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From Adoption to Assurance: How AI Capability and Explainable Governance Shape Credit Risk Management Efficiency in Indian Commercial Banks

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Abstract: This study develops and tests a capability-governance explanation of how artificial intelligence (AI) adoption influences credit risk management efficiency in Indian commercial banks. It distinguishes simple tool availability from an organizational AI capability and examines whether digital maturity and explainable-AI governance convert adoption into reliable improvements in underwriting, early warning, monitoring and decision speed.

The paper uses a two-stage research design. Stage 1 analyses an observed pilot survey of 70 employees from public, private, small-finance and foreign banks. The pilot results are evaluated using scale reliability, descriptive statistics, correlations, regression and group comparisons. Stage 2 specifies a multi-bank main study with employee responses nested within banks and demonstrates the proposed confirmatory factor analysis, moderated structural model, bootstrapped mediation, and robustness checks using a clearly identified simulated sample of 420 respondents. The expanded model integrates the resource-based view, dynamic capabilities, and responsible-AI governance.

In the observed pilot, AI adoption is positively associated with perceived credit risk management efficiency ($r = .65$, $p < .001$). The regression explains 42.0% of outcome variance, ($B = 0.48$, 95% CI [0.34, 0.61]), with a large local effect ($f^2 = .724$). Bank-type differences are small and non-significant ($\eta^2 = .04$). In the simulated main study, AI capability has a positive direct effect, while workflow integration partially mediates this relationship; digital maturity and explainable-AI governance strengthen it. Governance quality is therefore modeled as a value-enabling capability rather than a compliance cost alone.

The observed evidence is cross-sectional, perceptual, and based on a small convenience sample. It cannot establish causal changes in non-performing assets or validate the simulated structural results. A publishable test requires real multi-bank data, temporal separation or archival outcomes, and cluster-aware estimation.

The paper replaces a technology-centric adoption argument with an assurance-based model that explains when AI can improve credit risk decisions without weakening transparency, fairness, or human accountability in an emerging-market banking system.

Keywords: Artificial intelligence, credit risk management, explainable AI, digital maturity, model governance, commercial banks, India.

1. Introduction

Artificial intelligence is moving from peripheral automation to consequential decision support in banking. Machine-learning models can combine transaction patterns, bureau information, cash-flow data and behavioral signals to estimate default risk, prioritize monitoring alerts and accelerate loan decisions. These capabilities are especially relevant in India, where banks serve heterogeneous borrowers, including thin-file consumers and small enterprises, while managing prudential requirements, data-quality constraints and legacy technology.

The conventional argument is that more AI adoption produces more efficient credit risk management. This argument is incomplete. A model can be statistically accurate but operationally unused; fast decisions can be poorly explained;

automated recommendations can reproduce biased historical patterns; and multiple models can create validation, drift and third-party concentration risks. The Reserve Bank of India's FREE-AI report and international supervisory work increasingly frame responsible AI around trust, accountability, explainability, fairness, data governance and resilience. Consequently, the relevant question is not whether a bank possesses AI tools, but it can deploy, govern and integrate them as an organizational capability (Reserve Bank of India, 2025; Bank for International Settlements, 2024, 2025).

The supplied study offers valuable pilot evidence: 70 banking employees report high AI use and a strong positive association between adoption and perceived credit-risk efficiency. However, the original manuscript overstates its design by describing an unreported 2017-2025 panel and causal tests. It also proposes eight hypotheses while empirically testing only an aggregate adoption-efficiency relationship. This redraft corrects those inconsistencies and develops a focused theoretical model that can sustain Q1-level scrutiny.

Research question: How does AI capability improve credit risk management efficiency in Indian commercial banks, and under what conditions do workflow integration, digital maturity and explainable-AI governance strengthen or constrain that value?

1.1. Contributions

First, the study conceptualizes AI adoption as a second-order capability comprising data readiness, model competence, workflow integration and managerial commitment, rather than a binary installation decision. Second, it identifies workflow integration as the mechanism through which technical potential becomes process efficiency. Third, it treats explainable-AI governance as a complementary capability that can improve trust, challenge and controlled use. Fourth, it separates observed pilot evidence from a simulated main-study demonstration, thereby preserving transparency while showing the analytical architecture required for a stronger future submission.

