

Configurational Analysis of Alternative Data Underwriting for Thin-File Borrowers In Digital Financial Services

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Configurational Analysis of Alternative Data Underwriting for Thin-File Borrowers In Digital Financial Services

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Abstract

This study addresses the systemic credit exclusion of thin-file consumers in emerging financial markets by examining how alternative data infrastructures drive sustainable digital financial service delivery within India's Non-banking Financial Company (NBFC) ecosystem. Rather than viewing digital underwriting solely as a credit risk tool, we conceptualize alternative data analytics as a core financial services marketing innovation that reduces customer onboarding friction, expands market access and builds a long-term customer relationship. Using Fuzzy-set Qualitative Comparative Analysis (fsQCA) combined with a multi-case replication design of CRED and Paytm (FY2021-FY2025), this study identifies the configurational mechanisms underpinning sustainable service delivery. The analysis yields two principal findings: first, scalable customer acquisition and service sustainability are preserved through multiple equifinal configurations combining transactional velocity, zero-latency API syndication, and alternative data assets. Second, internal institutional risk governance acts as a mandatory necessary condition to prevent customer portfolio degradation, ensuring long-term institutional trust regardless of technological sophistication. By integrating Service-dominant (S-D) logic into the Technology-Organization-Environment (TOE) framework, the paper provides theoretical advances in financial services marketing while offering actionable strategies for Fintech platforms, NBFCs, and retail banking executives.

Keywords- Digital Underwriting, Non-banking Financial Companies (NBFCs), Retail Credit Sustainability, Risk Governance, Platform Ecosystems

JEL Codes- M31 (Marketing); M30 (Marketing & Advertising General); G21 (Banks, Other Depository Institutions); O33 (Technological Change: Choices & Consequences)

1. Introduction

In modern financial services marketing, high customer acquisition friction and information asymmetry remain primary barriers to expanding retail market share in emerging economies. This onboarding barrier is acutely felt among “thin-file” young consumers—specifically individuals aged 18-28 with verified earning potential who lack traditional credit bureau footprints. Traditional financial services onboarding relies heavily on retrospective bureau scores, resulting in severe drop-off rates, marketing inefficiencies, and systemic credit exclusion for prime target segments. However, alternative data footprints generated via real-time Unified Payments Interface (UPI) flows, mobile wallet interactions, and e-commerce transactions present an unprecedented financial marketing opportunity. By deploying alternative data analytics, financial service providers can substitute legacy friction points with zero-latency onboarding, enabling personalized product recommendations, inclusive credit access, and sustainable customer lifetime value (CLV) expansion.

To understand how digital financial service platforms can simultaneously expand customer access while maintaining sustainable lending performance, this study investigates the configurational mechanisms through which alternative-data infrastructures reshape financial service delivery for thin-file borrowers in Indian’s NBFC ecosystem. Rather than viewing digital lending solely as a credit risk management problem, the study conceptualizes it as a financial services innovation that enables customer acquisition, reduces onboarding frictions, enhances financial inclusion, and creates value through data-driven service personalization. Drawing upon the Technology-organization-Environment (TOE) framework, the study employs Fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify multiple configurations through which technology capabilities, organizational governance, and ecosystem partnerships jointly support sustainable digital financial services. The configurational findings are subsequently validated through comparative case replication using CRED and Paytm, thereby illustrating how distinct platform strategies can successfully deliver inclusive, scalable, and sustainable digital financial services.

2. Review of Literature

Payments design; platform intermediation and risk management have revolutionized emerging market financial architectures. While many underwriting methods utilize their computers for making decisions, their approach is to use fixed credit bureaus that routinely refuse to service “thin-file” consumers. But in the digital lending world, non-conventional data architectures can be used instead to create a customer's historical credit scores or other collateral. In order to capture this structural change, this section brings together the current literature to form a condensed and synthesised view, organised around three thematic pillars according to the Technology-Organization-Environment (TOE) model. This framework reflects not a linear output of credit sustainability, but as a phenomenon arising from a systemic process of co-conforming of technological competencies, the risk thresholds of the organization, and the syndications within the environmental ecosystem.

2.1. Technology: Fintech, Alternative Data & Thin-file Underwriting

Automated financial applications indicate a potential shift in the way capital is allocated, or moving from a compliance-based, backward-looking approach to an algorithmic, future-looking predictive approach to managing risk (Nobanee et al, 2024; Shetabi et al., 2024). Credit risk optimisation at near real-time and no delay requires hundreds of atypical behavioural variables processed by special architectures for feature selection. But with the emergence of new platforms for lending, new avenues of institutional susceptibility are also being created that can only be examined in detail in the context of a highly digitised emerging economy. This information asymmetry concept is the main constraint for retail credit growth, and it is acutely felt in the thin-file borrower cohort as selection risk. The recent works of corporate finance show that a network-based method with a credit profile based on a graph allows for the construction of an accurate proxy of financial discipline. High-speed APNs, such as Unified Payments Interface (UPI) in India, provide NBFIs with immediate access to consumers' transactional flows, thereby validating consumers' liquidity on the spot, without the need for lengthy verification procedures. In the TOE context, the technological aspect translates nearly imperceptible, unstructured behavioural footprints (UPI_Data) into usable and measurable data, which will serve as building blocks for institutional underwriting models.

2.2. Organization: Risk Governance & NBFC Stability

With alternative data engines, borrower visibility is significantly enhanced, but algorithmic capacity is still limited by internal corporate governance framework and balance sheet compositions. Technological adoption has not been the equation for balance sheet safety, or for regulation compliance either, with the operational efficiency and technical stability of Indian NBFCs hugely varying. Empirical evidence of the risks of exploding growth of asset sizes in the shadow banking sector in India comes from past market shocks, like the one faced by IL&FS, which led to the default of its loans. Primary causes of systemic risk and wide-spread financial contagion are corporate mismanagement and unhedged asset-liability mismatches (ALM). Existing evidence from across the country indicates that stress for banks during periods of defaults can be tackled through a range of internal risk buffers, a wide and adequate policy provisioning framework, and greater attention to capital adequacy compliance rules to protect the institutions from sudden withdrawal of funds. So, organizational governance provides the basic precondition for the preservation of the portfolio over the long-term/*Low_NPA*

2.3. Financial Inclusion & Sustainable Platform Systems

Sustainable corporate actions are theorized based upon the common framework of TOE (technology, organizational adaptability, and external regulation and market) and are regarded as a middle ground in the context of the three domains. Sustainable behavior of the company is understood within the TOE framework's unified perspective of technology, organizational adaptability, and outside regulatory and market conditions, as a middle ground between the three domains. In emerging markets, the concept of product-led financial inclusion is integral to driving up retail assets growth and sustainable profitability of financial institutions.

Digital financial architectures show capacity to generate systemic sufficiency associated with broader sustainability targets and carbon reduction, by mitigating the structural frictions and removing transaction costs from the financial cycle (Li et al., 2025; Wang & Zhang, 2025). To scale in order to be sustainable in terms of the environment in pastures, agile and traditional models cannot exist in a single enclave. Agile FinTech startups and traditional legacy banks cannot sustainably distribute credit in the thin-file consumers category when operating in isolation.

From a financial services marketing perspective, sustainable digital lending extends beyond technological efficiency to encompass customer value creation through accessible, convenient, and trustworthy financial services. Digital platforms reduce customer acquisition costs, shorten onboarding time, improve service accessibility for previously excluded borrower segments, and facilitate personalized financial interactions through alternative-data analytics. Consequently., successful digital lending ecosystems emerge not merely from technological capability but from coordinated platform strategies that integrate customer-centric service innovation with institutional governance and regulatory legitimacy. Within this ecosystem, financial inclusion becomes both a marketing outcome and a strategic capability that strengthens long-term customer relationships while preserving portfolio sustainability

Table 1: Comprehensive Literature Synthesis & TOE Structural Mapping

Theoretical Literature Domain & Empirical Citations	Core Pillar Assignment	TOE Target Finance Variable Assigned	Direct Analytical Contribution to the Study's Underwriting Model TXT
FinTech Credit Evolution & Transformation (Das, 2019; Nobanee et al., 2024; Shetabi, 2024; Gaviyau & Godi, 2025)	Technology	UPI_Data	Establishes the structural transition from historical credit bureau registries to dynamic, machine learning-driven feature selection models for predictive retail risk management.
Alternative Data Foundations & Asymmetry Resolution	Technology / Environment	UPI_Data	Demonstrates how alternative graph networks, transactional velocities, and live digital footprints substitute for missing

