Reconceptualizing Service Quality in Generative AI–Enabled Banking: Evidence from India

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ABSTRACT:

The fast uptake of generative artificial intelligence (GenAI) in banking services has altered the way customers interact with the company and casts doubt on the suitability of traditional models of service quality that had been created to operate in a human-mediated context. This paper reframes service quality as a connection to generative AI-based banking by the investigation of whether the traditional SERVQUAL dimensions are enough to describe customer assessments in intelligent financial ecosystems. The research suggests a newer framework that includes TrustQuality, InteractionQuality, Tangibles, Satisfaction, and BehaviouralIntention, based on the assumption that customers are increasingly evaluating the banking services based on integrated perceptions of trust, responsiveness, personalization and intelligent interaction. The quantitative research design was used and 205 AI-enabled banking service users were surveyed in India as primary data. In order to investigate the suggested correlations and demonstrate the improved framework's explanatory capacity, we used partial least squares structural equation modeling (PLS-SEM). According to the findings, however Tangibles do not significantly affect customer happiness, InteractionQuality and TrustQuality do. Customer satisfaction was shown to be a strong predictor of behavioural intention, which explains why AI-enabled banking services were intended to be used and recommended by consumers. The model shows that it can predict a significant amount of variance of Satisfaction and BehaviouralIntention through 77.6 and 78.8 respectively. This research serves as a contribution to the field of service quality theory, where the authors have shown that customer assessments of generative AI-founded banking are becoming gradually manifested in multidimensional perceptions of trust and interaction, and not as the splintered traditional service dimensions. The results present an updated service quality architecture of intelligent banking settings and also present viable recommendations to financial firms seeking to undergo AI-driven service transformation.

Keywords: Generative artificial intelligence; AI-enabled banking; service quality; customer satisfaction; behavioural intention; trust quality; interaction quality; intelligent banking; digital financial services; PLS-SEM; financial technology; India

1. Introduction

Banks are having to rethink their approach to client interaction and service design in light of the rapid advancements in artificial intelligence (AI) technology. The advent of generative artificial intelligence (GenAI), specifically the conversational AI systems that can produce context-dependent and human-like responses, has drastically transformed the conventional delivery of financial services. The banking institutions in the global community are becoming more and more focused on the use of AI-friendly chatbots, virtual finance assistants, automated advice systems, and smart recommendation systems to enhance customer interactions, overall efficiency, and accessibility to services [15,16]. Vedapradha and Hariharan Ravi [29] it was pointed out that AI is being used in investment banking is increasingly boosting predictive decision-making, automating operations, customer analytics, and advisory, transformation of intelligent financial ecosystems. Contrary to the traditional digital banking platforms, generative AI has the ability to be interactive in an adaptive manner, which allows customers to interact with financial services not only through the mediation of humans, but also through the mediation of intelligent conversations.

The increased use of AI-powered banking services has been gaining momentum over the past few years as the digital banking ecosystems and mobile banking infrastructure, as well as intelligent automation technologies, have been growing at an expedient pace. With the growing internet penetration, smartphone availability, and uptake of digital payments, in these emerging economies like India, the adoption of AI technologies in banking operations is further enhanced [27]. The intelligent systems that can offer customized service, 24/7 service support, automated response to queries and predictive customer responses are making financial institutions re-design customer service processes [17]. Such advancements have established a significant difference in the way customers consider the experiences of banking services in the context of AI-mediated settings. Bhatt and Mehta [28] also indicated that responsiveness, reliability, technological efficiency, and customer trust greatly impact how people view the quality of the service they get in an online banking setting especially in digitally transforming banking systems in India.

In traditional service quality framework, especially SERVQUAL, Service quality is often thought of in terms of several characteristics, such as responsiveness and dependability, along with assurance, empathy, and tangibles [1] [2]. Initially these models have been developed in the human centred service setting where the customer assessment was largely based on interpersonal communication and direct interaction with the employees. Nonetheless, AI-powered banking ecosystems are quite different compared to traditional service environments as customers consider technological potential, responsiveness of interaction, reliability of algorithms, assurance of security, and effectiveness of conversations during their interaction with intelligent systems at the same time [15,17]. As a result, the suitability of the fragmented traditional service quality dimensions in generating AI-based banking settings has become even more dubious. Ali [25] suggested that there is a growing necessity of relationship quality and behavioural intention in banking services that are influenced by integrated customer perception which is linked to trust recovery, responsiveness, and quality of service interface as opposed to the independent dimension of operation.

The role of technology acceptance, customer satisfaction, formation of trust as well as the adoption of digital banking has been widely analyzed in the existing literature [3-8]. Past research has established trust, responsiveness, reliability, and perceived usefulness are pivotal factors in customer behaviour towards digital platforms [6-23]. In the more recent AI-based literature, the theme of explainability, algorithmic transparency, adaptive interaction, and intelligent personalization is highlighted to influence customer attitudes towards AI-based services [18,24,31]. Chatterjee et al. hauntingly stated that AI-driven customer service is positively associated with customer satisfaction and continuance intention within a digital banking setting, whereas Al-Araj et al. indicated the increased importance of smart service quality in banking systems [26].

Updated articles from the Review of Economics and Business also stipulates the increased influence of the technology and artificial intelligence on the way of changing the banking services. The value of a technologically advanced banking sector in the context of sustainable economic development was highlighted by Narangua [26], because the proposed method implies that technological innovation and digital capabilities are becoming increasingly important to the quality of services offered by the industry. Loan [28] showed that Industry 4.0 technologies are transforming the way banks operate and customer experience coupled with introducing new issues concerning regulatory governance and technological preparedness. Green and Emon [29], likewise.

The current document does not provide any sources that stated that artificial intelligence increases customer engagement, quality of decision-making, operational efficiency, and performance of service delivery, yet implementation would be successful, assuming customer trust, transparency, accountability, and ethical governance systems.

