Economic Sciences
https://economic-sciences.com
ES(2026) 22, 6(S) , 537-554 | ISSN:1505-4683

Perceptions of Banking Professionals Toward Artificial Intelligence in Non-Performing Asset Management: A Cross-Sectional Survey Study from the Indian Banking Sector

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Abstract

Indian banking sector has not yet recovered from issue of increasing Non-Performing Assets (NPAs), specifically in the Public Sector Banks (PSBs). Nowadays, the AI (artificial intelligence) is introduced as the viable instrument for the early risk identification, loan rehabilitation, customer engagement, and operational cost reduction. Inspite of the increasing technological investment, attitudinal readiness of the frontline banking professionals — whose acceptance is crucial for the better AI deployment were not thoroughly studied. Also, the problem of NPAs presented the major challenges in financial sector, which affects the stability & profitability of the financial institutions, in the world. Hence, this study conducted the cross-sectional quantitative survey among the recruited 150 banking professionals from public, cooperative and private, Indian banks. This study used the purposive sampling method. Finally, the study findings indicates that the sustainable AI adoption in Indian banking needs the simultaneous attention to the data infrastructure, privacy governance, & the institutional trust-building rather than the technological capability.

Keywords: *AI, banking professionals, customer service, loan restructuring, NPAs*

1. Introduction

Generally, the India has the effective banking system from time immemorial. Banking sector acts as the pillar for monitoring and regulating the financial activities & it leads to the financial growth of the India. The Indian banks favor to the development of our economy by the growth, profitability and asset quality. The Banker's Bank & the government made many changes in banking policies & regulations to increase the banking sector strength. Some of changes like, strengthening prudential norms, increasing the cash disbursement, inculcating several banks regulations are introduced in India. The banking industry asset management has included several regulations & interventions because of the deteriorations happening in areas of asset quality & the capital enhancement.

In the present scenario, the asset classification is not done properly & classification of the bad –loan are delayed by the several banks. Also, in the early years the NPAs are managed & also controlled by utilizing the Basils Norms. Technological development has increased the transparency of assessing customer's credibility before providing them loans. The best indicator of health of the banking industry is its level of NPA. In the broader aspect NPA reflects the banking industry performance & development of our Indian economy. When there has the reduced level of the NPAs it may provides the view with regards to banks that banks have creditworthiness over years & when there has the increase in NPAs level it depicts significance of more provisions which will reduces the whole profitability of banks. Also, the Commercial banks in the India have faced the severe issues where the political impact is the high. The increased profitability and efficiency of the banking sector will decreases the NPA's quantity in India (K Shaji, 2019).

According to the RBI data, the gross NPA ratios in the public sector banks were crossed 14 percent in 2018, and however the subsequent resolution efforts under Insolvency & Bankruptcy Code were moderated these figures, fundamental credit quality challenges remained unresolved (RBI, 2023).

Generally, the Traditional methods to the NPA detection were primarily depends on the periodic financial statement reviews, relationship-based credit appraisals, & the branch-level monitoring —

methods which have inherently retrospective & susceptible to cognitive biases of the personal loan officers. When the borrower's account is categorized as the substandard, deterioration in the repayment capability has developing for months, if not longer. This lag between onset of financial distress & its recognition in the bank records is not just the technical inefficiency; it also represents the window in the time of early intervention such as the restructuring, counselling, or collateral review have meaningfully changed the outcomes for both borrower and lender (PIB, 2024).

Nowadays, the AI has developed as the credible answer to this question in the multiple financial systems, worldwide. Also, the ML-Machine learning algorithms has the capability to process the real-time data transaction, supply chain records, social media signals, & the macroeconomic indicators simultaneously detects the subtle financial & behavioural patterns which precede default well before the conventional triggers are activated. Beyond the detection, the AI applications are extending to the personalised loan restructuring plans, automated regulatory compliance reporting, and cost optimisation by the automation process (RBI, 2014). Most of the international banks & the fintech organisations were documented the measurable reductions in NPA ratios & the operational costs following AI-led credit risk transformations, lending the empirical weight to what was, until recently, largely theoretical advocacy (RBI, 2025).

1.1 Problem Statement

Despite this impetus, literature on Indian banking sector have remained as comparatively sparse in its empirical examination of how the frontline banking professionals perceive these technologies. AI Adoption in the credit risk was not determined by the algorithmic capability alone, also it can be equally shaped by trust levels, attitudes, & the domain-specific beliefs of practitioners who should ultimately operationalize these systems. The technology which is technically higher but institutionally distrusted has not the possibility to attain its potential impact. Hence, this gap between the professional readiness and technological possibility constitutes central motivating concern of this study.

1.2 Research Objectives

The major objectives of this study is

- To analyse the historical trends of NPA in the Indian Banks to understand the factors contributing to NPAs & the impact on the financial health of banking industry.
- To investigate the Banking professionals in India, perceptions across 4 domains, such as the early NPA detection, operational efficiency, AI-assisted loan restructuring, and AI-enabled customer service and, cost.
- To identify and evaluate key variables that contribute to the classification of loan as NPAs and explore the factors affecting loan restructuring decisions.
- To design the hypotheses for obtaining the favourable professional orientation towards the AI in each domain
- To examine the attitudinal and individual factors which predicts the overall AI adoption readiness.
- To analyse the findings which are intended to provide the empirical validation of these hypotheses and the actionable intelligence for regulators, bank leaders, and the technology strategists designing AI incorporation roadmaps for the India's developing banking landscape.

2. Materials and Methods

2.1 Study Design

This study used the cross-sectional quantitative survey design for the purpose of examining the perceptions of banking professionals about the AI applications in NPA management in Indian banking sector.

This study used the structured self-administered questionnaire to collect the primary data.

2.2 Sample Size

This study includes totally 150 banking professionals from the public, private, and cooperative banks in the India constituted the final analytical sample.

Sampling:

Purposive sampling was used to verify that the respondents possessed the direct working knowledge of loan monitoring, credit risk assessment, or the customer relationship functions, as perceptions from uninformed respondents carry the limited construct validity.

Inclusion Criteria:

Eligible participants such as the senior banking executives, branch managers, credit officers, relationship managers, and risk analysts, with 1 year experience of active service.

Exclusion Criteria:

Individuals whose primary responsibilities uninitiated exclusively in the non-banking operations were excluded.

2.3 Questionnaire Development

The survey instrument has included 42 items which covers 6 thematic domains.

Items Q01 through Q40 were constructed to operationalise 5 latent constructs such as the

H1 — Early NPA Detection (Q01–Q08, 8 items),

H2 — Loan Restructuring (Q09–Q16, 8items),

H3 — Customer Service (Q17–Q24, 8items),

H4 — Cost and Efficiency (Q25–Q32, 8items),

General AI Adoption (Q33–Q40, 8 items).

The Response formats differed by each item:

Binary (yes/no), 3-point ordinal scales, and 4-option categorical formats, depending on nature of attitude being measured.

Items are coded in the consistent favorable direction prior to the analysis, with higher scores representing more pro-AI orientations; items Q09, Q17, Q34, Q37, and Q38 were retained in raw format as their categorical structure precluded favorable recoding.

