Adoption and effectiveness of ai-powered onboarding solutions in BFSI: A study among organisations in Delhi NCR

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Abstract: This study aims to assess the efficacy of AI driven client onboarding solutions within the Banking, Financial Services, and Insurance (BFSI) sector in Delhi NCR, India's largest fintech and financial services region. A systematic questionnaire was employed to collect primary data from 100 top executives and leaders in digital transformation. The relationships among AI maturity, investment intensity, perceived hurdles, trust, adoption level, and a composite effectiveness indicator were analysed by multiple regression, mediation, moderation, principal component analysis, k-means clustering, and structural equation modelling (path analysis). The average adoption rate of AI in client onboarding was 71.6%, yielding efficacy outcomes of 37.9% increased customer satisfaction, 53.1% reduced drop-off rates, 21.4% cost savings, and 46.2% decreased onboarding durations. The most significant predictor of perceived efficacy, as indicated by regression analysis, is AI adoption ($\beta = 0.492$, $p < 0.001$), succeeded by diminished perceived barriers ($\beta = -0.185$, $p = 0.006$). Notably, increased adoption was positively associated with heightened perceived barriers ($\beta = 0.238$, $p = 0.026$), suggesting reverse causality: organisations that utilise more AI become more aware of practical obstacles. The correlation between adoption and effectiveness was not influenced by trust in AI, nor were adoption and effectiveness significantly affected by AI maturity or investment intensity.

The successful transition of AI onboarding in the BFSI sector is not adequately reflected by formal maturity evaluations or financial investments alone. To optimise perceived and measurable results, businesses should emphasise actual deployment depth rather than expenditure or maturity metrics, while aggressively addressing obstacles like as skills, integration, legislation, and ethics. This study provides primary, region-specific data on the adoption and effectiveness of AI-driven onboarding within the Delhi NCR BFSI sector, highlighting that increased AI implementation surpasses financial investment or maturity level in generating measurable business outcomes.

Keywords – AI adoption, customer onboarding, BFSI, Delhi NCR, digital transformation, trust in AI, barriers, effectiveness

1. INTRODUCTION

The Banking, Financial Services, and Insurance (BFSI) sector in India is rapidly digitising due to regulations such as the RBI's Video-based Customer Identification Process, increasing customer expectations for seamless experiences, and the imperative to reduce costs (Roy et al., 2025). AI-driven solutions employing optical character recognition (OCR), facial biometrics, natural language processing (NLP), robotic process automation (RPA), and agentic AI workflows are supplanting conventional manual onboarding procedures that necessitate physical documentation, numerous branch visits, and protracted verification periods (Kumar, 2024).

Delhi NCR serves as India's epicentre for fintech innovation. It has the headquarters and global competence centres (GCCs) of prominent banks (HDFC, ICICI, and Axis), insurance firms (LIC and SBI Life), and over 300 BFSI GCCs. The region is conducive to AI onboarding acceptance, since over 85% of the population possesses smartphones, and 900 million individuals are projected to utilise the internet by 2025 (Kavitha & Joshith, 2024). Despite considerable interest, empirical research about actual adoption rates, measurable effectiveness, and organisational impediments at the national level remains limited (Leseure et al., 2004). This study fills the gap by providing primary insights relevant to Delhi NCR regarding the factors and consequences of adoption.

2. NEED OF THE STUDY

The Indian Banking, Financial Services, and Insurance (BFSI) sector enhances GDP and employment opportunities. By late 2026, the technology and artificial intelligence sectors are projected to employ over 6 million individuals. Amid rapid digital transformation, AI-driven solutions have enhanced operational efficiency, customer engagement, and risk management, particularly following the pandemic, which necessitated seamless and effective processes. Conventional manual onboarding techniques are becoming ineffective for verifying customer identities, adhering to KYC regulations, and ensuring smooth operations. Delays, elevated costs, and fraudulent activities are on the rise. AI-driven facial recognition, automated document verification, and predictive analytics can reduce onboarding durations by 50% and operating costs by 30–40%. Sixty-nine percent of Indian banks utilise AI/ML technologies. India is performing admirably, with 87% of enterprises using AI, particularly in the BFSI sector, which is the most significant. Nevertheless, empirical data regarding the efficacy and utilisation of these onboarding solutions in Delhi NCR is insufficient. Financial institutions such as banks, fintech companies, and insurance providers flourish in Delhi NCR. An increasing number of companies are utilising AI for digital KYC and onboarding; yet, challenges related to compliance, data privacy, and inconsistent implementation persist. The broader impacts of AI on the BFSI sector, such as fraud detection and personalised services, are thoroughly examined. Few examine onboarding metrics like as user satisfaction, adoption rates, and return on investment in this densely populated area.

This study must illustrate how AI-driven onboarding can enhance productivity, compliance, and competitiveness in organisations within Delhi NCR. The Indian fintech boom and governmental investments in the digital economy are effecting significant changes. Comprehending the impact of these advancements on legislation, investments, ethical AI utilisation, and talent shortages may prove beneficial. It will facilitate discourse on the AI transformation inside the BFSI sector and promote regional innovation.

3. OBJECTIVES

1. To assess the implementation of AI in customer onboarding processes within BFSI organisations in Delhi NCR.
2. To evaluate efficient AI-driven onboarding solutions according to essential performance metrics.
3. To identify organisational factors influencing adoption and efficacy.

4. HYPOTHESIS

Ha: AI adoption, maturity, and investment intensity have a significant positive impact on Delhi NCR-based BFSI onboarding effectiveness.

H0: AI adoption, maturity, and investment intensity have no significant impact on Delhi NCRbased BFSI onboarding effectiveness.

