WHEN CREDIT BECOMES A CONSTRAINT: THE LONG-TERM DEBT PARADOX OF FINTECH LENDING AND BORROWER FINANCIAL RESILIENCE IN INDIA.

Abstract:

FinTech lending is designed and marketed around short tenor, instant disbursal, and flexible, one-off borrowing — the antithesis of long-term formal debt. This study tests whether that short-term design nonetheless produces a long-term debt paradox: a persistent, structurally embedded financial constraint that behaves like chronic long-term debt despite no single loan being long tenor. Using survey data from 432 digital-credit borrowers in Bangalore, India, the study separately tests four candidate long-term-constraint mechanisms — usage tenure, borrowing frequency, repayment-burden ratio, and concurrent loan stacking (holding three or more active digital loans simultaneously) — against over-indebtedness and financial resilience. Tenure, frequency, and repayment-burden ratio show no significant association with over-indebtedness or resilience. Loan stacking, by contrast, is a significant and independent predictor of over-indebtedness ($\beta = .131$, $p = .003$) and shows a clear dose-response relationship ($F = 5.66$, $p < .001$), with its effect on resilience fully mediated through over-indebtedness (Sobel $z = –3.62$, $p < .001$). Stacking prevalence (23.6% of borrowers) does not differ significantly by zone, occupation, or credit type, indicating a universal usage-pattern risk rather than a segment-specific vulnerability. This paper discusses implications for account-aggregator-based multi-lender exposure tracking.

Keywords: FinTech Lending, Loan Stacking, Over-Indebtedness, Financial Resilience, Digital Credit, Debt Paradox, Bengaluru, India

1. Introduction

FinTech lending products — instant personal loan apps, Buy-Now-Pay-Later (BNPL), UPI credit lines, and app-based microfinance — are built and marketed on a premise fundamentally different from traditional formal credit: short tenor, near-instant disbursal, and low commitment. Where a home loan or auto loan binds a borrower for years or decades, a typical fintech loan is designed to be repaid within weeks or a few months. This short-term design is central to the products' appeal and to their positioning as tools of 'financial freedom' — quick, flexible access to credit exactly when needed, without the long-term entanglement of conventional debt.

Yet a growing body of evidence, reviewed in Section 2, suggests that short-tenor credit products can produce financial strain that persists well beyond any single loan's term — a pattern first documented in the Western payday-lending literature (Melzer, 2011; Skiba &Tobacman, 2008) and increasingly observed in India's fintech ecosystem (Aggarwal et al., 2024; Yue et al., 2022). This creates an apparent paradox: instruments explicitly engineered to be short-term can, in aggregate, function as a long-term constraint on borrowers' financial lives — not because any individual loan is long-lived, but because of how borrowers use, renew, and combine these products over time.

This study interrogates that paradox directly by testing four distinct candidate mechanisms through which fintech lending could create long-term-like constraint: (1) tenure — how long a borrower has used digital credit; (2) frequency — how often they borrow; (3) repayment burden — what share of income services digital debt; and (4) loan stacking — how many digital loans a borrower holds concurrently across different apps and platforms. The fourth mechanism is structurally distinct from the first three: unlike tenure, frequency, or burden ratio, which describe a borrower's relationship with a single lender or product over time, loan stacking is a cross-platform phenomenon enabled specifically by fintech's decentralized, app-siloed credit assessment architecture (Berg et al., 2020), where multiple lenders can independently extend credit to the same borrower without shared visibility into that borrower's total exposure. Using the same 432-respondent Bangalore dataset analysed for usage-to-resilience pathways in companion research, this study isolates which of these four mechanisms drives long-term financial constraint—and which are intuitive but empirically unsupported red herrings.

2. Review of Literature

2.1 The Short-Term Design Logic of FinTech Lending

FinTech lending's competitive advantage over traditional banking rests on speed and convenience: Berg, Burg, Gombovic, and Puri (2020), publishing in the Review of Financial Studies, demonstrate that digital footprint data — information borrowers leave simply by browsing or registering online — can match traditional credit bureau scores in predicting default, enabling near-instant underwriting decisions without the documentation and time burden of formal lending. This same architecture, however, means each platform typically performs credit scoring independently and in isolation from other lenders' exposure to the same borrower, a structural feature this study argues is central to the loan-stacking mechanism tested below.