	API_Synd	historical documentation within thin-file borrower segments.
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(Muñoz-Cancino et al., 2023; Viridi & Mer, 2023; Guo & Wang, 2025)

Governance & Systemic Risk Boundaries	Organization	Risk_Gov	Provides evidence of why rapid technological expansion may trigger credit volatility.
(Dutta et al., 2020; Karamallappanavar, 2024; Anestiawati et al., 2025; Awasthi & Shukla, 2025)		Low_NPA	
Sustainable Credit Systems & Ecosystem Syndication	Integrated TOE Framework Core	Low_NPA	Frames retail credit sustainability and capital accessibility as emergent properties arising from collaborative, well-capitalized, and regulated bank-fintech co-lending networks.
(Zheng et al., 2023; Grégoire & Guay, 2023; Hasan et al., 2024; Wang & Zhang, 2025; Offiong et al., 2025; Manu et al., 2025; Li et al., 2025; Wang et al., 2025)		Sustainable Inclusion	

Source: Authors' Literature Compilation

2.4. Research Gaps

Based on the literature synthesis in Table 1 and the overall connection to the mapping of the TOE framework, the following gaps were identified:

Gap 1: The Symmetrical Net-Effects Bias in Risk Modelling

Existing credit risk management literature predominantly employs traditional linear econometric models that isolate variables to evaluate their independent, symmetric net effects on portfolio quality. There is a severe lack of empirical research exploring causal asymmetry and equifinality, which shows how different combinations of technological and organizational factors can lead to identical portfolio outcomes.

Gap 2: The “Blind Digitalization” Fallacy in Thin-file Underwriting

While studies show alternative data footprints (e.g., UPI, transactional flows) successfully substitute for legacy bureau scores, they frequently treat predictive analytics as an untethered solution for infinite credit expansion. Current literature lacks empirical evidence defining the structural boundaries where technological data capacity fails if decoupled from strict internal governance and capital adequacy frameworks.

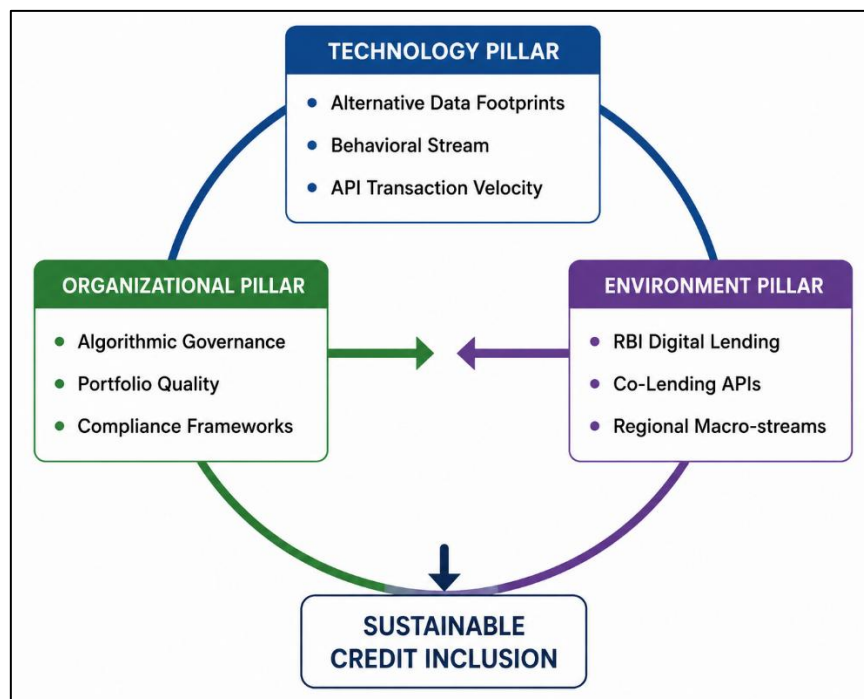
Gap 3: Fragmentation of Strategic Credit-Delivery Archetypes

Financial Inclusion literature often separates niche, high-value credit strategies from high-volume micro-lending networks. There is no unified, system-level framework that validates how these opposing market strategies (Precision v/s/ Scale) can function as equifinal pathways that interact with co-lending API networks to route alternative data originations into heavily capitalized institutional balance sheets

3. Theoretical Foundations & Conceptual Framework

The Technology-Organization-Environment (TOE) approach is well applicable in the case of digital lending and alternative underwriting models being offered in the NBFC products segment in India. The analysis of digital lending and alternative underwriting systems in the NBFC products segment can be examined using the Technology-Organization-Environment (TOE) model. The performance, asset quality and systemic sustainability of platform-based credit provision relied on a multi-dimensional structure of digital data infrastructures, self-regulation of credit risk on platforms, and the boundaries of the macroeconomic regulatory system framing digital commerce networks. The TOE model proposed by this study is, therefore, the primary theoretical lens used to examine the intersection of these different dimensions and how they work to promote responsible retail financial inclusion. Refer Figure 1.

Figure 1: Conceptual Framework on the TOE Synthesis



Source: Authors Compilation

To align with contemporary financial marketing paradigms, this study integrates Service-dominant (S-D) logic alongside the Technology-Organization-Environment (TOE) framework. S-D logic posits that financial service platforms do not merely deliver transactional credit products; rather they serve as value co-creation ecosystems where alternative data facilitates continuous, interactive customer engagement. Within this architecture, zero-latency API syndication acts as a service delivery pipeline, transforming raw behavioral streams into frictionless customer onboarding experiences. By framing alternative underwriting as a dynamic service capability, the model explicitly links front-end customer acquisition and trust preservation with back-end balance sheet governance.

3.1. The Three Core Pillars of the Conceptual Framework

- **The Technology Pillar:** Flows alternative data sourced from multiple different dimensions into ingestion, synthesis, and filtering of the structural infrastructure. This extends to ensuring the ability to process the high-velocity streams of UPI transactions, digital wallet velocities, mobile application interactions and e-commerce histories, all to reduce the information asymmetry that occurs at the bureau and to provide data visibility to the unscorable thin-file borrower.
- **The Organizational Pillar:** Concentrates on internal platform governance, corporate risk management mechanisms, and algorithmic safeguards that transform raw technological inputs into a stable credit decision. This pillar directly monitors the balance between the growth of operations and creation of credit, and the control of the quality of the portfolio (Gross NPAs) to also ensure long-term solvency of the institution.

- **The Environmental Pillar:** Describes the external conditions that will influence the ecosystem, such as new central bank regulations, macro-economic consumption vectors in tier-2 and tier-3 streams, and formal co-lending API syndication models connecting fintech platforms to the balance sheets of licensed NBFCs.

4. Research Boundaries & Configurational Hypothesis

4.1. Research Questions

- **RQ1:** What specific causal configurations of technological data infrastructures, organizational risk governance frameworks, and macro-environmental regulatory mandates are necessary or sufficient to achieve sustainable alternative-data credit underwriting for thin-file borrowers within the Indian NBFC ecosystem?
- **RQ2:** How do the set-theoretic interactions between alternative credit scoring and institutional corporate governance prevent portfolio asset quality degradation (Gross NPAs) while expanding retail credit access?
- **RQ3:** In what ways do the market-validated architectures of precision-driven networks (CRED) and scale-driven networks (Paytm) reflect distinct, equifinal pathways to sustainable credit inclusion under the TOE framework?

4.2. Research Objectives

- **RO1:** To systematically identify, calibrate and categorize multi-dimensional TOE variables shaping alternative credit assessment for thin-file, first time salaried segments within Indian's NBFC space
- **RO2:** To empirically test configuration solutions against causal asymmetries and equifinality using Fuzzy-set Qualitative Comparative Analysis (fsQCA), formulating an integrated framework that explains how platform-driven risk networks support credit asset stabilization
- **RO3:** To perform a comparative cross-case validation using CRED and Paytm to ground the empirical set - theoretical findings within active market-varying platform models

4.3. Configurational Hypothesis

- **Hypothesis 1 (H1):** High-velocity technological data architectures (Technology) are not globally sufficient on their own to achieve sustainable underwriting; their capacity to maintain low gross NPAs depends on a set-theoretic combination with stringent internal risk governance (Organization) and tight regulatory alignment (Environment).
- **Hypothesis 2 (H2):** Multiple equifinal configurations of alternative-data platforms and institutional risk governance exist that can produce sustainable financial inclusion, demonstrating that diverse platform operational strategies can achieve systemic stability.
- **Hypothesis 3 (H3):** Causal asymmetry exists within the underwriting ecosystem, meaning that the configurations leading to successful portfolio sustainability differ fundamentally from the configurations that cause asset quality degradation and corporate mismanagement.