2 additional ranking sections — Q41 (eight causes of loan default) and Q42 (eight credit quality improvement measures) — are administered by utilizing 5-point importance scales (1 = least important to 5 = most important). The instrument was piloted with 10 banking professionals not included in study, & minor wording adjustments were made on 3 items based on feedback regarding clarity(Prenio & Yong, 2021).

2.4 Statistical Analysis

All statistical analyses have been performed by utilizing the Python (version 3.x). Item-level descriptive statistics, such as the means, standard deviations, skewness, and excess kurtosis are computed on the raw scores, whereas the construct-level analyses utilized the favorable-coded aggregated scores. The Construct reliability is evaluated by the Cronbach's alpha coefficients alongside the corrected item–total correlations & alpha-if-deleted coefficients for the each item, allowing identification of the low-contributing items.

Bivariate relationships among the five constructs were examined using both Pearson product-moment correlation and Spearman rank-order correlation, with the latter serving as a non-parametric check given the observed distributional skewness in several constructs. Statistical significance was set at $\alpha = 0.05$, two-tailed, throughout.

Three separate OLS multiple regression models were estimated: Model 1 predicted General AI Adoption from all four construct scores and three individual-level moderators; Model 2 identified drivers of Loan Restructuring confidence; Model 3 decomposed predictors of Early NPA Detection beliefs. Prior to each model, the Breusch–Pagan test was applied to detect heteroscedasticity; where significant (all three models, $p < .05$), HC3 heteroscedasticity-consistent robust standard errors were substituted for conventional OLS standard errors. Variance inflation factors were inspected for each predictor to assess multicollinearity, with VIF > 10 set as the exclusion threshold. Standardised beta coefficients were derived from predictors standardised to zero mean and unit variance to enable cross-predictor comparison of effect magnitude. All of the reported confidence intervals are 95% intervals based on the robust standard errors.

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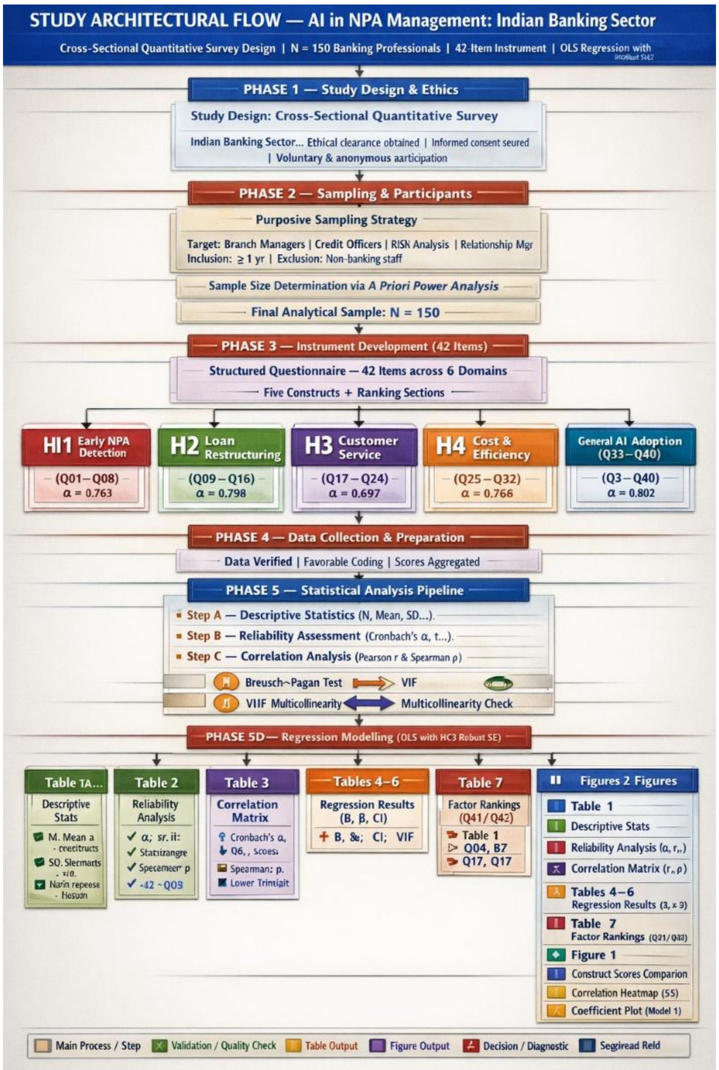

Figure 1. Study Architectural flowchart

The figure 1 depicts 7 sequential methodological phases of study: (1) cross-sectional survey design & the ethical clearance; (2) purposive sampling of the N = 150 banking professionals with the priori power justification; (3) 42-item questionnaire development in 5 theoretical constructs (H1–H4 & General AI Adoption) with the pilot testing; (4) data collection & the preparation such as the favorable item coding & the construct score aggregation; (5) statistical analysis pipeline which includes descriptive statistics, Cronbach's α reliability assessment, Pearson–Spearman correlation matrices, Breusch–Pagan heteroscedasticity diagnostics, VIF-based multicollinearity checks, & 3 OLS regression models with HC3 robust standard errors; (6) tabular & graphical outputs (Tables 1–7; Figures 1–4); & (7) interpretive synthesis encompassing discussion, conclusion, limitations, & future research directions. The Color coding denotes the construct identity: red = H1 (Early NPA Detection); green = H2 (Loan Restructuring); purple = H3 (Customer Service); orange = H4 (Cost and Efficiency); teal = General AI Adoption; yellow = tabular outputs; purple-shaded nodes = figure outputs.

3. Results

Item-Level Descriptive Statistics & Response Distributions

To characterise the attitudinal landscape of sample before hypothesis testing, the item-level descriptive statistics are computed for all 40 survey items (Q01–Q40), which includes the raw & the favorable-coded means, standard deviations, distributional shape statistics, & the full response-frequency distributions. Also, the Construct-level summary descriptive included 95 percent confidence intervals which are derived by aggregating the favorable-coded item scores within each of 5 theoretical constructs. The below table 1 presented these data.

Table 1A. Item-Level Descriptive Statistics & Response Distributions (Q01–Q40; N = 150)

Item	Construct	Question	N	Mean (Raw)	SD	Mean (Fav.)	SD (Fav.)	Skewness	Kurtosis	Response Distribution (n, %)
Q01	H1	Familiarity with AI's role in NPA detection	150	2.06	0.707	1.94	0.707	−0.085	−0.978	Very familiar: 33 (22.0%) | Somewhat familiar: 75 (50.0%) | Not familiar: 42 (28.0%)
Q02	H1	AI can identify NPAs earlier than traditional methods	150	1.48	0.775	2.52	0.775	1.208	−0.235	Yes, definitely: 104 (69.3%) | Possibly: 20 (13.3%) | No: 26 (17.3%)
Q03	H1	Traditional methods miss early signs of defaults	150	1.19	0.587	2.81	0.587	2.757	5.735	Very often: 135 (90.0%) | Sometimes: 1 (0.7%) | Rarely: 14 (9.3%)
Q04	H1	Importance of real-time data analysis for NPA detection	150	1.43	0.822	2.57	0.822	1.414	−0.002	Very important: 118 (78.7%) | Not very important: 32 (21.3%)
Q05	H1	AI analyses diverse data sources for NPA prediction	150	1.37	0.584	2.63	0.584	1.355	0.845	Yes: 103 (68.7%) | Maybe: 39 (26.0%) | No: 8 (5.3%)
Q06	H1	AI effectiveness in analysing transaction patterns	150	1.46	0.720	2.54	0.720	1.235	0.044	Very effective: 101 (67.3%) | Somewhat effective: 29 (19.3%) | Not effective: 20 (13.3%)
Q07	H1	AI alerts more effective than manual alerts	150	1.13	0.341	2.73	0.682	2.179	2.786	Yes: 130 (86.7%) | No: 20 (13.3%)
Q08	H1	Human biases affect traditional NPA detection	150	1.49	0.528	2.51	0.528	0.305	−1.301	Frequently: 78 (52.0%) | Occasionally: 70 (46.7%) | Rarely: 2 (1.3%)
Q09	H2	Aware of AI use in loan restructuring	150	1.64	0.482	—	—	−0.589	−1.675	Yes: 54 (36.0%) | No: 96 (64.0%)
Q10	H2	AI helps create personalised restructuring plans	150	1.32	0.659	2.68	0.659	1.834	1.843	Yes: 118 (78.7%) | Maybe: 16 (10.7%) | No: 16 (10.7%)