2.2 The Payday and Small-Dollar Credit Literature as a Precedent

The clearest precedent for a 'short-term product, long-term harm' pattern comes from the U.S. payday-lending literature. Melzer (2011), in the Quarterly Journal of Economics, finds that access to payday credit measurably increases borrowers' difficulty paying important bills, even though each loan is a two-week instrument. Skiba and Tobacman's (2008) analysis of payday-lending administrative data finds that many borrowers renew loans repeatedly rather than settling them within the nominal term, with default typically occurring only after a long sequence of interest payments — a pattern the authors attribute to naive hyperbolic discounting rather than deliberate long-term borrowing. This literature establishes that the 'short-term' framing of a credit product describes its contractual tenor, not necessarily borrowers' realised exposure duration, directly motivating this study's distinction between nominal loan tenor and realised borrower-level constraint.

2.3 Present Bias and the Psychology of Renewal

O'Donoghue and Rabin (1999), in the American Economic Review, formalize present-biased preferences: individuals who are naive about their own future self-control problems tend to underweight delayed costs relative to immediate rewards, which the authors show can drive repeated, seemingly irrational renewal or re-engagement with a source of immediate relief — a mechanism directly applicable to why a borrower might repeatedly re-access instant credit apps, or hold several simultaneously, without fully weighting the compounding future repayment obligation each additional loan creates.

2.4 India-Specific Evidence on FinTech Debt Accumulation

Aggarwal, Aggarwal, Dhingra, Batra, and Yadav (2024) document predatory recovery tactics used by Indian loan-app operators, frequently targeting borrowers who have already taken multiple loans across platforms. Yue, Korkmaz, Yin, and Zhou (2022), in Finance Research Letters, provide empirical evidence from Chinese households that digital finance access raises the probability of falling into a debt trap even as it expands credit-market participation — a finding this study extends by testing which specific behavioural mechanism (duration, frequency, burden, or stacking) accounts for that risk. The Reserve Bank of India's Financial Inclusion Index, which reached 67.0 in March 2025 (up from 64.2 the prior year), documents rapid growth in the Usage dimension of financial inclusion nationally — growth this study argues may be accompanied by an unmeasured rise in cross-platform borrowing that aggregate inclusion indices do not directly capture. Sharma (2026), assessing the RBI's Digital Lending Directions, 2025 in the International Journal of Research and Scientific Innovation, finds that while the directions have improved disclosure standards, gaps persist in cross-lender exposure visibility—the regulatory gap this study's loan-stacking findings speak to directly.

2.5 Financial Literacy and Resilience as Buffer and Outcome

Lusardi and Mitchell (2014), in the Journal of Economic Literature, establish financial literacy as a form of human capital with measurable protective effects on financial decision-making. Klapper and Lusardi (2020) and Kurowski (2021) extend this specifically to financial resilience and over-indebtedness, both used as this study's outcome and mediating constructs respectively.

2.6 Research Gap

No identified study decomposes 'long-term' fintech-credit risk into plausible constituent mechanisms—tenure, frequency, repayment burden, and concurrent multi-platform stacking—to test which actually drives constraint. The payday-loan literature (Melzer, 2011; Skiba &Tobacman, 2008) examines single-lender rollover within one product category; it does not address the cross-platform stacking phenomenon that fintech's siloed, digital-footprint-based underwriting (Berg et al., 2020) structurally enables. This study addresses that gap using India-specific, city-level empirical data.

3. Objectives of the Study

1. To test whether usage tenure (duration of digital credit relationship) is associated with over-indebtedness and reduced financial resilience.
2. To test whether borrowing frequency is associated with over-indebtedness and reduced financial resilience.
3. To test whether repayment-burden ratio (debt service as a share of income) is associated with reduced financial resilience.
4. To test whether concurrent loan stacking (holding multiple active digital loans simultaneously) is associated with over-indebtedness, debt repayment stress, and repeat borrowing.
5. To examine whether over-indebtedness mediates the relationship between loan stacking and financial resilience.
6. To examine whether digital credit usage intensity predicts loan-stacking behaviour, and whether financial literacy predicts either stacking or over-indebtedness.
7. To test whether loan-stacking prevalence varies across geographic zone, occupation, or digital credit type, or represents a universal usage-pattern risk.

8. To derive regulatory and lender-level implications for managing cross-platform credit exposure in India's fintech lending ecosystem.

