Embedded Finance and the Reconstruction of Credit Infrastructure in India: Co-lending, the Account Aggregator Network, and the Political Economy of Digital Credit

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Abstract. India's credit market stands at a structural inflection point. Decades of supply-side constraint — characterised by rigid collateral requirements, high transaction costs, and an entrenched informational asymmetry between lenders and thin-file borrowers — have left an estimated credit gap of ₹25–37 trillion for micro, small, and medium enterprises alone, and a comparable shortfall for underserved households. This paper argues that three concurrent innovations — the embedded finance paradigm, the Reserve Bank of India's Co-lending Model, and the Account Aggregator (AA) consent-based data framework — are collectively reconstructing India's credit infrastructure from first principles. This paper examines role of technology in reshaping the India's credit ecosystem using the reports of Reserve Bank of India and SIDBI. This study explores the role of digital platforms in reaching customers with low cost and simple borrowing process. Co-lending process improved the access to finance, consent based financial information sharing and informed credit assessment against the convention credit histories. Co-lending facilities offered by the banking and non-banking institutions supported the underserved borrowers and ensured fairness and transparency in the credit decision. This paper aims to propose a digital framework and transparent lending practices to facilitate the financial inclusion and develop a digital credit eco system in India.

Keywords: *embedded finance, co-lending, Account Aggregator, credit infrastructure, MSME finance, digital public infrastructure, regulatory sandboxes, fintech India, ULI, alternative data.*

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1 Introduction

Lack of access to formal credit has affected the productive activities and restricted the expansion of small enterprises and prevented the economically viable opportunities among low-income households. Nationalization of major banks were the outcome of recognizing the importance of credit for inclusive economic growth. Priority sector lending and programme like Pradhana Mantri Jan Dhan Yojana expanded the credit facility to the economically backward class and people excluded from the formal system. These schemes have offered timely and adequate credit support to the small entrepreneurs, informal workers lacking sufficient collateral. Financial inclusion programme ensured inclusive and efficient lending mechanism and savings gave a chance to participate in participate in financial system. Yet the credit gap persists. The Reserve Bank of India's 2023 Report on Currency and Finance estimates that formal credit reaches fewer than 16% of MSME units, and that the aggregate demand-supply gap for this segment alone stands at approximately ₹37 trillion [1]. For rural households, the World Bank Findex 2021 records that only 11% of adults in the lowest income quintile borrowed from a formal financial institution in the preceding year [2]. These figures are not simply a demand-side story: they reflect a structural failure in credit intermediation — the inability of incumbents to generate reliable risk assessments for borrowers without conventional collateral or documented income histories.This paper contends that India is currently witnessing a genuine architectural shift in credit intermediation, driven by three interlocking innovations. First, the rise of embedded finance — the integration of financial products, including credit, directly into non-financial digital platforms — dramatically reduces the cost of borrower acquisition and enables continuous, contextual creditworthiness assessment. Second, the RBI's Co-lending Model (CLM), introduced in 2020, creates a structured mechanism through which banks' low-cost capital can be combined with NBFCs' last-mile origination capabilities, resolving the capital-cost paradox that has historically prevented small-lender scale-up. Third, the Account Aggregator network, operationalised from 2021, collapses the informational asymmetry between lenders and thin-file borrowers by enabling verified, machine-readable, consent-gated sharing of financial data from across a borrower's financial life. Taken individually, each of these innovations is significant. Taken together — and this is the central argument of the paper — they constitute a reconstruction of credit infrastructure: not the paving of new roads on existing terrain, but the laying of new tracks in new terrain. The implications for financial inclusion, for the competitive structure of Indian banking, and for the regulatory posture of the RBI are substantial and, as this paper will argue, not yet fully appreciated.

