Impact Of Chatbot In Operational Efficiency In Banking Sector In Nepal

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Abstract

This research evaluates how chatbot integration affects operational efficiency and customer satisfaction in Nepal's banking sector, using Expectation Confirmation Theory (ECT) as a basis. It investigates the global trend towards digital banking, focusing on how AI-powered chatbots in Nepalese banks influence customer interactions and operational processes. The study fills gaps in existing literature on chatbot effects in banking, setting goals to assess customer expectations, chatbot performance, and the influence on customer satisfaction and trust. It utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore how these factors interplay and affect trust and corporate reputation, finding that chatbots significantly meet customer expectations, thereby improving efficiency and satisfaction. The findings offer insights for banking practitioners and policymakers on the benefits of chatbots, underscoring their positive role in operational efficiency and customer experience. This research enriches discussions on digital banking transformation, advocating for the strategic use of AI to address the digital age's challenges and opportunities.

Keywords: *Chatbots, Operational Efficiency, Customer Satisfaction, Digital Transformation, Artificial Intelligence, Banking Sector.*

1. Introduction

The introduction of technology, particularly AI-powered chatbots, has revolutionized the banking industry globally and in Nepal, transforming customer interactions and operational efficiencies. These advancements reflect a global shift towards innovative banking solutions, with Nepalese banks adopting technology to meet the expectations of a digitally-savvy customer base (Hakuduwal, 2021). Chatbots, equipped with Natural Language Processing (NLP), offer interactive and efficient customer service, aligning with worldwide banking trends (Saxena et al., 2023). This study investigates the impact of chatbot integration on Nepalese banks' operational efficiency, comparing global insights with the local context to assess the potential for digital transformation in banking.

2. Problem Statement

The relationship between chatbot use in banking and its effects on operational efficiency and customer satisfaction in Nepal is complex, with various chatbot architectures and models creating a diverse analysis landscape. The specific impacts of chatbots on satisfaction, efficiency, and overall banking performance in Nepal remain underexplored, despite literature pointing out the uncertainties of chatbot effectiveness (Lee et al., 2023; Mulyono and Sfenrianto, 2022). This study aims to fill these gaps by applying the Expectation Confirmation Model (ECM), initially proposed by Oliver (1980), to understand how customer satisfaction aligns with their expectations versus the actual performance of chatbot services in banking.

This research is driven by the need to delve into unexamined factors affecting operational and customer satisfaction outcomes of chatbot use in Nepal's banking sector, including trust, perceived risk, and user expectations (Svikhnushina et al., 2021; Eren, 2021). By examining the nuanced factors that influence user interactions and satisfaction, this study seeks to offer insights into the architectural, systemic, and engagement strategies of chatbots, aiming to align them more closely with customer expectations.

3. Research Questions

The following research questions are designed to provide a comprehensive understanding within the context of Chatbot implementations in the Nepalese banking sector.

i) How do customer expectations from Chatbot interactions influence the overall satisfaction of users in the Nepalese banking sector?
ii) What is the perceived performance of Chatbots in meeting user expectations within the Nepalese banking environment?
iii) To what extent does the confirmation of customer expectations during Chatbot interactions contribute to customer satisfaction in Nepalese banks?
iv) How does customer satisfaction with Chatbot interactions influence the perceived trust users place in these automated systems within Nepalese banks?
v) What role does corporate reputation play in shaping customer perceptions of Chatbot interactions in the context of Nepalese banks?

4. Objectives

The major objective followed by detailed objectives tailored to offer depth and clarity to this study are as follows:

Objective:

i) To assess the impact of Chatbots on operational efficiency in Nepalese banks.

Detailed Objectives:

i) To analyze customer expectations during Chatbot interactions within the Nepalese banking environment.
ii) To evaluate the perceived performance of Chatbots in meeting user expectations in Nepalese banks.
iii) To examine the role of confirmation of customer expectations in shaping customer satisfaction with Chatbot interactions in the Nepalese banking sector.
iv) To investigate the correlation between customer satisfaction with Chatbots and the perceived trust users place in these automated systems in Nepalese banks.
v) To explore the impact of Chatbot interactions on corporate reputation within the Nepalese banking industry.

5. Significance of the Study

This study is significant across academic, business, and societal spheres within Nepal's banking sector. Academically, it enhances the knowledge base about Chatbot integration in financial services, addressing the specific needs and challenges of Nepalese banks. For businesses, it provides actionable insights for using Chatbots to boost operational efficiency, guiding banks on improving service quality and customer relationships, potentially leading to cost savings and greater competitiveness. Societally, it adds to the conversation on technology's role in service industries of emerging markets like Nepal, emphasizing the importance of aligning Chatbot adoption with user expectations for fostering trust and financial inclusivity. Overall, the research offers comprehensive insights with wide-ranging implications for academia, banking practices, and societal adaptation to technological advancements.

6. Literature Review

The literature review encompassed a broad spectrum of studies exploring the integration of AI and chatbots across various sectors, with a significant focus on financial services. These studies provided insightful analyses on how chatbots influence customer experiences, privacy concerns, adoption of AI in banking, and the dynamics of technology acceptance among different demographics, including the elderly and millennials.

Studies like those by Silva et al. (2023) and Mostafa and Kasamani (2022) delve into consumer acceptance of chatbots, highlighting the crucial role of trust and perceived risk in shaping user intentions. Silva et al. suggest expanding research to consider cultural and demographic influences, while Mostafa and Kasamani point out that compatibility and ease of use significantly impact initial trust in chatbots. Research by Bouhia et al. (2022) on privacy concerns associated with financial service chatbots emphasizes the complexity of user perceptions towards privacy, suggesting the exploration of chatbot functionalities and the nature of information requested to mitigate these concerns.

Rahman et al. (2021) explore factors driving AI adoption in Malaysia's banking industry, identifying trust and perceived utility as key determinants. This suggests areas for further investigation, such as the influence of regulatory frameworks and technological infrastructure on AI adoption. Cheng et al. (2023) focus on senior people's intentions to use Financial Artificial Intelligence Customer Service (FAICS), underscoring the need for AI applications to cater to the unique needs of different user groups for enhancing digital inclusivity.

