AI Transparency and Financial Performance: Evidence from Indian Financial Services

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Digital lending in India has experienced exponential growth, with algorithmic decision-making now determining 47% of retail loan applications. However, the opacity of these AI systems has generated significant consumer protection concerns, with over 100,000 complaints filed regarding lending decisions in 2023-24 alone. This study examines whether AI transparency in lending decisions affects institutional performance across 50 major Indian financial institutions from 2021 to 2024. We develop the Indian Financial AI Transparency Score (IFATS) drawing on established frameworks to measure institutional disclosure practices. Using panel fixed effects regression analysis, we find that a 10-point increase in IFATS is associated with a 0.30 percentage point reduction in gross non-performing assets ($p < 0.05$), 4.2 percentage point improvement in stock returns ($p < 0.01$), and 23% fewer customer complaints ($p < 0.01$). These findings suggest that transparency mechanisms not only address ethical concerns but also deliver measurable business benefits through improved customer trust, better borrower self-selection, and reduced operational costs. Our research contributes to information asymmetry theory in the AI era and provides empirical guidance for regulatory policy under India's Digital Lending Guidelines.

Keywords: AI transparency, Explainable AI, Digital lending, Indian banking, Financial inclusion, Algorithmic decision-making, IFATS, Customer trust, Non-performing assets

1. Introduction

The rapid digitalisation of financial services in India has changed the way credit markets work. Digital lending touched around ₹2.2 lakh crore in FY2023, growing at a very fast pace (Reserve Bank of India, 2024a). A key reason for this growth is the use of artificial intelligence and machine learning systems that now make many credit decisions which were earlier taken by human officers (Viswanathan & Kumar, 2023). These technologies promise faster service and wider financial inclusion (Demirgüç-Kunt, Klapper, Singer, Ansar & Hess, 2018). At the same time, they have created a major transparency problem, as borrowers often do not understand why they are approved or rejected for loans.

This lack of clarity has raised serious consumer protection concerns. The Reserve Bank of India’s Ombudsman received 9,34,355 complaints in 2023–24, and almost 29% of them were related to loans and advances (Banking Ombudsman Scheme, 2024). Many of these complaints show similar patterns: borrowers receive generic rejection messages, do not understand how automated decisions are made, and find it difficult to question or challenge such decisions. This creates a large information gap between borrowers and lenders, where lenders have detailed data-driven insights but borrowers are left with very little information (Bar-Gill & Warren, 2013). Regulators have started responding to these issues, but the framework is still evolving. RBI’s Digital Lending Guidelines issued in September 2022 require lenders to be transparent about pricing and loan terms (Reserve Bank of India, 2022). However, the guidelines do not clearly specify what “transparency” should look like when AI systems make decisions. Other countries are taking different approaches. The European Union’s AI Act proposes specific rules on explainability for high-risk AI systems (European Commission, 2024), while the United States relies on existing laws like the Equal Credit Opportunity Act that require lenders to give clear reasons for rejecting applications (Consumer Financial Protection Bureau, 2022). In comparison, India’s approach is still taking shape, which creates uncertainty for both financial institutions and borrowers.

In this situation, a key question emerges for the industry: Does being transparent about AI systems help or hurt business performance? Many institutions hesitate to share more information than required. They worry that explanations may allow borrowers to game the system, expose their proprietary models to competitors, confuse customers with technical details, or increase compliance costs (Viswanathan & Kumar, 2023). Due to these concerns, most institutions follow only the minimum rules set by regulators.

However, several theories suggest that transparency may actually support better business outcomes. Information asymmetry theory argues that reducing information gaps improves market efficiency (Akerlof, 1970). Technology acceptance research shows that people trust and adopt automated systems more when they understand how decisions are made (Davis, 1989; Lee & See, 2004). Work on algorithm aversion also suggests that clear explanations help users accept algorithmic decisions (Dietvorst, Simmons & Massey, 2015; Shin, 2021). Together, these ideas indicate that transparency could have positive effects for financial institutions.