Q11	H2	AI improves success rate of restructuring	150	1.55	0.747	2.45	0.747	0.943	−0.574	Very likely: 90 (60.0%) | Somewhat likely: 37 (24.7%) | Not likely: 23 (15.3%)
Q12	H2	AI reduces time taken for restructuring	150	1.17	0.540	2.83	0.540	2.959	7.145	Yes: 135 (90.0%) | Maybe: 4 (2.7%) | No: 11 (7.3%)
Q13	H2	Importance of data-driven decisions in restructuring	150	1.25	0.433	2.75	0.433	1.187	−0.599	Very important: 113 (75.3%) | Important: 37 (24.7%)
Q14	H2	AI predicts long-term viability of restructured loans	150	1.43	0.736	2.57	0.736	1.384	0.287	Yes: 108 (72.0%) | Maybe: 20 (13.3%) | No: 22 (14.7%)
Q15	H2	Comfort with AI making restructuring decisions	150	1.65	0.742	2.35	0.742	0.658	−0.903	Very comfortable: 76 (50.7%) | Somewhat comfortable: 50 (33.3%) | Not comfortable: 24 (16.0%)
Q16	H2	AI helps negotiation between bank and borrower	150	1.27	0.501	2.73	0.501	1.697	2.051	Yes: 114 (76.0%) | Maybe: 24 (16.0%) | No: 12 (8.0%)
Q17	H3	Interacted with AI-powered customer service	150	1.37	0.484	—	—	0.559	−1.711	Yes: 95 (63.3%) | No: 55 (36.7%)
Q18	H3	Satisfaction with AI-powered customer service	150	1.61	0.490	2.39	0.490	−0.441	−1.830	Very satisfied: 59 (39.3%) | Somewhat satisfied: 91 (60.7%)
Q19	H3	AI chatbots address loan-issue queries	150	1.85	0.915	2.15	0.915	0.296	−1.752	Yes: 72 (48.0%) | Maybe: 50 (33.3%) | No: 28 (18.7%)
Q20	H3	Importance of personalised communication in distressed accounts	150	1.14	0.348	2.86	0.348	2.096	2.425	Very important: 129 (86.0%) | Important: 21 (14.0%)
Q21	H3	AI provides faster and more accurate customer responses	150	1.25	0.466	2.75	0.466	1.542	1.328	Yes: 114 (76.0%) | Maybe: 30 (20.0%) | No: 6 (4.0%)
Q22	H3	AI helps proactive outreach to distressed customers	150	1.64	0.771	2.36	0.771	0.722	−0.952	Yes: 82 (54.7%) | Maybe: 43 (28.7%) | No: 25 (16.7%)
Q23	H3	AI improves emotional intelligence in	150	1.92	0.807	2.08	0.807	0.147	−1.449	Yes: 61 (40.7%) | Maybe: 57 (38.0%) | No: 32 (21.3%)

		customer service								
Q24	H3	AI increases customer trust in the bank	150	1.20	0.433	2.80	0.433	2.004	3.239	Yes: 123 (82.0%) | Maybe: 21 (14.0%) | No: 6 (4.0%)
Q25	H4	AI reduces operational costs in banking	150	1.29	0.560	2.71	0.560	1.836	2.401	Yes: 115 (76.7%) | Maybe: 27 (18.0%) | No: 8 (5.3%)
Q26	H4	AI improves decision-making speed	150	1.41	0.715	2.59	0.715	1.450	0.532	Very significantly: 105 (70.0%) | Somewhat significantly: 28 (18.7%) | Not significantly: 17 (11.3%)
Q27	H4	AI automates repetitive banking tasks	150	1.32	0.736	2.68	0.736	1.874	1.531	Yes: 126 (84.0%) | Maybe: 12 (8.0%) | No: 12 (8.0%)
Q28	H4	Importance of data analysis automation for efficiency	150	1.19	0.396	2.81	0.396	1.569	0.467	Very important: 122 (81.3%) | Important: 28 (18.7%)
Q29	H4	AI reduces risk of human error	150	1.63	0.824	2.37	0.824	0.791	−1.063	Yes: 89 (59.3%) | Maybe: 36 (24.0%) | No: 25 (16.7%)
Q30	H4	Perceived ROI of AI implementation	150	1.89	0.545	2.11	0.545	−0.069	0.280	High ROI: 51 (34.0%) | Moderate ROI: 90 (60.0%) | Low ROI: 9 (6.0%)
Q31	H4	AI improves compliance & regulatory reporting	150	1.48	0.748	2.52	0.748	1.189	−0.164	Yes: 104 (69.3%) | Maybe: 27 (18.0%) | No: 19 (12.7%)
Q32	H4	AI reduces time taken for audits	150	1.15	0.397	2.85	0.397	2.574	6.255	Yes: 130 (86.7%) | Maybe: 10 (6.7%) | No: 10 (6.7%)
Q33	GA	Importance of AI adoption for future of Indian banking	150	1.37	0.699	2.63	0.699	1.622	1.033	Very important: 107 (71.3%) | Important: 33 (22.0%) | Not important: 10 (6.7%)
Q34	GA	Biggest challenges to AI adoption	150	3.70	0.642	—	—	−1.939	2.264	Data security: 5 (3.3%) | Skilled personnel: 12 (8.0%) | Regulatory hurdles: 23 (15.3%) | All of the above: 110 (73.3%)
Q35	GA	Indian banks investing enough in AI	150	1.53	0.501	2.47	0.501	−0.135	−2.009	Yes: 70 (46.7%) | No: 80 (53.3%)
Q36	GA	Comfort with banks using	150	1.54	0.692	2.46	0.692	0.904	−0.414	Very comfortable: 68 (45.3%) |

		personal data for AI								Somewhat comfortable: 55 (36.7%) | Not comfortable: 27 (18.0%)
Q37	GA	AI will replace human bankers	150	2.60	0.492	—	—	−0.412	−1.855	Yes: 8 (5.3%) | No: 62 (41.3%) | Maybe: 80 (53.3%)
Q38	GA	Type of AI training needed for bank employees	150	3.40	0.934	—	—	−1.232	0.110	Data literacy: 15 (10.0%) | AI tool usage: 13 (8.7%) | Ethical AI: 17 (11.3%) | All of the above: 105 (70.0%)
Q39	GA	Current level of AI integration in Indian banking	150	2.17	0.855	1.83	0.855	−0.328	−1.558	Very high: 26 (17.3%) | Moderate: 64 (42.7%) | Low: 60 (40.0%)
Q40	GA	Overall opinion about AI in Indian banking	150	1.85	0.992	2.15	0.992	1.009	−0.036	Very positive: 79 (52.7%) | Positive: 33 (22.0%) | Neutral: 23 (15.3%) | Negative: 15 (10.0%)