Together, these works suggest that the conventional service quality models might cease to comprehend customer reviews in the intelligent financial ecosystem. With the further transformation of banking services, based on the generative AI technologies, customers tend to evaluate service experiences by wider perceptions related to personalization, quality of interaction, the sense of trustworthiness, the sense of safety and security, and the intelligent service provision instead of, but not only, the dimension of the operational services. However, the trend of the existing research remains to conceptualize the service quality by means of fragmented dimensions of SERVQUAL without a critical analysis of the fact that generative AI technologies significantly change the mental map according to which customers consider banking services.

This shortcoming leaves a significant research gap to the conceptual sufficiency of conventional service quality frameworks in intelligent financial ecosystems. In contrast to the traditional banking setting, AI-mediated interactions enroll combined assessments of credibility, the quality of conversation, security guarantees, technological mastery, and individualized responsiveness. As such, customers can no longer have the dimensions of reliability, responsiveness, assurance and empathy as independent. Instead, more generic evaluations of experience pertaining to trust and relationship quality may include these variables. Few empirical studies have attempted to reimagine service quality in AI-enabled financial settings, despite the increasing usage of generative AI in banking services. [17,25,26].

The current paper fills the gap by suggesting a more sophisticated conceptualization of service quality in high-order generative AI-powered banking services. In particular, to capture integrated customer assessments that emerge in AI-mediated banking interactions, two larger constructs, namely TrustQuality and InteractionQuality, are presented in the study. Reliability, assurance, security, expertise conceptualized under TrustQuality and responsiveness along with empathy conceptualized dimensions are incorporated under InteractionQuality. The inclusion of tangibles is kept as a separate construct to investigate whether appearance on the interface and presentation of technology still plays a role in customer satisfaction in an intelligent banking ecosystem.

The research also examines how TrustQuality, InteractionQuality, and Tangibles contribute to customer satisfaction and future behavioural intention of AI-enabled banking services in India. Customers who had interacted with AI-based banking apps in the past were the subjects of a quantitative study that relied on empirical data. Researchers used partial least squares structural equation modeling (PLS-SEM) in their empirical studies because it is well-suited for conceptual restructuring and exploratory predictive modeling [11,13]. In many significant ways, the research contributes to what is already known. First, it complements the service quality theory by showing that the generative AI technologies can restructure the conventional cognitive frame through which customers can assess the banking services. Secondly, by introducing additional service quality measures of higher orders that are appropriate to intelligent banking settings, the study may contribute to the expanding body of literature on the integration of AI into financial ecosystems. Third, digital financial revolution in developing nations is better understood thanks to the work's empirical information based on the Indian banking context. Only customers of Indian banks employing AI-powered platforms would be considered for this study. How customers feel about the quality and happiness of the service they get, as well as their intentions to behave, in banking transactions mediated by AI, is the subject of this study. The other sections of the document adhere to this format. The subject's literature is reviewed in Section 2, which also develops the theoretical framework and assumptions. Section 3 lays out the assessment of the methodology used in the research and measurement model. The empirical data and structural model analysis are presented in Section 4. The study's key findings, limitations, and suggestions for future research are summarized in Section 6, while the policy implications for regulators and financial institutions are addressed in Section 5.

2. Literature Review

Rapid use of AI in the banking industry has considerably altered the way customer service is conceptualized and measured within banking ecosystems. The literature in traditional service quality was highly developed in the context of human mediated setting where the perceptions of customers were mainly developed by human mediation, physical infrastructure, and responsiveness of the employees [1,2]. Nevertheless, with the development of generative AI-based banking service, the smart conversational systems capable of adaptive communication, predictive aid, and algorithmic decision-making have emerged, and thus, the theoretical sufficiency of the traditional service quality models has been thrown into question [15-17]. As a result, the recent research has started to doubt the fact that the conventional fragmented service quality dimensions are conceptually relevant within AI-based financial contexts.

Parasuraman et al.'s [1] SERVQUAL model, which categorized service quality into five categories: tangibles, certainty, responsiveness, empathy, and dependability—dominated the early literature on service quality. Because it could operationalize customers' perceptions of service performance, the frame had a huge influence on digital service research and banking. Customer satisfaction, loyalty, and behavioral intention are positively impacted by service quality factors, according to subsequent studies [4,5]. However, SERVQUAL was initially created in the traditional human-service settings where there was a face-to-face communication and contact with employees. As such, the framework implicitly presupposes a cognitive evaluation of service attributes, independent of each other, by human mediated experiences.

Critical analysis of modern AI literature indicates that these assumptions might not be sufficient to account for the customer evaluation behaviour in the context of intelligent banking. Recent developments in generative AI have allowed banking organisations to offer chat-bot customer service, automated financial advice, query-solver AI and predictive customer service using AI-based interfaces [15,16]. Generative AI platforms are unique unlike conventional digital systems because they provide technology with responsiveness to interactions, contextual awareness, security, and adaptability of conversations in a single service experience. Consequently, customer ratings are becoming more of an integrated interaction experience instead of a separate appraisal of individual dimensions of service.

The current empirical study on AI in financial services shows a slow but steady change from an assessment framework focused on the quality of operational services to one that is experiential and trust-based. Chatterjee et al. [25] found that in the context of digital banking, customer satisfaction and continuation intention are significantly affected by AI-powered customer care. Likewise, AI-based banking systems enhanced customer satisfaction with banking systems by enhancing responsiveness and intelligent service delivery as reported by Al-Araj et al. [26]. But these studies mostly continued to use traditional fragmented SERVQUAL dimensions even though they were studying technologically integrated AI service settings. Therefore, the findings, although taking note of the increasing role of AI interaction quality, offer little theoretical argument of whether customers still judge service dimensions separately in conversational AI ecosystems.

Customer behavior in AI-enabled financial services is heavily influenced by the building of trust, according to recent research [7, 23]. Trust is not always developed in the traditional banking setting due to the reputation of the institutions as well as interpersonal communication. By contrast, AI-mediated banking involves having customers trust algorithmic systems, automated financial advice, and intelligent chatbots [31]. Accordingly, customer assessments are progressively appraisals of the notions of security, transparency, explainability, reliability, and institutional responsibility all in one [18,24]. Literature reveals that when customers get in touch with smart financial systems, they tend to feel the presence of technological reliability, data security, Confidence and knowledge are two sides of the same coin that, when combined, help build trust. [8,31-33].