Gonçalves et al. (2023) examine consumer responses to AI vs. human credit decisions, highlighting the influence of rejection sensitivity on satisfaction levels. This points to the importance of considering individual differences when designing AI systems in financial services. Shiyyab et al. (2023) assess the impact of AI disclosures on Jordanian banks' financial performance, suggesting a positive relationship but calling for further research to explore the depth of AI integration within banks' operational strategies.

Chen et al. (2023) investigates the role of AI chatbot service quality in promoting customer loyalty, proposing a sequential chain model of service quality-loyalty. This study emphasizes the complexity of customer loyalty dynamics and suggests exploring the longitudinal effects of service quality on loyalty. Li et al. (2023) identify factors impacting users' continued intentions to use chatbot services in Chinese Online Travel Agencies (OTAs), including the moderating role of technology anxiety on the relationship between chatbot quality aspects and user confirmation.

Each study contributes to a more nuanced understanding of the multifaceted interactions between users and AI technologies, highlighting areas for future research to further explore the implications of AI and chatbot integration in financial services and beyond. This narrative underscores the transformative potential of AI in enhancing customer experiences and operational efficiencies, while also acknowledging the complexities and challenges inherent in technology adoption and integration.

7. Methodology

This study is based on a rigorous framework employed to assess the impact of chatbots on the operational efficiency of the Nepalese banking sector. Embracing a quantitative methodology, the research harmonizes elements of constructive and analytical paradigms, navigating through the integration of chatbots within the banking operations. Data was meticulously gathered through a structured questionnaire distributed to 400 participants, analyzed using statistical software like SPSS and SmartPLS to probe into the intricate relationships among pivotal variables.

Rooted in empirical research principles as underscored by Creswell (2018), the study's design is predicated on delivering objective insights into how chatbots influence operational efficiency. This approach facilitated the collection of quantifiable data on key operational metrics, leveraging a questionnaire informed by an comprehensive literature review. The choice of a quantitative framework underscores the study’s aim to unveil measurable, statistically significant findings on chatbots' efficacy in streamlining banking operations.

At the core of the investigation is the Expectation Confirmation Theory (ECT), serving as the conceptual bedrock to explore chatbots' operational impact. The research model meticulously dissects the interaction between variables such as Customer Expectations (CE), Perceived Performance (PP), and Customer Satisfaction (CS), drawing on Eren (2021) and Oliver (1980) to ground the analysis in established theoretical perspectives.

The methodological narrative extends to the selection of data sources, combining firsthand insights from chatbot users with an extensive canvassing of relevant literature to enrich the empirical and theoretical foundation of the study. This blend of primary and secondary data sources ensures a comprehensive backdrop against which the impact of chatbots on banking efficiency is examined.

Dedicated to maintaining ethical rigor, the methodology adheres to principles of informed consent, data privacy, and voluntary participation, reflective of the ethical standards championed by Creswell (2018). Such ethical diligence ensures the integrity of participant data and the overall credibility of the research findings.

Emphasizing validity and reliability, the research design incorporates strategic sampling, pilot testing, and advanced statistical analysis to mitigate biases and enhance the study's credibility. The application of Cochran's formula, as highlighted by Ahmad and Halim (2017), exemplifies the meticulous attention to achieving a representative sample size, reinforcing the study's methodological robustness.

In essence, this study based on a sophisticated methodology for investigating chatbots' role in augmenting operational efficiency within Nepal's banking sector. Through a quantitative lens, the study meticulously navigates the examination of chatbots' operational implications, anchored by a solid theoretical framework, rigorous data collection and analysis procedures, and unwavering ethical standards. This methodological approach not only aims to shed light on empirical outcomes but also to contribute substantively to the discourse on technological advancements in banking, as guided by the insights of notable scholars like Creswell (2018), Eren (2021), and Oliver (1980).

Chatbots

This study explores the role of chatbots as virtual customer assistants in Nepal's banking sector, highlighted as key to Human-Computer Interaction (HCI) by Nguyen et al. (2021). These AI-driven conversational agents operate via text messaging and web chat, designed to understand and respond to customer queries effectively. Chatbots offer a broad spectrum of banking services, including customer relationship management, business development, investment assessment, and more, echoing findings from Eren (2021) in the Turkish banking context. Such tasks range from calculating deposits to providing credit card details and trading information. Their value lies in delivering timely, personalized, and cost-efficient services, thereby enhancing the operational efficiency of banks, as supported by studies from Nguyen et al. (2021) and Nyagadza et al. (2022).

Operational Efficiency in Banking

This study emphasizes the importance of operational efficiency in the banking sector, defined as the optimized use of resources, processes, and technology to meet organizational goals. The adoption of technological solutions, notably chatbots, plays a pivotal role in enhancing efficiency. According to Juniper Research (2019), chatbots in banking are projected to result in substantial cost savings, potentially exceeding US$8 billion by 2022. The use of chatbots streamlines banking operations by eliminating redundancies and improving productivity, as noted by Eren (2021), who highlights their strategic incorporation into the Turkish banking industry. This underlines the connection between banking efficiency and the strategic deployment of technology like chatbots.

Expectations Confirmation Theory

ECT, introduced by Oliver (1980), serves as a fundamental model for understanding customer satisfaction across various sectors. ECT suggests that customer satisfaction is rooted in the confirmation or disconfirmation of expectations against service performance (Nguyen et al., 2021). Alnaser et al. (2023) highlight ECT's effectiveness in analyzing the relationship between pre-purchase expectations and post-purchase perceived performance.

ECT progresses through four stages, starting with pre-purchase expectations, followed by the purchasing event influenced by these expectations. The third stage assesses whether perceived performance meets or falls short of expectations, impacting satisfaction levels. The final stage sees overall satisfaction determined by the match between expectations and perceived performance, with confirmation of expectations generally boosting satisfaction (Oliver and De Sarbo, 1988).

Its broad applicability, including in banking information systems, attests to ECT's capability to dissect the complex interplay between customer expectations, perceived performance, and satisfaction, making it a vital tool for analyzing customer experiences (Shiyyab et al., 2023).