5. Research Methodology

To capture the complex non-linear realities of India's digital credit markets, this study deploys Fuzzy-set Qualitative Comparative Analysis (fsQCA) as its principal empirical methodology. Traditional linear econometric models operate under symmetric assumptions that evaluate the independent, isolated net effects of variables on an outcome. However, real-world finance environments are characterized by equifinality (where multiple distinct combinations of factors lead to the same outcome) and causal asymmetry (where the causes of an outcome's success differ from the causes of its failure). By operating through set theory and applying the Quine-McCluskey Boolean minimization algorithm, the fsQCA models these systemic relationships without imposing symmetric net effect assumptions. Consistent with fsQCA's case-oriented logic, the objective of the study is not statistical generalization to all Indian lending institutions, but analytical generalization regarding the configurational

mechanisms through which technology, governance and ecosystem syndication jointly produce sustainable credit outcomes.

5.1. Institutional Data Calibration Protocols

The empirical corpus spanning corporate disclosures, central bank regulations, and publicly available industry data is calibrated into actionable fuzzy set scores ranging from 0.0 representing complete non-membership to 1.0 representing complete membership and the specific parameters (e.g., specific Gross NPA ratios, data velocity dimensions and compliance auditing metrics). Consistent with established fsQCA practice, 0.80 was treated as the minimum benchmark for assessing sufficient configurations. Following construction and inspection of the empirical truth table, a more conservative raw consistency cutoff of 0.964 was applied in the final sufficiency analysis to distinguish configurations strongly associated with the outcome

The study relies on secondary institutional and regulatory data obtained from publicly accessible sources. No surveys, interviews, experiments, or other forms of human participants data collection were undertaken for empirical analysis. Applying these theory driven constraints produces a bounded set of 20 comparable institutions while reducing structural heterogeneity and limiting the number of logical remainders in the configurational analysis. The resulting sample nevertheless remains subject to the survivorship and disclosure related limitations acknowledged in Section 9.1.

5.2. Case Selection, Boundary Violations & Sample Purpose

5.2.1. The Case Selection Strategy & Purposive Sampling

While a sample size of $N = 20$ is consistent with the case-oriented logic of small-N fuzzy-set Qualitative Comparative Analysis (fsQCA) (Greckhamer et al., 2013; Ragin, 2008), case selection was based on a theoretically bounded and purposive sampling strategy rather than empirical convenience. Within the Indian digital credit ecosystem, eligible cases were identified using three predefined inclusion criteria. First, the entity was required to operate digital retail-credit processes in which automated underwriting, transactional data, or API-enabled credit infrastructure forms a meaningful component of credit assessment delivery. Second, sufficient publicly accessible financial and institutional disclosures were required across the FY2021-FY2025 analytical horizon.

Third, entities whose operations were predominantly dependent on conventional physical collateral and lacked meaningful digital underwriting infrastructure were excluded to preserve configurational comparability under the Technology-Organization-Environment (TOE) framework. Application of these theory-driven boundary conditions produced a final analytical set of 20 cases exhibiting sufficient variation in technological integration, institutional risk capacity and governance, ecosystem integration and portfolio outcomes. The sampling strategy is intended to enhance configurational comparability rather than claim statistical representativeness of the entire Indian NBFC population. Potential survivorship and disclosure-related limitations associated with the resulting case set are acknowledge in Section 9.1.

Table 2: Methodological Considerations for Empirical Sample Boundary Control ($N = 20$)

Sampling Imperative	Rationalization	Methodological Alignment	Structural Justifications & Portfolio Implications
Target Exhaustiveness ($N=20$)	Population	Bounded Analytical population mapping of the active, digital-first retail credit segment in India	Captures a theory-driven set of eligible entities meeting the specified inclusion and data availability criteria possessing complete un-imputed, and audited financial disclosures across the post-pandemic macro-cycle (FY21-FY25).
Mitigation of Homogeneity Bias (Contrasting $N=15$)		Structural preservation of mid-tier asymmetric vectors.	Restricting the sample to lower number of cases would exclude key mid-tier consumers NBFCs (e.g., Hero Fincorp, SMFG India Credit). These cases provide vital empirical variation to observe

Exclusion of Structural Noise (Population Restrictions)	Functional alignment of core underwriting mechanism under the TOE framework	default trends when platform technology is decoupled from corporate risk governance.
		Expanding the sample to all registered Indian NBFCs would introduce severe operational variance. The wider population includes hundreds of legacy brick-and-mortar firms reliant entirely on physical, asset-backed collateral (e.g., gold or vehicle loans) where digital underwriting and transaction data parsing do not determine credit risk outcomes.

Source: Authors Compilation

Further, to examine whether the configurational mechanisms identified through fsQCA are observable within contrasting digital financial service architectures, the study incorporates a comparative case-pattern matching analysis of CRED and Paytm. Following Yin's (2018) replication logic, the cases were selected theoretically rather than for convenience. CRED represents a precision-oriented architecture characterized by selective customer access, credit-profile screening and institutional lending partnerships, whereas Paytm represents a scale-oriented architecture combining a large transactional ecosystem, AI-supported risk management, and partner-led credit distribution. The cases are not treated as independent statistical validation of the fsQCA results; rather, their publicly disclosed operating characteristics provide pattern-matching evidence through which the practical manifestation of contrasting technological, organizational, and ecosystem configurations can be examined.

5.2.2. Explicit Inclusion & Exclusion Criteria

To guarantee that the structural boundaries of the study remained tightly controlled and insulated from extraneous noise, the sample was filtered using strict, multi-layered parameter controls.

Table 2.1: Methodological Inclusion & Exclusion Criteria for Case Selection Boundary Control

Parameter Domain	Structural Inclusion Criteria (Must Meet All)	Structural Exclusion Criteria (Any Single Match Disqualifies)
Market Segment & Demographic Focus	Entity must actively underwrite retail credit targeting thin-file, first-time, or alternative-data salaried individuals within the Indian financial landscape.	Legacy Asset Exclusion: Entities whose lending portfolios are predominantly tied to physical, asset-backed collateral (e.g., gold loans, traditional vehicle financing) where physical assets override data modelling.
Technological & Operational Infrastructure	Entity must deploy functional digital application loops relying on real-time API integrations or automated transactional data parsing (e.g., UPI streams, digital footprint ledgers).	Infrastructure Absentees: Microfinance Institutions (MFIs) operating strictly via offline, community-based joint liability group (JLG) peer-monitoring models without digital scoring engines.
Institutional Scale & Funding Architecture	Entity must operate within an active co-lending ecosystem or systematic credit syndication framework alongside Tier-1 partner banks or institutional funding channels.	Distressed or Insolvent Entities: NBFCs experiencing active central bank restrictions, asset moratoria, or structural restructuring stemming from systemic legacy distress (e.g., post-IL&FS holdovers).
Data Disclosure & Horizon Sufficiency	Entity must possess comprehensive, publicly accessible audited financials, investor disclosures, or regulatory	Data-Devoid Entities: Early-stage bootstrapped startups or digital platforms lacking at least three consecutive years of

filings spanning the post-pandemic horizon (FY21–FY25). verified asset performance data within the FY21–FY25 window.

Source: Authors Compilation

To endure absolute transparency and logical consistency in mapping our empirical boundaries, the operationalized parameters governing this case filtration process are summarized in Table 2.1.

