Impact of AI-Based Chatbots and Digital Banking Services on Customer Satisfaction in Indian Private Sector Banks

* 1. **Dr. Y. Narendra**, Assistant Professor, BBA Department, KLEF, Vaddeswaram.

* 2. **Ms. Guthanti Neeharika Sai**, Research Scholar, BBA Department, KLEF, Vaddeswaram, g.neeharika123@gmail.com ,

Abstract

With the help of chatbots, recommendations, fraud alerts, and automated processing, AI has seeped into the front office of Indian private banks, providing real-time customer support and customer service.AI has transcended into the front office of Indian private banks with chatbots, personalized recommendations, and real-time fraud detection and automated processing, ensuring swift customer support and customer service. The purpose of this study is to explore the impact of these AI-driven services on customer experience. The questionnaire assessed the overall customer experience using a five-point Likert scale and customer perceptions of four AI service dimensions (chatbots and virtual assistants, personalization, fraud detection and security, and process automation and speed) likewise. Data of 300 customers of four different private sector banks were analyzed through Cronbach's alpha, chi-square test of independence, one way ANOVA and multiple linear regression in MS-Excel. There was a significant association between age group and level of use of AI service, according to the chi-square test (χ^2 (6) = 49.41, $p < 0.001$, Cramér's V = 0.29). The results of the One-way ANOVA indicated that there were significant differences among the low, moderate and high level of AI usage groups in customer experience (F (2, 297) = 42.16, $p < 0.001$, $\eta^2 = 0.22$). The regression model was significant and explained about 33% of the variance in customer experience ($R^2 = 0.333$, F (4, 295) = 36.83, $p < 0.001$); fraud detection and security ($\beta = 0.38$) and chatbots ($\beta = 0.34$) were the strongest predictors, followed by personalization ($\beta = 0.19$) and process automation ($\beta = 0.15$). The results indicate that banks need to emphasize security assurance and the quality of their conversation services and promote the use of AI in their interactions with their older customers.

Key phrase: Artificial intelligence; AI in banking; customer experience; private sector banks; chatbots; personalization; India

1. Introduction

In the last ten years, digital technology has revolutionized banking in India. Customers are now used to a lot of demands for speed, convenience and them round the clock, due to mobile banking, the Unified Payments Interface and the emerging fintech ecosystem. But the private sector banks like HDFC Bank (HDFC), ICICI Bank (ICIC), Axis Bank and Kotak Mahindra Bank (KMBK) have taken up measures by adopting artificial intelligence in customer-facing channels. This could be anything from conversational assistants (Chats) displayed on websites, mobile applications and messaging platforms, machine-learning models to predict which products customers would like to see, real-time algorithm detects suspicious transactions, and automated onboarding and loan processing systems.

Products are easily copied, and service quality is not, making it a key competitive edge for customers. In general, CX is defined as the cognitive, emotional and behavioral reaction of the customer at every interaction with a company (Lemon & Verhoef, 2016). One of the ways this experience can be enhanced is by utilizing artificial intelligence (AI) to streamline responses and ensure interactions are tailored to the specific individual's needs, however when chatbots miss the mark and don't grasp the message, or the consumer feels that their information is being misused, plus when human support becomes challenging to obtain, AI can reduce this experience.

While the use of AI in the banking sector has been rapidly embraced, there are fewer studies and data available about the customer experience in India, with limited coverage across different customer segments. This study seeks to fill that void in estimating how different demographic groups privately held banks are adopting AI, how experience varies with levels of adoption, and which aspects of AI service hold the greatest promise within the banking sector to create a positive experience for customers.

1.1 Research problem

Private sector banks are pouring a lot of money into AI, but it remains difficult to see how these investments are leading to improved customer experience—and more importantly, what features of AI are showing to be most key for banks. Otherwise, they might point resources to feature that customer doesn't value.

1.2 Research objectives

- To study the adoption of AI based banking services of the customers of the private banks in India.
- To understand the relationship between age group and the extent of using AI services of the customers.
- To compare the customer experience with AI service levels across different customers with varying low, moderate and high levels of AI service use.
- To evaluate the impact chatbots, personalization tools, fraud and security tools and process automation have had on customer experience.
- To recommend strategies to enhance the customer experience for banks using AI.