Customer Expectations

Customer expectations, defined as the anticipated outcomes or experiences from a product, service, or vendor, are critical in assessing a product or service's fundamental quality attributes (Nyagadza et al., 2022; Alnaser et al., 2023). These expectations are inherently dynamic, varying among individuals and changing over time, shifting from basic functionality to the desire for enhanced features to improve product appeal (Silva et al., 2022; Arora et al., 2023). Teas (1994) highlights the significant role of customer expectations in influencing perceptions of a product or service.

Customer satisfaction is conceptualized as a post-purchase attitude, resulting from comparing expected and perceived service or product quality (Gonçalves et al., 2023). This satisfaction is fundamentally linked to the ideal standards set by customer expectations, which are essential for evaluating satisfaction outcomes (Oliver, 1980; Eren, 2021). Within the Expectation Confirmation Theory framework, expectations are seen as precursors to satisfaction, playing a crucial role in the evaluative process that leads to satisfaction or dissatisfaction (Cadotte et al., 1987; Alnaser et al., 2023). In alignment with existing literature, the following hypothesis is proposed:

> **Hypothesis H1**: Customer expectations regarding the operational efficiency improvements through chatbots positively impact customer satisfaction resulting from chatbot use in banking services.

Perceived Performance

Perceived performance involves assessing the benefits or features derived from a product or service, distinguishing between its actual performance and individual evaluations (Silva et al., 2023). This study focuses on perceived performance through the effectiveness of chatbot use and its contribution to user productivity, aligning with methodologies from previous technology research (Silva et al., 2023; Li et al., 2023; Le, 2023). Customer engagement with technology is influenced by its perceived ability to facilitate tasks (Karahanna & Straub, 1999), where perceived usefulness denotes the expectation of time and effort savings (Adam et al., 2020).

Post-use evaluations by customers reflect their initial expectations, with perceived performance aligning closely when expectations meet actual outcomes, thereby affecting perceived usefulness (Lin et al., 2021; Shiyyab et al., 2023). The Expectation Confirmation Theory (ECT) highlights the significant link between initial expectations and perceived post-experience performance, emphasizing that customers' assessment of performance is measured against their pre-use expectations (Oliver, 2010; Bhattacherjee, 2001). In congruence with prior studies, the following hypothesis is posited:

> **Hypothesis H2:** Customer expectations from chatbots have a positive impact on chatbots' perceived performance in enhancing operational efficiency in banking.

Customer satisfaction is defined as a holistic assessment of whether a product or service meets, exceeds, or falls short of expectations (Alnaser et al., 2023). It directly relates to perceived performance, with perceived usefulness particularly critical in determining satisfaction with technology-based services like mobile banking (Suhartanto et al., 2021; Eren, 2021). According to Expectation Confirmation Theory (ECT), there's a direct link between the perceived performance of a service or product and customer satisfaction; a higher realized performance generally leads to greater satisfaction regardless of initial expectations (Sidaoui et al., 2020; Alnaser et al., 2023). Hence, the following hypothesis is advanced:

> **Hypothesis H3**: The perceived performance of chatbots in enhancing operational efficiency has a significant and positive impact on customer satisfaction resulting from chatbot use in banking.

Confirmation of Customer Expectations

Confirmation of customer expectations occurs when customers perceive that the performance of a product or service meets or exceeds their pre-purchase expectations. This involves a cognitive process where customers assess post-purchase outcomes against their initial expectations (Woodruff et al., 1983). In technology usage, including chatbot services, it reflects the degree to which the anticipated benefits, utility, and features are realized during use (Nguyen et al., 2021). The confirmation process is critical in evaluating a service or product's performance, with a direct correlation between customer expectations and their confirmation post-experience, as highlighted by ECT (Qazi et al., 2017). Essentially, confirmation signifies the achievement of expected advantages and satisfaction with the service provided. Building on these premises, the following hypothesis is posited:

> **Hypotheses H4**: Customer expectations from chatbots have a positive impact on the confirmation of customer expectations regarding operational efficiency improvements through chatbot use in banking.

ECT suggests that customer satisfaction arises from the interplay between customer expectations, perceived performance, and the confirmation of those expectations. Perceived performance is how customers evaluate a product or service's quality and value post-purchase (Mostafa & Kasamani, 2021), while confirmation of expectations compares these pre-purchase expectations to the actual performance experienced (Nguyen et al., 2021). Essentially, positive evaluations of perceived performance lead to the confirmation of expectations (Gonçalves et al., 2023). Research in technology products supports a positive link between higher perceived performance and the likelihood of confirming expectations, highlighting the crucial role of perceived performance in technology-based services (Chang et al., 2019). Building on these insights, the following hypothesis is advanced:

> **Hypotheses H5**: Chatbots' perceived performance in enhancing operational efficiency has a positive impact on the confirmation of customer expectations.

Customer Satisfaction

Customer satisfaction is defined as an emotional state that results from comparing expected and actual performance, as noted by Arora et al. (2023). Eren (2021) highlights that Expectation Confirmation Theory (ECT) explores customer satisfaction by examining the alignment between pre-use expectations and post-use performance. Satisfaction emerges when perceived performance meets or exceeds pre-purchase expectations, leading to a positive confirmation of those expectations (Zhang et al., 2021). Recent studies further confirm the link between expectation confirmation and customer satisfaction (Suchánek & Kŕaĺová, 2023). In light of these observations, the following hypothesis is posited:

> **Hypothesis H6**: The confirmation of customer expectations from the use of chatbots in enhancing operational efficiency has a positive impact on customer satisfaction in the banking sector.

Perceived Trust

Trust is the confidence in each other's reliability and the expectation of non-opportunistic behavior in an exchange relationship (Nyagadza et al., 2022; Mostafa & Kasamani, 2021). In the realm of web-based or technological applications, trust encompasses aspects of morality and reliability (Silva et al., 2023), and is distinguished into cognitive and emotional dimensions, with this study focusing on cognitive trust. Trust is essential for the adoption of technology applications, with its absence being a barrier to user satisfaction and adoption (Marengo & Pagano, 2023). Hong et al. (2023) suggest that pre-event trust enhances post-purchase satisfaction, underlining trust's significance in transactions involving virtual applications or where direct human interaction is absent. In technology applications, trust mitigates uncertainties and concerns, thereby positively influencing customer satisfaction, a relationship supported by numerous studies (Chen et al., 2023; Silva et al., 2022; Nyagadza et al., 2022; Mostafa & Kasamani, 2021). Drawing from the existing literature, the following hypothesis is put forward:

> **Hypothesis H7**: Perceived trust in the chatbot system's competence, integrity, and benevolence has a positive impact on customer satisfaction resulting from improved operational efficiency in banking.