Another similar conceptual intersection is seen in the literature about interaction quality. The conventional service quality models divided the concept of responsiveness and empathy into two different aspects since human workers were viewed as the main means of contact with customers [1]. Nevertheless, the latest generative AI applications mimic responsiveness in conversations, intelligent communication, and personal interaction in embedded interaction systems [15]. According to recent research, focusing on intelligent service systems, the customers are becoming more selective in terms of how promptly the platform in question is able to respond, comprehend the intent of the customer, personalize the interaction, and be effective in a conversation [20,21]. As a result, responsiveness and empathy might cease to be separate cognitive dimensions in banking settings mediated by AI. Rather, these attributes add more and more cumulatively to more comprehensive interaction quality perceptions.

In this way, the current studies show that there is a significant shift in the theoretical evaluation of customer service in financial ecosystems supported by artificial intelligence. Although previous research focused on operational aspects of service quality in small chunks, modern AI-based banking space seems to induce coherent experiential assessments, which relate to credibility, talkability, smart responsiveness, and system dependability. Despite efforts to examine AI service contexts that include technology, the majority of current empirical research continue to use a conventional SERVQUAL-based conceptualization of service quality [17,25,26].

Regarding the conceptual restructuring of service quality in relation to generative AI-powered financial services, this constraint highlights a substantial research need. Current literature lacks adequate empirical information on the issue of whether traditional dimensions of service quality continue to be discriminant in intelligent financial ecosystems with conversational AI interaction. More to the point, previous research has not tried to re-conceptualize the fragmented dimensions of service quality into the experiential construct of higher orders that can reflect AI mediated customer judgments in a better way.

To address this knowledge vacuum, the present research proposes a modified higher-order model for evaluating service quality in banking contexts powered by generative AI. In particular, the paper redefines assurance, reliability, security, and expertise as a larger construct, namely TrustQuality, and merges empathy and responsiveness as InteractionQuality. Tangibles are held separately to identify the continuation in customer satisfaction in smart banking systems of visual interface and technological presentation. The study aims to expand on the current service quality theory past the conventional human-mediated assumptions and contribute to a more contextually adept approach to understanding customer evaluation behaviour in AI-enabled financial services by empirically investigating these updated higher-order constructs in the Indian banking environment.

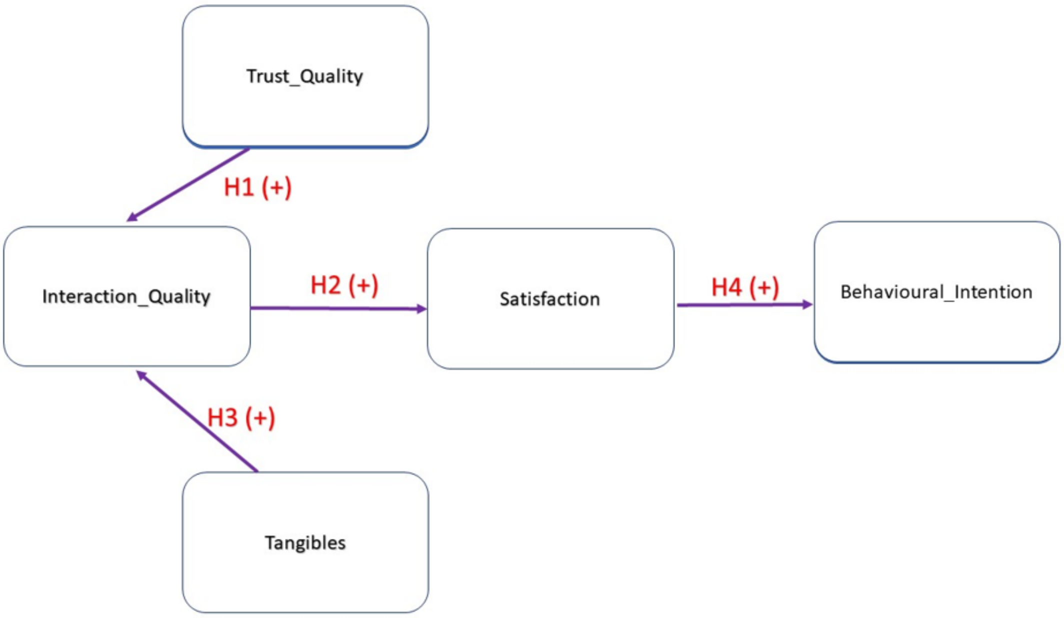


Figure 1 - Proposed Conceptual Framework

3. Methodology

3.1 Research Design

This article examines how consumers perceive the quality of services in generative AI-based banking situations using a cross-sectional and qualitative research approach. The primary objective of the study was to determine how customer satisfaction and behavioral intention towards banking services provided by AI were affected by altered higher-order characteristics of service quality. The study used partial least squares structural equation modeling (PLS-SEM) as the technique of empirical analysis [11,13]. This was due to the exploratory nature of the conceptual reorganization and the predictive emphasis of the proposed framework.

There are a lot of reasons why PLS-SEM was the best fit for our study. Initially, the study aims to rephrase the traditional aspects of service quality into new experiential notions that are more relevant to AI-mediated banking and of a higher order. The second point is that the model is structured to contain structural equations for predicting and a number of latent variables. Furthermore, while building an exploratory model or expanding theories, PLS-SEM is preferable than using SEM approaches based on covariance [10,11]. The study was carried out using the SmartPLS 4 program [35].

3.2 Data Collection and Sample Characteristics

The consumer having prior experience with AI-enabled banking was surveyed using a standardized questionnaire to get the main data.