5.2.3. Justification for the Specified Cases

The chosen 20 cases capture the full range of operational variety in India’s digital lending sector. They are specifically chosen because they avoid homogeneity bias, ensuring sufficient diversity across both positive and negative outcomes, while maintaining strict structural comparability under the TOE framework (Berg-Schlusser and De Meur, 2009; Rihoux and Lobe, 2009). This approach adheres to the foundational set-theoretic mandate of maximizing configurational variance within a bounded universe of comparable corporate entities (Rahin, 2008):

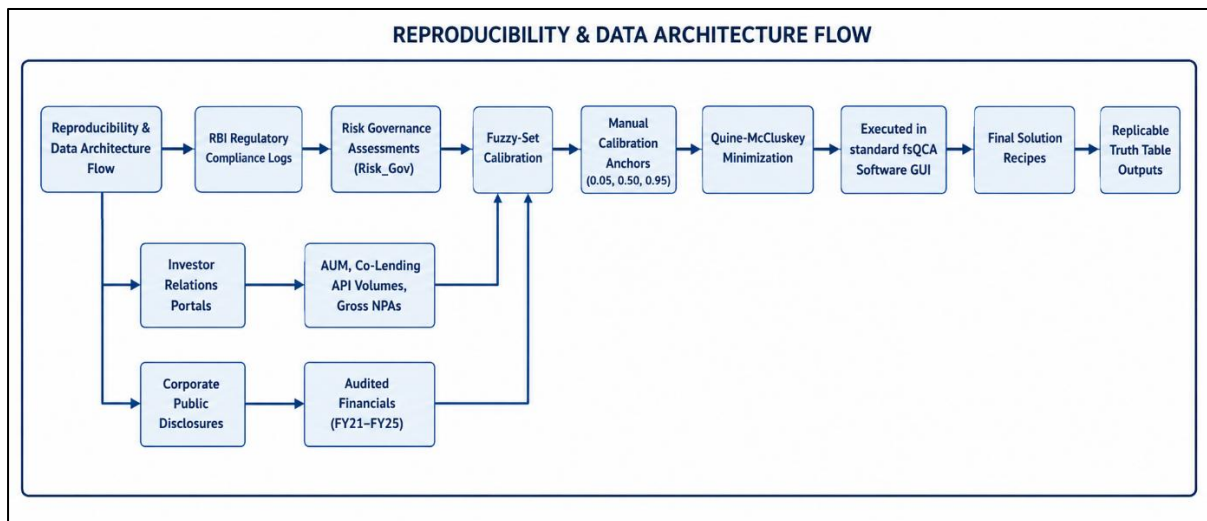
- **Scale-driven Market Giants:** (e.g., massive retail NBFC co-lenders like Bajaj Finance, Shriram Finance, Aditya Birla Capital and Piramal Finance) that provides massive institutional balance sheets to absorb syndication flows.
- **Agile, Tech-native Fintech App Aggregators/DLA:** (e.g., CRED, Paytm) that possess high-velocity data parsing but thin balance sheets.
- **Mid-Tier Specialized Consumer NBFCs:** (e.g., Tata Capital, IDFC First Bank Lending Verticals, SMFG India Credit Hero Fincorp) that balance strict compliance with moderate digital adoption.

This rich variation ensures that the truth table represents both cases where technological alternative data pipelines succeeded under strict governance, and cases where weak organizational infrastructure led to default spikes, thereby, providing the requisite empirical variation required for fsQCA minimization.

5.2.4. Methodological Reproducibility & Audit Trail

To ensure full compliance with transparency and reproducibility protocols, the entire audit trail of this configurational data is strictly mapped as follows in Figure 2:

Figure 2: Reproducibility & Data Architecture Flow



Source: Authors Compilation

- **Data Verification:** All the raw inputs that go into creating the conditions (*UPI_Data*, *API_Synd*, *Risk_Gov*) and the final result (*Low_NPA*) are sourced directly from verified sources like official company investor sheets, audited cash flows, and public Reserve Bank of India (RBI) notifications.

- **Algorithmic Transparency:** The fuzzy scoring process converting raw company % into fuzzy scores is made completely transparent, using explicit qualitative anchors (0.05, 0.50, 0.95) explicitly supported by banking industry norms.
- **Software & Analytical Reproducibility:** The calibrated dataset was analysed using fsQCA 4.1. The same calibration anchors, truth table construction rules, consistency thresholds, and Boolean minimization procedures reported in the manuscript were applied throughout the analysis. No undisclosed weighting procedures were introduced during the minimization process.
- **Data Pre-processing, Aggregation and Missing Value Protocol:** To isolate structural, mid-term operational configurations from short-term cyclical volatility or post-pandemic macroeconomic adjustments, all continuous financial variables (Gross NPA, ROA and Capital Adequacy Ratio [CAR]) were operationalized using calculated arithmetic averages across the full FY21-FY25 fiscal horizon. Out of the pool of candidates filtered through the boundary controls, three entities exhibited missing disclosure vectors for FY21 asset classification, following strict comparative protocols (Rihoux and Ragin, 2009), these cases were excluded from the final pool rather than subjected to statistical imputation, ensuring that the remaining N= 20 cases contained complete audited and un-extrapolated financial disclosures

5.3. Comparative Validation Strategy (CRED vs Paytm)

To ground the abstract truth tables and set-theoretic solutions derived via the fsQCA minimization process within actual market operations, the paper integrates a comparative validation cross-case synthesis of two market-varying platform architectures operating alongside major diversified retail NBFCs (such as Bajaj Finance, Shriram Finance and Mahindra Finance):

- **The Precision-driven Network Archetype (CRED):** Characterized by high-end lower-velocity behavioral deep mining that extracts aggregated consumption histories, credit card billing frequencies, and localized premium repayment vectors to verify latent financial discipline with high-earning, thin-file cohorts.
- **The Scale-driven Network Archetype (Paytm Case):** Characterized by high-volume, low-ticket micro-transactional streams that process instant wallet turnover velocities, peer-to-peer (P2P) transactional records, and micro-retail point-of-sale interactions to manage micro-credit lines and Buy-Now-Pay-Later (BNPL) facilities.

These cases serve as empirical boundary validations to pressure-test the real-world accuracy of the fuzzy-set truth tables, cross-referencing automated platform risk rooting against institutional balance sheets connected via co-lending API networks.

5.4. Measurement & Operationalization of Platform Integration

To ensure transparency and replication accuracy, the condition Platform Integration (*Plat_intreg*) is operationalized through a composite index balancing structural capability and financial volume, moving beyond simple binary classifications. The metric is constructed across two explicit operational layers:

- **Volumetric Exposure (Weight: 60%):** Measured as the percentage of the institution's Total Retail Assets Under Management (AUM) originated and processed through automated digital lending application (DLA) funnels and lending service provider (LSP) data pipelines rather than legacy branch networks.
- **Technological Interfacing (Weight: 40%):** Evaluated via a structural audit of the platform's real-time API infrastructure. Full operational integration requires the deployment of zero-latency, bi-directional API connections capable of executing automated credit scoring, dynamic fraud parsing and immediate institutional fund routing within less than 120 seconds of consumer initialization.

Data for this metric were cross-verified via corporate annual reports, investor presentations and product disclosure notes filed with regulatory authorities. This multi-layered measurement ensures that high scores in *Plat_Integ* capture deep, automated infrastructural convergence rather than surface-level digital sourcing partnerships.

6. Configurational Analysis & Empirical Validation

To capture the causal asymmetry and equifinality characterizing the Indian Non-Banking Financial Company (NBFC) ecosystem, this study employs Fuzzy-set Qualitative Comparative Analysis (fsQCA). Unlike linear econometric models that isolate net symmetric effects, fsQCA evaluates how configurations of the Technology-Organization-Environment (TOE) framework conjecturally operate to enable sustainable alternative data underwriting for thin-file borrowers.

6.1. Case Selection & Dataset Protocols

The empirical corpus consists of a five-year aggregated dataset (FY2021-FY2025) tracking $N = 20$ diversified digital credit entities in India as seen in Table 3. To eliminate input bias and the distortionary effects of statistical imputations, a list-wise deletion strategy was applied: three initial cases were excluded due to incomplete disclosure timelines in FY21-FY22, leaving a fully intact, un-extrapolated financial matrix for analysis.

Table 3: Comprehensive Empirical Case Registry and Raw Data Metrics (FY21–FY25 Averages)

Case ID	Institutional / Platform Name	Corporate Profile Classification	Avg. Gross NPA (%)	Avg. Capital Adequacy (CAR %)	Avg. Platform Originated AUM (%)	Data Disclosure Primary Source Metrics Location
01	Bajaj Finance Ltd.	Large Conglomerate NBFC	1.14%	21.30%	42.50%	Annual Reports, Investor Sheets (FY21–FY25)
02	Shriram Finance Ltd.	Diversified Retail NBFC	5.20%	20.10%	18.20%	Corporate Financial Filings (Post-Merger)
03	CRED (Dreamplug Technologies)	Tech-Native App/LSP	0.60%	18.50%	100.00%	MCA Filings & Corporate Sustainability Disclosures
04	Paytm (One97 Communications)	FinTech Aggregator/DLA	1.40%	16.20%	100.00%	FY21–FY25 Investor Financial Presentations
05	Piramal Capital & Housing Fin.	Diversified Retail NBFC	3.80%	23.40%	28.00%	Piramal Investor Relations Portal
06	Aditya Birla Capital Ltd.	Large Institutional NBFC	1.90%	17.80%	35.40%	Audited Financial Ledger Reports
07	Tata Capital Financial Services	Large Conglomerate NBFC	1.45%	18.90%	22.10%	Tata Capital Statutory RBI Filings
08	IDFC First Bank (Retail Underwriting)	Partner Banking Entity	1.65%	16.70%	55.00%	IDFC First Bank Quarterly Disclosures