This study examines this question in the Indian context. We develop the Indian Financial AI Transparency Score (IFATS), a 100-point framework that measures AI transparency across four dimensions: disclosure practices, explanation quality, customer communication, and regulatory compliance. Using this measure, we study 50 major financial institutions in India (20 banks, 20 NBFCs and 10 fintech platforms) over the period 2021–2024, creating a dataset of 200 observations. The methods used to analyse this dataset are explained in Section 3.

This study aims to make four contributions. First, it seeks to extend information asymmetry theory to AI-based lending by exploring how algorithms may create new forms of information gaps. Second, it attempts to bring insights from technology acceptance research into the financial sector, with a focus on the role of explainability. Third, it proposes the Indian Financial AI Transparency Score (IFATS) as a practical and replicable framework for assessing AI transparency in Indian financial institutions. Finally, it aims to offer guidance for policymakers, regulators, financial institutions, technology developers and consumers on how transparency can be improved in practice.

The rest of the paper is organised as follows. Section 2 reviews earlier literature on AI explainability, transparency in financial services, and trust in automated systems. Section 3 explains the research design and methodology. Section 4 presents the empirical findings. Section 5 discusses mechanisms, implications and limitations. Section 6 offers policy recommendations, and Section 7 concludes.

2. Literature Review

2.1 Evolution of Credit Decision-Making

Credit underwriting has passed through three major technological phases, each changing how information is shared between lenders and borrowers. Earlier, relationship-based lending depended on local knowledge and personal judgment. This created information gaps but still allowed borrowers to receive human explanations (Berger & Udell, 2002). The next phase introduced credit scoring models, which were more objective but less transparent (Thomas, Edelman & Crook, 2002). Today's machine learning systems offer very high predictive power but often work like "black boxes," even for the people who build them (Ribeiro, Singh & Guestrin, 2016). Research shows that many modern AI lending models use thousands of variables, including non-traditional data such as phone usage patterns, social networks and digital behaviour (Bjorkegren & Grissen, 2020). These models predict loan defaults better but are harder to explain. Earlier, a credit officer could say, "income too low," or "insufficient job stability." But explaining a model with a thousand features is far more difficult (Lundberg & Lee, 2017).

2.2 Technical Approaches to Explainable AI

Computer science researchers have proposed several methods to make AI systems more transparent. LIME explains predictions by approximating complex models with simple ones near each decision (Ribeiro et al., 2016). SHAP assigns each feature an importance value using game-theory ideas (Lundberg & Lee, 2017). Counterfactual explanations show the minimum change needed in inputs to get a different output (Wachter, Mittelstadt & Russell, 2018). Attention mechanisms highlight which inputs influenced a neural network's prediction (Bahdanau, Cho & Bengio, 2015). However, adoption in financial services is still limited. A survey of Indian banks found that while 73% use AI for lending, only 18% use any automated explanation tool (Viswanathan & Kumar, 2023). Banks cite technical complexity, legacy systems, and uncertainty about regulation as key barriers. This gap between technical possibility and real-world use is one of the issues addressed in this study.

2.3 Psychology of Algorithm Trust and Acceptance

Behavioural studies show that people respond differently to algorithmic decisions. Dietvorst et al. (2015) identified 'algorithm aversion', where people prefer human judgment even when algorithms perform better. This aversion increases when algorithms make mistakes, but reduces when people understand how the system works. Shin (2021) found that explainability strongly increases acceptance of AI decisions - often more than perceived usefulness or ease of use.

Trust in automation depends on performance, process and purpose (Lee & See, 2004). Explanations mainly improve process trust. When users understand how decisions are made, they develop balanced trust - neither blind acceptance nor extreme doubt. This suggests that transparency can improve acceptance and proper use of AI lending tools.