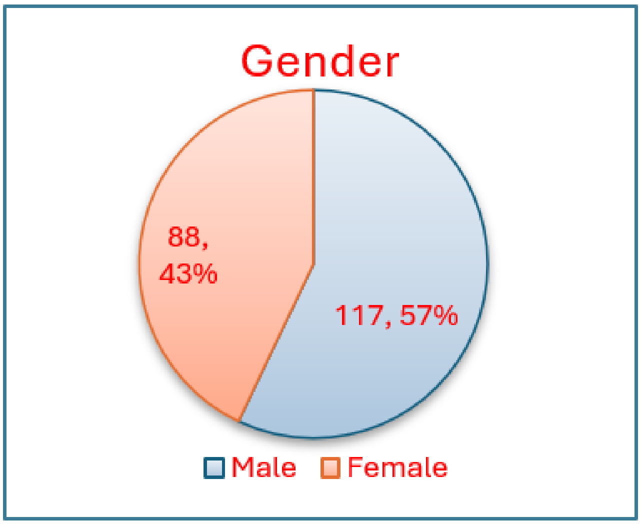
The respondents targeted were people who had used the AI-based banking systems including the chatbots, virtual banking assistants, automated customer support systems, and AI-driven digital banking systems. For the sake of accessibility and wide respondent engagement, data was collected using both online and offline survey techniques.

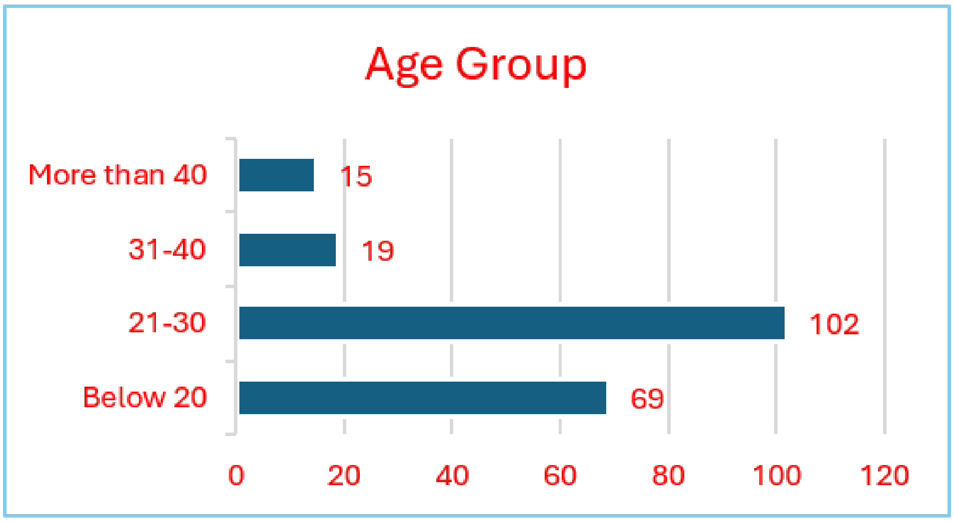
After removing invalid, missing, or inconsistent data from the first 205 replies, 205 were considered valid for further analysis. According to the recommendations for PLS-SEM analysis using higher-order measures and multiple structural connections, the sample size was sufficient [11,13].

Table 1 displays the respondent demographic profile. The sample consisted of 57% male respondents and 43% female respondents. Fifty percent of the respondents were between the ages of 21 and 30, followed by thirty-four percent who were under the age of twenty. Graduate respondents represented the best percentage of the sample (41%), and the next proportion was postgraduate respondents (35%). The demographic distribution indicates that the sample was mainly composed of younger and digitally conscious banking users who would more often be engaged in AI-powered financial technologies.

Table 1. Respondent Demographic Profile

Variable	Category	Frequency	Percentage
Gender	Male	117	57
	Female	88	43
Age Group	Below 20 Years	69	34
	21-30 Years	102	50
	31-40 Years	19	9
	Above 40 Years	15	7
Educational Qualification	School	39	19
	Diploma	3	2
	Graduate	85	41
	Post Graduate	72	35
	Ph.D.	6	3





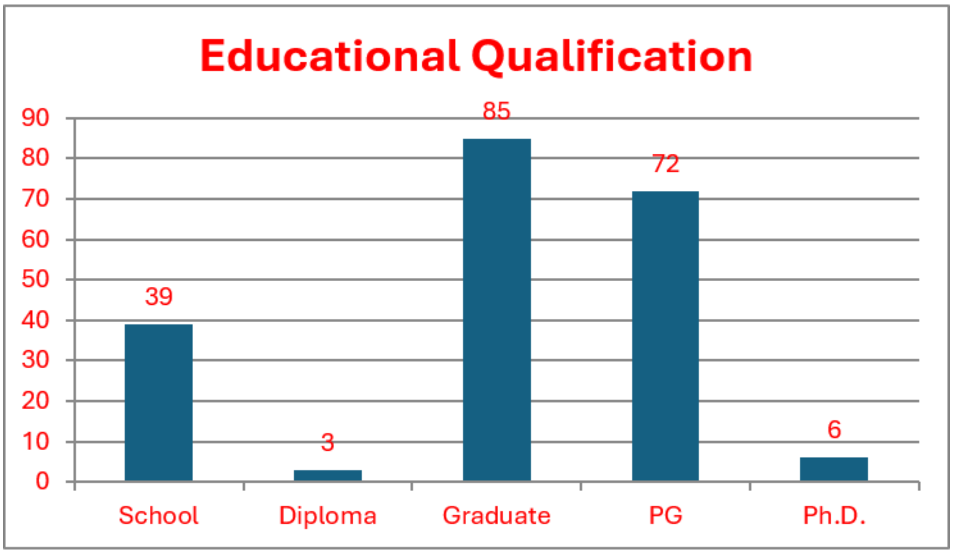


Figure 2 - Demographic Profile of Respondents

3.3 Measurement Instrument

The questions in the surveys were derived from previous research on AI-based service systems, customer happiness, technological adoption, trust creation, and service quality [1,3,5,7,15,18,25]. There were slight contextual differences to make the measurement items consistent with the generative AI-enabled banking services.