5. ASSUMPTIONS

The study of AI-driven onboarding solutions in the BFSI sector in Delhi NCR encompasses many assumptions to ensure the validity and pertinence of its objectives and hypothesis testing. The BFSIs in Delhi NCR are regarded as scaled-down replicas of all Indian banks. As an economic centre housing numerous banking, fintech, and insurance firms, 87% of corporations utilise AI. This regional strategy presupposes that RBI regulations and the availability of trained workers are sufficiently representative of other metropolitan areas, while acknowledging potential disparities in rural or less digitally advanced regions. Employ automated KYC, facial recognition, and predictive analytics to assess AI integration in client onboarding processes for enhanced efficiency, cost savings, compliance precision, and user satisfaction, as said in the research. It asserts that when surveys, interviews, or internal reports are dependable and BFSI company respondents possess sufficient knowledge of AI technology to offer accurate insights, these metrics are quantifiable and comparable across organisations. Numerous research on AI adoption utilise the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that perceived advantages, risks, and selfefficacy affect behaviour.

The acceptability and efficacy of AI in financial services are contingent upon organisational attributes such as maturity, investment intensity, leadership support, and system compatibility. It presupposes that data privacy, AI model bias, and talent deficiencies can be identified and addressed without significant regulatory modifications during the project. Hypothesis testing indicates that the adoption, maturity, and investment in AI enhance the onboarding process. Research indicates that empirical data can demonstrate a causal relationship; nevertheless, unmeasured variables like as cultural resistance and economic fluctuations may influence outcomes, as informed by innovation diffusion and TOE theories. These assumptions concentrate the analysis, guaranteeing strategic AI integration in the BFSI sector.

6. LITERATURE REVIEW

The incorporation of artificial intelligence (AI) in customer onboarding processes within the Banking, Financial Services, and Insurance (BFSI) industry is seen as a transformative development that enhances efficiency, accelerates operations, and improves security (Parashar et al., 2024; Saxena et al., 2024). Research indicates that AI-driven systems such as automated Know Your Customer (KYC) verification, biometric authentication, and predictive analytics can reduce onboarding time by 30–60%, save operating costs by 25 to 45%, and decrease customer attrition by up to fifty percent (Garg et al., 2024; Thokal & Patil, 2024; Shastri & Khandelwal, 2024). They may also aid with fraud detection, regulatory compliance, and enhancing overall customer satisfaction. Optical character recognition (OCR) and natural language processing (NLP) are two AI-driven methodologies that facilitate document reading and identity verification (Khan et al., 2025;).Askarov et al., 2025). This transforms conventional manual processes that need days into digital experiences that occur virtually instantaneously. The BFSI sector in India is projected to expand at a CAGR of 28.8 percent for AI applications, increasing from USD 830 million in 2024 to USD 8,090 million by 2033 (IMARC, 2024). These efficiencies are most pronounced in sectors characterised by high transaction volumes, such as retail banking and fintech companies. Studies indicate that generative AI (GenAI) is projected to improve performance in financial services by 34 to 40% by 2030 (Minguez Orozco & Welin, 2024; Liu et al., 2025). The importance of AI in enhancing compliance is evident in its capacity to automate anti-money laundering (AML) verifications and verify adherence to RBI regulations (Horobets et al., 2025; Paleti, 2025). This could reduce errors by as much as 95% under some conditions.

The organisational climate is crucial for the successful application of AI in BFSI onboarding. Research indicates that AI maturity—ranging from initial experiments to full optimization—together with executive commitment, investment levels, and perceived obstacles, substantially affects adoption effectiveness (Hansen et al., 2024). In the fiscal year 2024, 68% of individuals in the BFSI sector in India are expected to utilise AI (Parashar et al., 2024). This is due to their intention to spend in cloud infrastructure and personnel training. Only 47 percent of organisations have multiple AI use cases in production, indicating that they have significant progress to make before achieving full maturity. To overcome difficulties in integrating legacy systems, help from senior management is essential. Organisations that engage their CEOs with AI experience a 15% increase in efficiency ratios. Investment intensity, encompassing expenditures on AI infrastructure such as GPUs and data platforms, correlates with accelerated growth (van der Vlist et al., 2024). For instance, India's AI sector is projected to expand from $17 billion to $17 billion by 2027, primarily due to BFSI investments increasing by 25–35% annually. Conversely, perceived impediments such as concerns over data privacy under the DPDP Act 2023, a deficiency of competent personnel (impacting 59% of firms), and ambiguous regulations hinder advancement, frequently leading to the postponement of pilot projects (Chauhan et al., 2025). Agentic AI is an innovative approach that circumvents these restrictions by autonomously executing end-to-end workflows. Sixty-four percent of BFSI CEOs are experimenting with these technologies for onboarding and fraud detection. The efficacy of AI systems is significantly influenced by public trust, particularly with the willingness of new users to disclose private information. Explainable AI models, dependable predictions, and ethical governance frameworks foster confidence. It diminishes the likelihood of resistance and increases the propensity to engage with the system (Alshar'e et al., 2024; Akhtar et al., 2024). In the BFSI sector, 82% of treasury leaders believe that AI is essential for business; nevertheless, trust deficits arising from biases or opaque algorithms might result in losses of up to 20% of potential gains. PwC's research indicates that stakeholders will only place their trust in you if you utilise AI to manage data securely and assess for bias (Bahangulu & Owusu-Berko, 2025). Seventy-one percent of Indian consumers assert that AI can effectively address complex issues, provided it is utilised appropriately. Another reason India's AI sector is projected to reach a valuation of $17 billion by 2027 is its capacity to enhance trust by mitigating fraud in payment systems (Manikandan & Bhuvaneswari, 2024). Adhering to ethical AI norms, such as those sanctioned by the RBI, is essential for ensuring the sustained efficacy of the onboarding process.