Corporate Reputation

Corporate reputation represents a company's historical performance and its ability to fulfill stakeholder expectations, serving as an external reflection of the company's value (Huang et al., 2021; Eckert, 2017). It encompasses a comprehensive evaluation by customers based on their interactions with the company's products, services, and corporate actions (Von Berlepsch et al., 2022). In the banking sector, a strong reputation helps reduce customer uncertainty and risk perceptions (Meier et al., 2021). Xu et al. (2023) note that customers often use corporate reputation to gauge service quality and form future attitudes in scenarios of limited information. Consequently, reputation significantly influences customer attitudes and satisfaction, with empirical evidence highlighting its impact on satisfaction levels.

The relationship between reputation and satisfaction is supported by Festinger's Cognitive Dissonance Theory (1957), suggesting that a company's reputation can cause customers to adjust their perceptions, thus affecting their satisfaction. A positive corporate reputation enhances satisfaction, whereas a negative one detracts from it (Westermann, 1989). Research consistently indicates a positive link between corporate reputation and customer satisfaction (Islam et al., 2021; Ananaba et al., 2021). Therefore, the following hypothesis is posited:

> Hypothesis H8: The bank’s corporate reputation has a positive impact on customer satisfaction resulting from improved operational efficiency through chatbot use in banking.

Figure 4.1 depicts the proposed theoretical framework and associated research hypotheses.

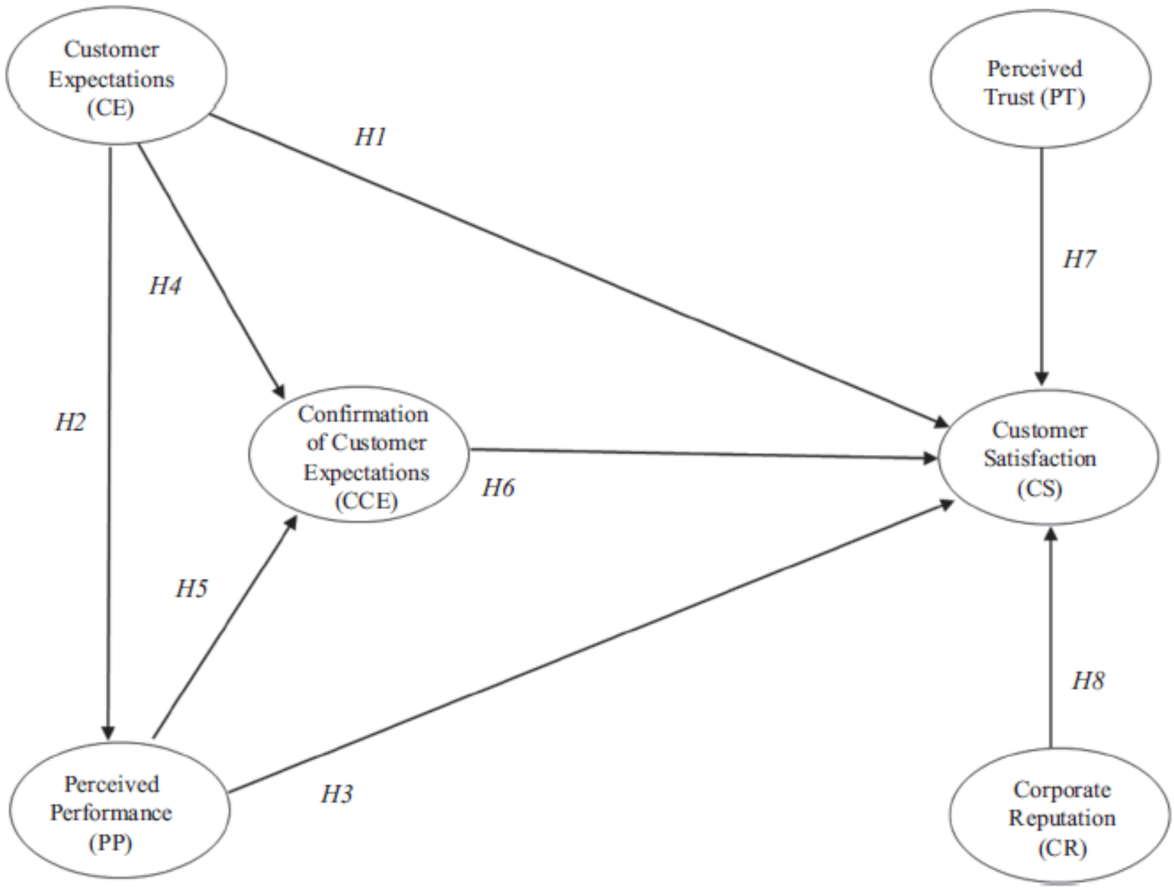

Figure 0.1: *Research Model (Eren, 2021)*

8. Data Analysis

Table 8.1

Respondent's Demographic Information

		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	197	49.3	49.3	49.3
	Female	203	50.7	50.7	100.0
Age Group	13-19	28	7.0	7.0	7.0
	20-30	160	40.0	40.0	47.0

	31-60	197	49.3	49.3	96.3
	60+	15	3.8	3.8	100.0
Education	High school or equivalent	41	10.3	10.3	10.3
	Technical or occupational certificate	48	12.0	12.0	22.3
	Bachelor's degree	138	34.5	34.5	56.8
	Master's degree	143	35.8	35.8	92.5
	Ph.D. or higher	30	7.5	7.5	100.0
Occupation	Student	211	52.8	52.8	52.8
	Self-employed	104	26.0	26.0	78.8
	Employed	58	14.5	14.5	93.3
	Unemployed	27	6.8	6.8	100.0
Income	Less than 180,000 NPR/year	74	18.5	18.5	18.5
	180,001 to 300,000 NPR/year	63	15.8	15.8	34.3
	300,001 to 500,000 NPR/year	107	26.8	26.8	61.0
	500,001 to 1,000,000 NPR/year	117	29.3	29.3	90.3
	More than 1,000,001 NPR/year	39	9.8	9.8	100.0
Province	Province 1: Koshi Pradesh	18	4.5	4.5	4.5
	Province 2: Madhesh Pradesh	39	9.8	9.8	14.2
	Province 3: Bagmati Pradesh	118	29.5	29.5	43.8
	Province 4: Gandaki Pradesh	106	26.5	26.5	70.3
	Province 5: Lumbini Pradesh	76	19.0	19.0	89.3
	Province 6: Karnali Pradesh	30	7.5	7.5	96.8
	Province 7: Sudur Pashchim Pradesh	13	3.3	3.3	100.0