2. Theoretical Background and Hypotheses

2.1. AI capability and the resource-based view

The resource-based view argues that performance differences arise from valuable and difficult-to-replicate resource configurations rather than isolated assets (Barney, 1991; Wernerfelt, 1984). Algorithms are widely accessible and therefore unlikely to create advantage alone. Value emerges when models are combined with proprietary data, skilled risk teams, validation routines, decision rights and integration with origination, monitoring and collections. AI capability should improve risk discrimination, reduce manual rework and accelerate consistent decisions.

H1: AI capability is positively associated with credit risk management efficiency.

2.2. Workflow integration as a dynamic capability

Dynamic-capability theory emphasizes the ability to sense risk signals, seize analytical opportunities and reconfigure processes. Predictions that remain in dashboards do not change outcomes. Banks must route alerts to accountable users, define escalation thresholds and connect model outputs to credit policy and recovery workflows. Integration is therefore a transmission mechanism rather than merely another adoption indicator.

H2: Workflow integration mediates the positive relationship between AI capability and credit risk management efficiency.

2.3. Digital maturity as an enabling condition

AI performance depends on interoperable systems, reliable data lineage, scalable infrastructure and staff capability. In digitally mature banks, models can access timely data and be embedded into decision processes. In low-maturity environments, legacy systems and fragmented data increase latency, manual overrides and implementation risk.

H3: Digital maturity positively moderates the AI capability-efficiency relationship, such that the relationship is stronger at higher levels of digital maturity.

2.4. Explainable-AI governance and controlled reliance

Responsible-AI governance includes documented model purpose, data provenance, independent validation, fairness testing, human review, monitoring and adverse-decision explanations. Although governance can add implementation cost, it can also enable effective reliance by reducing uncertainty, clarifying accountability and supporting regulatory challenge. Explainability is particularly material in credit decisions because an opaque error can affect both prudential soundness and customer rights (BIS, 2025).

H4: Explainable-AI governance is positively associated with credit risk management efficiency. H5: Explainable-AI governance strengthens the positive relationship between AI capability and efficiency.

2.5. Bank ownership as a contextual boundary

Ownership type may proxy differences in legacy architecture, procurement, customer mix, risk appetite and decision centralization. These differences may change the size of the AI effect, but ownership alone should not be treated as a causal mechanism. The analysis therefore evaluates ownership heterogeneity as an exploratory boundary condition rather than assuming that one category is inherently superior.

3. Method

3.1. Two-stage design

Stage 1 is an observed pilot based on the supplied July 2026 survey. A five-point questionnaire was completed by 70 employees: 29 from private banks, 22 from small-finance banks, 18 from public banks, and one from a foreign bank. Stage 2 is the recommended main-study design. It should recruit employees involved in underwriting, risk analytic, monitoring, collections, model validation and compliance across at least 20 banks. Responses should be temporally separated and linked, where permission permits, to non-sensitive operational indicators such as decision turnaround, override rates, alert conversion and slippage rates.

Status of evidence: The pilot statistics below are observed as reported in the source. The proposed main-study results are simulated and are included only as a model of the required analysis.

Table 1: measures

Construct	Pilot operationalisation	Recommended main-study operationalisation
AI adoption/capability	Two items: active use and tool/support availability	Data readiness, model competence, managerial commitment and breadth of credit-lifecycle deployment
Workflow integration	Embedded within the 10-item efficiency scale	Separate scale: routing, escalation, override documentation, monitoring and collections integration
CRM efficiency	Ten perceived outcome items	Multi-source latent construct: accuracy, speed, error reduction, monitoring and control quality
Digital maturity	Not directly measured	Legacy integration, data interoperability, scalable infrastructure and analytics skills
Explainable-AI governance	Compliance item only	Model documentation, validation, explanation, fairness testing, drift monitoring and human review

All multi-item scales should use established items where available, be reviewed by banking and measurement experts, and undergo cognitive interviews. To reduce common-method bias, predictor and outcome measurements should be separated in time, marker variables should be considered, and manager or archival outcomes should complement employee reports.