1.3 Research hypotheses

H01: Age group is not significantly related to level of AI service usage. (H11: There is a strong correlation.)

H02: No significant differences between level of use and mean 'Customer Experience'. (H12: There is a large difference.)

H03: The claim that chatbots and virtual assistants are not making any impact on customer experience is a negative one.

H04: Personalization does not significantly impact on customers' experiences.

H05: There is no significant impact of fraud detection and security on customer experience (H05).

H06: The implementation of automation and increasing speed make no significant difference to customers' experience.

1.4 Significance and scope

The study provides insights and evidence for bank managers developing an AI roadmap for their banks, for regulators who need to investigate the responsibilities of responsible digital banking and for researchers who follows technology-mediated service. The scope is narrow – retail customers of the four big private sector banks who have availed of at least one of the services in AI.

This is a literature review toward the conceptual framework.

2. Review of Literature and Conceptual Framework

2.1 Theoretical background

Research on the quality of services started with SERVQUAL, measuring the quality of services based on the components of reliability, responsiveness, assurance, empathy and tangibles (Parasuraman, Zeithaml & Berry, 1988). The expectancy-disconfirmation model accounts for satisfaction measuring the difference between the customer's expectation and performance (Oliver, 1980). The technology context is widely described by the technology accepted or failure model that emphasizes the perceived usefulness and usefulness and ease of use of the technology (Davis, 1989), as well as by the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis & Davis, 2003). Both, when taken together, offer the foundation for the expectation that AI will enhance the experience that is perceived as useful, easy and secure.

2.2 AI in services and banking

Huang and Rust (2018) define AI in service as evolving from mechanical to analytical, intuitive and empathetic intelligence and their potential applications for the delegation of work from machines to humans. Dwivedi et al. (2021) offer a multi-disciplinary examination of opportunities and challenges arising from the use of AI, and include trust, ethics and transparency. AI applications in the banking sector come in four areas that are applicable to this study, which are conversational interfaces, personalization and recommendation, fraud and risk detection, and process automation.

The dimensions of AI-powered financial services.

2.3 Scopes of AI in financial services.

Chatbots and Virtual Assistants. These give immediate answers to common questions – on the go at all times. Their worth is defined by accurate understanding, as well as low escalation cost to a real agent and high-resolution rate.

Personalization. AI capabilities such as analyzing transaction and behavioral data help deliver offers, alerts and financial advice that are more relevant and engage users.

Fraud detection and security. The real-time anomaly detection and authentication help to lower the financial risk and boost assurance component of service quality.

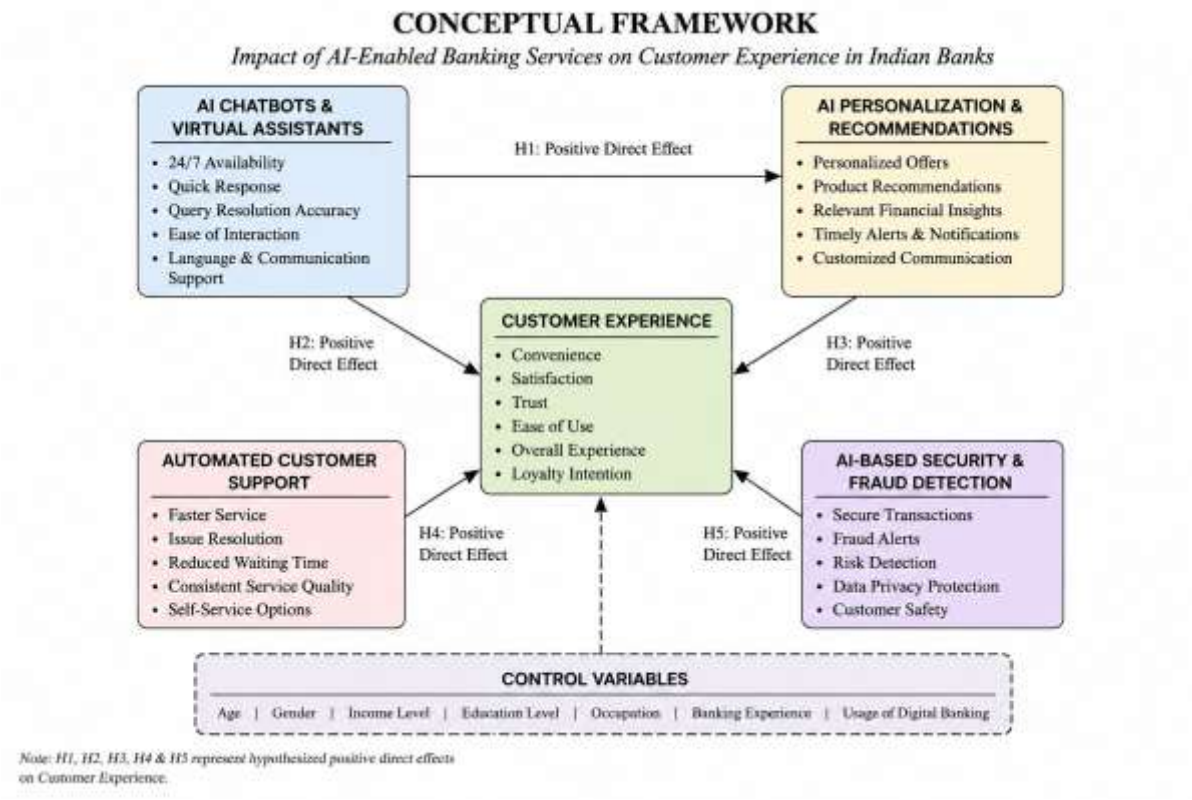
Automation and quickness in the process. Shortened turnaround times and minimized errors courtesy of automated KYC, onboarding, loan decisions and routing queries.