The paper is structured as follows. Section 2 reviews the theoretical and empirical literature on credit intermediation and digital lending. Section 3 analyses the embedded finance paradigm and its Indian expression. Section 4 examines the Co-lending Model's mechanics and outcomes. Section 5 assesses the Account Aggregator ecosystem. Section 6 maps the political economy of digital credit — who benefits, who is excluded, and who holds structural power. Section 7 identifies critical unresolved tensions. Section 8 proposes a second-generation policy architecture. Section 9 concludes.

2. Literature Review

2.1 The Economics of Credit Intermediation and Market Failure

The foundational theoretical framework for credit market failure is Stiglitz and Weiss [3], who demonstrate that asymmetric information between lenders and borrowers generates credit rationing as an equilibrium outcome: lenders cannot distinguish high-risk from low-risk borrowers ex ante, and raising interest rates to clear the market worsens adverse selection by deterring safe borrowers, producing a market where creditworthy borrowers are systematically excluded at any positive interest rate. The policy implication — that intervention to reduce information asymmetry, rather than interest rate liberalisation alone, is the appropriate remedy for credit market failure — remains as pertinent today as when first articulated.

Diamond [4] extends this analysis through the delegated monitoring theory of financial intermediation: banks exist because they specialise in producing costly information about borrowers, and their depositor-funded balance sheets provide the incentive to monitor loan performance ex post. The key insight for the fintech context is that intermediaries' value derives from information production and monitoring, not from balance-sheet size per se. Any institution — bank or non-bank — that can produce reliable borrower information at lower cost than incumbents can, in principle, displace them.

Petersen and Rajan [5] introduce the distinction between 'hard' and 'soft' information in small business lending: hard information (financial statements, credit bureau scores) is verifiable and transmissible; soft information (relationship history, character assessments, local knowledge) is not. They show that bank consolidation and distance erode soft-information advantages, explaining why credit to small firms declines as banking markets concentrate. The relevance to Indian fintech is direct: digital platforms, by generating continuous transactional data from merchant relationships, effectively convert previously soft information — a retailer's sales rhythm, a gig worker's income pattern — into hard, transmissible data assets.

2.2 Digital Lending: Evidence from Emerging Markets

The empirical literature on digital lending in emerging markets is expanding rapidly. Berg et al. [6] exploit a natural experiment in which a German lender used digital footprint data (email provider, device type, browser) to supplement traditional credit scoring, finding significant improvements in default prediction accuracy. While the German context differs substantially from India's, the methodological insight — that behavioural and contextual data carries credit-relevant signal — is widely generalisable.

Frost et al. [7] analyse BigTech credit provision across China, Kenya, and the United States, finding that BigTech lenders achieve lower default rates on equivalent loan terms because of superior data access through platform ecosystems, and that their credit expansions are less procyclical than bank credit — an economically significant finding given the amplification role of procyclical credit in financial crises. For India, the question of whether UPI transactional data and e-commerce merchant data generate comparable advantages is live and unanswered.

Claessens et al. [8] provide a systematic cross-country review of fintech credit models and their regulatory treatment, concluding that regulatory arbitrage — the tendency of fintech lenders to exploit gaps between regulatory perimeters — is the primary risk management challenge, and that activity-based rather than institution-based regulation is the appropriate response. This conclusion informs Section 7's analysis of India's regulatory architecture.

For India specifically, Agarwal and Zhang [9] analyse the credit expansion produced by a large Indian NBFC-fintech partnership, finding significant positive effects on consumption and investment for first-time borrowers, but also identifying over-indebtedness risks among borrowers who stack multiple short-tenure digital loans. Nair [10] documents the collapse of the microfinance sector in Andhra Pradesh in 2010 — a cautionary precedent for aggressive digital credit expansion without robust conduct regulation.

2.3 The Account Aggregator as Information Infrastructure

The consent-based data framework instantiated in India's Account Aggregator network draws on a growing literature on information infrastructure as a public good. Hirshleifer [11] established the theoretical tension between private incentives to produce information and social welfare: in credit markets, information that reduces adverse selection may not be privately profitable to produce if it cannot be appropriated. The Account Aggregator resolves this partially by creating a market structure in which financial information providers (banks, tax authorities, insurers) and financial information users (lenders) transact on a neutral platform, with the data principal (the borrower) controlling consent.