Construct-Level Descriptive Statistics with 95% Confidence Intervals (N = 150)

Construct	N	Mean	SD	SE	95% CI	Min	Max
H1: Early NPA Detection	150	2.616	0.436	0.036	[2.546, 2.686]	1.571	3.000
H2: Loan Restructuring	150	2.623	0.426	0.035	[2.555, 2.691]	1.571	3.000
H3: Customer Service	150	2.484	0.380	0.031	[2.423, 2.545]	1.286	3.000
H4: Cost & Efficiency	150	2.580	0.392	0.032	[2.517, 2.643]	1.625	3.000
General AI Adoption	150	2.308	0.572	0.047	[2.216, 2.400]	1.000	3.000

*GA = General AI Adoption construct. Fav. = favorable-coded direction (higher = more pro-AI). Items Q09, Q17, Q34, Q37, Q38 are binary/categorical; favorable coding not applicable. Scale: 1–3 raw; higher favorable-coded values indicates the more pro-AI orientation. Skewness & kurtosis computed on the raw scores. Scores on the favorable-coded 1–3 scale. SE = standard error of mean. 95 percent CI based on z = 1.96 × SE.

The distribution of the response data in the Table 1A reveals the near-unanimous endorsement for the several items: 90 percent of respondents agreed that the traditional methods "very often" miss the early signs of defaults (Q03), whereas 86.7 percent affirmed the AI-based alert systems are more effective than the manual alerts (Q07), & 86.7 percent endorsed AI's ability to decrease the audit time (Q32). Items which exhibits the high kurtosis (Q03 kurtosis = 5.74; Q12 kurtosis = 7.15) reflects the consensus clustering, making them ceiling items; Q08 (kurtosis = −1.30) and Q19 (kurtosis = −1.75) show flatter, more distributed response patterns, indicates the genuine disagreement or uncertainty. At construct level (Table 1B), all 5 means exceed 2.30 on 1–3 favorable scale — well above midpoint — & CIs are narrow, confirming estimate stability. H2 (Loan Restructuring, M = 2.623) & H1 (Early NPA Detection, M = 2.616) scored highest, whereas the General AI Adoption showed widest variability (SD = 0.572), consistent with greater individual heterogeneity in the overall macro-adoption readiness.

Construct-Level Score Comparison

To visually compare across all 5 constructs simultaneously & assess whether all mean scores exceed significantly scale midpoint, construct means

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ES(2026) 22, 6(S) , 537-554 | ISSN:1505-4683

with their 95 percent CIs are plotted is shown in the Figure 2.

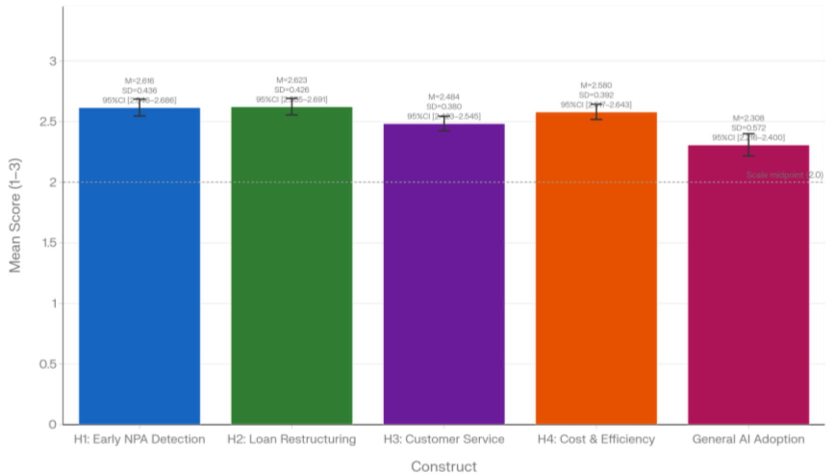

Figure 2. All five construct CI bars

The above bar chart displays the scale midpoint of 2.0 (dotted line), confirming that banking professionals significantly holds the pro-AI attitudes across all 4 hypothesised domains & at the general adoption level. The tight CIs for the H1 through H4 (all ≤ ±0.07) reflects the high within-sample consistency, while the General AI Adoption's wider CI (±0.09) mirrors its elevated SD. Also, the figure strengthens the rank-ordering of H2 > H1 > H4 > H3 > General AI Adoption — the gradient suggesting that the specific domain beliefs are stronger & more consistent than the overarching adoption attitudes.

Reliability Assessment of Constructs

Prior to correlation & the regression analyses, internal consistency is evaluated for all 5 constructs by utilizing the Cronbach's alpha, corrected item–total correlations (r_it), & the alpha-if-deleted coefficients (Δα). These diagnostics, are presented in the Table 2, which are essential to establish that the each construct scale measures the coherent primary dimension.

Table 2. Reliability Assessment: Cronbach's Alpha, Item–Total Correlations, and Alpha-if-Deleted (N = 150)

Construct (α)	Item	Question (Abbreviated)	r_it	α if Deleted	Δα	Flag
H1: Early NPA Detection (α = 0.763)	Q02	AI identifies NPAs earlier	0.676	0.686	−0.077	✓ Good
	Q03	Traditional methods miss defaults	0.277	0.771	+0.008	⚑ Low
	Q04	Real-time data analysis importance	0.875	0.625	−0.138	✓ Excellent
	Q05	AI analyses diverse data sources	0.553	0.722	−0.041	✓ Good
	Q06	AI effectiveness in transaction analysis	0.395	0.753	−0.010	△ Moderate
	Q07	AI alerts vs. manual alerts	0.561	0.717	−0.046	✓ Good
	Q08	Human biases in traditional detection	0.024	0.806	+0.043	⚑ Very Low
H2: Loan Restructuring (α = 0.798)	Q10	AI creates personalised plans	0.600	0.758	−0.040	✓ Good
	Q11	AI improves restructuring success rate	0.664	0.744	−0.054	✓ Good
	Q12	AI reduces restructuring time	0.103	0.835	+0.037	⚑ Low

