International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 6, Nov-Dec-2026, PP: 01-05

From Digital Finance to Intelligent Finance: The Role of AI in Transforming India'S Financial Ecosystem

Prof. (Dr.) Sreekanth Sreedharan[1] Dr Dhanalakshmi (Associate Professor) [2] Ms Srija R[3]
Assistant Professor Department Of Management Studies
Lead College Autonomous, Dhoni, Palakkad

Abstract- India built its payment, identity and data-sharing rails first and is now placing artificial intelligence (AI) on top of them. This paper asks what happens when cheap, interoperable public infrastructure meets machine learning, and where machine decisions should stop and human judgement take over. It is a structured desk review of 2016–2026 sources: peer-reviewed studies, Reserve Bank of India (RBI) reports and directions, government releases, industry data (NPCI, Sahamati, Tracxn) and assessments by the FSB, BIS and IMF, coded into four themes: infrastructure, intelligence, risk and governance. The rails are now large enough to feed AI at scale. UPI handled 24,162 crore transactions worth ₹314 lakh crore in FY2025-26, and the Account Aggregator network facilitated ₹1.07 trillion of loans in FY2024-25. Adoption is still thin: only 20.8% of regulated entities surveyed by the RBI's FREE-AI committee used AI, although 67% wanted to. Risk is rising. Reported bank-fraud value roughly tripled to ₹36,014 crore in FY2024-25 while case numbers fell, and the RBI now ranks AI-enabled cyber attacks as the leading near-term threat. The paper proposes the Rails–Reasoning–Guardrails (3R) framework: AI creates lasting value in finance only when open infrastructure, model capability and trust-building regulation advance together, with human override and institutional accountability built into the guardrails. Five testable propositions follow. The paper's value lies in treating national digital public infrastructure, rather than the single firm, as the unit of analysis, and in showing that AI outcomes in an emerging market may depend more on the design of rails and guardrails than on the algorithms themselves.

Keywords: artificial intelligence; fintech; digital public infrastructure; Account Aggregator; responsible AI; India

I. INTRODUCTION

Ten years ago, a street vendor in kochi could not take a digital payment without a card machine and a merchant account. Today she displays a printed qr code, and her phone reads each payment aloud. Behind that small scene sits one of the largest financial-system design experiments anywhere. In fy2025-26, the unified

Payments interface (upi) processed 24,161.69 Crore transactions worth ₹314.23 Lakh crore, up from 18,586.60 Crore transactions a year earlier, and about 55 crore people have been onboarded (newkerala/ani, 2026). Upi now carries an estimated 84% of india's digital payments (business today, 2026).

The first phase of india's fintech story was about rails: aadhaar for identity, upi for payments and the account aggregator (aa) network for consented data sharing. The second phase is about reasoning. Banks, non-bank lenders, insurers and the regulator are putting machine-learning models on these rails to score credit, flag fraud, answer customers and supervise institutions. That raises a question the first phase did not. Payment rails are rule-based and auditable; ai models are probabilistic, adaptive and often opaque. When opaque models run on infrastructure used by hundreds of millions of people, their errors and biases can travel across the system. The rbi recognised this in august 2025 with its framework for responsible and ethical enablement of ai (free-ai), which sets out seven "sutras" and 26 recommendations (rbi, 2025a).

Most research on ai in finance studies one firm, product or model at a time. Far less asks how ai interacts with a country's public digital infrastructure, a gap that matters most in emerging markets where the state builds the rails and private firms compete on top of them. This paper (a) brings scattered regulatory, industry and academic evidence into one picture of ai in indian finance as of 2026, (b) proposes the rails–reasoning–guardrails (3r) framework, and (c) derives five testable propositions with implications for regulators, institutions and educators.

II. REVIEW OF LITERATURE

Fintech As A Structural Force. Arner, barberis and buckley (2016) traced how the 2008 crisis opened space for technology firms in finance, and philippon (2016) argued that fintech could lower the stubbornly high cost of intermediation if regulation allowed entry. Thakor (2020) concluded that fintech both competes with and complements banks. Two strands add caution: buchak, matvos, piskorski and seru (2018) linked part of us fintech lending growth to regulatory arbitrage, and frost, gambacorta, huang, shin and

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 6, Nov-Dec-2026, PP: 01-05

zbinden (2019) showed that bigtech lenders reach borrowers banks overlook but raise concentration concerns.