Allen et al. [12] survey the literature on credit information sharing and find consistent evidence that mandatory credit bureaus improve credit market outcomes — lower interest rates, higher credit access — but that their benefits disproportionately accrue to borrowers with established histories. The AA network addresses this limitation by extending the information set to include current account flows, tax filings, investment records, and insurance data, enabling creditworthiness assessment for borrowers with thin bureau files.

3. Embedded Finance: The New Origination Frontier

3.1 Concept and Architecture

Embedded finance refers to the seamless integration of financial services — payments, credit, insurance, investment — into non-financial digital platforms, without redirecting the user to a standalone financial service provider. The canonical model is Amazon's Buy Now Pay Later integration: a consumer completes a purchase and activates credit in the same transactional flow, with the credit decision made in milliseconds using the platform's proprietary data on the consumer's purchase history, return behaviour, and account standing.

In the Indian context, embedded finance is unfolding across a diverse platform ecosystem. E-commerce platforms (Flipkart, Meesho, Myntra) offer seller working-capital loans underwritten on GMV data. Ride-hailing platforms (Ola, Rapido) extend vehicle financing to driver-partners using trip history as a proxy for repayment capacity. Agriculture platforms (DeHaat, Ninjacart) embed input-purchase credit within procurement relationships, repaying loans through crop-sale proceeds in a structure that eliminates the cash-handling risk of conventional agricultural lending. Salary-advance apps (Refyne, Advance, EarlySalary) offer short-tenure credit to salaried employees of partner employers, recovering repayments through payroll deduction [13].

Table 1 presents estimated market sizing for the principal embedded finance segments in India, extrapolated from NASSCOM, Redseer, and PwC sector reports.

Segment	FY2021 (₹ Bn)	FY2023 (₹ Bn)	FY2025E (₹ Bn)	CAGR (%)
Embedded Payments	420	1,180	2,950	62.8%
Embedded Lending (BNPL + Co-lending)	140	680	1,840	90.2%

Embedded Insurance	38	112	310	68.7%
Embedded Investment/Wealth	22	74	198	72.9%
Total Embedded Finance	620	2,044	5,298	71.1%

Table 1: Indian Embedded Finance Market — Segment Sizing, FY2021–FY2025E. Sources: NASSCOM Fintech Landscape 2024; Redseer Fintech Report 2024; PwC India Embedded Finance Study 2023.

3.2 The Information Advantage of Platform Lenders

The economic logic of embedded finance is straightforward but powerful. Conventional lenders incur customer acquisition costs (CAC) estimated at ₹1,200–2,500 per borrower for digital channels and ₹4,000–8,000 for branch channels [14]. Platform lenders operating within an existing user relationship incur near-zero marginal acquisition costs: the borrower is already a platform user, their identity is verified, and their behavioural history is available. This cost advantage is not merely operational; it enables platform lenders to profitably serve smaller loan sizes and higher-risk borrower segments that would be uneconomical for conventional lenders to underwrite.

The information advantage compounds this cost advantage. A logistics platform that tracks a small transporter's daily shipment volumes, fuel costs, and client payment schedules has a richer, more current picture of that transporter's cash flows than any bank credit analyst could construct from quarterly financial statements. This dynamic — where operational data generated within a platform relationship constitutes a superior credit signal relative to retrospective financial reporting — is what distinguishes embedded lending from conventional digital lending, and it is why the largest platform lenders globally (Alibaba's Ant Group, Amazon Lending, Grab Financial) have achieved default rates significantly below comparable market benchmarks [15].

3.3 Risks and Structural Concerns

The access to credit is enhanced the by the growth of digital commerce platforms. Merchants having access with online platforms received a great access to source of income and sustained credit facility. Digital banking has minimized the economic vulnerability and guaranteed greater access to market for micro and small enterprises.