2.4 Research gap

The literature tends to focus on intention with regards to using AI, adopts a singular perspective of AI, and hardly so far compares the various use groups in terms of their experience. In this research, AI is analyzed under four dimensions of services and correlated with customer experience in the Indian private sector banks. Add 8-12 articles from the last 12 months from the relevant journals about AI, digital banking and customer experience in India and summaries them here.

2.5 Conceptual framework

The four dimensions of the AI service—Chatbots, Personalization, Fraud and Security, and Process Automation—are regarded as independent variables while Customer Experience is the dependent variable. Demographic and behavioral factors examined include age group and level of AI usage as a measure of adoption and experience respectively.



3. Research Methodology

3.1 Research design

The descriptive and analytical research design practice of cross-sectional survey method was implemented.

3.2 Population, sample and sampling

The population consists of the retail customers of private sector banks in India who are availed AI enabled services. The four banks – HDFC Bank, ICICI Bank, the Axis Bank and Kotak Mahindra Bank – were chosen due to their size and prominence in their AI initiatives. The sample size (n = 300) is sufficiently large per the minimum sample size guidelines for populations of this size (Krejci and Morgan, 1970) and falls well within the 5 to 10 ratio of observations to predictors guideline for regression (Hair, Black, Babin and Anderson, 2019). It was done using the convenience sampling technique wherein the quotas for age and gender were checked. Author: State cities/regions, Survey period, Survey mode (online/offline).

3.3 Data collection

The two-part structured questionnaire (Appendix A) consisted of demographic and usage profile followed by 16 Likert type statements (ranging from 1 = strongly disagree to 5 = strongly agree) across four dimensions of AI – three for each dimension and four for customer experience. The secondary data collected from RBI publications and bank reports and from journals.

3.4 Variables and measurement

Construct	Items	Sample statement
Chatbots & virtual assistants (CB)	3	The bank's chatbot resolves my queries quickly and accurately.
Personalization (PZ)	3	The bank offers products and alerts relevant to my needs.
Fraud detection & security (FS)	3	I feel my transactions are protected by the bank's AI-based monitoring.
Process automation & speed (PA)	3	Automated processes such as KYC and loans save my time.
Customer experience (CX)	4	Overall, my experience with the bank's digital services is excellent.

Table 1. Constructs and measurement. AI usage level (low, moderate, high) was self-reported from frequency of use of AI features. Construct scores are the mean of their items.

3.5 Tools for analysis

Data was analyzed using MS Excel with formulas and corresponding workbook that will be provided: COUNTIFS, CHIDIST, FDIST, TDIST and LINEST, which is compatible with SPSS. Cronbach's alpha was used to determine the reliability, acceptable value of which was 0.70 (as per Nunnally, 1978). For H01 the chi-square test of independence was used; for H02, the one-way ANOVA with Levene's test and Bonferroni-adjusted pairwise comparisons were used; and the multiple linear regression was used for the testing of H03 through H06. The levels of significance were 0.05 in all senses.

