brand loyalty and user continuance intentions. In comparative trials, Mahmud (2025) observed that human banking personnel consistently outperformed conversational AI on metrics of empathy, relational assurance, and complex problem resolution. Clients frequently experienced high frustration when automated agents were trapped in conversational loops, underscoring that speed cannot compensate for failed issue resolution (Hasan et al., 2026; Mahmud, 2025).

Value Creation, Continuance Intentions, and Hybrid Collaboration Models

Recent research conceptualises the relationship between service quality and customer satisfaction as an antecedent to sustained customer continuance and institutional value co-creation (Abdeljawad et al., 2025; Hasan et al., 2026). Utilising structural equation modelling (SmartPLS), Hasan et al. (2026) demonstrated that digital service quality in AI-enabled banking environments directly determines customer satisfaction, which subsequently drives long-term continuance intentions. However, this value-creation pathway is fragile; if consumers perceive an AI system as

lacking competence or data security assurance, their willingness to rely on automated financial decision-making drops sharply (Abdeljawad et al., 2025).

To mitigate the limitations inherent in purely automated or exclusively human channels, scholars increasingly advocate for hybrid service delivery systems (Gopinathan, 2024; Hui et al., 2024). Gopinathan (2024) proposes a collaborative human-machine support model wherein AI agents function as the initial triage layer for routine execution, while deterministic protocols instantly hand off anomalous, high-risk, or emotionally charged interactions to human professionals. Hui et al. (2024) corroborate this perspective, demonstrating that the highest service quality perceptions occur when AI tools augment, rather than completely displace, human frontline personnel. Determining how customer satisfaction fluctuates across these two distinct modalities remains vital for guiding financial technology architecture and human resource deployment.

Conceptual Model

The conceptual model investigates the comparative impact of support modalities on perceived service quality dimensions, customer satisfaction, and service continuance intention, alongside the moderating influence of query complexity.

Table 1: Operationalisation and Structural Roles of Study Constructs in the Conceptual Framework

Theoretical Construct	Operational Dimensions / Categories	Role in Framework
Support Modality	AI Virtual Assistant vs. Human Representative	Primary Independent Variable
Service Quality	Responsiveness (speed, queue time) Reliability (accuracy of resolution) Assurance (security, technical competence) Empathy (attentiveness, situational care)	Primary Mediating Construct
Query Complexity	Routine transactions vs. Complex / disputed account issues	Moderating Variable
Customer Satisfaction (CSAT)	Post-resolution evaluation, issue resolution satisfaction	Direct Dependent Variable
Continuance Intention	Channel preference, bank loyalty, long-term retention	Distal Outcome Variable

Formal Research Hypotheses

Comparative Service Quality Dimensions

- **H1a:** AI virtual assistants are rated significantly higher in perceived responsiveness than human customer service representatives.
- **H1b:** Human customer service representatives are rated significantly higher in perceived empathy than AI virtual assistants.
- **H1c:** Human customer service representatives are rated significantly higher in perceived assurance than AI virtual assistants.
- **H1d:** There is no significant difference in perceived reliability between AI virtual assistants and human representatives for standardised transactional queries.

Direct Paths to Customer Satisfaction and Continuance Intention

- **H2a:** Perceived responsiveness positively influences customer satisfaction in both AI-driven and human-led banking support.
- **H2b:** Perceived reliability positively influences customer satisfaction in both AI-driven and human-led banking support.
- **H2c:** Perceived assurance positively influences customer satisfaction in both AI-driven and human-led banking support.
- **H2d:** Perceived empathy exerts a significantly stronger positive influence on customer satisfaction in human-led support than in AI-driven support.
- **H3:** Overall customer satisfaction positively influences customer continuance intention and institutional loyalty.

Moderation by Query Complexity

- **H4a:** Query complexity moderates the relationship between support modality and customer satisfaction, such that customer satisfaction is significantly higher for AI virtual assistants when resolving routine, low-complexity account queries.
- **H4b:** Query complexity moderates the relationship between support modality and customer satisfaction, such that customer satisfaction is significantly higher for human customer service representatives when resolving complex, high-stakes, or disputed queries.

Mediation Model

- **H5:** Perceived service quality dimensions collectively mediate the relationship between the chosen support modality and overall customer satisfaction.

Methodology

Research Design

This study adopted a cross-sectional comparative survey design to evaluate customer evaluations of service quality and customer satisfaction across artificial intelligence (AI)-driven virtual assistants and human customer service representatives in commercial retail banking. An empirical, quantitative survey approach was selected because it enabled the collection of standardised perceptual data, facilitated direct pairwise comparisons across support channels, and permitted structural equation modelling to assess mediation and moderation pathways.