Ai in financial intermediation. Berg, burg, gombović and puri (2020) found that simple digital footprints predict default about as well as a bureau score, a striking result for countries where many borrowers have no credit history. Flexibility carries distributional risk: fuster, goldsmith-pinkham, ramadorai and walther (2022) found that machine learning raised accuracy but could widen gaps between groups, and bartlett, morse, stanton and wallace (2022) found that algorithmic lenders discriminated less than face-to-face lenders without removing discrimination. The common lesson is that ai improves prediction, while fairness and accountability depend on choices people make around the model.

Digital public Infrastructure and Risk. D'silva, filková, packer and tiwari (2019) described india's "stack" of identity, payments and data as a public-goods approach to digital finance, and alonso et al. (2023) Credited it with faster account ownership and lower costs. This work explains why the rails grew fast but says little about ai layered on them. On risk, danielsson, macrae and uthemann (2022) argued that models trained on similar data tend to herd and fail together, and the financial stability board (fsb, 2024) named third-party concentration, cyber risk and model risk as the main ai vulnerabilities. Adoption theory (davis, 1989; venkatesh, morris, davis & davis, 2003) treats facilitating conditions and trust as drivers of uptake, but rarely links them to public rails and regulation.

Gap. Three gaps follow: few studies treat national infrastructure as the unit through which ai value and risk are created; most evidence on algorithmic credit and systemic risk comes from the us, europe or china; and the infrastructure, ai and regulation literatures run largely in parallel.

1. Research questions and method

The study asks: **Rq1** How large and mature are india's fintech rails as a base for ai? **Rq2** Where, and how widely, do indian institutions and the regulator use ai? **Rq3** What new risks does ai bring, and how is regulation responding? **Rq4** What framework explains the joint effect of infrastructure, ai and governance? A qualitative, conceptual design built on structured desk research suits these questions, because the field moves faster than primary surveys and much of the best evidence sits in regulatory and industry documents. Sources published between january 2016 (upi's launch) and october 2026 were included if they addressed ai, fintech or digital infrastructure in finance, came from an identifiable institution and reported checkable data. Press reports were used only to locate official figures, and the originating body is named. Evidence was extracted into a common matrix, coded into four themes (rails, reasoning, risk and guardrails) and then combined into a conceptual model. The study uses only public material and involves no human participants.

2. Findings

Rails: scale is no longer the constraint (RQ1)

Table 1. Scale of India's financial digital rails

Rail	Indicator and value	Period	Source
UPI	24,161.69 crore transactions worth ₹314.23 lakh crore	FY2025-26	NewKerala/ANI (2026)
UPI	55.49 crore users; 703 live banks (21 at launch)	2026	Business Today (2026)
Account Aggregator	115.8 million consented data transactions; ₹1.07 trillion across 12.2 million loans	FY2024-25	Business Standard (2025b)
Unified Lending Interface	600,000+ loans worth about ₹27,000 crore	to Dec 2024	Angel One (2025)

Upi volume grew about 30% in one year, and every transaction leaves a time-stamped record of cash flows for merchants and households who never had a credit file. The aa network turns that record into usable credit data with the customer's consent. Non-banks lead: nbfcs accounted for 60.08% Of aa consents in fy2024-25 and private banks only 2.05% (Business standard, 2025b). The newest rail, the unified lending interface (uli), shows that rails alone do not guarantee use; lenders cited integration difficulties and regulatory caution, and the rbi reviewed the rollout in 2025 (angel one, 2025). Finding 1: the rails can feed ai at scale; the constraint has shifted to institutions' ability to use them.

3. Reasoning: adoption is real but shallow (RQ2)

The free-ai committee's survey found that only 20.8% Of regulated entities were using ai, mainly in customer support, sales, credit underwriting and cybersecurity, while a further 67% wanted to explore it (khaitan & co., 2025, Summarising

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 6, Nov-Dec-2026, PP: 01-05

rbi, 2025b). Credit scoring on upi and aa cash-flow data, chatbots in local languages and robo-advice are the visible uses. The regulator itself is building ai: the rbi innovation hub's mulehunter tool, Live in six banks with 15 more expected, had identified 90 fraud patterns with fewer false alerts than other platforms, though an official noted that "the model is still learning" and banks must supply their own data scientists (business standard, 2025a). These claims have not been independently verified. Capital is following: indian fintechs raised usd 2.4 Billion in 2025, with early-stage funding up 78% (ians, 2026). Finding 2: ai use is concentrated in a minority of institutions and functions, led by agile non-banks and, unusually, by the regulator.