3.2. Analytical strategy

Pilot analysis report's reliability, item and construct descriptives, Pearson correlations, ordinary least-squares regression, confidence intervals, effect sizes and ownership-group comparisons. The recommended main study should use confirmatory factor analysis (CFA), composite reliability, average variance extracted, heterotrait-monotrait ratios, latent moderated structural equations or cluster-robust regression, percentile-bootstrap indirect effects and multi-group invariance tests. Bank-level clustering must be addressed through multilevel modeling or cluster-robust standard errors. Cross-sectional results should be described as associations, not causal effects.

Table 2: Respondent profile

Characteristic	Category	n	%
Gender	Male / Female	40 / 30	57.1 / 42.9
Age	21-30 / 31-40 / 41-50 / >50	33 / 34 / 2 / 1	47.1 / 48.6 / 2.9 / 1.4
Bank type	Private / Small finance / Public / Foreign	29 / 22 / 18 / 1	41.4 / 31.4 / 25.7 / 1.4
Designation	Officer / Assistant Manager / Manager	49 / 18 / 3	70.0 / 25.7 / 4.3
Experience	<5 / 5-10 / 11-15 / >15 years	43 / 24 / 1 / 2	61.4 / 34.3 / 1.4 / 2.9

Table 3: Two Item Adaptation scale

Highest/lowest pilot item	Mean	SD	Interpretation
AI will become essential for future CRM	4.49	.88	Strong future orientation
AI significantly improved CRM	4.14	1.00	High perceived contribution
AI actively used in credit assessment	4.09	1.03	High reported use
AI helped reduce NPAs	3.23	1.25	Cautious attribution
Benefits outweigh implementation challenges	3.26	1.26	Substantial respondent disagreement

4. 4 Observed Pilot Results (N = 70)

The pilot is weighted toward early-career officers and private or small-finance banks. The single foreign-bank response is insufficient for ownership comparison and is excluded from the ANOVA. This composition limits population inference but is informative for instrument refinement because frontline employees interact directly with operational credit systems.

4.1. Reliability and descriptive evidence

The two-item adoption scale has limited content coverage, and its alpha should not be defended solely by a relaxed exploratory threshold. The high overall alpha does not establish construct validity because it may reflect correlated but distinct concepts. The main study should therefore expand adoption into a multi-dimensional capability and validate the measurement model with CFA.

4.2. Correlations and regression

AI adoption explains 42.0% of the variance in perceived CRM efficiency. The effect is statistically significant in the pilot, but the magnitude may be inflated by same-source measurement, construct overlap, and common-method variance. The result supports H1 provisionally; it does not show that AI caused lower NPAs or improved archival portfolio outcomes.

Table 4: correlation

Construct	AI adoption	CRM efficiency	Perceived outlook
AI adoption	1	.648***	.573***
CRM efficiency	.648***	1	.676***
Perceived outlook	.573***	.676***	1

Note. Observed pilot correlations; *** $p < .001$.

Table 5: Regression

Model/parameter	Estimate	SE	95% CI	Test
R / R^2 / adjusted R^2	.648 / .420 / .412	–	–	$F(1, 68) = 49.25, p < .001$
Intercept	1.725	.281	[1.164, 2.286]	$t = 6.134, p < .001$
AI adoption B	.475	.068	[.339, .611]	$t = 7.018, p < .001$
Standardised β	.648	–	Fisher r CI [.48, .76]	Large association
Local effect f^2	.724	–	–	Large descriptive effect

5. Simulated Main-Study Demonstration (Replace Before Submission)

The simulated dataset assumes 420 valid respondents nested within 28 Indian commercial banks: 156 public-bank, 206 private-bank, and 58 small-finance-bank employees. Respondents are distributed across underwriting, risk analytics, monitoring, model validation, and compliance. This exceeds the requested minimum of 400 and provides more stable conditions for CFA, latent interaction testing, and ownership-group comparisons. No foreign-bank group is modelled because adequate group size would require targeted recruitment.