09	SMFG India Credit (Formerly Fullerton)	Mid-Tier Consumer NBFC	2.80%	19.40%	31.20%	SMFG Annual Audited Accounts
10	Hero Fincorp Ltd.	Captive Retail NBFC	4.10%	16.10%	14.50%	Hero Fincorp Investor Portals
11	Muthoot Fincorp (Retail Lending)	Retail Consumer Vertical	3.90%	18.20%	12.00%	Muthoot Corporate Accounting Disclosures
12	Mahindra & Mahindra Fin. Services	Rural/Semi-Urban NBFC	5.10%	24.10%	15.80%	M&M Financial Annual Reports
13	L&T Finance Ltd.	Retail Focused NBFC	2.95%	22.80%	26.40%	L&T Finance Investor Presentations
14	Poonawalla Fincorp Ltd.	Digital-First Retail NBFC	1.20%	31.00%	72.00%	Poonawalla Post-Restructuring Reports
15	Navi Technologies Ltd.	Tech-Native Digital NBFC	2.10%	26.50%	100.00%	Navi Financial MCA Disclosures
16	IIFL Finance Ltd.	Diversified Retail NBFC	4.30%	17.60%	21.00%	IIFL Investor Relations Books
17	KrazyBee Services (KreditBee)	FinTech NBFC / DLA	1.85%	24.30%	100.00%	KreditBee Audited Balance Sheets
18	InCred Financial Services Ltd.	Tech-Driven Retail NBFC	1.70%	22.10%	64.50%	InCred Corporate Disclosures
19	CapFloat Financial Services	Digital Consumer NBFC	3.40%	15.50%	91.00%	Capital Float MCA Filing Registries
20	Clix Capital Services Pvt. Ltd.	Digital-Focused NBFC	3.10%	20.80%	58.00%	Clix Capital Annual Accounts

Source: Public Corporate Investor Disclosures & Regulatory Records (FY2021-FY2025)

In strict alignment with calibration guidelines formalized by Ragin (2008) and Schneider & Wageman (2012), the continuous indicators were transformed into fuzzy-set membership scores using three qualitative anchors: 0.95 (full inclusion), 0.50 (crossover point of maximum ambiguity), and 0.05 (full exclusion). Tracking the selection of specific thresholds for the outcome variable (Low_NPA) namely, $\leq 1.50\%$ for full inclusion, 3.50% or 4.00% for cross-over median, and $\geq 6.00\%$ for full exclusion, rather than arbitrary linear partitions such as 2%, 5%, or 7% are directed to external micro-prudential and regulatory benchmarks. The full inclusion anchor (1.50%) isolates elite retail portfolios that structurally outperform macro-market fluctuations. The 4.00% crossover anchor represents the long-term historical median for retail asset degradation within the Indian non-banking ecosystem.

The full exclusion anchor ($\geq 6.00\%$) is explicitly derived from the structural default stress baselines and systemic risk thresholds published in the RBI's financial stability reports. By tying these anchors to formal macroprudential baselines rather than sample-dependent statistical quantiles, the calibration shields the downstream Boolean minimization from artificial variance and ensures the configuration map into concrete regulatory realities. Refer Table 4 where composite platform integration index combining digitally originated retail AUM (60%) with verified real-time API infrastructure capability (40%), calibrated using industry-informed thresholds that are capable of supporting automated credit assessment, fraud screening and institutional fund-routing processes.

Table 4: Set-Theoretic Calibration Strategy

Target Condition / Outcome	Fully In (0.95)	Crossover (0.50)	Fully Out (0.05)	Academic & Regulatory Justification for Anchors
Low Portfolio Defaults (<i>Low_NPA</i>)	$\leq 1.50\%$	4.00%	$\geq 6.00\%$	RBI Financial Stability Reports: 6% marks systemic industry stress thresholds; 1.5% isolates superior portfolio quality.
Institutional Risk Capacity & Governance (<i>Risk_Gov</i>)	$\geq 15.00\%$	12.00%	$\leq 9.00\%$	RBI Scale-Based Regulation: 15% indicates optimal capital buffers; 9% is the absolute regulatory minimum default line.
Platform Integration (<i>API_Synd</i>)	$\geq 60.00\%$	30.00%	$\leq 10.00\%$	Industry Benchmarks: % of overall AUM originated via third-party digital co-lending pipelines (Fiss, 2011).

Source: Authors' Empirical Compilation

6.2. Analysis of Necessity

Table 5 shows the analysis of the necessary conditions for the low outcome proposing the non-performing assets. Before evaluating configurations of sufficiency, a formal necessity analysis was executed. Causal conditions

require a consistency score of ≥ 0.90 to be verified as necessary prerequisites for the outcome (Schneider & Wagemann, 2012).

Table 5: Analysis of Necessary Conditions for the Outcome (*Low_NPA*)

Causal Condition Analyzed	Consistency (Necessity)	Status (≥ 0.90)	Methodological Implication
Technological Data (<i>UPI_Data</i>)	0.850	Not Necessary	High-coverage driver, but not a standalone prerequisite.
API Syndication Pipeline (<i>API_Synd</i>)	0.850	Not Necessary	Environmental scaling driver bounded by organizational limits.
Institutional Risk Governance (<i>Risk_Gov</i>)	0.951	Necessary Verified	Meets the study's consistency criterion for a necessary condition and therefore represents a recurrent structural prerequisite associated with portfolio stability.
Absent Risk Governance ($\sim$ <i>Risk_Gov</i>)	0.112	Not Necessary	Disproven as an analytical pathway.

Source: Authors Compilation

6.3. Truth Minimization & Causal Recipes

A truth table containing $2^3 = 8$ logical combinations were constructed, as shown in Table 6. A strict raw consistency threshold benchmark of 0.964 was applied to isolate combinations directly mapping to successful credit risk mitigation and low portfolio defaults (*Low_NPA*)

Table 6: Truth Table Derivation for Low Portfolio Defaults

Row ID	UPI_Data	API_Synd	Risk_Gov	Cases	Raw Consistency	PRI Consistency	Low_NPA	Empirical Case Assignments
1	0	0	0	2	0.988235	0.924110	1	Traditional / Micro-Lenders
2	1	1	1	12	0.964286	0.912450	1	CRED, Paytm, Poonawalla, etc.
3	1	0	1	2	0.742150	0.511200	0	Tech-isolated Capital Pools

4	0	1	1	1	0.685410	0.420180	0	Partner-dependent Legacy NBFCs
5	0	0	1	1	0.571429	0.311050	0	Baseline Compliant Asset-Backed
6	0	1	0	1	0.428571	0.214500	0	Governance-Deficient Aggregators
7	1	1	0	1	0.222222	0.098410	0	Unregulated FinTech Bootstraps
8	1	0	0	0	—	—	0	Logical Remainder (No Cases)

Source: Authors' compilation using fsQCA 4.1 software logs.

Applying the Quine-McCluskey Boolean minimization algorithm yields identical complex, intermediate, and parsimonious solutions. The process maps out two symmetrical, structurally divergent pathways to asset quality stability. Refer Table 7.