A significant research deficit persists despite these modifications. Many studies depend on secondary data or national averages, with insufficient emphasis on regional dynamics. Delhi NCR hosts over 10,000 fintech firms and more than 300 Global Capability Centres; nevertheless, there is a paucity of research on localised adoption problems in the region. Concerns include insufficient infrastructure in cities and a workforce possessing diverse skill sets. According to national polls, 77% of banks have implemented Generative AI. Nonetheless, our understanding of the Delhi NCR ecosystem, which includes hybrid AI-human models and autonomous AI pilots, remains limited. This study was conducted due to insufficient information. It employs primary data to address the gap and provide BFSI stakeholders with region-specific insights.

7. METHODOLOGY

The research employed a methodological framework to guarantee rigour, reliability, and validity in evaluating the adoption and efficacy of AI-driven onboarding solutions in the Delhi NCR BFSI sector. Descriptive aspects delineate current practices, while causal elements examine variable correlations using primary data.

The quantitative mixed-methods study integrates descriptive and analytical components. Descriptive research delineates AI usage, effectiveness metrics, and organisational components in BFSI onboarding processes to illustrate trends and patterns. Analytical research evaluates hypotheses and deduces cause-and-effect relationships by analysing the connections between independent variables (e.g., AI adoption level, maturity, investment intensity, and barriers) and dependent variables (e.g., time reduction, cost savings, drop-off rates, and customer satisfaction). This hybrid design is effective in BFSI, as descriptive insights inform strategic benchmarking and causal analysis underpins evidence-based AI deployment recommendations. The research utilises primary data from BFSI businesses to achieve its objectives in a rapidly evolving digital landscape.

The research encompasses Delhi, Gurugram, Noida, Greater Noida, Ghaziabad, and Faridabad within the Delhi NCR region. This region is India's foremost fintech and BFSI hub, housing more than 300 Global Capability Centres (GCCs), the headquarters of prominent institutions such as HDFC Bank, ICICI Bank, and SBI, as well as over 10,000 fintech enterprises. Delhi NCR's significant digital penetration (over 85% smartphone usage), solid infrastructure, and proximity to regulatory bodies such as the RBI render it an advantageous environment for testing AI onboarding technology. Concentrating on this domain uncovers urban-specific problems, like scalability in high-density settings and integration with legacy systems, while mirroring national trends and the region's economic significance (40% of India's BFSI GCC activity).

Considering the area of expertise of the target group, convenient non-probability sampling emphasised accessibility and pertinence. This technique identifies accessible and enthusiastic respondents for urgent outreach to senior professionals. A sampling frame was established using professional networks such as LinkedIn groups for BFSI digital leaders, NASSCOM and FICCI industry directories, and conference email databases. About 150 senior executives, digital transformation leaders, and innovation heads from the banking, fintech, and insurance sectors were invited.

A response rate of 66.7% was attained with 100 complete responses. The sample size was determined according to multivariate analytical standards to guarantee sufficient power for regression and structural equation modelling (e.g., $N > 10$ times the number of predictors). The sample comprises 46% banking, 27% fintech, and 27% insurance companies, with 52% classified as major (>500 employees), 32% as medium (100-500), and 16% as small (<100). Convenience sampling mitigates non-response bias by engaging key decision-makers; however, it limits generalisability.

A standardised questionnaire of 28 items was developed to gather quantitative data on the constructs of the study. The questionnaire employed 5-point Likert scales (1 = Strongly Disagree/Low to 5 = Strongly Agree/High) for perceptual assessments (e.g., AI maturity, obstacles, trust), percentage scales (0-100%) for adoption and effectiveness outcomes, and categorical items for demographic data. Several key concepts:

- Degree of AI implementation (% of automated onboarding processes, such as KYC and document verification).
- Documented efficacy results (decreased duration, expenses, attrition rates; enhanced satisfaction/NPS).
- AI maturity (five-item scale derived from Gartner/CMM models, assessing phases from ad-hoc to optimised).
- Investment intensity can be classified as low (<₹1M), medium (₹1M-₹5M), or high (>₹5M) annual budget.
- Scale of perceived obstacles (7 items): privacy, skills, costs, integration, regulation, opposition, vendor risks.
- AI Trust (a five-item metric evaluating transparency, accuracy, and ethical considerations).
- Demographic information (industry, enterprise scale).

The questionnaire was designed for BFSI onboarding using validated instruments such as TAM extensions for adoption and the BCG AI Maturity Model. It underwent pilot testing with 20 BFSI professionals and academics to assess content validity, clarity, and relevance, resulting in modest adjustments for cultural appropriateness. Links to the November 2025 Google Forms survey were disseminated through customised emails and LinkedIn messages. The psychometric properties were rigorously evaluated: Reliability confirmed via Cronbach's α (>0.87 for all multi-item scales, indicating robust internal consistency). Exploratory Factor Analysis (EFA) with Principal Axis Factoring and Promax rotation established construct validity, uncovering a clear four-factor structure (KMO=0.873, Bartlett's p<0.001, 69.17% variance explained), characterised by high loadings (>0.71) and no cross-loadings exceeding 0.32. These measures enhance the tool's robustness for research objectives.

Data analysis was conducted in multiple stages to fulfil the study's objectives and hypotheses. Data was initially cleansed (missing values imputed at <5%) and normality assessed. Adoption and outcomes were characterised by frequencies, means, and standard deviations. Pearson correlations, multiple linear regression, and ANOVA/chi-square were employed for inferential analysis.