4. The structural Problem it Addresses

Prior to the introduction of the Co-lending Model in 2020, Indian NBFCs faced a fundamental structural constraint: they were better than banks at originating credit in underserved segments — rural MSMEs, self-employed individuals, agricultural borrowers — because of their local presence, relationship networks, and operational agility, but their cost of capital was 200–400 basis points higher than banks, preventing them from offering competitively priced loans to price-sensitive borrowers [16]. Banks, conversely, had low-cost deposits and regulatory capital advantages but lacked the origination infrastructure to reach priority-sector segments efficiently.

The Co-lending Model, introduced through the RBI's November 2020 circular, creates a structured partnership in which a bank and an NBFC jointly disburse loans in a specified risk-sharing ratio (minimum 80% bank, maximum 20% NBFC for the mandatory portion). The bank contributes capital at its lower cost; the NBFC contributes origination, underwriting, and collection capability. Interest rates to the borrower are blended, yielding a rate lower than the NBFC could offer independently but accessible to borrowers that the bank could not reach independently. Priority-sector lending (PSL) classification attaches to the bank's portion, providing regulatory incentive for bank participation.

4.1 Empirical Outcomes

Table 2 presents the evolution of co-lending metrics between FY2020 and FY2024, drawn from RBI supervisory data, SIDBI reports, and industry disclosures.

Table 2: Co-lending Model — Key Performance Metrics, FY2020–FY2024.

Metric / Year	FY2020	FY2022	FY2024	Growth
Active Co-lending Partnerships	12	87	310	25.8x
Cumulative Disbursals (₹ Bn)	18	390	2,100	116.7x
Average Ticket Size (₹ '000)	95	64	42	–55.8%
New-to-Credit Borrowers (%)	18%	34%	51%	+33 pp
Average Loan Turnaround (Days)	9.4	3.2	0.9	–90.4%

Sources: RBI Supervisory Data; SIDBI MSME Pulse Report Q4 FY2024; Sa-Dhan Microfinance Industry Report 2024.

The data reveal three trends of analytical significance. First, the reduction in average ticket size — from ₹95,000 to ₹42,000 over four years — indicates that co-lending is successfully reaching smaller borrowers who were previously unserved by formal credit; this is not merely the formalisation of existing NBFC borrowers at lower cost. Second, the increase in new-to-credit borrowers (from 18% to 51% of the co-lending portfolio) confirms credit expansion rather than credit substitution. Third, the near-elimination of loan processing time — from 9.4 days to under one day — reflects the technology integration between bank and NBFC systems facilitated by the Account Aggregator framework and the API-based credit infrastructure that has developed around it.

4.2 The Unified Lending Interface

The RBI's Unified Lending Interface (ULI), piloted from August 2023 and announced for national rollout, represents the next architectural evolution beyond co-lending partnerships. ULI is conceived as a credit-market analogue to UPI: an open, interoperable platform on which any licensed lender can access a standardized borrower data package (AA-fetched financial data, land records, UIDAI identity verification, GST filings) and extend credit offers that borrowers can compare and accept in a single digital flow [17].

If successfully implemented, ULI would accomplish for credit what UPI accomplished for payments: the elimination of bilateral partnership dependencies and the creation of a market where multiple lenders compete for each borrower's business on transparent terms. The systemic implications are profound — ULI could break the oligopolistic structure of priority-sector credit, reduce interest rate spreads, and extend formal credit to the estimated 63 million MSME units that currently have no formal credit relationship.

5. The Account Aggregator Ecosystem: Consent-Based Credit Intelligence

5.1 Architecture and Institutional Design

The Account Aggregator framework, regulated under the RBI's 2016 Master Directions for Non-Banking Financial Company — Account Aggregator, creates a supervised intermediary between Financial Information Providers (FIPs) — banks, tax authorities, insurers, mutual fund depositories — and Financial Information Users (FIUs) — lenders, financial advisers, wealth managers. The AA itself holds no data; it is a consent broker, routing encrypted data flows between FIPs and FIUs under explicit, granular, time-limited, and purpose-specific consent granted by the data principal [18].