2.4 Legal and Regulatory Frameworks

Regulators across the world take different approaches to AI transparency. The European Union's GDPR introduced a debated 'right to explanation' for automated decisions (Goodman & Flaxman, 2017). The proposed EU AI Act goes further by classifying AI systems based on risk and requiring higher transparency for high-risk uses (European Commission, 2024). The United States relies mainly on existing regulations. The Equal Credit Opportunity Act requires lenders to give specific reasons for rejecting credit applications (Consumer Financial Protection Bureau, 2022). But it is unclear whether broad statements like "low credit score" are enough when algorithms use many more hidden factors (Gillis & Spiess, 2019). This creates legal uncertainty.

India's regulatory framework is still developing. RBI's 2022 Digital Lending Guidelines require transparency in pricing and terms, but do not define how AI-driven decisions should be explained (Reserve Bank of India, 2022). NITI Aayog's Responsible AI guidelines (2021) lay down principles but are not enforced. This gap creates risks but also opportunities for proactive institutions. International bodies have also issued guidance. The Basel Committee published principles on operational resilience that cover AI governance (Basel Committee on Banking Supervision, 2021). Singapore's Monetary Authority developed the FEAT principles—Fairness, Ethics, Accountability and Transparency (Monetary Authority of Singapore, 2018). The World Bank proposed an AI governance framework specifically for financial services (World Bank, 2021). These international frameworks provide important reference points for understanding how AI transparency is being approached globally.

2.5 Empirical Evidence on Transparency and Performance

Empirical research has mostly focused on general corporate transparency, not AI transparency. Prior studies show that greater corporate disclosure is linked to lower cost of capital, higher valuations and better operational performance (Leuz & Wysocki, 2016). But these studies deal with financial disclosures, not transparency in algorithmic decision-making.

Research specifically on AI transparency in financial services is limited, especially in non-Western contexts. Some international studies suggest transparency improves customer satisfaction, but these depend mainly on surveys rather than objective performance indicators (Araujo et al., 2020). Indian studies have documented algorithmic bias (Sharma, Gupta & Reddy, 2022) and different levels of AI adoption (Viswanathan & Kumar, 2023), but have not examined how transparency affects institutions' performance. This study addresses that gap.

2.6 Theoretical Framework and Hypotheses

This study draws from information economics, technology acceptance theory and institutional theory to build its hypotheses.

Information asymmetry theory (Akerlof, 1970) suggests that reducing information gaps improves market outcomes. When borrowers know the criteria, they apply more appropriately, reducing unsuitable applications and improving credit quality. Technology acceptance theories (Davis, 1989; Venkatesh & Davis, 2000) argue that understanding and usefulness drive adoption. Newer work shows that explainability is an important factor in accepting AI systems (Shin, 2021). Borrowers who understand AI decisions may trust the system more and respond more positively. Institutional theory highlights legitimacy and alignment with stakeholder expectations (Freeman, 1984). Transparent organisations appear more accountable, potentially reducing regulatory pressure and consumer complaints.

From these theories, we propose the following hypotheses:

- **H1:** Greater AI transparency is associated with better credit quality (lower NPAs).
- **H2:** Greater AI transparency is associated with higher operational efficiency.
- **H3:** Greater AI transparency is associated with stronger market performance.
- **H4:** Greater AI transparency is associated with higher customer satisfaction and fewer complaints.
- **H5:** Greater AI transparency is associated with lower regulatory risk.

3. Research Methodology

3.1 Sample Selection and Data Collection

We constructed a panel dataset covering 50 Indian financial institutions observed annually from 2021 to 2024, yielding 200 institution-year observations. The sample was selected using stratified purposive sampling to ensure representation across institutional types and sizes. Our final sample comprises: (a) 13 private sector banks including HDFC Bank, ICICI Bank, Axis Bank, and Kotak Mahindra Bank; (b) 12 public sector banks including State Bank of India, Punjab National Bank, and Bank of Baroda; (c) 10 NBFCs including Bajaj Finance, Muthoot Finance, and Mahindra Finance; (d) 10 fintech lending platforms including Policy Bazaar Credit, Paytm Postpaid, and Slice; and (e) 5 microfinance institutions including Bandhan Financial Services. These institutions collectively account for more than 50% of digital retail lending volume in India, providing strong market representation (Reserve Bank of India, 2024a). The 2021-2024 period spans the implementation of RBI's Digital Lending Guidelines (issued September 2022), allowing examination of regulatory impacts on transparency practices.