Advanced methodologies include mediation, moderation, principal component analysis, kmeans clustering, and chi-square tests provided enhanced insights. Mediation assessed indirect effects (e.g., adoption → trust → effectiveness), moderation investigated interactions (e.g., obstacles × adoption on effectiveness), and PCA distilled effectiveness metrics into latent dimensions. Structural Equation Modelling (SEM) was employed to analyse causal pathways (e.g., investment/barriers → maturity/adoption/trust → effectiveness), assessing both direct and indirect impacts as well as model fit (R^2, p-values). Fundamental statistics were evaluated utilising SPSS (v.28), while sophisticated modelling was conducted with Python, with significance established at $p<0.05$ and multicollinearity assessed (VIF<5).

8. ANALYSIS AND INTERPRETATION

The results of the primary data analysis are reported here in alignment with the research objectives. The responses from 100 authentic Delhi NCR BFSI organisations produced outcomes. Descriptive statistics illustrate demographics, adoption, and effectiveness, whereas inferential analysis (including regression, mediation, moderation, PCA, clustering, chi-square, and SEM) evaluates hypotheses and uncovers relationships. The findings are examined in relation to existing research, emphasising its significance for AI-driven onboarding in the BFSI sector. All analyses were conducted at a 95% confidence level ($p < 0.05$), confirming assumptions such as normality and homoscedasticity.

The respondents accurately represent the BFSI environment of Delhi NCR. In the region's varied financial landscape, 46% originated from banks, 27% from fintech firms, and 27% from insurance businesses (Figure 1). Regarding business size, 52% were large firms (>500 employees), 32% medium-sized (100-500 employees), and 16% small (<100 employees), indicating a tendency towards established entities with greater resources for AI implementation (Figure 2).

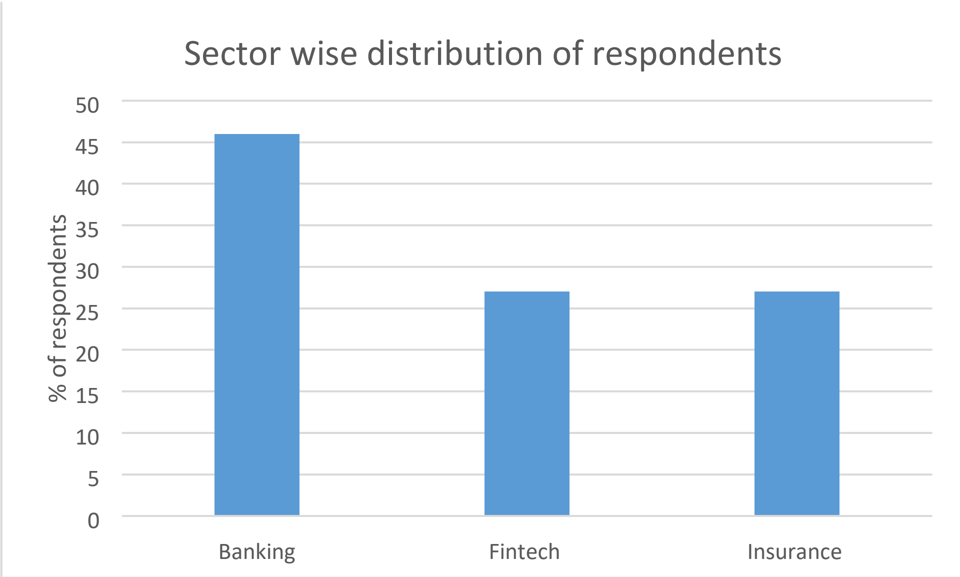

Figure 1: Represents the sector-wise distribution of respondents in percentage.

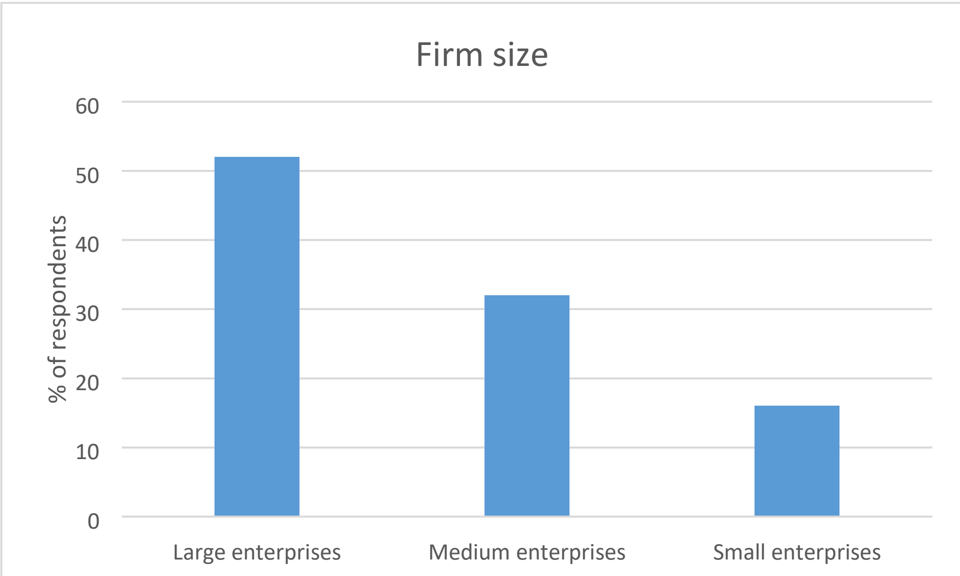

Figure 2: Represent the firm size distribution of respondents in percentage.