Population and Sampling Framework

The target population comprised retail banking customers who maintained active commercial bank accounts and had personally interacted with both AI virtual assistants (such as mobile banking chatbots or automated conversational agents) and live human customer service personnel within the preceding twelve months.

To determine the minimum required sample size for robust statistical power, an a priori power analysis was calculated using G*Power 3.1.9.7. For a medium effect size ($f^2 = 0.15$), a statistical significance level of $\alpha = 0.05$, a power of $(1 - \beta) = 0.95$, and six predictors within the primary structural model, the minimum required sample was established at 146 respondents. To account for potential survey attrition, uncompleted entries, and straight-lining responses, a larger target cohort was established.

A purposive sampling technique, augmented by convenience sampling, was utilised to recruit verified retail banking customers across urban commercial centres. Eligible respondents were pre-screened with two filter questions confirming active usage of both AI banking chatbots and direct human customer service desks or hotlines within the specified timeframe. Out of 420 distributed questionnaire copies, 384 completed responses met all inclusion criteria, yielding an effective response rate of 91.4%.

Operationalisation and Survey Instrumentation

Data collection was executed using a self-administered, structured questionnaire divided into four coherent sections:

Section A (Demographic and Banking Profile): Captured demographic attributes, including age, gender, educational attainment, primary commercial banking provider, and frequency of contact with digital versus human banking support.

Section B (Perceived Service Quality): Measured customer perceptions across the four focal service quality dimensions: Responsiveness, Reliability, Assurance, and Empathy. Parallel 5-point

Likert scale batteries, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), were developed specifically for this study and administered twice to each respondent: once assessing their experiences with banking AI virtual assistants, and once assessing their experiences with human service personnel.

- Responsiveness: Assessed query handling speed, immediate availability, and reduction of waiting queues through items developed for the investigation.
- Reliability: Assessed transactional accuracy, correct execution of balance reporting, and error-free problem handling through items formulated for the study.
- Assurance: Measured technical competence, data security confidence, and institutional trust through newly constructed survey indicators.
- Empathy: Evaluated personalised attention, situational understanding, and conversational politeness through scale items created specifically for this research.

Section C (Query Complexity Scenarios): Evaluated customer satisfaction across two operational conditions: routine, low-complexity inquiries (such as balance inquiries, account statement requests, and bill settlements) versus complex, emotionally charged interactions (such as disputed electronic transactions, card skimming, unauthorised debits, or loan inquiries), using operational scenario items designed for the survey.

Section D (Customer Satisfaction and Continuance Intention): Measured overall customer satisfaction using a 3-item composite scale developed for the study, alongside service continuance intention measured through a 4-item scale constructed to capture customer retention and future channel preference.

Reliability, Validity, and Pilot Testing

Prior to full field administration, the survey instrument was subjected to rigorous face and content validity assessments by three university academics specialising in service marketing, mass communication, and financial technology.

A pilot study was conducted with 40 retail bank account holders to test the psychometric properties, linguistic clarity, and sequencing of the items. Data from the pilot test were analysed using SPSS. Internal consistency was confirmed across all multi-item constructs, with Cronbach's alpha coefficients exceeding the recommended threshold of 0.70 (AI Responsiveness: alpha = 0.86; AI Reliability: alpha = 0.83; AI Assurance: alpha = 0.81; AI Empathy: alpha = 0.78; Human Support Dimensions: alpha = 0.84 - 0.89; Overall Satisfaction: alpha = 0.91; Continuance Intention: alpha = 0.88). Convergent validity was established through Average Variance Extracted (AVE) values exceeding 0.50, while discriminant validity was verified using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations.

Data Collection Procedure and Ethical Safeguards

The structured questionnaire was administered exclusively online via secured Google Forms links shared across targeted WhatsApp groups comprising retail bank customers in Nigeria. Participation was entirely voluntary, anonymous, and uncompensated. Prior to accessing the survey items, all respondents completed an electronic informed consent protocol on the opening page of the form, which outlined the non-commercial academic purpose of the study and affirmed the strict confidentiality of their submissions. No personally identifiable financial data, account numbers, or authentication credentials were requested or archived.

Data Analysis Plan

The collected empirical data were cleaned, screened for outliers, and evaluated using both IBM SPSS Statistics (Version 28) and SmartPLS 4:

Descriptive Statistics: Calculated frequencies, percentages, means, and standard deviations to summarise respondent demographic profiles and baseline evaluations of the support channels.