The demographic analysis of respondents shows a balanced gender split (49.3% male, 50.7% female) and a concentration in the 20-30 (40.0%) and 31-60 (49.3%) age groups, with fewer in the 13-19 (7.0%) and 60+ (3.8%) categories. Education levels are highest among those with Bachelor's (34.5%) and Master's degrees (35.8%). A majority of respondents are students (52.8%), with others self-employed (26.0%) or employed (14.5%), and a few unemployed (6.8%). Income levels mostly range from 300,001 to 500,000 NPR/year (26.8%) and 500,001 to 1,000,000 NPR/year (29.3%). Geographically, respondents are mainly from Province 3 (Bagmati Pradesh) (29.5%), followed by Province 4 (Gandaki Pradesh) (26.5%) and Province 5 (Lumbini Pradesh) (19.0%).

Table 8.2

Banking Activities Platform

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Physical branch	92	23.0	23.0	23.0
	Online platforms	171	42.8	42.8	65.8
	Both physical branch and online platforms	137	34.3	34.3	100.0
	Total	400	100.0	100.0	

The data shows how 400 respondents prefer to conduct banking activities: 23% use only physical branches, 42.8% exclusively opt for online platforms, and 34.3% utilize both methods. This indicates varied preferences, with a significant lean towards online banking for its convenience, while others remain reliant on traditional branches or adopt a hybrid approach.

Table 8.3

Chatbot Familiarity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not at all familiar	37	9.3	9.3	9.3
	Slightly familiar	103	25.8	25.8	35.0
	Somewhat familiar	128	32.0	32.0	67.0
	Moderately familiar	105	26.3	26.3	93.3
	Extremely familiar	27	6.8	6.8	100.0
	Total	400	100.0	100.0	

Figure 4.5 details respondents' familiarity with banking chatbots among 400 participants: 9.3% are "Not at all familiar," 25.8% are "Slightly familiar," 32.0% are "Somewhat familiar," 26.3% are "Moderately familiar," and 6.8% are "Extremely familiar." This distribution shows a broad range of familiarity with chatbot technology in banking, with most respondents identifying as having some degree of familiarity, particularly within the "Slightly," "Somewhat," and "Moderately familiar" categories.

Table 8.4

Synopsis of Descriptive Statistics

	N	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error

CE	400	3.1265	.69028	.476	-1.035	.122	1.918	.243
PP	400	3.1545	.68805	.473	-.908	.122	1.741	.243
CCE	400	3.1515	.66412	.441	-.999	.122	2.101	.243
CS	400	3.1295	.68021	.463	-.950	.122	1.702	.243
PT	400	3.1555	.65191	.425	-.959	.122	1.963	.243
CR	400	3.1530	.69151	.478	-.927	.122	1.877	.243
Valid N (listwise)	400							

The study's descriptive statistics reveal the respondents' perceptions across various constructs, with mean values for Customer Expectations (CE), Perceived Performance (PP), Confirmation of Customer Expectations (CCE), Customer Satisfaction (CS), Perceived Trust (PT), and Corporate Reputation (CR) ranging from 3.1265 to 3.1555, indicating moderate levels of agreement or perception. Standard deviations range from 0.65191 to 0.69151, showing consistent responses across the sample. Skewness values (-1.035 to -0.908) suggest a slight leftward skew, indicating most responses are towards the higher end of the scale. Kurtosis values (1.702 to 2.101) show slightly peaked distributions, meaning responses are concentrated around the mean with few extremes. These statistics collectively provide insight into respondents' attitudes and perceptions regarding the constructs analyzed.

Evaluation of Measurement Model

Content validity in this study is ensured by thoroughly reviewing existing literature to select indicators that accurately represent each construct's domain. Indicators for constructs like Customer Expectations, Perceived Performance, Confirmation of Customer Expectations, Customer Satisfaction, Perceived Trust, and Corporate Reputation were chosen based on their theoretical relevance and empirical validation in prior research. For instance, Customer Expectations indicators capture anticipatory standards based on relevant literature, while Perceived Performance and Confirmation of Customer Expectations indicators reflect customers' performance assessments and how well initial expectations are met. Satisfaction indicators cover both affective and cognitive satisfaction aspects, whereas Trust indicators focus on reliability, credibility, and integrity. Reputation indicators encompass social responsibility, financial performance, and quality. This meticulous indicator selection, grounded in literature and validated by prior studies, ensures the model accurately captures the dynamics between constructs, highlighting the importance of content validity in measuring construct domains effectively.

Reliability assessment is critical to ensure the consistency of the research instrument. This study's reliability was tested to confirm the survey questionnaire's effectiveness in capturing variables relevant to chatbot adoption in the Nepalese banking sector. Using the Cronbach's alpha test, a standard for measuring internal consistency with values above 0.7 deemed acceptable, the reliability of variables and survey responses was examined. The alpha coefficients for each variable and the dataset's overall reliability were analyzed using SPSS, ensuring the questions effectively measured the intended variables (Nunnally, 1978; Fornell & Larcker, 1981). This analysis underscores the data's consistency and the research findings' credibility.

Table 8.5

Cronbach`s Alpha for all Items

Cronbach's Alpha	N of Items

.884	30

Table 8.6

Reliability Analysis of Each Construct

Variables	Cronbach's Alpha	Mean	Std. Deviation	N Of Items
CE	0.718	3.148	1.014	5
PP	0.731	3.176	1.011	5
CCE	0.720	3.154	0.965	5
CS	0.747	3.144	0.965	5
PT	0.703	3.156	0.975	5
CR	0.725	3.176	0.998	5

In the survey, each variable corresponds to a specific construct, with Cronbach's Alpha values between 0.703 and 0.747 indicating acceptable to good internal consistency. The mean and standard deviation for each variable reveal the average response and dispersion of responses, respectively.