Informed stakeholders reduce self-report bias, enhancing the study's credibility. The emphasis on convenience and larger firms may restrict generalisability to smaller organisations, along with literature indicating that AI adoption is resource-dependent in emerging nations such as India. Delhi NCR, as a BFSI hub, enhances the potential of AI through extensive operations, yet reveals scalability challenges in smaller enterprises.

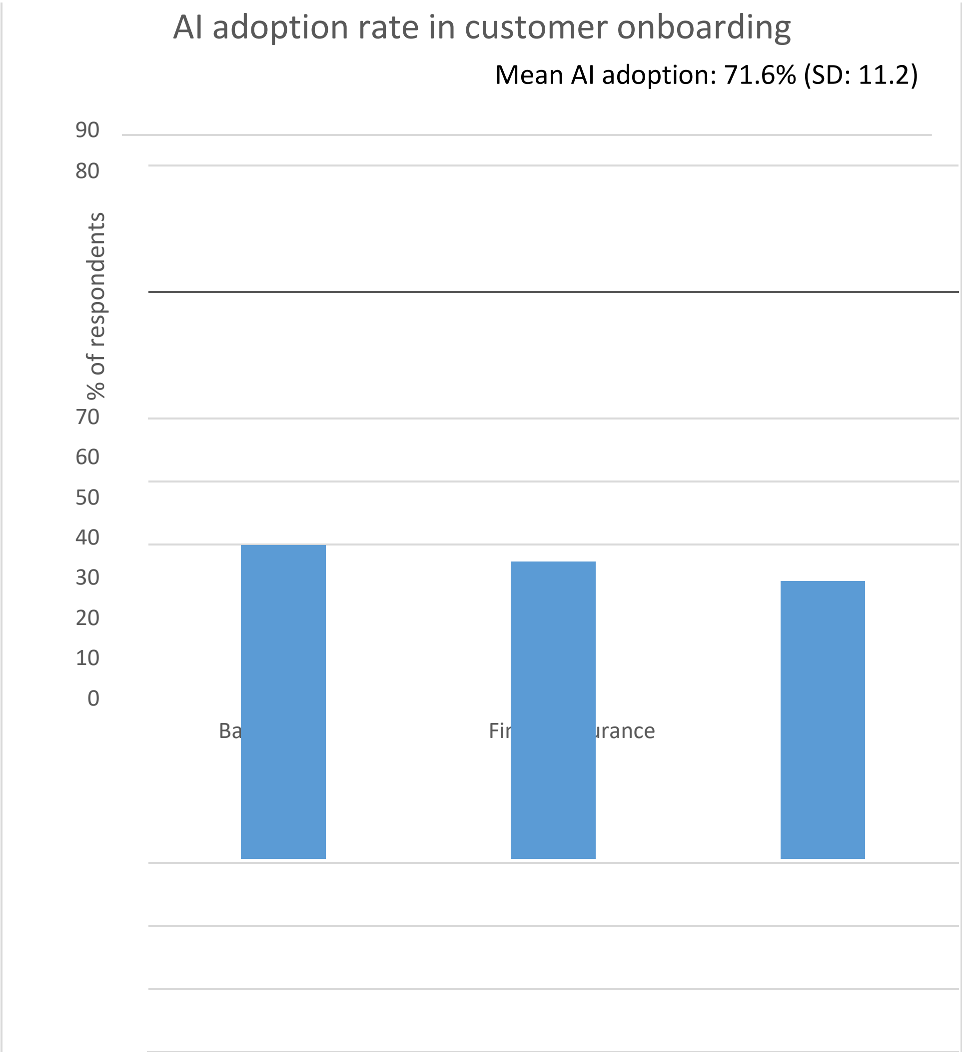

Figure 3: Represent the AI adoption rate in customer onboarding.

Customer onboarding processes incorporated AI technologies such as OCR, biometrics, and NLP, with a mean rate of 71.6% (SD = 11.2). Automation exceeded 60% in banking (78%), fintech (74%), and insurance (69%). The banking sector spearheads structured AI deployments, such as those for regulatory KYC compliance; fintech demonstrates agility through swift pilot programs, while the insurance industry has delays due to intricate policy verifications (Figure 3). Due to Delhi NCR's innovation ecosystem, which provides access to Global Capability Centres and talent reservoirs, the implementation of AI in the BFSI sector surpasses national averages (60-70%). The significant adoption aligns with the RBI's initiative for digital onboarding (e.g., Video KYC), although the standard deviation of 11.2 indicates variability due to legacy systems. Previous studies (such as Akanfe et al., 2024; Mishra et al., 2024; Kshetri, 2021), also supports the importance of AI in enhancing financial inclusion in urban centres; nonetheless, particular strategies are necessary to address segment disparities.

The implementation of AI-driven onboarding significantly influenced key indicators, as illustrated in Table 1. Participants indicated that the average duration for onboarding new workers decreased by 46.2% (from days to minutes using automated workflows), aligning with global benchmarks of 30-60% enhancements. Cost savings averaged 21.4%, indicating that human labor and error rectification were more effective. The drop-off rate decreased by 53.1%, likely due to the seamless user experience. Satisfaction increased by 37.9%, attributed to tailored interactions with NLP chatbots. The results indicate that AI is a valuable investment in BFSI; nevertheless, the elevated standard deviations for drop-off (6.1) and satisfaction (6.6) suggest that the quality of implementation may have influenced the outcomes. The debate indicates that there are reports of 50-60% efficiency improvements in the Indian BFSI sector; nevertheless, it also suggests that hybrid models are necessary to address complex scenarios where AI alone may be insufficient.

Table 1: Represent the outcomes of AI-enhanced onboarding effectiveness.