By October 2024, nine AA entities were licensed, over 75 FIP institutions were live, and cumulative consent artefacts processed exceeded 100 million — a measure of the number of data-sharing transactions executed on the network. The AA ecosystem has been adopted for credit underwriting by over 40 banks and 120 NBFCs, with credit decisions using AA-fetched data accounting for an estimated 18% of all digital lending disbursals by value in H1 FY2025 [19].

5.2 The Information Asymmetry Collapse

The credit bureau system — CIBIL, Experian, Equifax, CRIF High Mark — captures repayment history on formal loans and credit cards. For the estimated 400 million adult Indians with no formal credit history, bureau scores are unavailable or unreliable. The AA network fundamentally expands the observable financial universe for these individuals by making the following data categories lender-accessible with borrower consent: bank statement flows (salary credits, recurring payments, average balance patterns), GST filings (revenue, input costs, compliance regularity), ITR data (declared income over three years), and mutual fund and equity portfolio values.

A practical illustration: a self-employed tailor operating from a small workshop in Varanasi has no formal employer, no credit card, and no prior loans. Her CIBIL score is zero. Her Jan Dhan savings account, however, shows a consistent monthly credit of ₹18,000–22,000 from retail fabric purchases and a pattern of prompt telephone, electricity, and insurance premium payments. Her ITR shows three consecutive years of declared income above the formal credit threshold for micro-business loans. Via the AA framework, a digital lender can access this evidence with her consent in under two minutes, price her loan accurately, and disburse within the day — an outcome that the conventional credit infrastructure could not achieve.

5.3 Limitations and Friction Points

The AA ecosystem faces significant adoption friction. Surveys by the Dvara Research Foundation [20] find that the majority of consent requests generated by lenders are declined or abandoned by users, reflecting low awareness of the framework's purpose and concern about data privacy. The user experience of the consent flow — navigating multiple applications across FIP and FIU interfaces — is materially more complex than a standard bank account sign-up, creating attrition that disproportionately affects low-literacy users. The very population for whom the AA promises the largest credit-access benefit is the population least equipped to navigate its consent interface.

6. The Political Economy of Digital Credit

6.1 Who Benefits from Credit Infrastructure Reconstruction?

The reconstruction of credit infrastructure described in the preceding sections is not distributionally neutral. Understanding who captures the gains — and who remains excluded — requires attention to the structural positions of different actors within the emerging credit ecosystem.

Digital lending platforms and NBFC-fintech hybrids are the primary beneficiaries of co-lending and embedded finance. They gain access to bank capital at regulated cost, retain fee income from loan origination and servicing, and build proprietary data assets as a by-product of credit relationships. Banks benefit from PSL target fulfilment without proportional operational expenditure and from technology risk offloading to NBFC partners. Borrowers — particularly first-time borrowers in underserved segments — gain access to formal credit at lower cost and with faster processing than was previously possible.

However, the distribution of gains within the borrower population is uneven. Urban, smartphone-literate, formally employed individuals who generate rich digital transaction histories benefit most from alternative-data underwriting. Rural, informally employed, feature-phone users — the population with the largest credit deprivation — remain at the margins of digital credit markets despite the infrastructure's theoretical reach. The MSME Pulse Report published jointly by SIDBI and TransUnion CIBIL [21] shows that digital lending growth has been concentrated in manufacturing and retail MSMEs in Tier 1 and Tier 2 cities, with agricultural and services MSMEs in Tier 3 and below remaining significantly underserved.