The new conceptual framework comprised five key constructs:

1. Trust_Quality,
2. Interaction_Quality,
3. Tangibles,
4. Satisfaction,
5. Behavioural_Intention.

As a higher-order construct, the conceptualization of TrustQuality included the dimensions related to assurance, reliability, security, and expertise. InteractionQuality as a combination of responsiveness-related and empathy-related appraisals arising in the context of the banking interactions mediated by AI. The tangibles were held separately to study interface perceptions in regards to intelligent banking ecosystems.

With 1 representing "Strongly Disagree" and 5 representing "Strongly Agree," all of the evaluation questions were based on a five-point Likert scale. Table 2 displays the elements of measurement together with their corresponding sources.

Table 2. Items and Sources for Measurements

Construct	**Code**	**Measurement Item**	**Adapted From**
Trust_Quality	ASS1	The Gen AI system is able to respond appropriately to my underlying emotional state.	[1,15]
	ASS2	I am confident in the knowledge and expertise of the information provided by the Gen AI system.	[1,7]
	EXP1	The Gen AI system demonstrates a high level of expertise in answering financial queries.	[1,15]
	REL1	The information provided by the Gen AI is clear and easy to understand.	[1]
	REL2	The Gen AI service is consistently available and technically reliable.	[1]
	REL3	The AI system keeps its promises regarding financial services and transactions.	[1]
	REL4	The recommendations provided by the Gen AI are trustworthy and consistent.	[7]
	SEC1	I believe my financial information is secure while interacting with the Gen AI system.	[8]
	SEC2	The Gen AI service follows financial regulations and compliance standards.	[8]
Interaction_Quality	EMP1	The Gen AI interface is visually appealing and professional.	[1]
	EMP2	The navigation and ease-of-use of the Gen AI tool is excellent.	[3]
	EMP3	The Gen AI system provides accurate responses to financial queries.	[1]
	EMP4	The Gen AI system recognizes customer-specific banking needs.	[15]
	RES1	The Gen AI service resolves my issues effectively.	[1]
	RES2	The Gen AI service responds immediately to customer inquiries.	[1]
	RES3	The bank's Gen AI system provides timely assistance during interactions.	[1]
Tangibles	T1	The bank clearly explains what the Gen AI system can and cannot do.	[18]

Construct	Code	Measurement Item	Adapted From
	T2	The Gen AI interface is modern and user-friendly.	[3]
	T3	The Gen AI system presents information in a visually organized manner.	[1]
Satisfaction	SAT1	The Gen AI banking service has met my expectations, all things considered.	[4,5]
	SAT2	The Gen AI banking service meets my expectations.	[5]
	SAT3	My interaction with the Gen AI banking service has been positive.	[4]
Behavioural_Intention	BI1	Gen AI's financial services are ones that I want to keep utilizing.	[3,6]
	BI2	I would recommend AI-enabled banking services to others.	[6]
	BI3	I prefer AI-enabled systems over human agents for routine banking queries.	[15]
	BI4	I consider my bank technologically advanced because of its AI services.	[6]

3.4 Conceptual Framework and Hypotheses Development

According to the study's literature assessment, AI-enabled banking settings are seeing an increase in customer ratings based on integrated perceptions of trust and interaction quality. Since customer happiness impacts behavioral intention toward AI-enabled financial services, the suggested framework investigates how Trust_Quality, Interaction_Quality, and Tangibles impact customer satisfaction.

Consequently, the following theories were developed:

H1: Trust_Quality positively influences customer satisfaction toward AI-enabled banking services.

H2: Interaction_Quality positively influences customer satisfaction toward AI-enabled banking services.

H3: Tangibles positively influence customer satisfaction toward AI-enabled banking services.

H4: Customer satisfaction positively influences behavioural intention toward AI-enabled banking services.

The conceptual framework estimated through SmartPLS is presented in Figure 1.

3.5 Data Analysis Procedure

Evaluating the measurement model and the structural model were the two primary phases in the data analysis process [11,13]. As part of the evaluation, we looked at the measuring model's markers of dependability, internal consistency reliability, discriminant validity, and convergent validity. We used outer loading values as an indication of reliability and Cronbach's alpha, composite reliability (CR), and rho_A as measures of internal consistency dependability.

We used average variance extracted (AVE) to test for convergent validity, and the heterotrait-monotrait ratio (HTMT) and the Fornell-Larcker criteria [9,12] to establish discriminant validity. After that, we used bootstrapping techniques with 5,000 resamples to evaluate the structural model. We looked at path significance, explanatory power (R^2), effect size (f^2), and model fit (SRMR) values [11,13].

4. Results and Discussion

4.1 Measurement Model Assessment

As part of the evaluation process, the measuring model was tested for internal consistency, convergent validity, discriminant validity, and the indicators' reliability of the d higher-order framework. The evaluation was carried out using SmartPLS 4 in accordance with the prescribed procedures for PLS-SEM analysis [11,13].

4.1.1 Indicator Reliability

The outer loading values were used to assess the indicator's dependability. Table 3 shows that all the indicators that were kept had loading values higher than the suggested criterion of 0.70, which means that the indicators are reliable and reflect the constructs well [11]. The values of the outer loading varied between 0.723 and 0.906. As far as the indicators are concerned, SAT3 had the best loading value (0.906) and EMP4 the worst (0.723). The d model did not need further deletion of items because all the retained indicators met the minimum threshold criteria.