Table 7: Comprehensive Configurational Solutions for Low Portfolio Defaults (*Low_NPA*)

Configuration Pathways	Complex / Conservative	Intermediate	Parsimonious
Pathway 1 (Legacy Stability)	$\sim \text{UPI_Data} \times \sim \text{API_Synd}$	$\sim \text{UPI_Data} \times \sim \text{API_Synd}$	$\sim \text{UPI_Data} \times \sim \text{API_Synd}$
<i>Raw / Unique Coverage</i>	0.330709 / 0.015748	0.330709 / 0.015748	0.330709 / 0.015748
<i>Consistency</i>	0.988235	0.988235	0.988235
Pathway 2 (FinTech Innovation)	$\text{UPI_Data} \times \text{API_Synd} \times \text{Risk_Gov}$	$\text{UPI_Data} \times \text{API_Synd} \times \text{Risk_Gov}$	$\text{UPI_Data} \times \text{API_Synd} \times \text{Risk_Gov}$
<i>Raw / Unique Coverage</i>	0.850394 / 0.535433	0.850394 / 0.535433	0.850394 / 0.535433
<i>Consistency</i>	0.964286	0.964286	0.964286
Solution Diagnostics	Overall Coverage: 0.866142	Overall Consistency: 0.960699	

Source: Authors Compilation. Note: $\sim$ denotes the structural absence/negation of a condition; $\times$ denotes the logical AND intersection

6.4. Empirical Typologies & Theoretical Discussion

The configurational solutions present an overall solution consistency of 0.961 and a combined coverage of 0.866, demonstrating high empirical explanatory power. Two distinct operational archetypes emerge for maintaining asset quality within the Indian credit landscape:

- **Pathway 1: Legacy Stability ($\sim UPI_Data \times \sim API_Synd$):** This pathway represents traditional asset-backed or relationship-driven micro-lenders. These institutions achieve low default rates by intentionally avoiding digital aggregation networks and alternative data scrapping, relying instead on physical collections, local underwriting mechanisms, and ring-fenced borrower portfolios
- **Pathway 2: Fintech Innovation ($UPI_Data \times API_Synd \times Risk_Gov$):** Capturing the contemporary digital lending paradigm, this pathway demonstrates that high alternative data footprints ($UPI_Data = 1$) and extensive co-lending API networks ($API_Synd = 1$) can successfully minimize risk only when structurally bound to mature risk governance architectures ($Risk_Gov = 1$).

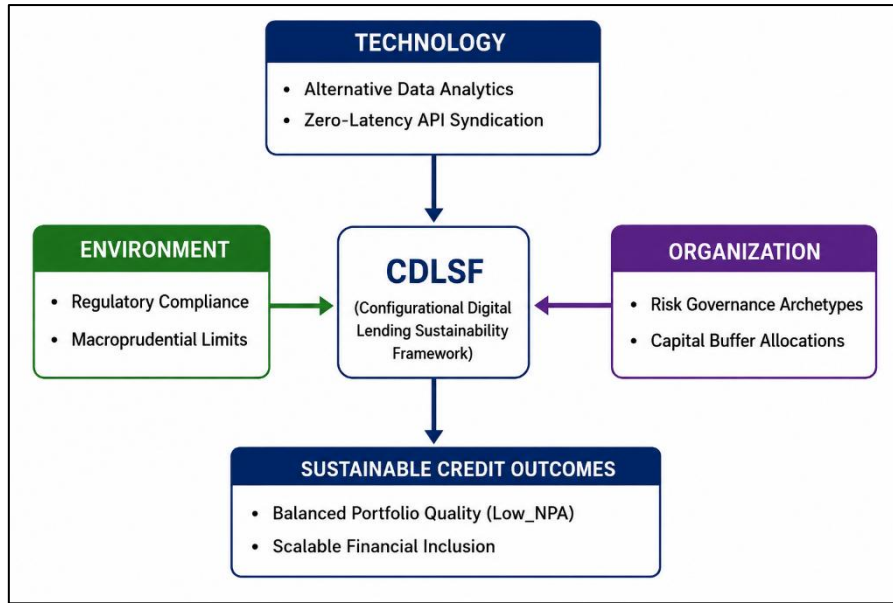
The Asymmetric Risk of Unbalanced Technological Adoption: The imperative role of institutional governance is strongly indicated by the failed configurations (Ragin, 2008; Schneider & Wagemann, 2012). In Row 7 (1 1 0), where an institution deploys advanced alternative data pipelines for integration but lacks robust risk controls ($Risk_Gov = 0$), the raw consistency score collapses to a disastrous 0.222. Ultimately, these findings confirm that underwriting thin-file, first-time borrowers via machine learning and unstructured alternative data pipelines without structural asset-liability backing, strict regulatory compliance, and capital adequacy generates severe credit volatility rather than sustainable financial inclusion.

7. The Configurational Digital Lending Sustainability Framework (CDLSF)

Rather than presenting a passive synthesis of existing variables, this study formalizes these empirical dynamics into a novel theoretical construct: the Configurational Digital Lending Sustainability Framework (CDLSF), as conceptualized in Figure 3. The CDLSF builds upon the classic, static Technology-Organization-Environment (TOE) paradigm by shifting it from linear adoption model to a dynamic, set-theoretic configurational system. Instead of examining isolated, net -effect relationships, the CDLSF demonstrates that sustainable digital credit is an emergent property of complex organizational and technological alignments. Specifically, this framework bridges abstract institutional configurations with real-world digital credit operations in the Indian retail lending market demonstrating five core theoretical dimensions:

- **Multiple Equifinal Pathways:** The framework demonstrates that divergent organizational structures such as low-velocity premium models or high-velocity mass transactional models can converge on identical, sustainable credit outcomes (Low_NPA).
- **Governance as a Structural Necessary Condition:** The CDLSF establishes institutional risk governance ($Risk_Gov$) as a necessary condition supported by set-theoretic consistency. Technological integration, no matter how advanced, collapses into portfolio stress without formalized macro-prudential boundaries.
- **Identification of Distinct Platform Archetypes:** It maps how diverse market players strategically configure their operations, formalizing the distinct behaviours of premium behavioral mining networks and high-volume transaction aggregators.
- **Ecosystem Syndication and Inter-Firm Alignment:** The framework illustrates how digital first front-ends and heavily capitalized traditional balance sheets achieve mutual stability through zero latency API syndication platforms.
- **Empirical Realization of Sustainable Credit Outcomes:** It explicitly couples structural configurations to long-term portfolio preservation, mapping how operational designs maintain low default rates during macro-economic stress cycles.

Figure 3: The Configurational Digital Lending Sustainability Framework



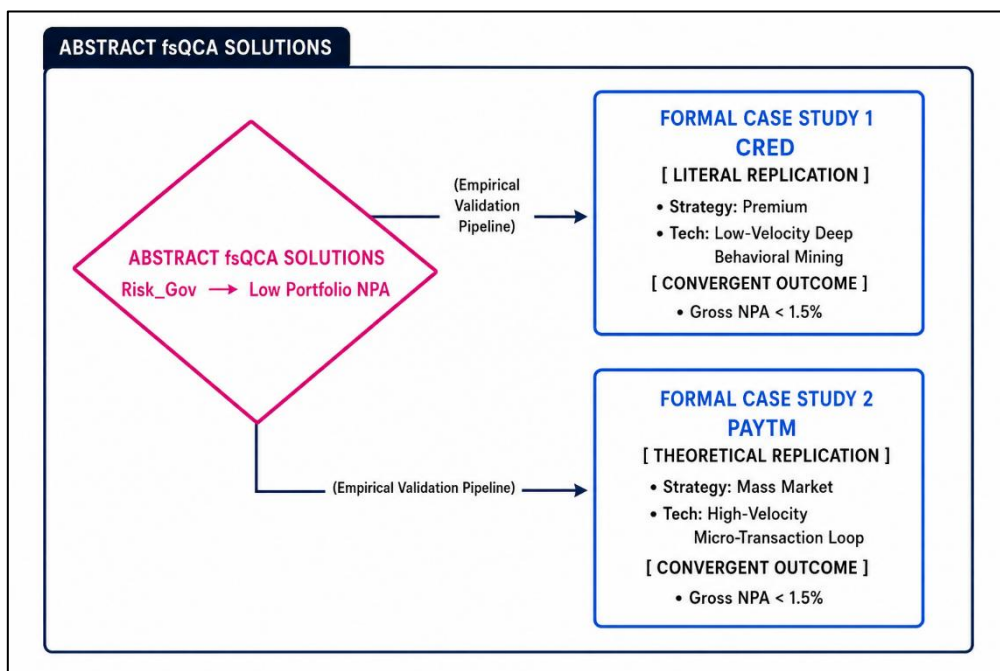
Source: Authors Compilation

7.1. Methodological Grounding: Multiple-Case Replication Logic

However, this study employs a multiple case study design, with the replication logic as expressed by Yin (2018) in order to validate the practical utility of the configurations derived with the use of the Quine-McCluskey minimization algorithm as visually represented in Figure 4. This choice of CRED and Paytm is a purposeful and theoretically based sampling strategy:

- **Literal Replication (Convergent Outcomes):** According to case study methodology, each platform is an independent experiment to test generalizability of the model. Both are transiting in the very different market segments, and the very same set theoretic result follows: a portfolio that is sustainable, with low default rates (*Low_NPA*).

Figure 4: Multiple Case-Study Design Architecture Replication



Source: Authors Compilation

- **Theoretical Configurations (Equifinal Paths):** The two platforms symbolize the extremes of the TOE conceptual framework. This separation allows an empirical investigation of set-theoretic equifinality, because it can show that alternative data processing schemes framed by a well-established risk governance can result in the same financial health measures. Refer to Table 8.