6.2 Women and Informal Workers: Structural Exclusion

Gender disaggregation of digital credit data reveals a striking exclusion. Women account for approximately 28% of digital loan disbursals by count, and their share of the total portfolio by value is lower still — approximately 19% — reflecting smaller average loan sizes [22]. The drivers of this exclusion are structural rather than individual: women's digital transaction histories are shorter and sparser than men's because of lower smartphone ownership, lower formal employment rates, and social norms that route household expenditure decisions through male household members even where women are the primary economic agents.

Informal workers — gig economy participants, domestic workers, street vendors — present an analogous challenge. Their income is real, regular, and verifiable in principle (through platform earnings records, UPI receipts, or utility payment histories) but is not yet consistently incorporated into mainstream credit models. The Self-Employed Women's Association (SEWA) and the Dvara Research Foundation have piloted credit models using SEWA's internal member records and UPI transaction data to underwrite loans for informal sector women; early results are promising but the models remain outside the mainstream AA framework [23].

6.3 Regulatory Timeline and Institutional Contestation

Table 3 situates the key regulatory events of the past decade within a chronology that reveals the oscillating pattern of Indian fintech regulation: periods of expansive enabling followed by corrective tightening when risks materialise.

Table 3: Regulatory Timeline — Indian Digital Credit Infrastructure, 2016–2024.

Year	Regulatory Event	Key Provision	Fintech Impact
2016	Payment Banks Licensing	Limited deposit-taking; payments focus	Airtel, Paytm, IPPB enter market
2018	P2P NBFC Framework	Platform registration; exposure caps	Faircent, i2iFunding legitimized
2020	Co-lending Model (CLM)	80:20 risk sharing, bank + NBFC	MSME credit democratised
2021	Account Aggregator Launch	Consent-based data sharing	Alternative credit scoring enabled
2022	PPI Circular (BNPL)	Credit loading on PPIs prohibited	ZestMoney collapse; model shift
2023	DPDP Act	Data principal rights; consent norms	Compliance overhead; AA realignment
2024	ULI Pilot	Public credit rail launched	Digital lending interoperability

Sources: RBI Circulars; Ministry of Finance Notifications; NPCI Guidelines.

The pattern visible in Table 3 is characteristic of what regulatory scholars' term 'reactive regulation' [24]: the regulator permits innovation to proceed within a permissive environment until adverse outcomes — consumer harm, systemic risk, market failure — become salient, at which point corrective intervention occurs. The PPI circular of 2022, which effectively eliminated the dominant BNPL model without notice, is a paradigmatic example: it resolved a genuine risk (unregulated consumer credit loading onto wallets) but imposed abrupt costs on both regulated entities and their customers.

7. Critical Unresolved Tensions

7.1 Algorithmic Bias and Explainability

The use of machine-learning models — gradient boosting, deep learning, large language model-based document parsing — in credit underwriting raises fundamental questions about fairness and explainability. A credit model trained on historical lending data inherits historical biases: if women, informal workers, or certain geographic communities have historically been underserved by formal credit, a model trained to predict default on historical loan performance data will reflect those exclusions in its feature weights. The technical literature on algorithmic fairness — Dwork et al. [25], Hardt et al. [26] — distinguishes between individual fairness (similar individuals receive similar outcomes), demographic parity (approval rates are equal across groups), and equalised odds (false positive and false negative rates are equal across groups). These criteria are mathematically inconsistent, meaning that a model that satisfies one fairness criterion necessarily violates others in any real data environment.

For Indian regulators, the practical implication is that algorithmic fairness cannot be mandated by specifying a single fairness criterion; it requires ongoing audit of model outputs against observed demographic outcomes, with mechanisms to detect disparate impact before it crystallizes into large-scale exclusion. The RBI's 2024 discussion paper on AI in financial services acknowledges the explainability problem but does not yet propose mandatory bias audit requirements [27]. This is a significant regulatory gap given the speed at which ML-based credit decisions are scaling.

7.2 Platform Concentration and Systemic Risk

The embedded finance model generates a structural tendency toward concentration: platforms that accumulate more users accumulate more data, which improves their credit models, which attracts more borrowers, which generates more data. This dynamic — a data network effect amplifying a user network effect — is the credit market analogue to the concentration already observed in UPI (where PhonePe and Google Pay command approximately 85% of transaction volume) [28].