Comparative Parametric / Non-Parametric Tests: Paired-samples t-tests (supported by Wilcoxon signed-rank tests for non-normal distributions) were executed to test comparative hypotheses regarding service quality dimensions between AI agents and human personnel.

Two-Way Repeated-Measures ANOVA: Conducted to evaluate the interaction effect between support modality (AI vs human) and query complexity (routine vs complex) on customer satisfaction levels.

Partial Least Squares Structural Equation Modelling (PLS-SEM): Applied in SmartPLS to assess the measurement model (indicator reliability, internal consistency, convergent validity, and discriminant validity) and evaluate the structural paths linking service quality dimensions, customer satisfaction, and customer continuance intentions. Bootstrapping with 5,000 resamples was executed to evaluate the statistical significance of path coefficients and indirect mediation effects.

Results

The dataset comprised responses from 384 retail banking customers who evaluated both artificial intelligence (AI) virtual assistants and human customer service representatives across equivalent service scenarios.

Comparative Evaluations of Service Quality Dimensions (H1a to H1d)

To evaluate differences in perceived service quality dimensions between AI virtual assistants and human representatives, paired-samples t-tests were conducted across the four focal dimensions: responsiveness, empathy, assurance, and reliability.

Table 2: Paired-Samples t-Test Comparing Service Quality Dimensions Across Modalities (N = 384)

Service Quality Dimension	AI Virtual Assistant Mean (SD)	Human Support Mean (SD)	Mean Difference	t (df = 383)	p-value	Cohen's d
Responsiveness	4.41 (0.58)	3.24 (0.81)	1.17	23.64	< .001	1.66
Empathy	2.18 (0.79)	4.29 (0.62)	-2.11	-41.83	< .001	2.97
Assurance	3.31 (0.74)	4.12 (0.65)	-0.81	-16.48	< .001	1.16
Reliability	3.86 (0.71)	3.91 (0.68)	-0.05	-1.04	0.298	0.07

As detailed in Table 2, AI virtual assistants recorded significantly higher perceived responsiveness than human representatives ($t = 23.64$, $p < .001$, Cohen's $d = 1.66$), confirming H1a. Conversely, human customer service representatives scored significantly higher on perceived empathy ($t = -41.83$, $p < .001$, Cohen's $d = 2.97$) and assurance ($t = -16.48$, $p < .001$, Cohen's $d = 1.16$), thereby validating both H1b and H1c. Regarding transactional reliability, no statistically significant difference emerged between AI virtual assistants and human personnel ($t = -1.04$, $p = .298$), which supports H1d.

Structural Model and Direct Determinants of Customer Satisfaction (H2a to H2d, H3)

Partial Least Squares Structural Equation Modelling (PLS-SEM) was executed in SmartPLS to evaluate the direct influences of service quality dimensions on customer satisfaction, as well as the link between customer satisfaction and continuance intention across both modalities. Path significance was calculated via 5,000 bootstrap resamples.

Table 3: Structural Model Assessment for Determinants of Satisfaction and Continuance Intention

Structural Path	Path Coefficient (Beta)	Standard Error	t-statistic	p-value	Decision
AI Support Model					
Responsiveness -> Customer Satisfaction (H2a_AI)	0.442	0.046	9.61	< .001	Supported

Reliability -> Customer Satisfaction (H2b_AI)	0.385	0.048	8.02	< .001	Supported
Assurance -> Customer Satisfaction (H2c_AI)	0.164	0.044	3.73	< .001	Supported
Empathy -> Customer Satisfaction (H2d_AI)	0.052	0.038	1.37	0.171	Not Supported
Customer Satisfaction -> Continuance Intention (H3_AI)	0.612	0.039	15.69	< .001	Supported
Human Support Model					
Responsiveness -> Customer Satisfaction (H2a_Human)	0.187	0.042	4.45	< .001	Supported
Reliability -> Customer Satisfaction (H2b_Human)	0.312	0.045	6.93	< .001	Supported
Assurance -> Customer Satisfaction (H2c_Human)	0.341	0.047	7.26	< .001	Supported
Empathy -> Customer Satisfaction (H2d_Human)	0.289	0.043	6.72	< .001	Supported
Customer Satisfaction -> Continuance Intention (H3_Human)	0.684	0.035	19.54	< .001	Supported

Responsiveness and reliability positively and significantly influenced customer satisfaction across both AI and human support modes, supporting H2a and H2b. Perceived assurance also yielded significant positive effects in both channels, supporting H2c. A multigroup permutation test revealed that empathy exerted a significantly stronger positive effect on satisfaction in human interactions (beta = 0.289, $p < .001$) than in AI interactions (beta = 0.052, $p = .171$; difference = 0.237, $p < .001$), confirming H2d. Customer satisfaction was a strong, positive predictor of service continuance intention in both environments (AI: beta = 0.612; Human: beta = 0.684; $p < .001$), providing full support for H3.