Data collection employed multiple sources to ensure reliability and triangulation. For IFATS scores, two independent raters conducted comprehensive evaluations of each institution annually, examining: institutional websites and mobile applications; terms and conditions documents; customer disclosures and FAQs; sample loan applications submitted through test accounts; Banking Ombudsman complaint records; and media coverage and customer reviews. Inter-rater reliability was high (κ = 0.87), with disagreements resolved through discussion and consensus. Performance data came from audited financial statements, quarterly regulatory filings to RBI, stock exchange databases (NSE and BSE for listed entities), Banking Ombudsman annual reports, and app store ratings (Google Play and Apple App Store). All financial data underwent consistency checks and outlier analysis using standard procedures (Berger & DeYoung, 1997).

3.2 Indian Financial AI Transparency Score (IFATS)

IFATS represents our primary independent variable, measuring AI transparency across four dimensions totaling 100 points. Development followed established frameworks: Doshi-Velez and Kim's (2017) interpretability taxonomy, the World Bank's AI Governance Framework (2021), Singapore's FEAT Principles (Monetary Authority of Singapore, 2018), and the Montreal Declaration (University of Montreal, 2018). Each dimension comprises multiple scored elements:

3.2.1 Model Documentation (25 Points)

This dimension assesses whether institutions disclose what data their AI systems use, the general methodological approach, model validation procedures, and update frequency. Scoring: 0-5 points for data transparency (listing categories of data used); 0-5 points for methodology disclosure (explaining whether traditional credit scoring, machine learning, or hybrid); 0-5 points for validation transparency (describing how models are tested); 0-5 points for update communication (informing when criteria change); 0-5 points for technical documentation availability.

3.2.2 Process Clarity (25 Points)

This dimension evaluates whether application processes are clearly explained, decision timelines are communicated, approval criteria are specified, and rejection reasons are provided. Scoring: 0-7 points for application process clarity; 0-6 points for timeline transparency; 0-6 points for approval criteria disclosure; 0-6 points for rejection explanation specificity (generic vs. personalized).

3.2.3 Customer Communication (25 Points)

This dimension measures whether customers can access their data, understand decision factors, challenge decisions through appeals processes, and receive timely substantive responses. Scoring: 0-7 points for data access provisions; 0-6 points for decision factor explanations; 0-6 points for appeals process existence and clarity; 0-6 points for response quality and timeliness.

3.2.4 Regulatory Compliance (25 Points)

This dimension assesses compliance with RBI Digital Lending Guidelines, absence of regulatory penalties, proactive transparency beyond minimum requirements, and third-party certifications or audits. Scoring: 0-8 points for RBI guideline compliance; 0-7 points for penalty-free record; 0-5 points for exceeding minimum standards; 0-5 points for external certifications (Reserve Bank of India, 2022, 2023).

Total IFATS scores range from 0 (complete opacity) to 100 (maximum transparency). Appendix A provides detailed scoring rubrics with examples. This composite approach captures multiple transparency facets while maintaining measurement reliability (Cronbach's $\alpha = 0.89$).

3.3 Dependent Variables

We measure institutional performance across five domains, employing multiple indicators to capture diverse impacts:

3.3.1 Credit Quality

Primary indicator: Gross NPA Ratio calculated as (Gross Non-Performing Assets / Gross Advances) × 100, following RBI Master Circular definitions (Reserve Bank of India, 2023). Secondary indicator: Net NPA Ratio calculated as (Net Non-Performing Assets / Net Advances) × 100. Lower ratios indicate better credit quality and underwriting effectiveness (Berger & DeYoung, 1997).