4. Hypotheses

H1: Usage tenure is positively associated with Over-Indebtedness (OI).

H2: Borrowing frequency is positively associated with Over-Indebtedness (OI).

H3: Repayment-burden ratio is negatively associated with Financial Resilience (FR).

H4: Loan stacking (active concurrent digital loans ≥ 3) is positively associated with Over-Indebtedness (OI), Debt Repayment Stress (DRS), and Repeat Borrowing (RB).

H5: Over-Indebtedness (OI) mediates the relationship between loan stacking and Financial Resilience (FR).

H6: Digital Credit Usage (DCU) intensity is positively associated with loan-stacking behaviour.

H7: Financial Literacy (FL) is negatively associated with Over-Indebtedness (OI).

H8: Loan-stacking prevalence does not differ significantly across geographic zone, occupation, or digital credit type (i.e., it is a universal usage-pattern risk rather than a segment-specific vulnerability).

5. Theoretical Framework

The hypotheses draw on five theoretical perspectives that together explain why short-tenor credit can produce long-term-like constraints, and why concurrent stacking—rather than duration, frequency, or burden ratio alone—is the mechanism this study foregrounds.

5.1 Present-Bias / Behavioural Self-Control Theory

O'Donoghue and Rabin's (1999) model of present-biased preferences explains why borrowers repeatedly re-access immediate-reward, delayed-cost credit products: naive borrowers systematically underweight the future repayment burden each new loan adds, making repeated or concurrent borrowing individually rational-seeming even when its cumulative effect is not. This theory motivates H4 and H6: usage intensity and present-biased renewal behaviour are expected to predict stacking specifically, more than the passage of time (tenure) itself.

5.2 Small-Dollar Credit Rollover Theory

The payday-lending literature (Melzer, 2011; Skiba &Tobacman, 2008) establishes that short-tenor credit's realised harm operates through repeated renewal and rollover within a single lending relationship, not contractual duration. This study extends the same logic to a fintech-specific, cross-platform setting, motivating the distinction between within-platform frequency (H2) and cross-platform stacking (H4) as separate, testable mechanisms.

5.3 Information Asymmetry in Digital Footprint-Based Credit Scoring

Berg, Burg, Gombović, and Puri's (2020) finding that digital-footprint-based underwriting operates effectively without traditional credit-bureau infrastructure explains the structural precondition for loan stacking: because each fintech platform scores borrowers largely on its own data, multiple platforms can independently approve credit to the same borrower without visibility into that borrower's total concurrent exposure — a gap that does not exist in the same way in traditional, bureau-checked lending. This theoretical mechanism is unique to the fintech context and is the basis for treating loan stacking as a structurally distinct — not merely behaviourally distinct — predictor of over-indebtedness.

5.4 Human Capital Theory of Financial Literacy

Lusardi and Mitchell (2014) frame financial literacy as capital that improves the quality of financial decisions. This motivates H7: literacy is expected to reduce over-indebtedness by improving borrowers' ability to evaluate the cumulative cost of multiple concurrent credit commitments.

5.5 Conservation of Resources (COR) Theory

Hobfoll's (1989) Conservation of Resources theory frames Financial Resilience as a resource buffer that is depleted by resource loss. Under this framing, over-indebtedness represents active, ongoing resource loss, and — critically for this study's paradox framing — the loss need not derive from any single long-tenor obligation: COR theory is agnostic to the contractual duration of the resource-depleting event, predicting that repeated or compounding short-duration losses (multiple concurrent short-tenor loans) can produce the same resilience-depleting effect as a single long-term one. This directly underpins H5's mediation hypothesis.

Synthesising these five perspectives: present-bias and rollover theory explain why borrowers accumulate concurrent obligations despite each loan's short tenor; information-asymmetry theory explains the fintech-specific structural mechanism that makes such accumulation possible without lender-side detection; human capital theory positions financial literacy as a protective factor; and Conservation of Resources theory explains why the resulting resilience harm is functionally equivalent to long-term debt exposure even though no single loan is long-tenor — the theoretical basis for this study's 'long-term debt paradox' framing.