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	Q13	Data-driven decisions importance	0.682	0.759	−0.039	✓ Good
	Q14	AI predicts long-term loan viability	0.380	0.805	+0.007	△ Moderate
	Q15	Comfort with AI restructuring decisions	0.729	0.729	−0.069	✓ Good
	Q16	AI helps bank–borrower negotiation	0.687	0.751	−0.047	✓ Good
H3: Customer Service (α = 0.697)	Q18	Satisfaction with AI customer service	0.509	0.647	−0.050	✓ Good
	Q19	AI chatbots address loan queries	0.587	0.608	−0.089	✓ Good
	Q20	Personalised communication importance	0.211	0.703	+0.006	⚑ Low
	Q21	AI provides faster responses	0.520	0.647	−0.050	✓ Good
	Q22	AI proactive outreach to distressed customers	0.457	0.651	−0.046	△ Moderate
	Q23	AI improves emotional intelligence	0.289	0.707	+0.010	⚑ Low
	Q24	AI increases customer trust	0.441	0.664	−0.033	△ Moderate
H4: Cost & Efficiency (α = 0.768)	Q25	AI reduces operational costs	0.460	0.746	−0.022	△ Moderate
	Q26	AI improves decision-making speed	0.606	0.717	−0.051	✓ Good
	Q27	AI automates repetitive tasks	0.711	0.693	−0.075	✓ Good
	Q28	Data automation importance for efficiency	0.614	0.735	−0.033	✓ Good
	Q29	AI reduces human error	0.170	0.811	+0.043	⚑ Low
	Q30	Perceived ROI of AI	0.656	0.716	−0.052	✓ Good
	Q31	AI improves regulatory compliance	0.270	0.784	+0.016	⚑ Low
	Q32	AI reduces audit time	0.633	0.732	−0.036	✓ Good
General AI Adoption (α = 0.802)	Q33	Importance of AI for Indian banking's future	0.686	0.736	−0.066	✓ Good
	Q35	Banks investing enough in AI	0.651	0.765	−0.037	✓ Good
	Q36	Comfort with personal data use	0.747	0.718	−0.084	✓ Good
	Q39	Current AI integration level	0.400	0.827	+0.025	△ Moderate
	Q40	Overall opinion on AI in Indian banking	0.609	0.769	−0.033	✓ Good

r_it = corrected item–total correlation. Δα = alpha-if-deleted minus construct alpha (positive values indicate the deletion improves α). Flag criteria: ✓ r_it ≥ 0.50; △ Moderate 0.30–0.49; ⚑ Low r_it < 0.30.

All 5 constructs exceed or meet widely accepted α ≥ 0.70 threshold, with the General AI Adoption (α = 0.802) & H2 (α = 0.798) achieving "good" reliability. The highest item–total correlation in the entire instrument belongs to Q04 within H1 (r_it = 0.875), confirming real-time data analysis importance as the conceptual anchor of the early NPA detection scale. Six items are flagged with low r_it values: Q08 (r_it = 0.024) and Q08's deletion raises H1's α to 0.806, indicating human bias awareness taps a discriminant dimension; similarly, Q12 (r_it = 0.103) and Q29 (r_it = 0.170) would marginally improve their respective construct alphas if removed, suggesting these items capture distinctive aspects of restructuring immediacy and error reduction rather than the shared construct core. These items should be revised or split into a separate facet scale in future administrations.

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Construct-Level Correlations

Bivariate relationships among the five constructs were examined using both Pearson r (appropriate for normally distributed interval-level data) and Spearman ρ (non-parametric alternative robust to the observed skewness in several constructs). Table 3 presents both matrices in a single combined display, and Figure 3 visualises the Pearson heatmap.

Table 3. Construct-Level Correlation Matrix: Pearson r (Upper Triangle) & Spearman ρ (Lower Triangle)

	H1	**H2**	**H3**	**H4**	**Gen. AI**
H1: Early NPA Detection	—	0.551***	0.138 ns	0.597***	**0.849***†
H2: Loan Restructuring	0.370***	—	0.439***	**0.805***†	0.713***
H3: Customer Service	0.185*	0.403***	—	0.490***	0.378***
H4: Cost & Efficiency	0.328***	0.687***	0.482***	—	0.673***
Gen. AI Adoption	0.717***	0.536***	0.389***	0.262**	—

Upper triangle = Pearson r; lower triangle = Spearman ρ. N = 150. ns = non-significant. * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed). † Pearson–Spearman divergence ≥ 0.10, indicating moderate non-normality in at least one variable.

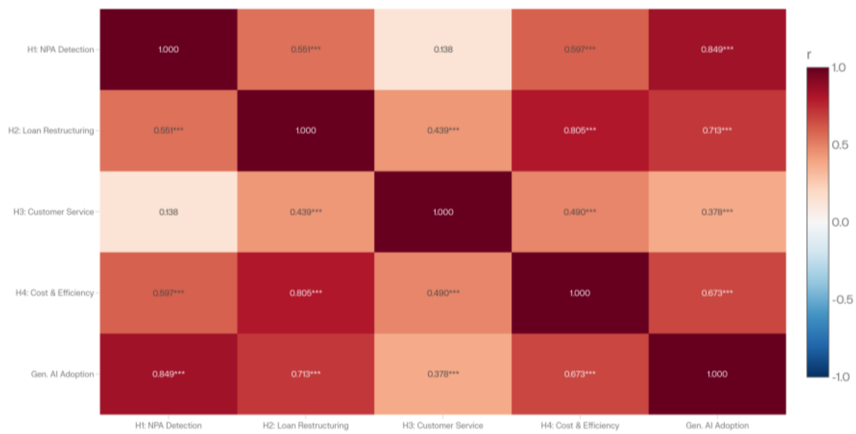

Figure 3 - Pearson Correlation Matrix of Al Adoption Constructs

The main association in matrix is H1–General AI Adoption (Pearson r = 0.849, Spearman ρ = 0.717, both $p < .001$), making the NPA detection confidence strongest construct-level predictor of overall AI acceptance. H2–H4 correlation (r = 0.805) revealed that the beliefs about cost efficiency & loan restructuring are tightly coupled — professionals who perceives the AI as operationally efficient are also more confident in the AI-led rehabilitation. Pearson–Spearman divergence for this pair (Δ = 0.118) & for H1–General AI (Δ = 0.132) signals the distributional non-normality, validating application of HC3 robust standard errors in consequent regression models. Critically, H3 (Customer Service) is most independent construct: its Pearson correlation with the H1 is non-significant (r = 0.138, p = .093), & its Spearman correlation barely reaches the significance (ρ = 0.185, $p < .05$), indicates that the customer-service AI perceptions are partially orthogonal to the NPA domain beliefs — the finding with theoretical implications for discriminant instrument validity.

Regression Analysis — Determinants of General AI Adoption (Model 1)

To find which of the construct-level beliefs & the individual-level moderators independently predicts the General AI Adoption, the OLS regression model was estimated with all 4 construct scores (H1–H4) & 3 control items (Q09 awareness, Q17 AI service experience, Q36 data comfort) as simultaneous predictors. Given confirmed heteroscedasticity (Breusch–Pagan p = .005), HC3 heteroscedasticity-consistent robust standard errors are throughout applied. Table 4 presented full model with

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standardised and unstandardised coefficients, 95% CIs, and VIFs. Figure 4 visualises standardised coefficients.