Table 6: Sample and measurement model

Construct	Items	α	CR	AVE	Loading range
AI capability	8	.91	.92	.60	.68–.86
Workflow integration	5	.88	.89	.62	.70–.84
Digital maturity	5	.89	.90	.64	.71–.87
Explainable-AI governance	6	.93	.94	.71	.76–.90
CRM efficiency	8	.92	.93	.63	.69–.88

The simulated CFA indicates acceptable fit: $\chi^2/df = 1.78$, CFI = .954, TLI = .947, RMSEA = .050 (90% CI [.043, .057]), and SRMR = .044. Composite reliability exceeds .70, AVE exceeds .50, and all HTMT ratios are below .85. A single-factor model fits poorly (CFI = .612, RMSEA = .137), while addition of an unmeasured method factor does not materially alter focal loadings. These values illustrate the evidence required; they do not validate the actual instrument.

Table 7: Structural model

Path	Standardised β	SE	p	95% bootstrap CI	Decision
AI capability → CRM efficiency	.38	.06	< .001	[.26, .49]	H1 supported
AI capability → workflow integration	.56	.05	< .001	[.46, .65]	–
Workflow integration → CRM efficiency	.29	.06	< .001	[.17, .40]	–
Indirect AI → workflow → efficiency	.16	.04	< .001	[.09, .24]	H2 supported
Digital maturity → CRM efficiency	.18	.05	.001	[.08, .28]	–
AI x digital maturity	.14	.05	.008	[.04, .24]	H3 supported
XAI governance → CRM efficiency	.23	.06	< .001	[.12, .35]	H4 supported
AI x XAI governance	.12	.05	.021	[.02, .22]	H5 supported

The simulated model explains 61% of CRM-efficiency variance. The remaining direct AI effect after mediation indicates complementary channels beyond workflow integration. Simple-slope analysis illustrates that the AI-efficiency association is stronger at high digital maturity ($\beta = .52$) than at low maturity ($\beta = .25$), and stronger under high explainable-AI governance ($\beta = .50$) than under weak governance ($\beta = .28$).

Table 8: Structural model

Path	Standardised β	SE	p	95% bootstrap CI	Decision
AI capability → CRM efficiency	.38	.06	$< .001$	[.26, .49]	H1 supported
AI capability → workflow integration	.56	.05	$< .001$	[.46, .65]	–
Workflow integration → CRM efficiency	.29	.06	$< .001$	[.17, .40]	–
Indirect AI → workflow → efficiency	.16	.04	$< .001$	[.09, .24]	H2 supported
Digital maturity → CRM efficiency	.18	.05	.001	[.08, .28]	–
AI × digital maturity	.14	.05	.008	[.04, .24]	H3 supported
XAI governance → CRM efficiency	.23	.06	$< .001$	[.12, .35]	H4 supported
AI × XAI governance	.12	.05	.021	[.02, .22]	H5 supported

Table 9: Structural model

Specification / Check	Key Result	Interpretation / Conclusion
Cluster-robust estimation	Focal coefficients remain significant	Not driven by within-bank dependence
Alternative efficiency specification	AI $\beta = .31, p < .001$	Robust to removal of NPA-attribution item
Marker-variable control	AI β changes from .38 to .35	Limited common-method inflation
Private vs public multi-group model	$\beta_{\text{private}} = .44$; $\beta_{\text{public}} = .30$; $\Delta\chi^2$ $p = .048$	Possible ownership heterogeneity
Endogeneity sensitivity	Omitted-variable robustness value = .21	Moderate unobserved confounding needed
Nonlinearity	Quadratic AI term $\beta = -.07, p = .118$	No demonstrated diminishing return

These checks are intentionally more conservative than the original manuscript. A real study should avoid claiming causality unless it uses temporal ordering, matched bank-level outcomes, a credible natural experiment or a defensible instrument. Technology-spend cycles should not be described as an instrumental variable without demonstrating relevance and exclusion restrictions.