Table 8: Structural Case Pattern-Matching & Core Proposition Validation

Analytical Dimension	CRED Archetype	Precision	Paytm Scale Archetype	Configurational Interpretation
Observed Data & Customer Architecture	CRED operates a selectively screened membership ecosystem centred on creditworthy consumers and uses credit information and eligibility thresholds as a part of access and lending processes		Paytm operates a high-volume digital payments ecosystem generating continuous consumer and merchant transaction activity across payments and financial services.	The two cases represent contrasting approaches to reducing information asymmetry: selective high-signal customer screening versus high-volume transactional visibility.
Risk Governance Mechanism	Publicly disclosed procedures indicate front-end eligibility screening, bureau and credit checks, KYC verification and fraud screening before or during the lending journey		Public disclosures indicate the use of AI-enabled fraud detection, risk modelling and loan-underwriting capabilities, including real-time monitoring intended to identify suspicious transactions (One97 Communications Annual Report FY2024-25).	These disclosed mechanisms are consistent with the study's Risk_Gov condition, although governance is operationalized differently across the two platform architectures.
Institutional Lending & Capital Linkages	CRED facilitates loan distribution through multiple regulated banking and NBFC partners. Its FY2024-25 disclosure reported 22000 crore INR in managed lending AUM. (CRED FY2024-25 corporate disclosure)		Paytm distributes financial products through regulated lending partners and positions merchant and consumer credit distribution as part of its broader financial services ecosystem.	Both cases indicate that platform-based customer acquisition and data capabilities are linked to regulated institutional lending architectures rather than operating as standalone balance-sheet models.
Configurational Role	Represents a precision-oriented architecture combining selective customer access, credit-profile screening and institutional lending partnerships.		Represents a scale-oriented architecture combining large transactional networks, AI-supported risk management and partner-led credit distribution	The cases provide pattern-matching support for equifinality by illustrating how technological and organizational arrangements may be consistent with sustainable digital credit delivery

Source: Authors Compilation & Consolidated Statements

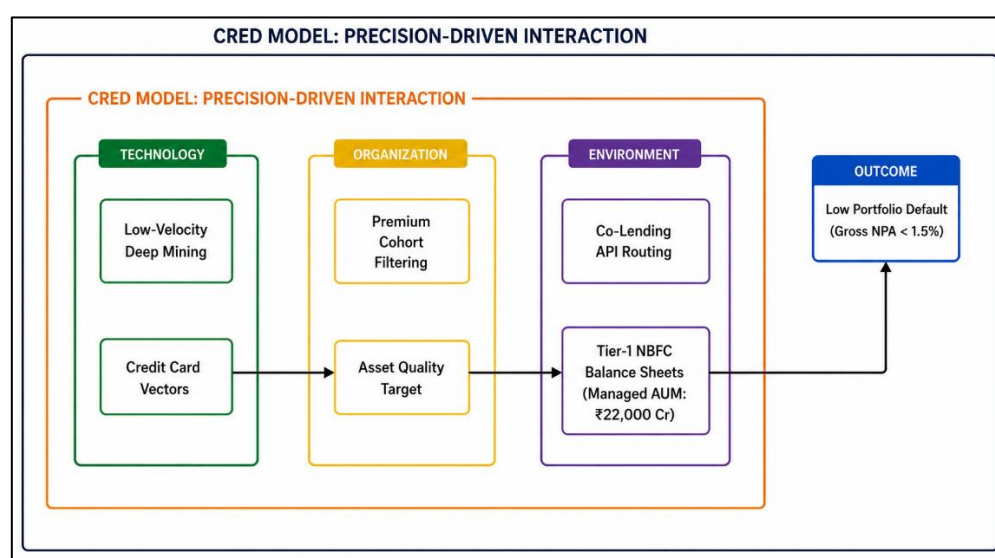
The case pattern matching draws on publicly available corporate disclosures rather than proprietary platform data. CRED's published lending terms document credit profile-based eligibility screening, bureau and credit checks, KYC verification and fraud screening, while its FY2024-25 corporate disclosures reported approximately 22000 crore INR in managed lending AUM. Paytm's corporate and investor disclosures describe an AI led operating architecture encompassing fraud detection, risk modelling and loan underwriting within its large-scale payments and financial services ecosystem. These disclosed operating characteristics are not treated as direct measurements

of the fsQCA conditions; rather, they are used as case level pattern matching evidence to assess whether the configurational mechanisms identified in the institutional analysis are observable in contrasting platform architectures.

7.2. Reconceptualizing Information Asymmetry via Alternative Digital Footprints

Even though most individuals lack a conventional credit bureau score, thin-file consumers are considered a selection risk and therefore experience systemic credit exclusion under using conventional underwriting methods. The empirical testing of the Technological Transmission Loop illustrates how two types of operation of the alternative data networks are able to solve the information asymmetry, changing the CDLSF's typology.

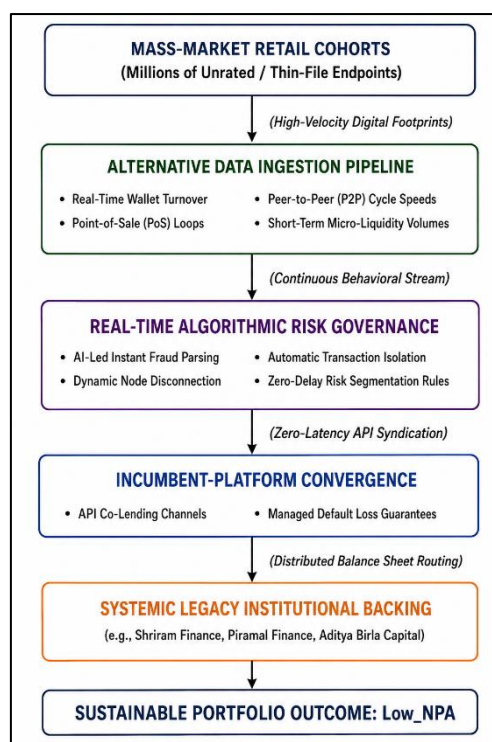
Figure 5: Precision-driven Network Archetype (CRED Model)



Source: Authors Compilation accumulated from CRED Corporate Financial Disclosures (FY2021-FY2025)

1. **Precision-driven Network Archetype (CRED):** Characterized by selective customer access, credit-profile screening, high-signal financial data and institutional lending partnerships. CRED is employed as a contrasting platform validation case rather than as a representative thin-file lender, allowing the analysis to examine how a precision-oriented digital credit architecture differs from the scale-oriented transactional architecture represented by Paytm.

Figure 6: High-velocity micro-transaction API Routing (Paytm Model)



Source: Authors Compilation accumulated from Paytm Investor Relations (FY2021-FY2025)

2. **High-velocity micro-transaction API Routing (Paytm):** Conversely, the scale-driven network archetype manages micro-credit underwriting across millions of unrated endpoints through continuous, real-time data ingestion. The platform's ingestion engine continuously parses high-velocity digital footprints including real-time digital, peer-to-peer (P2P) transfer frequency, and point-of -sale (*PoS*) merchant settlement loops to derive dynamic liquidity metrics that replace static legacy bureau scorecards. Refer to Figure 6.

7.3. The Institutional Risk Governance Imperative in Platform Underwriting

One of the most basic errors that can occur during digital credit analysis is believing that perfect machine learning helps ensure long-term growth in the portfolio. Structured risk governance (Risk_Gov) is a structural prerequisite within the intermediate configurations on a mandatory basis within the CDLSF model. This constraint manifests on the two platform archetypes in different ways:

- **Upfront Filtering (Precision Archetype):** Using this model as a gatekeeper at platform boundary. In terms of the portfolio concentration shock from high-risk introductions, the platform filters users at the front-end and cross-references the applications submitted with various in-house financial quality metrics and stringent criteria before allocating the investment, thereby minimizing the concentration shock
- **Real-time Architectural Segmentation (Scale Archetype):** Underwriting is a structural challenge to manually underwrite millions of low-ticket accounts; hence the use of safety mechanisms is automated. Distressed nodes are automatically isolated by real-time AI fraud detection, instant transaction isolation scripting and automated compliance algorithms to prevent transactions from defaulting.