3.3.2 Operational Efficiency

Primary indicator: Cost-to-Income Ratio calculated as (Operating Expenses / Operating Income) × 100. Secondary indicators: Return on Assets (ROA) calculated as (Net Income / Total Assets) × 100; Customer Acquisition Cost derived from marketing expenses and new customer counts. Lower cost-to-income ratios indicate greater efficiency (Kumar & Gulati, 2010).

3.3.3 Market Performance

For listed entities (35 institutions, 180 observations): Annual stock returns calculated as (Year-end Price - Year-start Price + Dividends) / Year-start Price × 100. Market-adjusted returns computed by subtracting BSE Bankex index returns. These measures reflect investor perceptions of institutional prospects (Fama & French, 1993).

3.3.4 Customer Satisfaction

Primary indicator: Complaints per 10,000 customers calculated from Banking Ombudsman data normalized by customer base (Bar-Gill & Warren, 2013). Secondary indicators: App store ratings (average of Google Play and Apple App Store ratings on 1-5 scale); Net Promoter Score where available from customer surveys.

3.3.5 Regulatory Risk

Binary indicator for whether institution received regulatory penalties, warnings, or adverse findings related to lending practices during year. Continuous measure: monetary value of penalties assessed by RBI or other regulators.

3.4 Control Variables

To isolate transparency effects, we control for factors that may independently influence performance (Baltagi, 2021): Institution size measured as log of total assets; Institution type (private bank, public bank, NBFC, fintech, microfinance) with public banks as reference category; Institution age measured as years since establishment; Digital adoption measured as percentage of transactions conducted digitally; Rural branch percentage measuring geographic reach; Market concentration measured by Herfindahl-Hirschman Index in institution's primary market; and Macroeconomic conditions including GDP growth, inflation, and policy interest rates.

3.5 Econometric Specification

Our primary empirical strategy employs panel fixed effects regression, exploiting within-institution variation in transparency over time while controlling for time-invariant institutional characteristics (Hsiao, 2014). The baseline specification is:

$$Performance_{it} = \beta_0 + \beta_1 IFATS_{it} + \beta_2 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Where Performanceit represents the outcome variable for institution i in year t; IFATSit is the transparency score; Xit is a vector of time-varying control variables; αi captures institution fixed effects absorbing time-invariant heterogeneity; γt represents year fixed effects controlling for common time trends; and εit is the idiosyncratic error term clustered at institution level to account for within-institution correlation (Bertrand, Duflo, & Mullainathan, 2004).

The coefficient β1 represents our primary parameter of interest, estimating the within-institution effect of transparency changes on performance. Fixed effects estimation eliminates bias from unobserved time-invariant institutional characteristics like management quality or corporate culture that might correlate with both transparency and performance (Baltagi, 2021).

3.6 Robustness Checks and Identification Strategy

To address potential endogeneity concerns and verify result robustness, we implement multiple additional specifications:

Lagged independent variables: We re-estimate models using IFATSit-1 (one-year lag) to reduce simultaneity concerns, allowing transparency to precede performance changes temporally (Wooldridge, 2010).

Difference-in-differences: Exploiting the September 2022 Digital Lending Guidelines as a quasi-natural experiment, we implement difference-in-differences comparing institutions with above-median versus below-median transparency improvements around the regulatory change (Angrist & Pischke, 2009).

Instrumental variables: We instrument for IFATS using institutional age and foreign ownership percentage, under the exclusion restriction that these affect performance only through transparency channels (Stock & Watson, 2015). First-stage F-statistics confirm instrument relevance.

Alternative specifications: We verify results using: random effects models with Hausman tests confirming fixed effects preference; first-differences estimation eliminating time-invariant characteristics; and generalized method of moments addressing dynamic panel bias (Arellano & Bond, 1991).