4. Risk: the attack surface is growing (RQ3)

Table 2. Reported bank frauds, FY2023-24 vs FY2024-25

Category	Cases 2023-24	Amount 2023-24	Cases 2024-25	Amount 2024-25
All bank frauds	36,060	₹12,230 crore	23,953	₹36,014 crore
Card and internet frauds	29,082	₹520 crore	13,516	₹1,457 crore

Source: rbi annual report 2024-25, as reported by deccan chronicle (2025).

Card and internet fraud cases fell by more than half while their value nearly tripled. Fewer, larger and better-aimed attacks fit what generative ai makes cheap: convincing phishing, cloned voices and synthetic identities. The rbi's mid-2026 systemic risk assessment named ai-enabled cyber attacks the most important near-term challenge and flagged weak staff awareness and forensic readiness (outlook business, 2026). Less visible risks add to this: bias hidden in alternative-data models (fuster et al., 2022), Herding when many lenders depend on the same models and cloud providers (danielsson et al., 2022; Fsb, 2024), and growth driven by lighter rules rather than better technology (buchak et al., 2018). Finding 3: ai strengthens defenders and attackers alike, and its risks are becoming systemic rather than firm-specific.

5. Guardrails: India is choosing enabling regulation (RQ3)

India's response has three layers. The rbi (digital lending) directions, 2025, effective 9 may 2025, keep lenders responsible for outcomes when they outsource to apps and partners (rbi, 2025c). Free-ai (rbi, 2025b) sets out seven sutras, six pillars and 26 recommendations, including an ai sandbox, board-approved ai policies, ai inventories, incident reporting and disclosure to customers. The digital personal data protection rules, 2025, phased in over 12–18 months, govern the data on which financial ai is trained (deccan herald, 2025). Two sutras speak directly to the boundary between machine and human: customers must be told when ai is used and people keep final authority to override it, and the deploying institution stays accountable whatever the model's level of autonomy (khaitan & co., 2025). Another sutra prefers responsible innovation to cautionary restraint, extending india's infrastructure philosophy from payments to ai itself. Finding 4: the guardrails converge on open rails, accountable deployers and consented data, but implementation and enforcement remain untested.

6. The Rails–Reasoning–Guardrails (3R) framework

The findings point to one idea: ai's effect on a financial system depends on three layers moving together (figure 1). Rails supply consented data; reasoning turns it into decisions; guardrails set trust and accountability for every layer, including where human judgement must override the model. Rails without reasoning produce volume without insight, as in indian credit before 2020. Reasoning without rails produces clever models that Reach few people, as where data stays locked inside a few large firms (frost et al., 2019). Rails and reasoning without guardrails produce fast growth and then a loss of trust, as the digital-lending app episode showed.

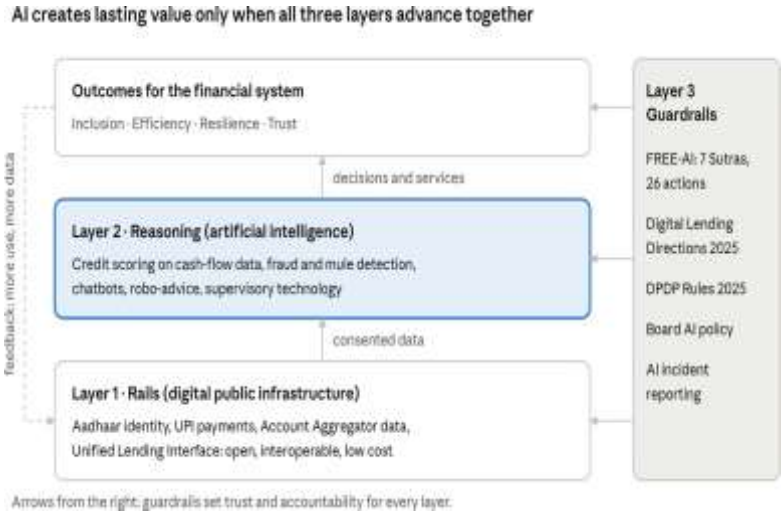

Figure 1. The rails–reasoning–guardrails (3r) framework (author's construction) the framework yields five propositions for empirical testing:

- P1. The more open and interoperable a country's rails, the cheaper ai adoption is for smaller institutions and the less it is concentrated among the largest firms.
- P2. Ai credit using consented cash-flow data expands lending to thin-file borrowers more than bureau-based models, without a proportionate rise in defaults.

- P3. The gains in p2 are fairer when guardrails require explainability, disclosure and human override.
- P4. Clear accountability of the deploying institution, including for third-party models, reduces conduct failures in ai-enabled lending.
- P5. As ai spreads across shared rails, risk shifts from single-firm failure to correlated model and cyber failure, so supervision must become system-wide.

7. Discussion and implications

In india the main driver of ai's impact on finance is the architecture the algorithms sit on, not the algorithms themselves. Berg et al. (2020) Showed that digital footprints carry credit signal; india has made a richer footprint, consented transaction data, available to every licensed lender. That explains why nbfcs and advisers, not the largest banks, dominate aa consents. The same architecture concentrates risk, turning danielsson et al.'S (2022) warning about herding into a national concern. By building tools such as mulehunter and proposing a shared sandbox, the rbi is supplying ai as well as supervising it, which goes beyond the "smart regulation" described by zetzsche, buckley, arner and barberis (2017). For theory, the national rail-and-guardrail system deserves to be treated as a unit of analysis, and in tam and utaut terms public rails act as a facilitating condition while regulation supplies institutional trust.

For regulators, the priority is closing the gap between 20.8% Use and 67% interest: publishing aggregate ai inventories, making uli work before building new rails, stress-testing concentration in shared models and cloud Providers (fsb, 2024), and applying the dpdp rules and free-ai together. For institutions, it means a board-approved ai policy, audits that reach partners' algorithms, clear points at which a person reviews and can overturn a model's decision, and investment in data scientists and forensic skills, since talent is the binding input. For business schools, graduates entering finance need working knowledge of digital infrastructure, model risk, data protection and responsible-ai governance.

III. LIMITATIONS AND CONCLUSION

This is a desk-based conceptual study, so it is only as good as the published evidence. System-wide data on ai use is scarce and rests mainly on the free-ai survey; some figures reach the public through press reports of official releases; and rules such as the dpdp rules are still being phased in. Future work should test the propositions with lender-level data, audit alternative-data credit models for fairness by gender, region and occupation, compare banks that adopt regulator-built tools with those that do not, and test whether disclosing ai use raises customer trust.

India spent a decade building some of the world's most-used financial rails. It is now deciding how intelligent those rails should become, and who answers when that intelligence fails. The rails are ready, adoption is real but shallow, risks are rising and becoming systemic, and india has chosen enabling, infrastructure-led guardrails. Ai will improve india's financial system only if the rails stay open, the reasoning stays accountable, and people keep the final say where judgement matters.

1. Declaration

This is original work. All statistics are traced to the sources listed below and none were estimated or imputed. The study uses only public material and involves no human participants.

REFERENCES

1. Alonso, C., Bhojwani, T., Hanedar, E., Prihardini, D., Uña, G., & Zhabska, K. (2023). Stacking up the benefits: Lessons from India's digital journey (IMF Working Paper No. 2023/078).
2. International Monetary Fund.
3. Angel One. (2025, July 17). RBI reviews ULI rollout with lenders amid slow lending adoption. https://www.angelone.in/news/rbi-reviews-uli-rollout-with-lenders-amid-slow-lending-adoption
4. Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of fintech: A new post-crisis paradigm? Georgetown Journal of International Law, 47(4), 1271–1319.
5. Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2022). Consumer-lending discrimination in the FinTech era. Journal of Financial Economics, 143(1), 30–56.
6. Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies, 33(7), 2845–2897.
7. Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics, 130(3), 453–483.
8. Business Standard. (2025a, August 1). 15 more banks to adopt RBI's MuleHunter fraud detection tool by October. https://www.business-standard.com/amp/industry/banking/15-more-banks-to-adopt-rbi-s-mulehunter-fraud-detection-tool-by-october-125080101845_1.html
9. Business Standard. (2025b, October 6). NBFCs, capital markets lead consents in account aggregator system. https://www.business-standard.com/finance/news/nbfcs-lead-account-aggregator-consents-in-fy25-with-60-share-125100600872_1.html