Table 3. Measurement Items' Outside Loads

Construct	Indicator	Outer Loading
Trust_Quality	ASS1	0.785
	ASS2	0.801
	EXP1	0.848
	REL1	0.790
	REL2	0.822
	REL3	0.846
	REL4	0.861
	SEC1	0.768
	SEC2	0.826
Interaction_Quality	EMP1	0.809
	EMP2	0.847
	EMP3	0.876
	EMP4	0.723
	RES1	0.801
	RES2	0.854
	RES3	0.863
Tangibles	T1	0.883
	T2	0.843
	T3	0.879
Satisfaction	SAT1	0.887

Construct	Indicator	Outer Loading
	SAT2	0.875
	SAT3	0.906
Behavioural_Intention	BI1	0.850
	BI2	0.901
	BI3	0.811
	BI4	0.837

4.1.2 Reliability and Convergent Validity

Internal consistency reliability and convergent validity were assessed using Cronbach's alpha, composite reliability (CR), rhoA, and average variance extracted (AVE). Table 4 displays the results of the reliability and convergent validity tests.

Results for Cronbach's alpha ranging from 0.838 to 0.937 show an adequate level of internal consistency reliability, above the suggested alpha of 0.70 [11,13]. Concurrently, all of the latent variables had good construct reliability, as shown by composite reliability scores ranging from 0.902 to 0.947. TrustQuality showed the strongest CR value (0.947) with the lowest though still not too bad CR value (0.902) reported by Tangibles.

To ensure convergent validity, AVE was used. All of the AVE values were higher than the threshold of 0.50, which is considered optimal [13]. The values of the AVE were between 0.667 and 0.791, thus confirming that there was sufficient convergent validity with the d measurement model.

Table 4. Reliability and Convergent Validity Assessment

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Behavioural_Intention	0.872	0.877	0.912	0.723
Interaction_Quality	0.922	0.923	0.937	0.682
Satisfaction	0.868	0.869	0.919	0.791
Tangibles	0.838	0.848	0.902	0.755
Trust_Quality	0.937	0.939	0.947	0.667

4.1.3 Discriminant Validity Assessment

We used the HTMT and Fornell-Larcker criterion to find out whether the test was discriminant, [9,12].

According to the HTMT results in Table 5, it is found that a number of construct relationships had a relatively high HTMT value especially between TrustQuality, InteractionQuality and Satisfaction. Nonetheless, the found proximity of the constructs seems to have a theoretical significance in AI-mediated banking contexts where clients concurrently assess the trustworthiness, responsiveness, effectiveness in conversation, and technological competence in the process of interacting with intelligent systems.

The high values of the HTMT are thus indicative of conceptual integration and not redundancy of the constructs. It is also one more confirmation of the theoretical suggestion of the current research that the traditional divided dimensions of SERVQUAL can be transformed into wider experiential assessments in generative AI-based banking ecosystems.

Table 5. HTMT Discriminant Validity Assessment

Construct Relationship	HTMT Value
Interaction_Quality ↔ Behavioural_Intention	0.915
Satisfaction ↔ Behavioural_Intention	1.016
Satisfaction ↔ Interaction_Quality	0.956
Tangibles ↔ Behavioural_Intention	0.847
Tangibles ↔ Interaction_Quality	0.908
Tangibles ↔ Satisfaction	0.888
Trust_Quality ↔ Behavioural_Intention	0.920
Trust_Quality ↔ Interaction_Quality	0.938
Trust_Quality ↔ Satisfaction	0.936
Trust_Quality ↔ Tangibles	0.921

The presented findings of the Fornell-Larcker criterion in Table 6 also reveal significant conceptual closeness between d higher-order constructs. However, the results are conceptually aligned to AI-based banking experiences where customer reviews gradually become a part of enhanced experiential perception and not by means of separate dimensions of operational services.

Table 6. Fornell–Larcker Criterion

Construct	Behavioural_Intention	Interaction_Quality	Satisfaction	Tangibles	Trust_Quality
Behavioural_Intention	0.850				
Interaction_Quality	0.821	0.826			
Satisfaction	0.888	0.856	0.889		
Tangibles	0.733	0.803	0.764	0.869	
Trust_Quality	0.835	0.873	0.846	0.821	0.817

The overall results indicate that the perception of customers in generative AI-driven banking services might not act in completely autonomous dimensions of service quality any longer. Rather, the AI-mediated interactions seem to produce integrated assessments related to trust, the effectiveness of interaction and smart responsiveness, as well as the overall service experience.

4.2 Structural Model Assessment

The significance of the hypothesis relations in the structural model was evaluated using bootstrapping with 5,000 resamples once the measurement model was established.

4.2.1 Testing Hypotheses

Figure 3 and Table 7 both show the structural model's findings. The findings validate H1 by demonstrating that TrustQuality significantly impacts customer satisfaction in a favorable way (b = 0.371, t = 3.767, p < 0.001). The outcome suggests that the perception linked to the concept of security, reliability, assurance, and institutional trust significantly help in consumer satisfaction in AI-integrated banking conditions.

We can validate H2 since InteractionQuality had the most favorable impact on customer satisfaction (b = 0.460, t = 4.521, p < 0.001). The conclusion suggests that these are key elements that influence customer experience in generative AI-powered banking services.

The association between Tangibles and customer satisfaction, on the contrary, was statistically small (b = 0.090, t = 1.175, p = 0.240). Therefore, H3 was rejected. This observation suggests that the elements of visual interfaces and technological presentation can cease to be the factors defining high levels of customer satisfaction in intelligent banking eco-systems.

Supporting H4, we found that customer satisfaction significantly influenced behavioral intention (b = 0.888, t = 52.290, p < 0.001). Customers are more likely to maintain using AI-enabled banking services and develop positive behavioral intents of intelligent financial platforms when they are happy, according to the extraordinarily big coefficient.