In credit markets, concentration risk is systemic as well as competitive. If a small number of embedded lending platforms account for a large fraction of digital credit disbursals to a particular sector — say, agricultural lending through three dominant agri-tech platforms — then the failure, withdrawal, or algorithmic malfunction of any one of those platforms could produce a significant and sudden contraction of credit to that sector. This is not a hypothetical concern: the collapse of ZestMoney in 2023, which had served approximately 12 million borrowers, created genuine distress among borrowers seeking short-tenure credit for medical and educational expenses with no comparable alternative [29].

7.3 The Over-Indebtedness Risk

The speed and convenience of digital credit, while economically valuable, also lowers the psychological and transactional friction that historically served as a natural brake on borrowing. Research by the Centre for Financial Inclusion [30] documents the emergence of a 'multi-lender stacking' pattern among digital borrowers: individuals who simultaneously carry loans from three or more digital lenders, with combined EMI obligations that exceed their demonstrated repayment capacity. Bureau data for FY2024 shows that approximately 7.2 million digital borrowers carry active loans from four or more lenders, up from 2.1 million in FY2021 [31].

Stacking is partly a consequence of real-time bureau refresh limitations: a borrower can apply to multiple lenders within a 24-hour window, each of whom sees a clean bureau at the time of their individual query. The RBI's proposed real-time bureau inquiry data sharing — under which lenders would see pending applications in addition to existing liabilities — would close this window. Implementation, however, requires all major bureaus and digital lenders to integrate into a common real-time query infrastructure, an undertaking complicated by competitive incentives and technical heterogeneity.

8. A Second-Generation Policy Architecture for Digital Credit

8.1 From Reactive to Adaptive Regulation

The central regulatory challenge in digital credit is not the absence of regulatory intent — the RBI has demonstrated sustained commitment to financial stability and consumer protection — but the structural lag between financial innovation cycles and regulatory response cycles. A fintech product can move from pilot to national scale within 12–18 months; a regulatory consultation, impact assessment, and circular issuance process routinely takes 24–36 months. In this temporal mismatch lies the space for regulatory arbitrage.

An adaptive regulatory architecture would have three components. First, technology-specific supervisory capacity: a dedicated RBI fintech supervision division staffed with data scientists capable of conducting real-time algorithmic audits, rather than relying exclusively on self-reported compliance data. Second, a standing fintech regulatory sandbox with automatic transition rules: innovations that pass sandbox thresholds within defined timeframes receive provisional licensing automatically, rather than awaiting formal circular issuance. Third, a cross-regulator fintech coordination committee — encompassing RBI, SEBI, IRDAI, and the Ministry of Finance — with the authority to issue joint guidance on cross-sectoral products such as investment-linked insurance, credit-linked savings, and hybrid payment-lending instruments.

8.2 Mandatory Fairness Audits and Explainability Standards

The RBI should mandate, for all lenders using ML-based credit scoring affecting priority-sector populations, biannual third-party algorithmic audits assessing: (i) disparate impact by gender, geographic category, and income decile; (ii) accuracy and stability of alternative-data features across economic cycles; (iii) explainability of adverse credit decisions, including a plain-language account of the primary factors driving rejection, accessible to the borrower within 48 hours of a declined application. The adverse action notice requirement already exists under the Credit Information Companies Regulation Act for bureau-based rejections; extending it to alternative-data models is a natural regulatory evolution.

For lenders above a defined disbursal threshold, explainability should be operationalised using interpretable ML methods — SHAP (SHapley Additive exPlanations) values, LIME (Local Interpretable Model-agnostic Explanations) — that can generate borrower-specific factor attribution without requiring model disclosure. This approach preserves proprietary model confidentiality while enabling meaningful regulatory audit and borrower rights.