Factor analysis was applied to assess the validity and reliability of variables related to operational efficiency of chatbots in the Nepalese banking sector, analyzing variables like Customer Expectations, Perceived Performance, and others, to uncover underlying components (Kaiser, 1974). The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test confirmed data suitability for factor analysis, with a KMO value of 0.855 and a significant Bartlett's Test result, indicating a strong foundation for conducting factor analysis (Kaiser, 1974).

Table 8.7

KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.855
Bartlett's Test of Sphericity	Approx. Chi-Square	3502.645
	df	435
	Sig.	.000

Communalities, indicating the variance each variable shares with extracted factors, ranged from 0.484 to 0.701 after extraction, suggesting the factors adequately represent the variance in the variables. Eigenvalues, key for determining the significance of factors, guided the retention of factors for analysis, with the initial and extracted eigenvalues reflecting the variance explained by each component before and after extraction.

Table 8.8

Factor Loaded and Communalities

	CCE	CE	CR	CS	PP	PT	Communalities
CCE1	0.639						.605
CCE2	0.643						.583
CCE3	0.739						.593
CCE4	0.697						.484
CCE5	0.725						.551
CE1		0.692					.607
CE2		0.586					.496
CE3		0.695					.521
CE4		0.727					.541
CE5		0.728					.488
CR1			0.691				.628
CR2			0.658				.620
CR3			0.755				.501
CR4			0.69				.492
CR5			0.638				.568
CS1				0.707			.661

CS2	0.615			.507
CS3	0.742			.543
CS4	0.75			.569
CS5	0.709			.514
PP1		0.693		.569
PP2		0.658		.502
PP3		0.707		.587
PP4		0.685		.514
PP5		0.732		.578
PT1			0.624	.701
PT2			0.545	.526
PT3			0.745	.529
PT4			0.711	.512
PT5			0.746	.495

Factor loading analysis, crucial for understanding variable relationships with latent constructs, showed strong associations between items and their constructs, especially for Perceived Trust (PT) and Customer Satisfaction (CS), indicating strong construct validity.

Table 8.9
Overview of Construct Reliability and Validity

Construct	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CCE	0.727	0.819	0.477
CE	0.727	0.817	0.473

CR	0.731	0.817	0.473
CS	0.750	0.832	0.499
PP	0.733	0.824	0.484
PT	0.731	0.808	0.460

Convergent validity, assessed through Average Variance Extracted (AVE) scores, showed values close to the acceptable threshold 0.5, with composite reliability scores ensuring the constructs' convergent validity remains satisfactory despite AVE scores slightly below the ideal mark (Fornell & Larcker, 1981).

In summary, the factor analysis, encompassing KMO and Bartlett's Test, communalities, eigenvalues, and factor loading, along with assessments of convergent validity, establishes a strong foundation for the reliability and validity of the measurement model, underscoring the robustness and credibility of the research findings.

The significance and relevance of the model's indicators were rigorously assessed using bootstrap analysis with 5000 subsamples and a 0.05 significance level, following Hair et al. (2016). The analysis focused on evaluating the indicators' outer weights and loadings to determine their importance within the constructs. While all indicators showed statistically significant contributions, except one with a non-significant outer weight, its substantial outer loading above 0.50 justified its retention in the model.

The bootstrapping results confirmed the statistical significance of all outer loadings well above the 0.50 threshold, with P values below 0.01, validating each indicator's significant contribution. Confidence intervals for outer weights and loadings did not span zero, further affirming the indicators' significance. This detailed validation underscores the measurement model's robustness, supporting the progression to structural model evaluation within the context of chatbot adoption in the Nepalese banking sector.

The bootstrapping outcomes, illustrating the original sample estimates, mean values, standard deviation, empirical T statistics, and significance levels for each indicator. This thorough evaluation confirms the indicators' significant roles in accurately capturing the constructs of interest, laying a solid foundation for further research on operational efficiency and chatbot adoption in the banking sector.

Evaluation of Structural Model

Table 8.10

Coefficient of Endogenous Constructs

Endogenous Constructs	R^2 Value	Adjusted R^2 Value
Confirmation of Customer Expectation	0.318	0.314
Customer Satisfaction	0.247	0.240
Perceived Performance	0.178	0.176

The results indicate substantial predictive power for the construct CCE, with R^2 values of 0.318 and 0.314, respectively, demonstrating a significant proportion of variance explained by the model. The CS construct shows moderate predictive power with R^2 values of 0.247 and 0.24, suggesting a reasonable explanation of variance. The PP construct, with R^2 values of 0.178 and 0.176, also contributes to the model's predictive capability but to a lesser extent.

The effect size (ƒ2) analysis within the structural model evaluates the impact of independent variables on dependent ones, crucial for understanding the strength of constructs like Customer Expectations on Perceived Performance (Cohen, 2013). The summary below outlines the effect sizes and statistics for each relationship:

Table 8.11

Coefficient of Effect Size ƒ2

Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CE -> CCE	0.084	0.094	0.051	1.645	0.100
CE -> CS	0.004	0.009	0.012	0.342	0.732
CE -> PP	0.217	0.236	0.094	2.317	0.021
CR -> CS	0.016	0.024	0.020	0.812	0.417
PP -> CCE	0.191	0.204	0.090	2.124	0.034
PP -> CS	0.090	0.098	0.057	1.576	0.115
PT -> CS	0.025	0.033	0.028	0.866	0.386

The effect size analysis within the model highlights diverse impacts: Customer Expectations (CE) modestly influence Confirmation of Customer Expectations (CCE) and Perceived Performance (PP) significantly, with minimal impact on Customer Satisfaction (CS). Corporate Reputation (CR) and Perceived Trust (PT) show limited effects on CS. Perceived Performance (PP) significantly affects CCE and has a small but noteworthy influence on CS, demonstrating the varied importance of each variable in affecting perceived performance and customer satisfaction.