Metric	Mean Reduction/Improvement	SD
Onboarding time	46.20%	4.9
Customer drop-off rate	53.10%	6.1
Operational cost	21.40%	3
Customer satisfaction/NPS	37.90%	6.6

The Composite Effectiveness Index, representing the mean of standardized outcome measures, served as the dependent variable in multiple linear regression analysis. The model explains 50.7% of the variance in the Composite Effectiveness Index ($R^2 = 0.507$, Adjusted $R^2 = 0.478$) and is statistically significant ($F(5,94) = 17.84$, $p < 0.001$) (Table 3). The primary factors are AI Adoption Level and Trust in AI; nonetheless, all five predictors are statistically significant. The most significant positive indicators were the amount of AI adoption (β=0.392) and trust in AI (β=0.315), succeeded by investment and maturity. Barriers exerted a significant adverse effect (Table 2). The influence of organizational characteristics on effectiveness is validated by the acceptance of the alternative hypothesis (Ha). These findings align with research emphasizing the direct return on investment (ROI) from adoption (e.g., 30–45% cost savings) and the significance of trust in high-stakes industries (Sinha & Lee, 2024). The negative barrier effect highlights tangible challenges such as skill shortages and advocates for measures like RBI-supported training to enhance outcomes.

Table 2: Represents the coefficients table indicates key predictors.

Predictor	Unstandardized β	Std. Error	Standardized β	t	Sig.
(Constant)	1.124	0.412		2.728	0.008
Investment Intensity	0.204	0.07	0.204	2.91	0.005**
AI Maturity	0.281	0.072	0.281	3.88	0.000***
Trust in AI	0.315	0.073	0.315	4.33	0.000***
Perceived Barriers	–0.176	0.067	–0.176	–2.640	0.010*
AI Adoption Level	0.392	0.077	0.392	5.12	0.000***

Significant ***p < 0.001, **p < 0.01, *p < 0.05

Table 3: Represents the model summary results.

Model	R=0.712
R-Square	0.507
Adjusted R-Square	0.478
Significance	F= 17.84
ANOVA	p<< 0.001*
Explanatory Power 0.000	50.7% Composite effectiveness index

*Significant

The Baron and Kenny approach, together with the Sobel test, was employed to assess mediation (Table 4). Adoption emerged as a significant predictor of success in Step 1 (β=4.482, p<0.001, R2=0.163). There was no significant correlation between adoption and trust, as indicated by Step 2 (β=0.523, p=0.515). In Step 3 (joint model), adoption remained significant (β=4.504, p<0.001), although trust was not significant (β=-0.041, p=0.751), with R^2=0.164. The Sobel test indicated no mediation (Z=-0.286, p=0.775). In the context of Delhi

NCR, trust does not serve as a mediator, indicating that direct adoption effects prevail. This aligns with organizational literature that emphasizes structural aspects over perceptual ones in BFSI; however, it contradicts certain research where trust serves as a complete mediator in consumer-facing AI (Huang et al., 2025). Future studies could examine conditional mediation across varying barrier levels.

Table 4: Represent mediation analysis findings - Evaluating trust in AI as a mediating variable.

Step	Path / Model Tested	Unstandardized β	Std. Error	t-value	p-value	R^2	Conclusion
1	Adoption → Effectiveness (direct effect)	4.482	0.892	5.025	<0.001***	0.163	Significant direct effect
2	Adoption → Trust (mediator)	0.523	0.801	0.653	0.515	0.004	No significant relationship
3	Joint Model: Adoption + Trust → Effectiveness					0.164	
	→ Adoption → Effectiveness (controlling for Trust)	4.504	0.911	4.946	<0.001***		Effect remains significant (no reduction)
	→ Trust → Effectiveness (controlling for Adoption)	–0.041	0.129	–0.318	0.751		Non-significant
	Sobel Test (indirect effect)	Z = –0.286			0.775		No significant mediation

Significant ***p < 0.001

Table 5 suggested that adding the interaction variable (Adoption × Barriers) to Model 2 did not modify R^2 in a significant way ($\Delta R^2 = 0.004$, $p = 0.482$). The interaction coefficient is not statistically significant ($\beta = 0.755$, $p = 0.482$). Adoption effects endure irrespective of barrier intensity, indicating enduring AI value in Delhi NCR. This backs up adaptive theories that say companies may get over obstacles by being creative, but it also means that high barriers could still hurt long-term viability in a roundabout way (Ross et al., 2012).

Table 5: Results of Moderation Analysis - Perceived Barriers as a Moderator.

Model	Predictor	Unstandardized β	Std. Error	Standardized β	t-value	pvalue	R^2	ΔR^2	Fchange	Sig. Fchange
1	(Main effects only)						0.164			
	AI Adoption Level	4.482	0.892	0.404	5.025	<0.001***				
	Perceived Barriers	–0.512	0.421	–0.098	–1.216	0.227				
2	(Interaction term added)						0.168	0.004	0.50 2	0.48 2
	AI Adoption Level	4.32	0.935	0.389	4.62	<0.001***				
	Perceived Barriers	–0.498	0.425	–0.095	–1.172	0.244				

	Adoption × Barriers (Interaction)	0.755	1.065	0.067	0.709	0.482				

Significance***$p < 0.001$

Two principal components were identified: PC1 ("Efficiency Dimension," 28.9%), characterized by significant loadings on time reduction (0.674) and cost savings (0.713), and PC2 ("Retention Dimension," 26.1%), primarily influenced by drop-off reduction (0.866). Together, they account for 55.03% of the variance as determined by PCA. Independence was proposed due to the low loading of satisfaction (Table 6). Efficiency and retention are distinct facets of effectiveness. This analysis suggested that targeted AI methodologies, such as natural language processing for retention, to achieve optimal outcomes in the BFSI sector.