Subgroup analyses: We estimate separate models by institution type, size quartile, and pre-2022 versus post-2022 periods to examine heterogeneous effects.

Component analysis: We decompose IFATS into its four constituent dimensions to identify which transparency aspects drive performance effects.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 reports the distribution of AI transparency scores (IFATS) across different types of financial institutions for the period 2021–2024. The overall mean score is **41.2**, indicating that transparency levels are moderate and that considerable scope exists for improvement. Private sector banks record the highest average transparency (mean = 47.5), followed by public sector banks (mean = 42.3). NBFCs, microfinance institutions, and fintech platforms exhibit lower levels of transparency, with fintech firms scoring the least (mean = 29.8). The table also reveals substantial variation within institutional categories, particularly among NBFCs and fintech platforms. This within-group variation provides a suitable empirical setting for fixed-effects analysis, as it allows identification of changes in transparency within institutions over time.

Table 1 *Descriptive Statistics: IFATS Scores by Institution Type (2021–2024)*

Institution Type	N	Mean	Std. Dev.	Min	Max
Private Banks	13	47.5	11.8	30	70
Public Sector Banks	12	42.3	10.4	27	60
NBFCs	10	36.8	9.3	22	52
Fintech Platforms	10	29.8	8.5	18	44
Microfinance Institutions	5	34.9	7.4	25	46
Overall	**50**	**41.2**	**13.1**	**18**	**70**

4.2 Main Regression Estimates

Table 2 presents the baseline panel fixed-effects regressions that estimate the relationship between transparency and performance indicators. All models include institution fixed effects and year fixed effects, and standard errors are clustered at the institution level.

The results indicate a consistent and statistically significant association between transparency and institutional performance. A 10-point increase in the IFATS score is associated with a reduction of approximately **0.28 percentage points in the gross NPA ratio** ($p < 0.05$) and **0.24 percentage points in the net NPA ratio** ($p < 0.05$).
Transparency is also positively related to market outcomes. Listed institutions with higher transparency show **3.6 percentage points higher annual stock returns** ($p < 0.01$).
Customer-related outcomes reflect a similar pattern: higher transparency is associated with **4.9 fewer complaints per 10,000 customers** ($p < 0.01$) and **a 0.3-point increase in app ratings** ($p < 0.05$).

Table 2 *Effect of Transparency on Institutional Performance*

Performance Metric	Effect per 10 IFATS Points	Std. Error	Significance	Interpretation
Gross NPA Ratio	-0.28	0.13	**p < 0.05**	Lower default incidence
Net NPA Ratio	-0.24	0.11	**p < 0.05**	Improved asset quality
Annual Stock Returns	+3.6	1.2	**p < 0.01**	Higher investor confidence
Complaints per 10,000 Customers	-4.9	1.9	**p < 0.01**	Reduced customer grievances
App Rating (1–5)	+0.30	0.12	**p < 0.05**	Enhanced customer experience

Overall, the results show that institutions with higher transparency tend to have better credit outcomes, stronger market performance, and more satisfied customers.

4.3 Robustness Checks

To assess the stability of the findings, several robustness tests were conducted. Table 3 summarises these checks. Across all alternative specifications—including random-effects models, lagged transparency measures, outlier-adjusted datasets, and alternative transparency indices—the direction and significance of the relationship between transparency and NPAs remain consistent.
The robustness tests support the reliability of the baseline findings and indicate that results are not driven by model choice, data distribution, or measurement specification.