Path coefficients analysis within the structural model reveals all positive relationships between constructs, indicating affirmative links. Notably, Customer Expectations (CE) significantly impact Perceived Performance (PP) with a coefficient of 0.422, underscoring a strong positive influence. Similarly, PP's effect on Confirmation of Customer Expectations (CCE) is substantial, with a coefficient of 0.398, highlighting the importance of performance in confirming expectations. Conversely, CE's impact on Customer Satisfaction (CS) is minimal, with a weak coefficient of 0.065, suggesting expectations might not significantly affect satisfaction. Corporate Reputation to CS shows a modest significant effect, whereas Perceived Trust to CS demonstrates a moderate positive impact, indicating trust as a relevant but less dominant factor for satisfaction compared to performance. These findings emphasize Perceived Performance's key role in enhancing satisfaction and confirming expectations in the Nepalese banking sector, validating the hypothesized model relationships.

Table 8.12

Path Coefficient of Relationships

Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CE -> CCE	0.265	0.268	0.073	3.613	0.000
CE -> CS	0.065	0.064	0.069	0.941	0.347

CE -> PP	0.422	0.426	0.069	6.087	0.000
CR -> CS	0.125	0.135	0.061	2.037	0.042
PP -> CCE	0.398	0.398	0.077	5.141	0.000
PP -> CS	0.303	0.299	0.080	3.796	0.000
PT -> CS	0.160	0.164	0.076	2.117	0.034

The coefficient of determination (R2) indicates the structural model's in-sample predictive power, while its out-of-sample predictive relevance is assessed through Stone-Geisser's Q2 value, determined via SmartPLS's PLSpredict/CVPAT technique with a recommended omission distance of 7 (Andreev et al., 2009; Hair et al., 2016). Positive Q2 values for the endogenous constructs—Confirmation of Customer Expectations (CCE), Customer Satisfaction (CS), and Perceived Performance (PP)—signify the model's predictive relevance, confirming its ability to predict new, unseen data. The Q2 values for CCE (0.174), CS (0.136), and PP (0.164) demonstrate this relevance, with the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics further validating the model's predictive accuracy by quantifying the average error and the average absolute difference between observed and predicted values, respectively (Geisser, 1974; Stone, 1974).

Table 8.13

Predictive Relevance Q^2 Statistics

Endogenous Construct	Q^2predict	RMSE	MAE
CCE	0.174	0.915	0.638
CS	0.136	0.937	0.631
PP	0.164	0.921	0.628

9. Results and Discussions

Path Model Analysis

The PLS-SEM analysis examined relationships within the Nepalese banking sector focusing on Customer Expectations, Perceived Performance, Confirmation of Customer Expectations, Customer Satisfaction, Perceived Trust, and Corporate Reputation. The analysis revealed:

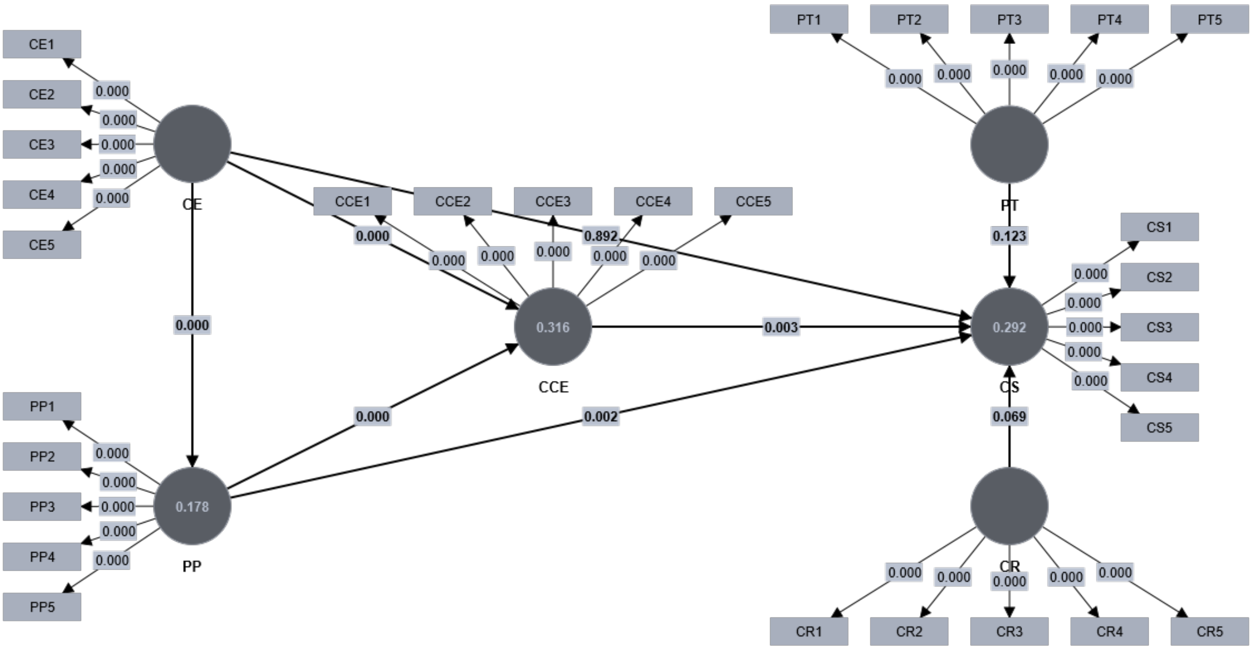

Figure 9.1: *Estimated Path Model*

Table 9.1

Path Model Statistics6

Hypothesis	Relationship	Path Coefficient	T-Statistics	P-Value	Supported ?
H1	CE -> CS	0.009	0.136	0.892	No
H2	CE -> PP	0.422	6.086	0.000	Yes
H3	PP -> CS	0.217	3.111	0.002	Yes
H4	CE -> CCE	0.264	3.615	0.000	Yes
H5	PP -> CCE	0.397	5.119	0.000	Yes
H6	CCE -> CS	0.262	3.003	0.003	Yes
H7	PT -> CS	0.117	1.543	0.123	No
H8	CR -> CS	0.109	1.821	0.069	No

Hypotheses H2, H3, H4, H5, and H6 were supported, demonstrating significant impacts of customer expectations and perceived performance on both the confirmation of these expectations and customer satisfaction. This highlights the critical role of matching chatbot capabilities with customer expectations to enhance service quality.