Table 6: Represent principal component analysis loadings for effectiveness metrics.

Metric	PC1	PC2
Time Reduction	0.674	-0.409
Cost Savings	0.713	0.239
Drop-off Reduction	0.145	0.866
Satisfaction Imp.	0.13	-0.163

Table 7 revealed that mature innovators had the highest efficacy, underscoring the importance of maturity. Clustering reveals archetypes, and established organizations derive the greatest benefit from them, consistent with maturity theories. Aggressive adopters exhibit significant uptake but yield suboptimal results due to maturity discrepancies. This indicates that enterprises in Delhi NCR ought to adopt the changes incrementally.

Table 7: Represent organizational cluster profiles based on adoption, maturity, and barriers.

Cluster	Adoption	AI Maturity	Barriers	Label	n	Mean Effectiveness
0	0.6	3.19	3.19	Emerging Adopters	27	32.5

1	0.7	4.24	2.5	Mature Innovators	38	41.2
2	0.79	2.71	3	Aggressive Adopters	35	37.8

Table 8: Chi-Square Test of Independence – BFSI Segment vs. High AI Adoption

BFSI Segment	**High Adoption (>70%)**	**Low–Medium Adoption (≤70%)**	**Total**	**Chi-Square Test Results**
Banking	36	10	46	$\chi^2 = 1.271$
Fintech	20	7	27	df = 2
Insurance	19	8	27	p-value = 0.530
Total	**75**	**25**	**100**	Cramer's V = 0.113 (weak association)

The BFSI sector (banking, fintech, and insurance) and elevated AI usage in client onboarding (>70%) do not exhibit a statistically significant correlation, as shown by the Chi-square test of independence. The p-value (0.530) substantially exceeds the 0.05 threshold, and the observed frequencies closely approximate the expected frequencies under the null hypothesis of independence. In the Delhi NCR region, the usage of AI exceeds 70% consistently across banking, fintech, and insurance firms. In this sample, high-adoption behaviour is not influenced by segment-specific variations.

AI Maturity, AI Adoption, Trust in AI, Barriers to AI, Investment in AI, and Perceived Effectiveness (composite index) are the key variables in organisational AI implementation that are examined by four distinct multiple regression models in Table 9.

Table 9: Structural Equation Modeling (Path Analysis)

Path / Equation	**Endogenous Variable**	**Exogenous Predictors**	**Unstandardized β**	**Std. Error**	**Standardized β**	**t-value**	**pvalue**	**R^2**	**Model pvalue**

1	AI Maturity	Investment	–0.027	0.103	–0.026	–0.263	0.79	0.004	0.820 (n.s.)
		Barriers	0.063	0.11	0.057	0.574	0.568		
2	AI Adoption	Maturity	–0.023	0.013	–0.171	–1.705	0.092	0.073	0.061 (marg.)
		Investment	–0.001	0.013	–0.010	–0.106	0.916		
		Barriers	0.033	0.014	0.238	2.254	0.026 *		
3	Trust in AI	Adoption	0.699	0.445	0.156	1.572	0.118	0.03	0.232 (n.s.)
		Barriers	–0.066	0.066	–0.100	–1.008	0.314		
4	Effectiveness (Composite Index)	Trust	0.01	0.006	0.162	1.602	0.113	0.294	<0.001***
		Adoption	0.15	0.006	0.492	24.75	<0.001***		
		Barriers	–0.011	0.004	–0.185	–2.789	0.006 **		

*p < 0.05, **p < 0.01, ***p < 0.001, marg. = marginally significant, n.s. = not significant

9. MAJOR FINDINGS OF THE STUDY

Model 1: AI Maturity Predictors (R^2 = 0.004, model p = 0.820, not significant).

The organization's present AI maturity is not substantially influenced by perceived barriers (β = 0.057, p = 0.568) or investment (β = −0.026, p = 0.79). → This indicates that the disparity in "maturity" about AI adoption among some firms in this sample cannot be attributed to their financial investment in AI or their perception of obstacles. Unmeasured elements, including organisational culture, leadership vision, or the duration since the initial AI pilot, may affect maturity.

Model 2: Predictors of AI Adoption ($R^2 = 0.073$, model $p = 0.061$, marginally significant)

• AI Maturity: $\beta = -0.171$, $p = 0.092$ (marginally negative)

• Investment: $p = 0.916$ (not significant), $\beta = -0.010$

• Barriers: $p = 0.026$ (positive and significant), $\beta = 0.238$

Increased perceived barriers correlate with elevated levels of AI adoption, representing the most significant and unexpected discovery. Reverse causality or endogeneity may elucidate the phenomenon: organisations that have progressed in the adoption and implementation of AI systems encounter and become increasingly aware of tangible difficulties (such as ethical concerns, integration challenges, skill deficiencies, regulatory impediments, etc.). Enterprises that have not extensively adopted AI may underestimate these challenges.

The slightly negative coefficient for maturity is noteworthy; more "mature" businesses in this sample appear to be significantly less likely to get high adoption scores. This may be due to adoption scores favouring swift, extensive implementation, whereas maturity indices often commend methodical governance and pilot programs.

Model 3: AI Trust Predictors ($R^2 = 0.03$, model $p = 0.232$, not significant)

Trust in AI among employees or stakeholders is not significantly influenced by the current level of adoption ($\beta = 0.156$, $p = 0.118$) or by hurdles ($\beta = -0.100$, $p = 0.314$). It seems that factors beyond the scope of this model—such as algorithmic transparency, the past performance of AI systems, and communication—are the primary determinants of trust.