3.6 Limitations of the method

Limits generalizations with convenience sampling, biases may exist with the self-report measure, and the cross-sectional design lends only association and not causation.

4. Data Analysis and Interpretation

4.1 Profile of respondents

Variable	Category	Frequency	Percent
Age	18-25	65	21.7
	26-35	116	38.7
	36-45	70	23.3
	46 & above	49	16.3
Gender	Male	161	53.7
	Female	139	46.3
Education	Graduate	97	32.3
	Postgraduate	141	47.0
	Professional/Other	62	20.7
Bank	HDFC Bank	99	33.0
	ICICI Bank	79	26.3
	Axis Bank	70	23.3
	Kotak Mahindra Bank	52	17.3
AI usage level	Low	73	24.3
	Moderate	96	32.0
	High	131	43.7

Most respondents (60.4%) were aged 18 to 35, and 43.7% were high users of AI-enabled services, indicating substantial adoption in the sample.

4.2 Chi-square test: age group and AI usage level

H01: There is no significant association between age group and level of AI usage.

Age group	Low	Moderate	High	Total
18-25	5	20	40	65
26-35	19	39	58	116
36-45	21	27	22	70
46 & above	28	10	11	49
Total	73	96	131	300

Table 4. Observed frequencies, age group by AI usage level.

Statistic	Value
Pearson chi-square	49.415
Degrees of freedom	6
Critical value (α = 0.05)	12.592
p-value	< 0.001
Cramér's V	0.287
Minimum expected count	11.92

Table 5. Chi-square test of independence. Source: Excel workbook, Chi-square sheet

Chi-square value calculated (49.41) is greater than critical value (12.59) and p value smaller than 0.05, therefore null hypothesis is rejected. There is a strong correlation between the level of use of AI and age. As per table 4, it is seen that there is a definite pattern: High users constitute 61.5% of the customers aged 18-25 years and 22.4% of the customers aged 46 and above are high users, whereas 57.1% of the customers aged 46 and above are low users. The strength of the association is moderate as the V value in Cramér was found to be 0.29.

4.3 One-way ANOVA: customer experience across AI usage levels

H02: Mean customer experience does not differ across low, moderate and high AI usage groups.

Usage group	n	Mean CX	SD	Std. error
Low	73	3.47	0.43	0.05
Moderate	96	3.86	0.47	0.05
High	131	4.07	0.44	0.04
Total	300	3.86	0.50	0.03

Table 6. Group descriptive statistics for customer experience.

Source	Sum of squares	df	Mean square	F	p-value
Between groups	16.851	2	8.425	42.162	< 0.001
Within groups	59.351	297	0.200		
Total	76.202	299			

Table 7. One-way ANOVA. Eta squared = 0.221. Levene's test for homogeneity of variance: F(2, 297) = 1.23, p = 0.293 (assumption met).

Pairwise comparison	Mean difference	Bonferroni p
Low vs Moderate	-0.390	< 0.001
Low vs High	-0.600	< 0.001
Moderate vs High	-0.209	0.002

Table 8. Post-hoc pairwise comparisons (pooled-variance t-tests, Bonferroni-adjusted).

The F-value of 42.16 is highly significant ($p < 0.001$), so H02 is rejected. The higher ones that use more AI, the more satisfying their customer experience becomes, starting from 3.47 for the low supporters to 4.07 for the as much supporters. Based on the typical criteria of Cohen (1988), the Eta squared of .22 suggests a large effect (about 22% of variation in experience related the usage level of the product). All differentials have been found to be significant, with the separation between moderate and high users (0.21) being less than the separation between low and moderate users (0.39) implying that the benefits of further increasing usage are limited. This is cross sectional and therefore associates the experience with some other factor: those who are accustomed to digital may be more inclined to make more use of that experience.

4.4 Multiple regression: drivers of customer experience

The model is: CX = b0 + b1(CB) + b2(PZ) + b3(FS) + b4(PA) + e.