Table 4. Regression Results — Determinants of the General AI Adoption (Model 1, N = 150)

Predictor	B	Sig.	Robust SE	95% CI	Std. β	Sig.	p-value	VIF
Constant	−0.835	***	(0.181)	[−1.189, −0.481]	—		<.001	—
H1: Early NPA Detection	**0.701**	***	(0.036)	[0.629, 0.772]	**0.534**	***	<.001	2.30
H2: Loan Restructuring	0.139	*	(0.065)	[0.011, 0.266]	0.103	*	.033	3.53
H3: Customer Service	0.026	ns	(0.077)	[−0.124, 0.177]	0.018	ns	.732	2.19
H4: Cost & Efficiency	−0.018	ns	(0.069)	[−0.153, 0.116]	−0.012	ns	.792	4.24
Awareness of AI Restructuring (Q09)	0.035	ns	(0.047)	[−0.056, 0.127]	0.030	ns	.449	2.80
AI Customer-Service Interaction (Q17)	**−0.214**	***	(0.039)	[−0.290, −0.137]	**−0.181**	***	<.001	1.76
Comfort with Data Use (Q36)	**0.427**	***	(0.041)	[0.348, 0.506]	**0.516**	***	<.001	3.85
Model Fit								
N	150							
R²	0.932							
Adjusted R²	0.929							
F-statistic overall	p < .001							
Breusch–Pagan p	0.005		HC3 robust SEs applied					
Max VIF	4.24		All VIF < 5; multicollinearity acceptable					

ns = not significant. *** p < .001; * p < .05. Bold = significant predictors. Std. β = standardised beta from Z-scored predictors.

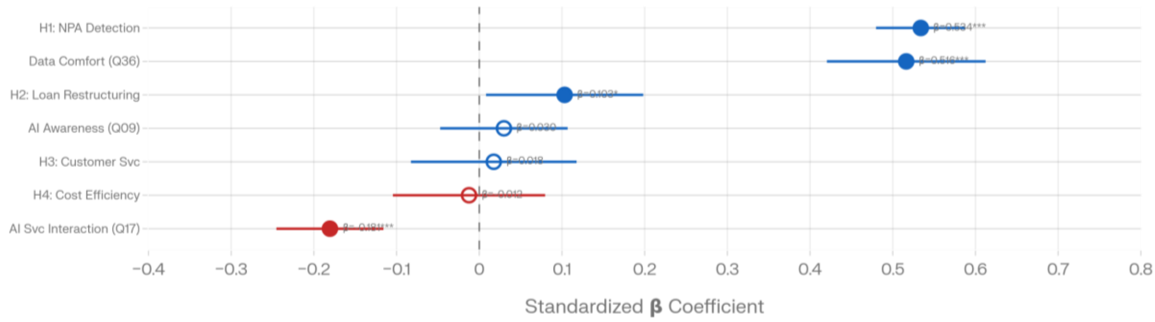

Figure 4 - Standardized B Coefficients: General AI Adoption (Model 1)

Model 1 explained 93.2% of the variance in General AI Adoption (Adjusted R² = 0.929), confirming that the construct-level beliefs are near-comprehensive determinants of adoption attitudes. H1 (β = 0.534, p < .001) & the Comfort with Data Use/Q36 (β = 0.516, p < .001) are 2 major predictors of the nearly equal magnitude — together, these 2 variables account for the lion's share of the explained variance. H2 contributed small but statistically reliable positive increment (β = 0.103, p = .033), whereas the H3 and H4 are rendered non-significant after controlling for other predictors, suggesting their bivariate associations with adoption are mediated by the H1 and Q36. Also, negative, and the highly significant effect of prior AI customer-service interaction (β = −0.181, $p < .001$) is the key finding: respondents who had experienced personally the AI banking services rated overall adoption more conservatively, consistent with the disconfirmation-of-expectations mechanism where direct AI experience reveals limitations invisible to non-users. All VIF values are below 5, confirming that the acceptable multicollinearity throughout.

Regression Analysis — Drivers of Loan Restructuring (Model 2)

To examine which are the specific attitudinal and experiential factors independently predicts the H2 (Loan Restructuring) beliefs, a targeted OLS model was estimated using H1, H4, AI restructuring awareness (Q09), comfort with AI decision-making (Q15), & the data-use comfort (Q36) as predictors. HC3 robust standard errors were again applied given confirmed heteroscedasticity (Breusch–Pagan p = .029). Full results are presented in Table 5.

Table 5. Regression Results — Drivers of Loan Restructuring (Model 2, N = 150)

Predictor	B	Sig.	Robust SE	95% CI	p-value
Constant	0.734	***	(0.119)	[0.501, 0.966]	<.001
H1: Early NPA Detection	0.068	ns	(0.051)	[−0.033, 0.168]	.188
H4: Cost & Efficiency	**0.324**	***	(0.081)	[0.166, 0.482]	<.001
Awareness of AI Restructuring (Q09)	0.004	ns	(0.063)	[−0.119, 0.127]	.948
Comfort with AI Decisions (Q15)	**0.283**	***	(0.063)	[0.160, 0.406]	<.001
Comfort with Data Use (Q36)	0.086	ns	(0.066)	[−0.043, 0.215]	.193
Model Fit					
N	150				
R^2	0.786				
Adjusted R^2	0.778				
F-statistic overall	$p < .001$				
Breusch–Pagan p	0.029		HC3 robust SEs applied		

ns = not significant. *** $p < .001$. Bold = significant predictors.

Model 2 accounted for 78.6 percent of variance in the Loan Restructuring perceptions (Adjusted R^2 = 0.778). H4 (Cost & Efficiency; B = 0.324, $p < .001$) is strongest structural driver, establishing that the belief in AI's operational efficiency is main pathway to endorsing AI-led loan rehabilitation — professionals who trust the AI to decrease the costs & increase the processes extend that trust naturally to restructuring. Comfort with the AI making restructuring decisions (Q15; B = 0.283, $p < .001$) is critical psychological enabler, with its 95% CI [0.160, 0.406] entirely positive & non-overlapping with 0, confirming robustness. Conversely, H1 (B = 0.068, p = .188) & the simple awareness of AI restructuring use (Q09; B = 0.004, p = .948) are the non-significant, demonstrating that the NPA-domain knowledge and passive familiarity do not independently translate into the restructuring confidence — active trust in AI autonomy (Q15) is required.

Regression Analysis — Drivers of Early NPA Detection (Model 3)

The third regression model is constructed to find the item-level cognitive drivers specifically explaining H1 (Early NPA Detection) confidence, by utilizing the perceived ROI (Q30), recognition of human bias in the traditional methods (Q08), real-time data analysis significance (Q04), and diverse data capability (Q05) as predictors. HC3 robust SEs are applied (Breusch–Pagan p = .001). Results are in Table 6.

Table 6. Regression Results — Drivers of Early NPA Detection (Model 3, N = 150)

Predictor	B	Sig.	Robust SE	95% CI	p-value
Constant	0.611	***	(0.075)	[0.465, 0.758]	<.001
Perceived ROI of AI (Q30)	**0.096**	***	(0.016)	[0.066, 0.126]	<.001
Human Bias in Traditional Methods (Q08)	**0.103**	***	(0.016)	[0.073, 0.134]	<.001
Real-Time Data Analysis Importance (Q04)	**0.416**	***	(0.014)	[0.390, 0.443]	<.001
Diverse Data Source Analysis (Q05)	**0.180**	***	(0.017)	[0.147, 0.213]	<.001

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Model Fit					
N	150				
R^2	0.945				
Adjusted R^2	0.943				
F-statistic overall	p < .001				
Breusch–Pagan p	0.001		HC3 robust SEs applied		

**** p < .001. All predictors significant. Bold = all included.*

The Model 3 attains highest explanatory power in all 3 models (R^2 = 0.945, Adj. R^2 = 0.943), with the every predictor significant at $p < .001$. The real-time data analysis prominence item (Q04; B = 0.416) is dominant driver — its coefficient is more than double next largest predictor and its 95% CI [0.390, 0.443] is strikingly tight, reflecting high precision in this estimate. This confirms that the early NPA detection confidence is basically the data-infrastructure belief: professionals who value immediacy & data access speed are significantly more confident in AI's early-warning capability. The Diverse data source analysis (Q05; B = 0.180) independently contributes, suggesting breadth of the data complements speed. The Human bias recognition (Q08; B = 0.103) & the ROI perception (Q30; B = 0.096) provides the parallel cognitive & the economic pathways — professionals who acknowledges the traditional methods are biased, and who perceive the AI as financially justified, are jointly more convinced of AI's NPA-detection superiority.