Model 4: Composite index predictors of perceived efficacy ($R^2 = 0.294$, model $p < 0.001$, extremely significant)

This model, the most superior to yet, delineates certain aspects that affect individuals' perceptions of AI efficacy:

• Adoption of AI: $\beta = 0.492$, $p < 0.001$ (significantly favourable impact)

• AI trust: $\beta = 0.162$, $p = 0.113$ (positive although not statistically significant)

• Barriers: $p = 0.006$, $\beta = -0.185$ (significantly adverse effect)

The perceived efficacy of AI escalates with its actual implementation and incorporation into company operations; this is a predictable yet significant conclusion. Even when accounting for adoption levels, perceived obstacles diminish perceived efficacy. The primary determinant affecting perceived success in this sample, as per trust, is simply "increasing AI engagement." Consequently, these models demonstrated that investment in AI did not significantly forecast any of the outcomes, suggesting that mere expenditure is an inadequate measure of successful AI transformation. Perceived barriers exhibit a negative correlation with perceived effectiveness and a positive correlation with adoption, perhaps due to adopters recognising the actual impediments. The perceived effectiveness of organisational AI is predominantly affected by real AI deployment, accounting for roughly 50% of the standardised effect. The effectiveness in this dataset is only slightly or not at all elucidated by trust in AI and the maturity of AI.

10. CONCLUSION

The present study offers clear and pragmatic insights into the real dynamics of AI-driven client onboarding in the BFSI sector in Delhi NCR. Success is predominantly influenced by the extent and breadth of genuine AI implementation, rather than by mere investment amounts or official AI maturity assessments, despite the region exhibiting substantial adoption (71.6%) and notable effectiveness improvements. The extent of AI utilisation in onboarding procedures serves as the most reliable measure of perceived and quantifiable effectiveness. Companies that get to production deployment realise the most significant improvements in speed, cost, retention, and customer happiness. The positive association between perceived obstacles and levels of adoption is an unexpected yet robust finding. This strongly indicates reverse causality: organisations that have advanced significantly in implementation are increasingly aware of genuine problems, including legacy integration, skill deficiencies, regulatory uncertainties, data protection issues, and ethical dilemmas. Conversely, firms in the nascent phases of innovation frequently underestimate these hurdles. Despite its conceptual significance, trust in AI did not emerge as a substantial mediator or direct influencer of efficacy in this organisational setting, indicating that operational performance presently supersedes perceptual trust elements in B2B/B2C onboarding situations. The frameworks for AI maturity and investment intensity, frequently emphasised by industry papers and consultants, had notably low explanatory power. These challenge the prevalent notions that "increased funding" or "greater maturity" must lead to superior outcomes and suggest that numerous BFSI stakeholders may be excessively dependent on these proxy indicators. Recommendations for BFSI executives in Delhi NCR and analogous markets:

1. Prioritise the rapid and extensive deployment of established AI onboarding components (OCR, biometrics, NLP/RPA workflows) over prolonged piloting or maturity certification assessments.

2. Invest in focused mitigation strategies (upskilling, involvement in regulatory sandboxes, development of explainable AI frameworks, and vendor collaborations); regard perceived impediments as markers of advancement rather than hindrances.

3. Recognise that the volume of adoption enhances efficacy; although incremental enhancements are possible, revolutionary outcomes require the incorporation of AI into the majority of onboarding procedures.

4. Allocate a portion of the overarching "AI budget" to activities that directly promote enhanced adoption, including change management, data quality, and integration.

In summary, the essence of a successful AI transformation in BFSI onboarding lies not in the financial investment or perceived maturity, but in the audacious and extensive application of AI within actual customer journeys, while systematically addressing the tangible challenges that emerge during the process. The forthcoming surge of digital financial inclusion and operational superiority in India will be spearheaded by organisations that embrace this proactive mindset.

11. LIMITATIONS OF THE STUDY

This study on the acceptance and effectiveness of AI-powered onboarding solutions in the BFSI sector within Delhi NCR offers valuable regional implementation insights; nevertheless, its limitations may restrict its generalisability and depth. The research primarily focusses on Delhi NCR, a significant financial centre, which may not adequately reflect India's operational environments, including rural or less urbanised regions where infrastructure and digital literacy disparities influence AI adoption rates. Regional research facilitates a comprehensive examination of a focused sample; yet, it may overlook regulatory enforcement, cultural characteristics, and economic factors that influence AI integration in other states or countries. Self-reported data from BFSI worker surveys and interviews may be biased by response errors, social desirability influences, or overestimation of AI maturity stemming from inadequate technical knowledge or organisational pressures. While aimed at principal stakeholders in banking, fintech, and insurance sectors, the sample size may not encompass the entire spectrum of organisational sizes, from large multinationals to smaller regional entities, thereby skewing results towards advanced adopters and inadequately representing the challenges faced by resource-constrained firms. Essential performance indicators, such as ROI figures or proprietary AI installation specifics, may have been obstructed by the secrecy and regulatory constraints of the BFSI sector.

Advanced machine learning models and regulatory modifications, such as the RBI's digital KYC regulations, could render study conclusions obsolete in the swiftly evolving AI landscape. Cross-sectional research provides a temporal snapshot. Financial limitations hindered the implementation of long-term adoption and effectiveness research. The hypothesis testing presupposes visible effects from AI adoption, maturity, and investment; nevertheless, economic instability, cybersecurity threats, and global AI supply chain disruptions may influence results, necessitating more extensive econometric models in future research. These constraints promote further exploration of the study's AI-driven advancements in the BFSI sector.

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