6. Conceptual Framework

Figure 1 presents the study's conceptual framework. Digital Credit Usage intensity is modelled as a predictor of loan-stacking behaviour (H6), which in turn drives Over-Indebtedness (H4) and mediates itseffect on Financial Resilience (H5). Financial Literacy is modelled as a direct protective factor against Over-Indebtedness (H7) and a direct positive predictor of Financial Resilience. Critically, the framework also depicts three alternative 'long-term' mechanisms — usage tenure, borrowing frequency, and repayment-burden ratio (H1–H3) — as tested but, per the results in Section 8, empirically non-significant pathways (shown with dotted, greyed arrows). This visual contrast is deliberate: it represents the study's central finding that intuitive proxies for a 'long-term' credit relationship do not predict constraint, while a structurally distinct mechanism — concurrent cross-platform loan stacking — does. A boundary condition (H8) tests whether stacking is concentrated in particular borrower segments or represents a universal usage-pattern risk.

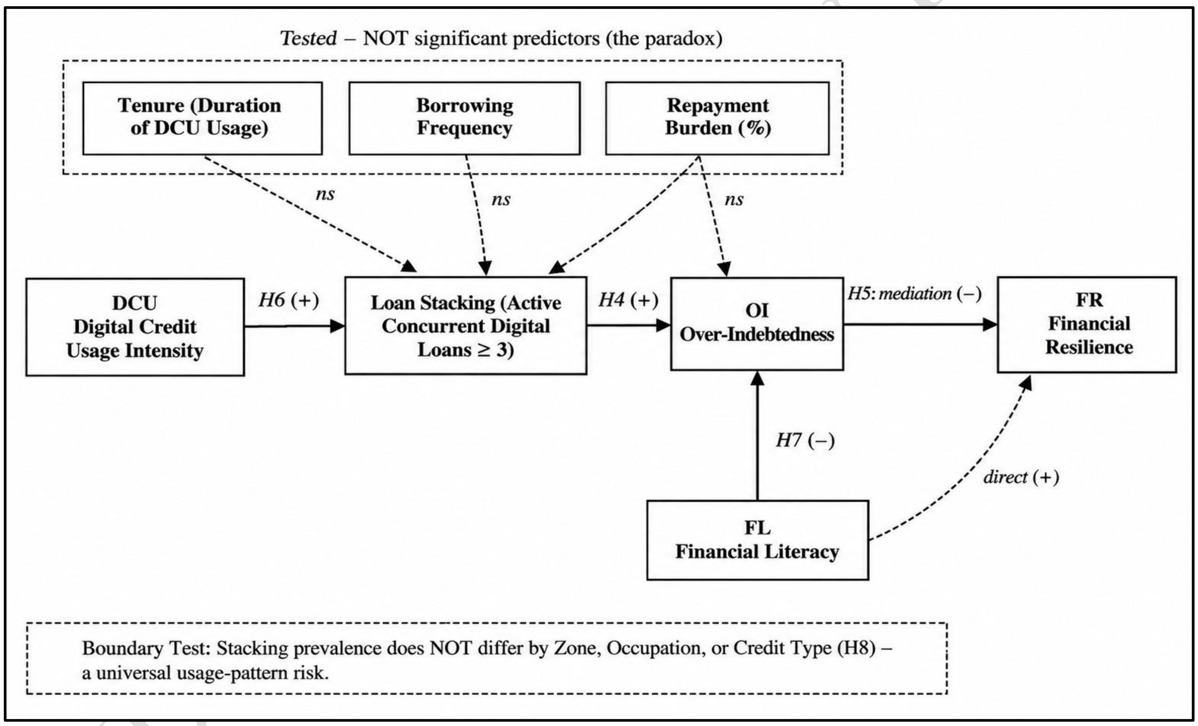

Figure 1: Conceptual Framework — The Long-Term Debt Paradox

7. Research Methodology

7.1 Population, Scope, and Sampling

This study uses the same target population, stratified sampling design, and 432-respondent Bangalore sample described in the companion study of this dataset: individuals aged 18–60 who had availed fintech/digital credit at least once in the preceding 24 months, stratified proportionately across the IT Corridor, Commercial/Trading Hub, and Peri-urban/Working-class zones (144 respondents each).

Reusing the same sample allows this study's mechanism-decomposition analysis to be read alongside the companion study's usage-to-resilience pathway findings without sampling-design confounds.