Top-Ranked Factors: Loan Default Causes (Q41) and Credit Quality Measures (Q42)

To find the banking professionals' strategic priorities beyond primary hypotheses, respondents rated 8 causes of loan default (Q41) and 8 credit quality improvement measures (Q42) on a 1–5 importance scale. Rankings by the mean score are presented in the Table 7 & visualised in Figure 5.

Table 7. Ranked Mean Ratings for Q41 (Loan Default Causes) and Q42 (Credit Quality Measures) — N = 150

Rank	Variable	Factor Description	Category	Mean	SD	95% CI	Status vs. Midpoint
1	Q42a	Strengthen credit risk assessment procedures	Q42 – Measure	**4.16**	0.68	[4.05, 4.27]	↑ Above
2	Q42g	Proactive communication & transparency with borrowers	Q42 – Measure	4.05	0.83	[3.92, 4.18]	↑ Above
3	Q42c	Borrower education & financial literacy programmes	Q42 – Measure	3.99	0.90	[3.85, 4.14]	↑ Above
4	Q41a	Economic slowdown	Q41 – Cause	3.89	0.96	[3.74, 4.04]	↑ Above
5	Q42e	Collaborating with regulatory authorities	Q42 – Measure	3.88	1.10	[3.70, 4.06]	↑ Above
6	Q42d	Promoting responsible lending practices	Q42 – Measure	3.75	1.23	[3.55, 3.95]	↑ Above
7	Q42b	Implementing stricter loan recovery policies	Q42 – Measure	3.67	0.97	[3.52, 3.83]	↑ Above
8	Q42h	Incentives for timely repayment & good credit behaviour	Q42 – Measure	3.49	1.28	[3.28, 3.69]	↑ Above
9	Q41f	Ineffective recovery measures	Q41 – Cause	3.43	1.13	[3.25, 3.61]	↑ Above
10	Q42f	Investing in advanced technology for NPA management	Q42 – Measure	3.39	1.50	[3.15, 3.63]	↑ Above
11	Q41c	Wilful defaults	Q41 – Cause	3.13	1.19	[2.94, 3.32]	↑ Above
12	Q41b	Poor credit appraisal	Q41 – Cause	2.71	1.10	[2.53, 2.88]	↓ Below
13	Q41e	Frauds & corruption	Q41 – Cause	2.37	0.98	[2.22, 2.53]	↓ Below

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14	Q41d	Lending to risky sector	Q41 – Cause	2.28	1.01	[2.12, 2.44]	↓ Below
15	Q41g	Restructuring/evergreening of loans	Q41 – Cause	2.18	1.15	[1.99, 2.36]	↓ Below
16	Q41h	Agriculture distress	Q41 – Cause	**1.97**	1.06	[1.80, 2.14]	↓ Below

Scale: 1 = Least important/responsible to 5 = Most important/responsible. Midpoint = 3.0. ↑/↓ relative to scale midpoint (3.0). 95% CI = Mean ± 1.96 × (SD/√150).

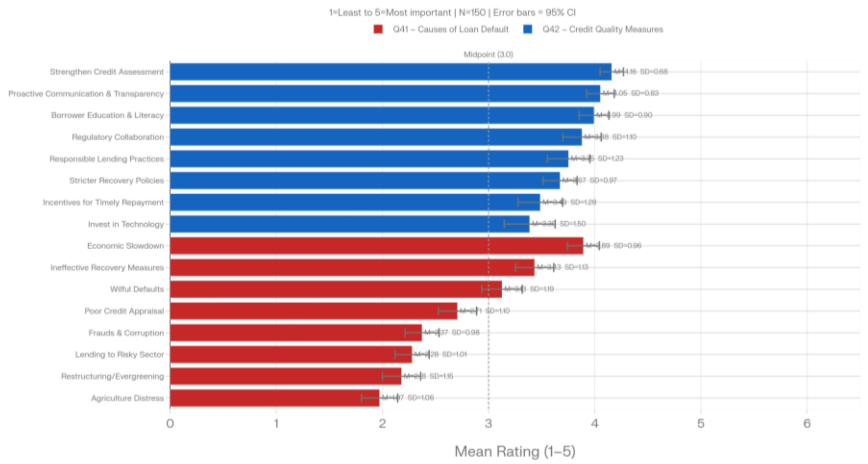

Figure. **5** - Factor Rankings: Loan Default Causes (Q41) & Credit Quality Measures (Q42)

The ranking data in the Table 7 & Figure 5 reveals the clear asymmetry: all eight Q42 development measures the cluster in top 10 ranks, whereas the Q41 default causes are distributed in the full range. Strengthening the credit risk assessment procedures (Q42a; M = 4.16, SD = 0.68) ranks 1st with narrowest dispersion among the high-scoring items, indicating near-consensus on its primacy. Among 7 Q42 measures with the means above scale midpoint, technology investment (Q42f; M = 3.39) ranks the lowest — suggesting professionals prioritise procedural, regulatory and communicative, reforms over the technological solutions, which is the important nuance for the AI adoption strategy. Among the Q41 causes, economic slowdown (Q41a; M = 3.89) is only factor rated above 3.5, with remaining causes —specifically the agriculture distress (Q41h; M = 1.97), evergreening (Q41g; M = 2.18), & the risky sector lending (Q41d; M = 2.28) — rated well below midpoint, indicating these are not viewed as the primary default drivers by surveyed professionals.

4. Discussion

This study set out to examine how the banking professionals in the India perceive AI across 4 operational domains — early NPA detection, loan restructuring, customer service, & the cost efficiency — and to understand what drives their broader readiness to adopt the AI at an institutional level. Taken together, findings paint the picture which is broadly optimistic but meaningfully nuanced, with the certain attitudinal patterns carrying specific implications for how the banks must plan & communicate the AI integration strategies.

Perceptions Across the Four Hypothesised Domains

All 4 construct scores exceeded scale midpoint comfortably, providing the empirical support for each of study's primary hypotheses. H2 (Loan Restructuring, M = 2.623) & H1 (Early NPA Detection, M = 2.616) registered strongest endorsement, closely followed by the H4 (Cost and Efficiency, M = 2.580) & H3 (Customer Service, M = 2.484). That the NPA-related beliefs cluster at top is not surprising —chronic NPA problem in the Indian public sector banking has been extensively

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documented, & frontline professionals likely encounter its consequences in their daily work. This experiential familiarity sharpen their AI's diagnostic potential appreciation in ways which the more abstract cost arguments cannot match. The relatively lower scores for the H3 are worth noting. Customer service perceptions are the weakest in absolute terms and most independent statistically, showing the non-significant correlation with H1. This divergence suggests that the professionals mentally separates the AI's analytical & the relational functions — they readily accept the machine judgement over data but are less convinced which algorithms can replace human quality of the client interaction in distress situations (Venkatesh, Morris, Davis, & Davis, 2003).