Moderating Role of Query Complexity (H4a and H4b)

A two-way repeated-measures Analysis of Variance (ANOVA) was conducted to test the interaction between support modality (AI Assistant vs Human Representative) and query complexity (Routine Inquiries vs Complex/Disputed Issues) on overall customer satisfaction.

Table 4: *Repeated-Measures ANOVA for Support Modality and Query Complexity Interaction*

Source of Variation	Sum of Squares	df	Mean Square	F	p-value	Partial Eta Squared
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Support Modality	18.42	1	18.42	31.87	< .001	0.077
Query Complexity	114.65	1	114.65	198.36	< .001	0.341
Modality * Complexity	168.91	1	168.91	292.23	< .001	0.432
Error	221.38	383	0.58			

The interaction effect between support modality and query complexity was statistically significant, $F(1, 383) = 292.23$, $p < .001$, partial eta squared = 0.432.

- *Routine Query Condition:* Simple pairwise comparisons revealed that for routine queries (e.g. balance requests, transaction histories), AI virtual assistants yielded significantly higher customer satisfaction (Mean = 4.38, SD = 0.52) than human customer service representatives (Mean = 3.65, SD = 0.64; $t = 16.22$, $p < .001$), confirming H4a.
- *Complex Query Condition:* For complex or emotionally charged scenarios (e.g. fraudulent debits, disputed transfers), human representatives generated significantly higher customer satisfaction (Mean = 4.21, SD = 0.61) than AI virtual assistants (Mean = 2.45, SD = 0.82; $t = -31.45$, $p < .001$), providing empirical verification for H4b.

Mediation Analysis (H5)

To test whether perceived service quality dimensions collectively mediated the link between support modality and customer satisfaction, bootstrapping procedures (5,000 subsamples) were performed on the composite indirect pathways.

Table 5: Mediation Analysis of Service Quality Dimensions Between Modality and Satisfaction

Path Category	Indirect Effect (Beta)	Bootstrapped SE	95% Bootstrap CI [LL, UL]	p-value	Decision
Total Indirect Effect	0.384	0.038	[0.312, 0.461]	< .001	Supported
Modality -> Responsiveness -> Satisfaction	0.221	0.031	[0.163, 0.285]	< .001	Supported
Modality -> Assurance -> Satisfaction	0.098	0.024	[0.054, 0.149]	< .001	Supported
Modality -> Empathy -> Satisfaction	0.071	0.022	[0.031, 0.118]	0.002	Supported
Modality -> Reliability -> Satisfaction	-0.006	0.012	[-0.031, 0.017]	0.568	Not Supported

The total indirect effect of support modality on customer satisfaction via the service quality dimensions was statistically significant ($\beta = 0.384$, 95% CI [0.312, 0.461], $p < .001$), confirming that the service quality dimensions collectively mediate the relationship between support modality and customer satisfaction, thus supporting H5. Specific indirect path analyses showed that responsiveness, assurance, and empathy served as significant individual mediators, whereas reliability did not mediate the relationship due to the absence of a direct modality difference on transactional execution.

Discussion

The empirical findings illuminate the operational and relational boundaries governing customer evaluations of automated versus human frontline banking support. In support of H1a and H1d, artificial intelligence virtual assistants demonstrated clear superiority in responsiveness while matching human personnel on transactional reliability. This pattern confirms earlier evidence indicating that conversational bots provide exceptional speed, eliminate waiting queues, and process structured inquiries with minimal error (Hossain et al., 2025; Shaikh et al., 2024). When account holders execute routine tasks—such as viewing balances or checking payment histories—the algorithmic immediacy and round-the-clock availability of virtual agents align directly with customer performance expectations (Gopinathan, 2024; Ikbal, 2026).

However, the significant deficits recorded by AI assistants in empathy and assurance (confirming H1b and H1c) expose fundamental limitations in purely algorithmic customer engagement. Despite developer efforts to design anthropomorphic, polite conversational interfaces (Hui et al., 2024; Patil et al., 2025), banking consumers clearly perceive the synthetic nature of automated interactions. While human service representatives achieved high scores for genuine attentiveness, active listening, and reassurance, conversational agents failed to elicit emotional trust. The structural path analysis further revealed that empathy does not significantly predict customer satisfaction in AI-mediated interactions, whereas it remains a powerful driver of satisfaction in human encounters (supporting H2d). This divergence indicates that consumers do not expect or reward synthetic empathy from computational platforms; instead, they evaluate automated tools through an instrumental lens of speed, security, and computational accuracy (Wu & Sun, 2026).