7.2 Operationalisation of Long-Term Constraint Mechanisms

We operationalised four candidate mechanisms from the survey's credit-usage profile items. Usage tenure was measured categorically (<1 year, 1–2 years, 3–5 years, >5 years) and coded ordinally (1–4). Borrowing frequency was measured categorically (once, 2–3 times, 4–6 times, more than 6 times in the past 24 months) and coded ordinally (1–4). We measured repayment burden as the approximate share of monthly income servicing digital debt, in five bands (<10%, 10–20%, 21–30%, 31–40%, >40%), and recoded to band midpoints for analysis. Loan stacking was measured directly as the count of currently active digital loans (range 1–5) and additionally dichotomised (1–2 loans = non-stacked; ≥3 loans = stacked) for group-comparison analysis, consistent with regulatory usage of multi-loan thresholds in over-indebtedness screening.

7.3 Data Analysis Techniques

Data were analysed in Python (pandas, statsmodels, scipy). Techniques applied were: Pearson correlation between each chronicity mechanism and Over-Indebtedness, Debt Repayment Stress, Repeat Borrowing, and Financial Resilience; multiple OLS regression testing each mechanism's independent effect controlling for the others; independent-samples t-tests and one-way ANOVA comparing stacked versus non-stacked borrowers and across loan-count levels; the Sobel test for mediation of the stacking–resilience relationship through Over-Indebtedness; binary logistic regression predicting stacking status from usage and literacy constructs; and chi-square tests of stacking prevalence across zone, occupation, and credit-type segments (H8).

8. Results and Analysis

8.1 Sample Profile on Chronicity Variables

Table 1
Descriptive Profile of Long-Term Constraint Variables (N = 432)

Variable	**Category**	***n***	**%**
Usage Tenure	< 1 year	72	16.7
	1–2 years	127	29.4
	3–5 years	148	34.3
	> 5 years	85	19.7
Borrowing Frequency	Once	75	17.4

Variable	Category	*n*	%
	2–3 times	167	38.7
	4–6 times	137	31.7
	More than 6 times	53	12.3
Repayment Burden	< 10%	99	22.9
	10–20%	132	30.6
	21–30%	98	22.7
	31–40%	79	18.3
	> 40%	24	5.6
Active Digital Loans	1 (non-stacked)	186	43.1
	2 (non-stacked)	144	33.3
	3 (stacked)	50	11.6
	4 (stacked)	34	7.9
	5 (stacked)	18	4.2

Note. Non-stacked = 1–2 active digital loans (n = 330, 76.4%); Stacked = 3 or more concurrent active digital loans (n = 102, 23.6%). Mean Active Digital Loans = 1.97 (SD = 1.11).

8.2 Correlation Analysis: Testing the Four Candidate Mechanisms

Table 2 presents Pearson correlations between each candidate long-term-constraint mechanism and the study's outcome constructs. Usage tenure, borrowing frequency, and repayment-burden ratio show uniformly small and statistically non-significant correlations with Over-Indebtedness, Debt Repayment Stress, Repeat Borrowing, and Financial Resilience (all $|r| \leq .07$, all $p > .14$). Active Digital Loans (loan stacking), by contrast, correlates significantly with Over-Indebtedness ($r = .20$, $p < .001$), Debt Repayment Stress ($r = .23$, $p < .001$), and Repeat Borrowing ($r = .23$, $p < .001$), though not directly with Financial Resilience ($r = –.06$, ns) — a pattern consistent with full mediation, tested formally in Section 8.5.

Table 2
Pearson Correlations Between Candidate Mechanisms and Outcome Constructs (N = 432)

Mechanism	OI	DRS	RB	FR
Usage Tenure (ordinal)	0.034	0.025	0.052	0.030
Borrowing Frequency (ordinal)	0.002	-0.071	-0.025	-0.057
Repayment Burden (%)	-0.042	0.023	-0.008	-0.046
Active Digital Loans (stacking)	0.202***	0.231***	0.229***	-0.055

Note. OI = Over-Indebtedness; DRS = Debt Repayment Stress; RB = Repeat Borrowing; FR = Financial Resilience. ***$p < .001$. Usage Tenure, Frequency, and Repayment Burden show no significant association with any outcome; Active Digital Loans is the only mechanism significantly associated with OI, DRS, and RB.

8.3 Regression Analysis

Two OLS regression models were estimated (standardised variables), each including all four candidate mechanisms simultaneously alongside relevant controls, to test whether loan stacking retains a significant independent effect once tenure, frequency, and burden are accounted for.