What Actually Drives General AI Adoption?

The regression analysis for the General AI Adoption (Model 1, $R^2 = 0.932$) clarified that 2 variables carry greatest explanatory weight. H1 ($\beta = 0.534$) & the respondents' comfort with banks by utilizing their personal data (Q36, $\beta = 0.516$) together nearly accounted for model's explained variance in the equal measure. The NPA confidence role is theoretically coherent — if the professional is persuaded already that the AI can outperform the human judgement in credit risk, which extends that acceptance to the broader adoption is a short conceptual step. The data-comfort finding, although, is arguably more actionable. It tells the practitioners that AI adoption is not just the technology problem; it is the privacy & consent problem. Until the staff & the customers alike are at ease with how the data can be collected & then processed, attitudinal buy-in will remains partial regardless of how capable underlying models become.

One of more striking results is negative effect of the prior AI customer service experience (Q17, $\beta = -0.181$, $p < .001$). Respondents who had interacted with the AI-based banking services rated the overall adoption more cautiously than those who had not. This pattern is consistent with the expectation-disconfirmation effect: exposure to current-generation AI tools — which remains imperfect in the conversational contexts —introduces the form of institutional scepticism that the hypothetical endorsement does not encounter. For the bank leadership, this is the useful warning. Also, deploying the underpowered AI interfaces prematurely may erode very goodwill which creates the broader adoption possible (Bhattacherjee, 2001; Lundberg & Lee, 2017).

Drivers of Domain-Specific Confidence

The Model 3 was specifically informative in decomposing what underpins the NPA detection confidence. The Real-time data analysis (Q04, B = 0.416) dominated the all other predictors by the considerable margin, & its narrow 95% CI [0.390, 0.443] signals that this relationship robustly holds across sample rather than being driven by the subset of responses. Put plainly, the professionals who believes that immediacy and speed of the data access matter for credit risk also believes that the AI, which is inherently built for the continuous data processing, and it is well suited to task. Alongside this, recognising that the human reviewers are biased (Q08, B = 0.103) contributed independently — bias awareness & the ROI consciousness apparently reinforce each other as the complementary justifications for technological substitution (Machado, Chen, & Osterrieder, 2025).

For Loan Restructuring (Model 2), the two significant predictors were H4 Cost and Efficiency (B = 0.324) and comfort with AI making decisions (Q15, B = 0.283). The latter is particularly meaningful because restructuring involves consequential, individualised judgements about borrowers facing financial hardship. The willingness to delegate such decisions to an algorithm reflects a degree of trust that goes beyond general technological optimism — it speaks to a belief that algorithmic fairness, when paired with operational efficiency, may actually serve borrowers better than judgement calls made under cognitive or relational pressure(Zubair & Tiwary, 2024).

Practitioner Priorities and the Technology Ranking Anomaly

Among ranked Q42 credit quality development measures, strengthening the credit assessment procedures (M = 4.16) & the proactive borrower communication (M = 4.05) ranked highest, whereas investing in the advanced technology for NPA management (Q42f, M = 3.39) ranked lowest among the all enhancement measures. This ordering deserves the attention. Inspite of the strong pro-AI attitudes documented throughout, when professionals are directly asked what interventions would most increase the credit quality, they prioritised the people-centred & process-centred reforms over technological ones. Whether this reflects genuine priority assessment or the implicit assumption that the technology serves process rather than the replaces it is unclear, but finding cautions against the purely techno-centric implementation strategies. On default causes side, economic slowdown (M = 3.89) was rated primary driver, whereas the agriculture distress & the sector-specific lending risk received strikingly low ratings. This may reflect urban-sector composition of sample, or the tendency among banking professionals to the attribute systemic defaults to macro forces rather than to structural vulnerabilities in the lending practices (India, 2018).

Study Limitations

Many limitations temper these findings generalisability. The sample of 150 banking professionals, while adequate for analytical techniques employed, was drawn from the specific geographic & the institutional context; perceptions among the rural cooperative bank staff or retail banking customers may substantially vary. Cross-sectional survey designs cannot establishes the causal direction —finding that H1 predicts the General AI Adoption does not rule out reverse, whereas broadly pro-adoption professionals interpret the every domain more favourably. Moreover, the social desirability bias may have inflated endorsement of the AI-friendly items, specifically given current institutional emphasis in the India on fintech modernisation. Hence, the Future research using longitudinal designs, objective performance metrics, or the experimental methods comparing AI-assisted and traditional NPA identification outcomes would strengthen causal inferences that this study's correlational evidence can only tentatively support.

5. Conclusion

This study demonstrates that the banking professionals in the India holds the broadly favourable attitudes towards the AI in NPA detection, customer service, loan restructuring, and cost efficiency, with the NPA-related confidence & the personal data comfort emerging as twin pillars of the general AI adoption readiness. The Domain-specific regression models confirms that the real-time data capability beliefs & trust in the AI autonomy are clearest operational levers. Prominently, the premature AI deployment & the unresolved data privacy concerns risk undermining adoption momentum. The Banks seeking sustainable AI integration must simultaneously invest in the robust infrastructure, targeted staff capacity-building, & the transparent data governance frameworks — treating adoption as the institutional culture challenge as much as the technological one.

REFERENCES

1. Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model1. MIS quarterly, 25(3), 351-370.
2. India, I. a. B. B. o. (2018). Retrieved from https://ibbi.gov.in/
3. K Shaji, A. (2019). A Study on the Management of NPA's in Banking Sector Using Artificial Intelligence. 22, 118-126.
4. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.
5. Machado, M., Chen, D., & Osterrieder, J. (2025). An analytical approach to credit risk assessment using machine learning models. Decision Analytics Journal, 16, 100605. doi:10.1016/j.dajour.2025.100605
6. PIB. (2024). Public Sector Banks: A Resurgent Force [Press release]. Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2084546&reg=48&lang=2
7. Prenio, J., & Yong, J. (2021). Humans keeping AI in check-emerging regulatory expectations in the financial sector: Bank for International Settlements, Financial Stability Institute.
8. RBI. (2014). Financial Stability Report. Retrieved from https://www.rbi.org.in/Scripts/FsReports.aspx
9. RBI. (2023). Master Circular - Prudential norms on Income Recognition, Asset Classification and Provisioning pertaining to Advances [Press

release]. Retrieved from https://rbi.org.in/scripts/BS_ViewMasCirculardetails.aspx?id=12472

10. RBI. (2025). REPORT ON TREND AND PROGRESS OF BANKING IN INDIA. Retrieved from https://www.rbi.org.in/Scripts/AnnualPublications.aspx?head=Trend%20and%20Progress%20of%20Banking%20in%20India
11. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. MIS quarterly, 27(3), 425-478.
12. Zubair, D., & Tiwary, D. (2024). Early Warning System Model for Non-performing Loans of Emerging Market Fintech Firms. In (pp. 221-240).