Table 7. Structural Model Results and Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	Trust_Quality → Satisfaction	0.371	3.767	<0.001	Supported
H2	Interaction_Quality→Satisfaction	0.460	4.521	<0.001	Supported
H3	Tangibles → Satisfaction	0.090	1.175	0.240	Not Supported
H4	Satisfaction→Behavioural_Intention	0.888	52.290	<0.001	Supported

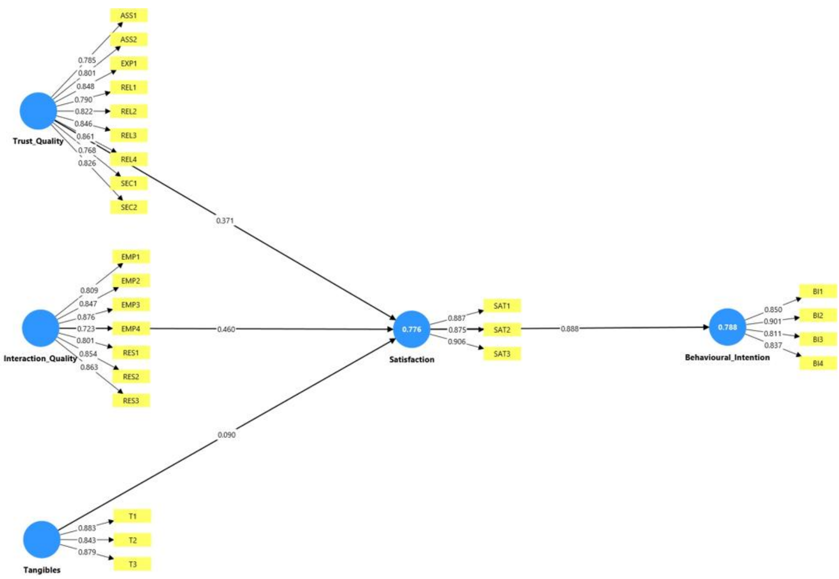


Figure 3. Structural Model of the Framework

4.2.2 Explanatory Power of the Model

Using the coefficient of determination (R2), we examined the suggested framework's ability to explain the data. As shown in Table 8, the model explained a significant portion of the variance in both satisfaction and behavioral intention, accounting for 77.6% and 78.8%, respectively. According to the current PLS-SEM guidelines, these results indicate that the enhanced conceptual model has a strong predictive potential [11,13].

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2
Behavioural_Intention	0.788	0.787
Satisfaction	0.776	0.773

The results suggest that merged experiential concepts like TrustQuality and InteractionQuality have high explanatory power to predict customer satisfaction and behavioural intention in AI-based banking systems.

4.2.3 Effect Size Assessment

Analyses (f2) were done to estimate the contribution made by exogenous constructs to the endogenous variables. With an f-value of 0.204 for InteractionQuality and an f-value of 0.122 for TrustQuality, Table 9 shows that these variables had a medium impact on Satisfaction. Tangibles had a small effect size (f2 = 0.011), which supports its weak explanatory contribution to the banking interactions with AI.

BehaviouralIntention exhibited the largest effect size of Satisfaction (f2 = 3.710), which corroborates the conclusion that customer satisfaction is still the strongest predictor of continuance intention to AI-enabled banking services.

Table 9. Effect Size (f^2) Assessment

Relationship	f^2	Interpretation
Interaction_Quality → Satisfaction	0.204	Medium
Satisfaction → Behavioural_Intention	3.710	Very Large
Tangibles → Satisfaction	0.011	Negligible
Trust_Quality → Satisfaction	0.122	Small

4.2.4 Model Fit Assessment

The SRRM was used to assess the degree to which the model was in agreement with the data. Both the saturated model's and the estimated model's SRMRs are smaller than the suggested value of 0.08, as shown in Table 10. This suggests that the models are well-fitting and structurally consistent [11].

Table 10. Model Fit Assessment

Model Fit Indicator	Saturated Model	Estimated Model	Recommended Threshold
SRMR	0.053	0.058	<0.08

The overall results of the structural model are increasingly reflected in the integrated trust-based and interaction-based experiential perceptions, as opposed to the conventional service quality dimensions, in the review of the generative AI-based banking environment by customers, as they contribute significantly to the theoretical hypothesis. The results, therefore, offer support in terms of reconsidering the quality of service within AI-driven financial systems.

5. Policy Implications

The results of this research are potentially beneficial to financial regulators, technology developers, and banking institutions alike because they are related to AI-based financial ecosystems. The results indicate that in the generative AI-based banking world, the ratings of customers are increasingly being affected by trust-oriented and interaction-oriented experiential perceptions rather than more traditional tangible services qualities. Consequently, in order to guarantee successful traditional digital service strategies, banking institutions must re-architect customer service systems with AI-powered customer service systems that emphasize the quality of intelligent interaction, transparency, trust building, and flexible engagement mechanisms.

One of the key findings of the research is the significant effect that InteractionQuality has on customer satisfaction. The result suggests that conversational effectiveness, time responsiveness, adaptive communication, and personal interaction could be deemed as the most crucial elements that lead to customer experience in the person of intelligent banking. Therefore, financial institutions should prioritize the development of conversational AI-based solutions that can understand and respond to customers' intentions, respond in context-specific ways, and continue to interact with the customer under various circumstances in the service context. Not only the AI-based banking systems that can be used as an automated response system but also enable customer-centric interaction experiences that can recreate the experience of intelligent human assistance without undermining the operation effectiveness should be encouraged.

The other important result of the study is that TrustQuality significantly contributes to the heightened customer happiness due to AI-mediated banking. This finding suggests that institutional trust, technological trust, security assurance and algorithmic accountability grow in importance in intelligent financial ecosystems. Banking institutions are therefore advised to augment the cybersecurity infrastructure and data protection procedures, as well as explainable AI operations to raise customer trust in AI-enhanced services. Customers in contact with the smart banking systems will tend to evaluate, not only by the ultimate outcome of transactions, but also by the credibility, fairness and transparency of the decision-making processes that are conducted by algorithms [18,24].

The findings also reveal that Tangibles did not have statistically significant effect on customer satisfaction. This observation indicates that customer evaluation behaviour will change greatly in the AI-enabled banking ecosystems. Traditional literature on service quality concentrated on the physical infrastructures and the appearance of the interface as the important predictors of the customer experience [1,2]. Still, the existing data shows that in the banking environment of generative AI, the conversation intelligence, the quality of interaction, responsiveness, and trustworthiness are more popular among customers as compared to the features of the visual interface. Consequently, the financial sector may also be forced to shift their approach of strategic investment to a further scale of interface enhancement towards intelligent interaction maximization and trust-based AI management devices.