Hypotheses H1, H7, and H8 were not supported, indicating that customer expectations alone don't directly increase satisfaction, and similarly, perceived trust and corporate reputation alone may not significantly impact customer satisfaction.

These findings emphasize the essential roles of perceived performance and confirmation of customer expectations in fostering customer satisfaction, while the impacts of customer expectations, perceived trust, and corporate reputation on satisfaction are comparatively less substantial in this context.

Major Findings

This research investigates the impact of chatbot technology in Nepal's banking sector, focusing on enhancing operational efficiency and customer experience through digitalization. It examines the effects of chatbots on customer expectations, satisfaction, perceived performance, trust, and corporate reputation, offering insights into their multifaceted impacts. The findings, linked to the study's initial questions and objectives, shed light on the role of chatbots in shaping banking practices within Nepal's evolving technological landscape.

This finding directly addresses the first research question and the first objective by revealing that customer expectations have a moderate influence on satisfaction. While expectations provide a benchmark for chatbot interactions, they are not the sole determinant of satisfaction levels in the Nepalese banking sector. This indicates that while expectations set the stage, actual experience with chatbot performance plays a more critical role in shaping overall user satisfaction.

Tied to the second research question and detailed objective, the perceived performance of chatbots emerged as a crucial factor. The finding shows that when chatbots meet or exceed user expectations, there is a significant uptick in perceived operational efficiency. This underscores the importance of chatbot performance in user experience and satisfaction, aligning with the objective to evaluate chatbots' efficiency within the banking environment.

This finding relates to the third research question and objective by quantifying how confirmation of customer expectations through chatbot interactions drives satisfaction. It demonstrates that the degree to which chatbots validate user expectations is directly proportional to the levels of customer satisfaction, reinforcing the necessity for banks to align chatbot capabilities closely with customer anticipations.

Corresponding to the fourth research question and objective, this finding illustrates that customer satisfaction with chatbot interactions moderately influences the perceived trust in these systems. It highlights a feedback loop where positive interactions with chatbots can build and reinforce trust, which is essential for the sustained adoption of this technology in the banking sector.

The last finding answers the fifth research question and addresses the final objective by indicating that chatbot interactions have a tangential but noticeable impact on the corporate reputation of banks. It suggests that effective chatbot services can enhance the perception of a bank's modernity and customer-centric approach, thus positively influencing overall corporate reputation within the Nepalese banking industry.

The findings from the research provide pivotal insights into the nexus between customer expectations, perceived performance, and the operational efficiency of chatbots within the Nepalese banking sector. The analysis reveals that customer expectations have a moderate influence on overall satisfaction, highlighting the importance of not just setting but also meeting these expectations to enhance user experiences. This has implications for both the marketing of these technologies, to set realistic user expectations, and the technology deployment itself, ensuring that services provided can meet these expectations.

The study highlights perceived performance as a crucial determinant of user satisfaction and operational efficiency in chatbot implementation within the banking sector. It suggests that banks should prioritize enhancing chatbot functionalities to meet user needs, emphasizing user-centric design. Confirmation of customer expectations during interactions is vital for satisfaction, advocating for feedback mechanisms and iterative service improvement. Although chatbot interactions moderately contribute to building trust, they form part of a broader, long-term trust-building strategy requiring consistent service quality. Additionally, effective chatbot services can bolster a bank's corporate reputation, suggesting that chatbots should be viewed not just as operational tools but as strategic assets for branding. The findings advocate for a strategic approach in deploying chatbots, aligning them with customer expectations, and using them to enhance brand image and trust among users.

This analysis contrasts the findings of chatbot satisfaction research in the Turkish banking sector by Eren (2021) with those from the Nepalese banking sector. It highlights similarities and differences, particularly regarding customer expectations, satisfaction, and perceived chatbot performance. While both studies identify perceived performance and trust as crucial to customer satisfaction, differences emerge in the impact of customer expectations and the confirmation process on satisfaction, suggesting cultural or operational differences between Turkish and Nepalese banks. Additionally, the importance of corporate reputation in enhancing digital banking experiences is noted across both contexts, offering insights into chatbot deployment strategies suitable for varying banking environments and customer preferences.

10. Conclusion

This study concludes that the implementation and effectiveness of chatbots in the Nepalese banking sector significantly influence customer satisfaction, operational efficiency, and the overall banking experience. The detailed analysis reveals that customer expectations, when accurately met by chatbots, enhance satisfaction levels, highlighting the importance of aligning chatbot capabilities with customer needs. Furthermore, the study underscores the pivotal role of chatbots in digital transformation strategies for banks, suggesting that when effectively deployed, chatbots can substantially improve operational efficiency and customer service quality. The comparative analysis with a Turkish banking study by Eren (2021), further enriches the understanding, indicating similar trends in the significance of perceived chatbot performance and trust across different geographical contexts, while also revealing distinct cultural and operational nuances. This comprehensive analysis offers valuable insights for banking professionals, encouraging the strategic integration of chatbot technologies to meet evolving customer demands and enhance competitive advantage in the digital era.

For banking professionals, especially in emerging markets like Nepal, the findings advocate for enhancing chatbot technologies to meet and exceed customer expectations, thereby building trust and improving the bank's reputation. The research suggests investing in AI and machine learning to create personalized chatbot interactions, pointing out that sophisticated chatbots can streamline customer service, reduce costs, and increase engagement. This study positions chatbots as strategic assets for redefining the banking experience, aiming for higher customer satisfaction and loyalty.

This study suggests future research to address its limitations and gaps by exploring the integration of chatbots with more complex banking services and analyzing their impact on customer behavior and satisfaction in different banking sectors. It encourages the development of more personalized and intelligent chatbot services through the application of advanced AI technologies. Additionally, future studies could investigate the long-term effects of chatbot interactions on customer loyalty and trust, and how these factors influence the overall digital transformation strategy of banks. Furthermore, expanding the scope of research to include a broader spectrum of banking services and demographic segments would offer richer, more diversified insights, enhancing the generalizability of the findings.

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