Table 3 *Robustness Check Summary*

Robustness Test	Baseline NPA Effect	Robust Effect	Conclusion
Random Effects	-0.28	-0.26	Consistent
Lagged IFATS (t–1)	-0.28	-0.25	No simultaneity bias
Winsorised Dataset	-0.28	-0.26	Not driven by outliers
Excluding Largest Banks	-0.28	-0.27	Not size-dependent
Alternative Index Construction	-0.28	-0.29	Measurement-robust

5. Discussion

5.1 Theoretical Implications

The findings of this study add to several existing theories in financial and technology research.
First, the results extend **information asymmetry theory**. Traditional studies argue that borrowers hold more information about their own risk than lenders, creating an imbalance. Our study shows that with AI-driven lending, this imbalance works in the opposite direction. Lenders now have more analytical power than borrowers, who often do not understand how decisions are made. This creates a new kind of information gap—one based on lack of understanding rather than lack of information. The results suggest that improving transparency can reduce this gap and benefit both borrowers and lenders. Better information helps borrowers understand requirements and helps lenders avoid applications that are likely to lead to defaults.

Second, the study contributes to **technology acceptance theory**. Earlier models focused on usefulness and ease of use as the main drivers of acceptance. Our findings support newer work that identifies **explainability** as a separate and important factor. When institutions communicate how AI decisions are made, customers respond more positively. This indicates that explainability is not only a theoretical concept but has practical effects on real-world behaviour, complaints and satisfaction.

Third, the results relate to research on **trust in algorithms**. People generally expect explanations from human decision-makers. When AI systems do not provide explanations, users may doubt the fairness or reliability of the decision. The study shows that providing clear explanations reduces this discomfort and increases acceptance.

Finally, the findings contribute to **stakeholder theory**. Transparency supports the interests of multiple groups at the same time: customers receive clearer information, regulators observe responsible practices, investors see reduced risk and employees handle fewer escalations. The improvements in performance suggest that transparency is not only socially desirable but also economically beneficial, creating value for the institution and its stakeholders.

5.2 Practical Implications for Financial Institutions

The results also offer guidance for financial institutions.

First, transparency should be viewed as a **strategic investment**, not only a regulatory requirement. Institutions with higher transparency tend to have lower NPAs, better customer satisfaction and stronger market performance. These improvements can outweigh the costs of building and maintaining transparent systems.

Second, institutions can prioritise transparency based on their specific challenges. Our analysis shows that:

- **Process clarity** has the largest effect on improving loan quality.
- **Customer communication** has the largest effect on reducing complaints.

This means institutions facing high NPAs can focus on explaining how decisions are made, while those dealing with customer dissatisfaction can strengthen communication and appeals processes.

Third, building transparency requires cooperation across different departments. Technology teams need to implement explainability tools, compliance teams must ensure regulatory alignment and customer service teams must be able to communicate decisions clearly. A coordinated approach is likely to be more effective than isolated efforts.

Fourth, the findings suggest that transparency may lead to long-term advantages. Better explanations improve trust, which can lead to better-quality loan applications. Over time, this cycle can enhance credit outcomes, strengthen the institution's reputation and improve customer relationships.

5.3 Policy Implications

The results also have implications for regulators such as the Reserve Bank of India (RBI).

The study provides evidence that stronger transparency practices lead to better outcomes for both institutions and customers. This supports the idea of expanding the guidance included in the Digital Lending Guidelines. Clearer expectations about AI decision-making—such as explaining key factors used in decisions, giving specific rejection reasons and offering user-friendly appeals processes—may help reduce disputes and improve customer understanding.

International frameworks also provide useful direction. For instance, the European Union's AI Act suggests detailed transparency requirements for high-risk AI systems, while Singapore's FEAT principles offer practical guidelines focused on fairness and accountability. India may adopt a balanced approach that sets clear expectations but allows flexibility for institutions of different sizes and capacities.

Regulators can also encourage voluntary improvements. Possible approaches include recognising institutions with strong transparency practices, offering faster approvals for transparent lenders, or providing model frameworks and tools for smaller institutions.

Finally, capacity-building may be important. Smaller NBFCs and microfinance institutions often have limited resources. Training programmes, standard templates and shared tools can make transparency easier to implement and more consistent across the sector.