There are a lot of concerns around regulatory accountability, cybersecurity, the ethics of AI, and the openness of AI algorithms brought up by the rapid expansion of AI-based financial services. The safe use of artificial intelligence (AI) in banking services should be regulated by integrating policy frameworks established under the supervision of financial supervisors like the Reserve Bank of India (RBI) and other regulatory entities. These buildings must aim at clarity, transparency, customer approval, privacy and the accountability of algorithmic decision-making of financial consumers [31-33].

The increasing dependence on AI-mediated financial exchange also demands even more powerful digital literacy campaigns among the consumers of the banking setting. A large number of users might lack the complete knowledge of operation constraints, the decision-making mechanism, and operational risks involved with AI systems of generative AI. In this regard, banking systems should implement the open customer education systems, in which the capabilities, limitations, and security of AI-based financial services are explained. Raising the level of awareness of clients can positively affect the establishment of trust and the need to promote ethical AI implementation in financial ecosystems.

The current results also suggest that the customer satisfaction has an unusually high impact on behavioural intention to AI-enabled banking services. This implies that customers who are pleasured will be considerably more inclined to keep utilizing smart banking systems and suggest the same to others. As a result, customer satisfaction must continue to be a key strategic goal of transformational efforts in AI-based banking. Banks with the capacity to build credible, flexible, and relation-based AI service environments can thus gain high competitive edge on more digitized financial markets.

Generally, the article indicates that the future of AI-enabled banking services will be more reliant on how financial institutions can harmonise technological intelligence and customer confidence, ethical governance of AI, adaptive quality of interaction, and service design transparency. The results hence have valuable strategic implications on banks that are trying to re-architecture customer services systems in fast changing intelligent financial ecosystems.

6. Conclusion

The accelerated adoption of generative artificial intelligence in the banking services have fundamentally changed the way customers interact in the modern financial ecosystems. In contrast to conventional banking settings where the nature of service experience is human-mediated, AI-based banking services are increasingly being based on intelligent conversational platforms, which are adaptively interactive, automated in decision-making, and customized in offering financial support. As a result, the traditional notion of the quality of service in terms of the divided operational dimensions could be not sufficient to describe customer assessment behaviour in smart banking contexts.

In this study, a modified higher-order model that can be used to analyze the quality of services provided by generative AI-based financial services has been suggested and covers this theoretical challenge. Precisely, the research re-conceptualized the ancient SERVQUAL dimensions to broader experiential constructs that were embodied in Trust Quality and Interaction Quality and Tangibles was retained as a separate dimension. A study on the topic applied partial least squares structural equation modeling (PLS-SEM) to customer satisfaction and behavioral intention to examine how these revisiting constructs relate to these variables, based on actual data obtained on customers in India regarding AI-based banking systems.

The researchers determined that TrustQuality and InteractionQuality in AI-based banking setting significantly boost consumer happiness. The findings indicated that the InteractionQuality had the greatest ability to predict consumer happiness, which means that conversational effectiveness, adaptive communication, responsiveness, and customized interaction remained to have a role in customer perceptions of smart banking services. TrustQuality had the strongest influence, demonstrating the growing role of reliability, promise of safety, trustworthiness of the institutions, and technological competence in the AI-mediated financial transactions.

Contrarily, there was no statistically significant relationship between consumer happiness and tangibles. The discovery is a significant conceptual shift of the conventional assumptions of service quality and indicates that customers who will experience generative AI systems might place greater emphasis on smart interaction experiences and assessments related to trust than visual interface features and technological display. The results, therefore, show that customer commentaries regarding AI-assisted banking ecosystems are becoming increasingly integrated along experiential perceptions rather than autonomous levels of working services.

The results of the trial also showed that the level of customer satisfaction greatly affects their inclination to use financial services that are enabled by artificial intelligence. The high explication rate of the structural model demonstrates that clientele who are content to be served are significantly more probable to keep utilizing smart banking frameworks and establish positive perceptions towards AI-powered money platforms. The overall results of these studies reinforce the thesis according to which generative AI technologies are reshaping the cognitive paradigm with the help of which a customer assesses the quality of banking services.

The study contributes significantly to the existing knowledge in many ways. To start with, it expands the traditional service quality theory because it shows how AI-mediated financial settings can necessitate conceptual reorganization of traditional SERVQUAL dimensions. Second, by elevating TrustQuality and InteractionQuality to the level of higher-order experiential notions that intelligent financial ecosystems may benefit from, the study contributes to the expanding corpus of literature on AI-enabled banking services. Thirdly, the study contributes to our understanding of digital financial revolution in developing nations by providing empirical data on the banking environment in India.

With its contributions, the research has some limitations. Results may not be applicable to other cultural and technology contexts due to the fact that respondents' empirical analysis was confined to their usage of AI-enabled financial services in India alone. Another limitation is that it is a cross-sectional research, so it can't look at how people's habits change over time as a result of using AI in banking. Additionally, in the study, the researchers focused mostly on customer perceptions and failed to analyze organizational, operational, and regulatory aspects relating to AI implementation in the financial services sector.

Future studies can therefore build up on the current study with cross-country comparative studies of banking ecosystems with different levels of maturity of AI adoption. Longitudinal research on the modification of customer perceptions of generative AI systems over a period of time could also further shed some theoretical light on the evolution of trust and technology acceptance behaviour. In addition, future studies could integrate ethical guidelines for AI governance, algorithm transparency, financial inclusion, and responsible AI usage into broader service quality metrics for intelligent banking systems.

In general, the paper shows that the future of the banking service quality assessment is more and more based on the intelligent interaction potential, the construction of trust with the customer and dynamic customer experiences with the usage of the intelligent AI that is not just based on the standard service delivery dimensions. As a result, banking organizations trying to compete in the intelligent financial ecosystems at high speed should rearchitect customer service strategies based on trust-oriented and interaction-oriented experiential models that can support sustainable AI-facilitated financial change.

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