Predictor	B	Std. error	Std. beta	t	p-value
(Constant)	1.170	0.239	-	4.90	< 0.001
Chatbots (CB)	0.233	0.033	0.341	7.15	< 0.001
Personalization (PZ)	0.162	0.040	0.192	4.04	< 0.001
Fraud detection & security (FS)	0.276	0.035	0.378	7.94	< 0.001
Process automation (PA)	0.108	0.035	0.145	3.04	0.003

Table 9. Regression coefficients. Dependent variable: customer experience. Source: Excel workbook, Regression sheet (LINEST).

Model statistic	Value
R	0.577
R squared	0.333
Adjusted R squared	0.324
F (4, 295)	36.83
Std. error of estimate	0.415
Durbin-Watson	1.95
Max. correlation among predictors	0.07

Table 10. Model summary and diagnostics.

The model is statistically significant with $F = 36.83$, $p < 0.001$ and an adjusted R^2 of 0.324 which accounts for a considerable amount of the variance in the customer experience, particularly in perception-based research about service. All the four predictors are significant thus the following H03 to H06 are rejected. Meanwhile, of the three, fraud detection and security has the greatest impact ($\beta = 0.38$): Other things equal, a 1-point rise in the perceived security is correlated with a 0.28-point increase on the experience measure. Chatbots follow ($\beta = 0.34$; B = 0.23), then personalization ($\beta = 0.19$). Process automation is found to have the least but still significant effect ($\beta = 0.15$, $p = 0.003$). Multicollinearity and autocorrelation are not of concern because the correlation between the four predictors are very small (the largest $|r| = 0.07$) and the Durbin-Watson statistic is near 2.

5. Findings, Discussion and Suggestions

5.1 Major findings

• AI adoption is high but uneven: 43.7% of respondents are high users and use falls sharply with age (61.5% of those aged 18-25 are high users versus 22.4% of those aged 46 and above).
• Customer experience increases significantly with AI usage level (mean CX 3.47 for low users, 3.86 for moderate and 4.07 for high users; $\eta^2 = 0.22$).
• The four AI dimensions jointly explain about 33% of the variance in customer experience.
• Fraud detection and security and chatbots and virtual assistants are the most influential dimensions; process automation has the weakest effect.

5.2 Discussion

The importance of fraud detection and security aligns with the assurance dimension of service quality and with the trust concerns highlighted in AI research (Parasuraman et al., 1988; Dwivedi et al., 2021): customers appear to value visible protection of their money and data above other AI features. The strong role of chatbots is consistent with the view that responsiveness and availability are core service quality attributes. The modest effect of process automation may reflect that speed is now an expected baseline and therefore differentiates less. The age gradient in usage matches technology acceptance theory, where perceived ease of use and familiarity shape adoption (Davis, 1989; Venkatesh et al., 2003). [Author: compare these results explicitly with the studies you reviewed in Section 2.]

5.3 Suggestions

•Communicate AI-based security measures clearly, for example instant fraud alerts and transparent dispute resolution, to build assurance.
•Invest in chatbot accuracy, multilingual support and a visible, quick hand-off to human agents.
•Improve personalization with relevant, consent-based offers rather than intrusive marketing.

• Run digital literacy and assisted onboarding programmed for customers aged 46 and above to close the adoption gap.
• Treat process automation as a hygiene factor: maintain speed but do not expect it alone to differentiate the bank.

5.4 Implications, limitations and future research

For managers, the results indicate where AI investment is most likely to raise experience. Limitations include convenience sampling, self-reported data and a cross-sectional design. Future studies could use probability sampling, include public sector and small finance banks, add constructs such as trust, privacy concern and perceived empathy, use structural equation modelling, and follow customers over time.

6. Conclusion

AI-enabled services are significantly associated with better customer experience in private sector banks. Usage differs by age, experience improves as usage rises, and security assurance, chatbots and personalization are the strongest drivers. Banks that combine visible security, reliable conversational service and inclusive adoption strategies are best placed to convert AI investment into customer satisfaction and loyalty.

References

1.Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

2.Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297-334.

3.Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

4.Dwivedi, Y. K., et al. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

5.Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.

6.Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172.

7.Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607-610.

8.Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69-96.

9.Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

10.Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. Journal of Marketing Research, 17(4), 460-469.

11.Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. Journal of Retailing, 64(1), 12-40.

12.Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.