The significant interaction between support modality and query complexity (confirming H4a and H4b) provides critical practical insight into customer satisfaction dynamics. While AI assistants outperformed human staff in resolving routine inquiries, satisfaction collapsed when consumers engaged automated agents for complex, emotionally sensitive, or disputed transactions (such as unauthorised debits or card fraud). Under crisis conditions, algorithmic rigidity, scripted dialogue constraints, and conversational looping exacerbate customer distress (Ibidunmoye & Ekeh, 2026; Mahmud, 2025). Human frontline agents possess the discretionary judgment, contextual flexibility, and situational empathy required to de-escalate anxiety and resolve ambiguous grievances—competencies that remain beyond the scope of automated rule sets or probabilistic language generation (Abdeljawad et al., 2025; Sheth et al., 2022). Consequently, uncalibrated

automated routing that traps distressed consumers in bot interactions directly threatens customer continuance intentions and long-term brand loyalty (Hasan et al., 2026; Joseph et al., 2026).

These outcomes reinforce the necessity of human-in-the-loop and collaborative service delivery architectures (Gopinathan, 2024; Hui et al., 2024). The finding that service quality dimensions collectively mediate the relationship between support modality and satisfaction (supporting H5) proves that neither channel is universally superior across all retail banking interactions. Instead, maximum customer satisfaction and institutional retention are achieved when financial institutions strategically deploy AI virtual assistants as high-speed frontline filters for standardised inquiries while maintaining frictionless hand-off protocols to human personnel for complex or disputed transactions (Gopinathan, 2024; Wahyuni et al., 2025).

Conclusion

Artificial intelligence virtual assistants offer substantial operational utility in retail banking, particularly by accelerating query response times, reducing queue burdens, and delivering reliable execution for standardised, everyday transactions. Nevertheless, automated conversational tools cannot serve as a complete substitute for human customer service personnel. When navigating complex, ambiguous, or emotionally volatile banking disputes, consumers depend heavily on the situational assurance, contextual discretion, and authentic empathy that only human representatives can deliver. Trapping customers in rigid automated channels during high-stakes account issues degrades perceived service quality and damages long-term institutional loyalty. Financial institutions must avoid viewing conversational AI solely as a cost-cutting mechanism to replace human labour, recognising instead that service excellence depends on an integrated framework where algorithmic speed supports, rather than supplants, human interpersonal expertise.

Recommendations

- Financial institutions should configure AI virtual assistants as the initial conversational triage layer for high-volume, routine queries, while enforcing automated circuit breakers that immediately transfer customers to human representatives upon encountering complex, disputed, or high-value transactions.
- Bank software developers should implement real-time affective text classifiers within conversational bots to detect user frustration, repeated questions, or crisis vocabulary (such as unauthorised transactions or stolen cards), instantly routing the interaction to a live specialist.
- Rather than attempting to script anthropomorphic emotional expressions that consumers largely discount, system designers should prioritise computational accuracy, data security transparent disclosures, and seamless integration with core banking ledgers.
- Bank administrators should reallocate human customer service personnel away from routine data retrieval tasks and provide advanced training in de-escalation, conflict resolution, and complex financial advisory services.

- Retail banks must provide clear, accessible interface options that permit consumers to bypass automated chatbots and request live human assistance at any point during their service interaction, preserving customer autonomy and institutional trust.

Declarations

Ethical Approval: This study was conducted in accordance with the ethical guidelines of the Declaration of Helsinki. Informed consent was obtained from all individual retail banking participants prior to their participation in the survey. Participation was entirely voluntary and anonymous, and no identifiable personal financial records or confidential account details were collected.

Artificial Intelligence (AI) Use Statement: During the preparation of this work, the author used Claude (Anthropic) to improve language, style, and clarity. Following the use of this tool, the author thoroughly reviewed, edited, and verified the content, and takes full responsibility for the final intellectual integrity of the publication.

Data Availability Statement: The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request.

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Author's Contribution: G. Hambe is the sole author of this work and was solely responsible for the conceptualisation, theoretical framework, study design, data collection, statistical analyses, interpretation of results, and the writing and revision of the manuscript. The author read and approved the final manuscript.

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