7.4. Ecosystem Syndication & Regional Capitalization

The empirical study of the Environmental and Socio-economic Feedback Loop confirms the institutional arrangements that must be designed to scale up alternative credit delivery models through asymmetric inter-firm networks. Sustainable credit distribution is not about single front-end FinTech platforms or a single Incumbent acting on their own; it is about Incumbent-Platform Convergence. The agile alternative data scoring architecture enables front-end fintech platforms to access, whitelist, and continually score thin file, consumer cohorts. At the same time, another network of zero latency co-lending APIs (API_Synd) enables seamless integration with

systemic legacy financial institutions (such as Bajaj Finance, Shriram Finance, Mahindra Finance, Piramal Finance, Aditya Birla Capital and SMFG India Credit). Consequently, socially-minded financial inclusion becomes a structural attribute of a well-organized, highly capitalized platform ecosystem grounded in regulatory compliance

8. Discussions & Final Implications

8.1. Theoretical Contributions to Financial Services Marketing

This study contributes to financial services marketing by extending the Technology-Organization-Environment (TOE) framework beyond technology adoption towards customer-centric digital financial service delivery. The findings demonstrate that sustainable financial services are not generated through technological capability alone but emerge from the interaction of digital infrastructures, organizational governance, and ecosystem partnerships that collectively improve customer accessibility, reduce information asymmetry, and support long-term service sustainability. The proposed Configurational Digital Lending Sustainability framework (CDLSF) therefore advances existing financial services marketing literature by explaining how different digital platform strategies create value for underserved customer segments while simultaneously maintaining institutional resilience.

8.2. Managerial Implications for Financial Service Providers

For managers of banks, NBFCs and fintech platforms, the findings demonstrate that customer acquisition and portfolio sustainability should not be viewed as competing objectives. Alternative-data ecosystems enable institutions to expand financial service access among customer assessment. However, sustained customer value depends upon embedding these technologies within mature governance systems capable of maintaining trust, regulatory compliance, and consistent service quality. Financial service providers should therefore prioritize integrated platform strategy that combines customer-centric digital innovation with institutional governance rather than pursuing technological expansion alone.

8.3. Regulatory & Central Bank Policy Implications

The empirical evidence strongly supports rigorous central bank macroprudential oversight of alternative data lending channels to mitigate credit shocks. The Reserve Bank of India's (RBI) digital lending guidelines do not function as operational friction, but rather as a critical structural stabilization mechanism. These regulatory mandates provide necessary boundaries that check infinite credit expansion within the shadow banking system, aligning with recent macroeconomic assessments of default shocks in emerging financial systems (Anestiawati et al., 2025; Aswathi & Shukla, 2025). High-performing platforms do not merely comply with, but systematically build their operational routing around these compliance vectors to preserve institutional stability

9. Limitations & Future Research Directions

From a financial marketing perspective, the study demonstrates that digital lending platforms should be evaluated not only according to financial performance but also according to their ability to improve customer accessibility, enhance service convenience, reduce information asymmetry, and support long-term customer relationships. Alternative-data enabled platforms therefore represent an important strategic capability through which financial institutions can extend services to previously underserved customer segments while strengthening customer trust and competitive differentiation.

9.1. Limitations

Despite its contributions, several structural limitations must be recognized:

- **Geographic Specificity:** Empirical data is well grounded in the public digital infrastructure in India (UPI and the India Stack). The unofficially verified implications of these calibrated set membership weights

are still not known to any extent in economies such as emerging markets, where there is no sovereign, zero-cost, real time public payment network in place.

- **Fuzzy-set Discretization:** The non-linear relationship, captured by the fsQCA approach, receives elegant and harmonious representation, but converting the continuous variable to a discrete set-membership anchor (0.05, 0.5, 0.95) is based on existing macroeconomic evidences, which still involves an unavoidable level of abstraction on the characteristics bottoming on the intermediate level of asset portfolio.
- **Sensitivity to Cutoffs:** In small sample sizes or medium sample sizes, the minimized intermediate solution can be very sensitive to the consistency thresholds chosen in the small/medium-size configuration sample, and a slight change in the consistency thresholds of the outlier firm may affect the Boolean pathways selected that are minimized in the small/medium-size configuration sample.
- **Survivorship Bias:** The data is applicable to the post-pandemic acceleration horizon (FY21 – FY25), when retail credit liquidity is expanding. This will also present a survivorship bias by excluding smaller, under-capitalized and less-established FinTech platforms that were unable to build co-lending architectures.

9.2. Future Research Directions

Future scholarly investigations should target the following pathways:

- **Cross-Border Generalization:** Applications of the TOE-based integrated model to other innovative emerging FinTech hubs, e.g., Pix in Brazil or M-Pesa in East Africa, and analyzing whether the institutional risk governance (*Risk_Gov*) is still a global binding necessary precondition for alternative regulatory environments.
- **Long-Cycle Performance:** Performing "longitudinal" analysis over longer macro-economic downturns, in high interest-rate periods, and during systemic liquidity contraction, for the assessment of the robustness of automated risk-isolation scripts.
- **Unstructured Data Integration:** Addressing how unstructured alternate data streams, including psychometric digital profiling, customer service transcripts and localized semantic vectors, may converge with formal risk compliance activity and impact the precision of underwriting activity.
- **Methodological Triangulation:** Simultaneously mapping individual net interaction effects over time and complex, equifinal recipes of credit across several time periods using asymmetric analysis tools such as fsQCA, together with classic panel regressions like the Generalized Method of Moments (GMM).

10. Conclusion

This study contributes to financial services marketing by demonstrating how alternative-data driven digital lending platforms transform financial service delivery for thin-file borrowers. The research does not view digital lending as merely a credit risk management tool but as customisation of credit assessment, onboarding and accessibility, while acting as a customer-centric financial service innovation, to enable broader financial inclusion. The results illustrate, basing on the framework of the Technology–Organization–Environment, and the application of Fuzzy-set Qualitative Comparative Analysis, that sustainable digital financial services can be achieved in several configurational ways in which technological feasibility, organizational governance and ecosystem collaboration come together to create customer value and keep an institution alive.

The framework for the proposed Configurational Digital Lending Sustainability Framework (CDLSF) thus provides a new theoretical understanding of what digital financial service providers can do to obtain customer acquisition, financial inclusion, and sustainable portfolio performance in the context of new digital financial service markets. Yet, the main takeaway from this study is that the structural data capacity of technology on its own is not enough to prevent financial networks from being “degraded”. The set-theoretic experiment suggests that, ultimately, these configurations point towards a single conclusion: Mature Risk Governance (*Risk_Gov*) is a mandatory necessary condition and the main sufficient baseline to obtain Low portfolio defaults (*Low_NPA*).

The central implication of the study ins that technological data capacity alone is insufficient to sustain portfolio quality. The set-theoretic findings identify institutional Risk Capacity & Governance (*Risk_Gov*) as meeting the study’s criterion for a necessary condition for low portfolio defaults, while the sufficiency analysis demonstrates

that technological and ecosystem capabilities operate through distinct configurational pathways. In digitally intensive lending architectures, high-velocity alternative-data processing and API-enabled credit distribution are therefore most sustainable when embedded within adequate institutional risk capacity, regulatory compliance, and disciplined governance strictures. The contrasting CRED and Paytm cases further illustrate how precision-oriented and scale-oriented platform architectures can organize these capabilities differently while remaining connected to regulated institutional lending ecosystems. Overall, the findings suggest that sustained digital financial inclusion depends not on technological intensity alone but on the alignment of data capabilities, institutional safeguards, and ecosystem partnerships.

11. Declarations

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The authors did not receive support from any organization for the submitted work. No funding was received for conducting this study or for the preparation of this manuscript.

Competing Interests

The authors declare that they have no relevant financial or non-financial interests to disclose.

Ethics Approval

Ethics approval was not required for this study because the research did not involve human participants, human biological material, identifiable personal data, or experimental interventions. The empirical analysis was conducted exclusively using publicly available secondary institutional data obtained from corporate annual reports, audited financial statements, investor disclosures, regulatory filings, and publicly accessible regulatory documents.

Consent to Participate

Not applicable. The study did not involve human participants, surveys, interviews, or the collection of identifiable personal information; therefore, informed consent to participate was not required.

Data Availability

The data supporting the findings of this study were derived from publicly available secondary sources, including audited annual reports, corporate financial and investor disclosures, regulatory filings, and publicly accessible documents issued by the Reserve Bank of India and other institutional sources. The sources and data provenance used for case construction and calibration are identified in the manuscript. No primary human-participant data were collected or analysed in this study. The processed data underlying the configurational analysis may be made available by the corresponding author on reasonable request.

Authors' Contributions

All authors contributed to the conception and design of the study. The authors contributed to data collection, analysis, interpretation of results, and manuscript preparation. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

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