8.3 Building Credit Infrastructure for the Excluded

Reaching women, informal workers, and rural populations through the existing digital credit architecture requires both demand-side and supply-side interventions. On the demand side, the proposed Pradhan Mantri Digital Sakhi programme — a network of female digital finance facilitators operating at the gram panchayat level — should explicitly include Account Aggregator consent facilitation in its mandate, enabling rural women to activate their AA profiles with guided support.

On the supply side, the RBI should create a dedicated MSME Credit Support Facility under the ULI framework that pre-populates the data package for GST-registered micro-enterprises, reducing the data-fetching burden on borrowers in the ₹1–10 lakh ticket size range where the credit gap is most severe. A blended-finance mechanism — combining public risk guarantees from the Credit Guarantee Fund Trust for Micro and Small Enterprises (CGTMSE) with private NBFC capital within the co-lending framework — would enable commercial viability for loans in this size range without requiring interest rate subsidies.

8.4 Privacy-Preserving Credit Infrastructure

The long-term legitimacy of consent-based financial data sharing depends on the integrity of the consent framework and the security of data in transit. The implementation of federated learning — in which credit models are trained on locally held data without the data leaving the FIP's servers, and only model updates are aggregated centrally — would enable the informational benefits of data pooling without creating centralised data stores that constitute high-value breach targets. The technology is mature; the regulatory framework permitting its use in supervised financial applications requires articulation.

The DPDP Act 2023, once its implementing rules are finalised, will impose data minimisation requirements that may create tension with the AA framework's comprehensive data-sharing model. The Ministry of Electronics and Information Technology and the RBI should jointly clarify that purpose-limited, consent-gated, time-bounded AA data sharing is consistent with DPDP's data minimisation principle, rather than leaving this question to be resolved through adversarial regulatory interpretation after the fact.

9. Conclusion

India's credit infrastructure is being reconstructed at a speed and scale without precedent in the country's financial history. The co-occurrence of embedded finance's data advantages, the Co-lending Model's capital-cost resolution, and the Account Aggregator network's information asymmetry collapse creates a structural environment in which first-time formal credit access for previously excluded segments is, for the first time, commercially viable at national scale. The empirical evidence reviewed in this paper — the more-than-hundredfold growth of co-lending disbursals, the decline in average ticket size, the expansion of new-to-credit borrowers — confirms that the architecture is generating inclusion gains, not merely digitising existing credit flows.

These gains, however, are neither automatic nor equitable. The structural logic of platform-based credit intermediation creates concentration tendencies that, if unchecked, will reproduce the oligopolistic market structures that characterised the pre-digital era. The information advantages of embedded lending accrue primarily to urban, formally employed, digitally active borrowers, while the populations with the most acute credit deprivation — rural women, informal workers, agricultural households — remain at the margins of the digital credit ecosystem. The speed of credit disbursement, while economically valuable, generates over-indebtedness risks that require a regulatory response that the current framework does not yet provide.

The second-generation policy agenda for Indian credit infrastructure must, therefore, be more architecturally ambitious than a series of corrective circulars. It requires: adaptive regulatory capacity that moves at the pace of fintech innovation rather than behind it; mandatory fairness audits that make algorithmic bias visible before it scales; targeted supply- and demand-side interventions for excluded populations; and privacy-preserving data infrastructure that sustains the long-term legitimacy of consent-based financial intelligence.

India has demonstrated, through UPI, that state-built digital public infrastructure can achieve market transformation at a scale and pace that no private actor or regulatory mandate alone could produce. The Unified Lending Interface, if designed with the same architectural discipline and political commitment as UPI, has the potential to do for credit what UPI did for payments. Whether it will depend less on technology than on the quality of the institutional choices made in the next three to five years — choices about regulatory design, market structure, privacy governance, and the political prioritization of genuinely inclusive outcomes over aggregate headline metrics. This paper has attempted to illuminate those choices. The decisions themselves remain, as they must, in human hands.

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