10. Business Today. (2026, August 24). 10 years of UPI: Transaction value surges 4,000-fold to reach₹314 lakh crore. https://www.businesstoday.in/india/story/10-years-of-upi-transaction-value-surges-4000-fold-to-reach-rs314-lakh-crore-550975-2026-08-24
11. Danielsson, J., Macrae, R., & Uthemann, A. (2022). Artificial intelligence and systemic risk. Journal of Banking & Finance, 140, 106290.
12. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
13. Deccan Chronicle. (2025, May 29). Bank fraud amount triples to ₹36,014 cr in FY25 despite fewer cases: RBI. https://deccanchronicle.com/nation/bank-fraud-amount-triples-to-36014-cr-in-fy25-despite-fewer-cases-rbi-1882116
14. Deccan Herald. (2025, November 14). Centre notifies DPDP Rules; implementation planned in phases spread over 12–18 months. https://www.deccanherald.com/amp/story/india%2Fcentre-notifies-dpdp-rules-implementation-planned-in-phases-spread-over-12-18-months-3798465
15. D'Silva, D., Filková, Z., Packer, F., & Tiwari, S. (2019). The design of digital financial infrastructure: Lessons from India (BIS Papers No. 106). Bank for International Settlements.
16. Financial Stability Board. (2024, November 14). The financial stability implications of artificial intelligence. FSB.
17. Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., & Zbinden, P. (2019). BigTech and the changing structure of financial intermediation. Economic Policy, 34(100), 761–799.
18. Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. The Journal of Finance, 77(1), 5–47.
19. IANS. (2026, January 16). India's fintech sector raises $2.4 billion in 2025, ranks third globally. https://ianslive.in/indias-fintech-sector-raises-24-billion-in-2025-led-by-surge-in-earlystage-deals--20260116135202
20. Khaitan & Co. (2025, August 28). ERGO: FREE-AI framework. https://www.khaitanco.com/sites/default/files/2025-08/Ergo%20-%20FREE%20AI%20Framework%20-%2028%20Augusut%202025.pdf
21. NewKerala / ANI. (2026, July 20). UPI user base reaches 55.49 crore; FY26 transactions at 24,161.69 crore. https://www.newkerala.com/news/a/upi-user-base-reaches-5549-crore-fy26-transactions-249.htm
22. Outlook Business. (2026, July 1). AI-enabled cyber attacks emerge as most important near-term challenge: RBI. https://www.outlookbusiness.com/amp/story/news/ai-enabled-cyber-attacks-emerge-as-most-important-near-term-challenge-rbi
23. Philippon, T. (2016). The fintech opportunity (NBER Working Paper No. 22476). National Bureau of Economic Research.
24. Reserve Bank of India. (2025a, August 13). RBI releases the report of the Committee to develop a Framework for Responsible and Ethical Enablement of Artificial Intelligence (FREE-AI) [Press release 2025-2026/902]. https://www.rbi.org.in/scripts/BS_PressReleaseDisplay.aspx?prid=61018
25. Reserve Bank of India. (2025b). Report of the Committee to develop a Framework for Responsible and Ethical Enablement of Artificial Intelligence (FREE-AI). https://rbi.org.in/Scripts/PublicationReportDetails.aspx?ID=1306
26. Reserve Bank of India. (2025c). Reserve Bank of India (Digital Lending) Directions, 2025. RBI.
27. Thakor, A. V. (2020). Fintech and banking: What do we know? Journal of Financial Intermediation,41, 100833.
28. 30. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.
29. 31. Zetzsche, D. A., Buckley, R. P., Arner, D. W., & Barberis, J. N. (2017). Regulating a revolution: From regulatory sandboxes to smart regulation. Fordham Journal of Corporate & Financial Law, 23(1), 31–103.