6. Discussion

6.1. Interpretation of observed evidence

The pilot provides a clear but bounded finding: employees who report greater AI adoption also report more efficient credit risk management. The association is large and precisely estimated within the sample. However, respondents are more confident about AI's future importance and general contribution than about direct NPA reduction. This asymmetry is theoretically meaningful. NPAs are stock outcomes shaped by underwriting vintages, macroeconomic conditions, recognition rules, recovery mechanisms, and write-offs. Frontline employees may reasonably perceive faster or more consistent processes without attributing system-level asset-quality changes solely to AI.

The absence of significant ownership differences is also informative but inconclusive. It suggests that perceived value is not confined to private banks, yet the small pilot cannot distinguish technology, process, and portfolio differences across ownership categories. A stronger test must measure digital maturity and governance directly rather than using ownership as a crude substitute.

6.2. Theoretical implications

The proposed model advances the resource-based view by identifying AI as a composite capability. Algorithms become valuable when embedded in data, routines, and expertise. It extends dynamic-capability reasoning by specifying workflow integration as the conversion mechanism between prediction and action. Finally, it contributes to responsible-AI research by treating explainability and governance as productive complements. Well-designed challenge, documentation, and human review can increase controlled reliance on models, reducing both blind automation and reflexive rejection.

6.3. Practical implications

Bank boards should define risk appetite for AI use cases, assign accountable owners and require independent validation proportionate to the consequence of the decision.

Credit functions should track operational and prudential outcomes separately: turnaround time, override rates, alert precision, false negatives, slippage, approval stability and borrower-level fairness.

Model explanations should be designed for distinct users—borrowers, credit officers, validators, auditors and supervisors—rather than treated as a single technical output.

Legacy integration and data lineage should be prioritised before scaling complex models; weak infrastructure can convert predictive gains into operational risk.

Human overrides should remain possible but be reason-coded and monitored. Excessive overrides may indicate low trust, poor calibration or incentive misalignment; zero overrides may signal automation bias.

6.4. Regulatory implications

A proportionate, lifecycle-based regime is appropriate for Indian banking. High-impact credit models require stronger documentation, fairness testing, validation, monitoring, incident response and customer explanation than low-risk productivity tools. Supervisors can encourage innovation while requiring traceable data, reproducible decisions and clear responsibility for third-party models. The FREE-AI principles provide an Indian foundation, while BIS work underscores explainability, data quality, concentration and model risk as prudential concerns.

6.5. Limitations and Future Research

The observed pilot is small, convenience-based, cross-sectional, and dominated by early-career respondents. Predictor and outcome variables are self-reported in the same instrument, increasing common-method and social-desirability risk. The adoption construct contains only two items, and construct validity was not established through factor analysis. The study cannot infer that AI reduced bank NPAs, because neither bank-linked asset-quality outcomes nor a counterfactual design is available. Secondary system-level NPA trends should be used as context, not as validation of an AI effect.

Future research should collect a larger probability-oriented or stratified sample, separate measurement waves, and link perceptions to de-identified operational measures. A bank-year panel could combine a reproducible annual-report AI index with GNPA/NNPA, slippage, provision coverage, credit costs and macro controls. Causal claims would require staggered adoption dates, event-study diagnostics and credible parallel trends. Research should also test model fairness for thin-file borrowers and MSMEs, examine third-party concentration, and compare human-only, AI-assisted and highly automated decision regimes.

7. Conclusion

The pilot evidence indicates a strong positive association between AI adoption and perceived credit risk management efficiency in Indian commercial banks. Yet adoption is not assurance. Banks realise value when AI is supported by reliable data, integrated workflows, digitally mature infrastructure and governance that makes consequential decisions explainable, contestable and auditable. The proposed capability-governance model therefore offers a more credible explanation than a simple technology-effect argument.

For publication, the observed pilot can support instrument development and preliminary evidence, but the simulated main-study results cannot be submitted as findings. Replacing them with real multi-bank data would allow the paper to make a meaningful contribution to the literature on responsible AI, banking capabilities and credit-risk transformation in emerging markets.

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