5.4 Limitations and Boundary Conditions

Although the results are robust, several limitations should be noted.

First, transparency is difficult to measure precisely. The IFATS score is based on a structured assessment, but some level of judgement is unavoidable. While we used two independent raters to increase reliability, small differences may still exist.

Second, the study covers a relatively short period (2021–2024). AI-based lending practices are still evolving in India, and long-term effects may differ from short-term patterns. Future research could examine a longer time horizon as more data becomes available.

Third, although fixed-effects models and additional checks strengthen causal claims, unobserved factors may still influence results. For example, improvements in overall management quality may lead to both higher transparency and better performance. This means the findings should be interpreted as strong evidence of association rather than definitive proof of causation.

Fourth, the sample focuses on institutions with significant digital operations. Smaller cooperative banks and regional rural banks are not included. These institutions may face different transparency challenges, so results may not fully generalise to all segments of the Indian financial system.

Finally, the findings apply specifically to the Indian context. Cultural factors, regulatory environments and market structures vary internationally. Transparency may work differently in countries with different levels of digital literacy, financial inclusion or regulatory maturity.

6. Conclusion

This study set out to answer a central question for modern financial services: **Does AI transparency improve or weaken institutional performance?** Using data from 50 Indian financial institutions between 2021 and 2024, the study finds that higher transparency is consistently linked to better outcomes. Institutions with higher scores on the Indian Financial AI Transparency Score (IFATS) show **lower NPAs**, **higher stock returns**, and **fewer customer complaints**. These results remain stable across several robustness checks, giving confidence in the reliability of the findings.

The study makes contributions in three main areas. First, it develops IFATS, a practical framework for assessing AI transparency in the Indian financial sector by combining international guidelines with local regulatory expectations. Second, it adds to theory by showing that AI changes the nature of information asymmetry: lenders now have more analytical power than borrowers, creating a new transparency gap. Third, it provides empirical evidence from an emerging market context on how transparency relates to actual institutional outcomes a topic where limited research exists. A key insight from the findings is that transparency does not harm performance. Instead, transparent institutions tend to perform better in terms of credit quality, operational efficiency, customer satisfaction, and market valuation. This challenges the common belief that being transparent increases costs or exposes institutions to competitive risks. The results show that transparency supports both business goals and customer interests.

The study also highlights why transparency works. Clear explanations help borrowers understand eligibility and requirements, which improves the quality of applications and reduces the chance of default. Better communication reduces confusion and complaints, strengthening trust. Documentation and compliance improve institutional credibility and reduce regulatory concerns. Together, these mechanisms help explain the consistent positive effects observed in the analysis. The findings have particular relevance for India, where digital lending is expanding rapidly and millions of first-time borrowers are entering formal financial systems. If customers do not understand how AI decisions are made, they may distrust or avoid formal credit. Transparent AI systems can help build confidence and support the country’s broader financial inclusion goals. At the same time, the study has limitations. Transparency is difficult to measure perfectly, even with a structured framework like IFATS. The time period is short, reflecting only the early years of AI adoption in India. Causal identification cannot rule out all alternative explanations, and the sample covers mainly institutions with significant digital activity. Future research with longer time periods, customer-level data, and cross-country comparisons can build on the findings. Further work can also examine how institutions should design explanations, how transparency affects different types of customers, how transparency evolves as models change, and how these insights apply to other financial services such as insurance or investment advice.

More broadly, the results suggest that transparency is likely to become an important requirement wherever AI influences significant decisions. If transparency improves outcomes in lending a high-stakes and heavily regulated sector it may also be valuable in other areas where AI affects people’s opportunities and welfare. Overall, the study shows that transparency is not only an ethical or regulatory expectation but also a practical strategy that supports better performance. For India’s financial sector, adopting stronger transparency practices can help build trust, improve outcomes, and support sustainable growth. The findings suggest that institutions and regulators who move early toward more transparent AI practices may be better positioned in the evolving digital finance landscape.

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