Table 3

OLS Regression Predicting Over-Indebtedness from Candidate Mechanisms (Model 1)

Predictor	*B*	*SE* B	*β*	*t*	*p*	95% CI
Active Digital Loans	0.131	0.044	0.131	2.98	0.003	[0.04, 0.22]
Usage Tenure	0.031	0.043	0.031	0.72	0.470	[-0.05, 0.12]
Borrowing Frequency	0.020	0.044	0.020	0.47	0.639	[-0.07, 0.11]
Repayment Burden	-0.057	0.043	-0.057	-1.32	0.186	[-0.14, 0.03]
DCU	0.412	0.044	0.412	9.29	< .001	[0.32, 0.50]
FL	-0.148	0.044	-0.148	-3.36	< .001	[-0.23, -0.06]

Note. DV = Over-Indebtedness (standardized). $R^2 = .211$, Adjusted $R^2 = .200$, $F(6, 425) = 18.99$, $p < .001$. Only Active Digital Loans (stacking) is significant among the four candidate mechanisms; Usage Tenure, Frequency, and Repayment Burden are not.

Table 4

OLS Regression Predicting Financial Resilience from Candidate Mechanisms (Model 2)

Predictor	*B*	*SE* B	*β*	*t*	*p*	95% CI
Active Digital Loans	0.014	0.046	0.014	0.32	0.751	[-0.08, 0.11]
Usage Tenure	0.029	0.045	0.029	0.66	0.512	[-0.06, 0.12]
Borrowing Frequency	-0.025	0.045	-0.025	-0.55	0.580	[-0.11, 0.06]
Repayment Burden	-0.049	0.045	-0.049	-1.10	0.270	[-0.14, 0.04]
FL	0.218	0.045	0.218	4.82	< .001	[0.13, 0.31]
OI	-0.305	0.046	-0.305	-6.66	< .001	[-0.39, -0.22]

Note. DV = Financial Resilience (standardized). $R^2 = .155$, Adjusted $R^2 = .143$, $F(6, 425) = 13.04$, $p < .001$. Once Over-Indebtedness is controlled, none of the four candidate mechanisms — including Active Digital Loans — retains a significant direct effect on FR, consistent with full mediation through OI (Section 8.5).

Table 3 confirms that among the four candidate long-term-constraint mechanisms, only Active Digital Loans (loan stacking) is a significant independent predictor of Over-Indebtedness ($\beta = .131$, $p = .003$), even after controlling for Digital Credit Usage intensity ($\beta = .412$, $p < .001$) and Financial Literacy ($\beta =$ –

.148, $p < .001$). Usage tenure, borrowing frequency, and repayment burden are all non-significant. Table 4 shows that none of the four mechanisms — stacking included — retains a significant direct effect on Financial Resilience once Over-Indebtedness is controlled, indicating that stacking's harm to resilience operates entirely through the over-indebtedness channel rather than directly.

8.4 Dose-Response and Group Comparison: Stacked vs. Non-Stacked Borrowers

A one-way ANOVA across the five levels of Active Digital Loans confirms a significant dose-response relationship with Over-Indebtedness ($F(4, 427) = 5.66$, $p < .001$), rising from M = 2.86 among borrowers with one active loan to M = 3.75 among those with five (Figure 2, left panel). The equivalent ANOVA for Financial Resilience across loan-count levels is non-significant ($F(4, 427) = 0.65$, $p = .630$), reinforcing that stacking's effect on resilience is indirect.

Table 5

Stacked (≥ 3 Loans) vs. Non-Stacked (1–2 Loans) Borrowers: Group Comparison

Outcome	Non-stacked M (SD)	Stacked M (SD)	*t*	*p*
Over-Indebtedness (OI)	2.95 (1.04)	3.28 (0.98)	2.90	0.004
Debt Repayment Stress (DRS)	2.90 (1.03)	3.25 (0.99)	3.03	0.003
Repeat Borrowing (RB)	2.87 (1.03)	3.23 (1.02)	3.08	0.002
Financial Resilience (FR)	3.07 (1.07)	2.99 (1.04)	-0.60	0.549

Note. Non-stacked n = 330; Stacked n = 102. Independent-samples t-tests, two-tailed. Stacked borrowers report significantly higher OI, DRS, and RB, but not significantly lower FR directly — again consistent with mediation through OI.

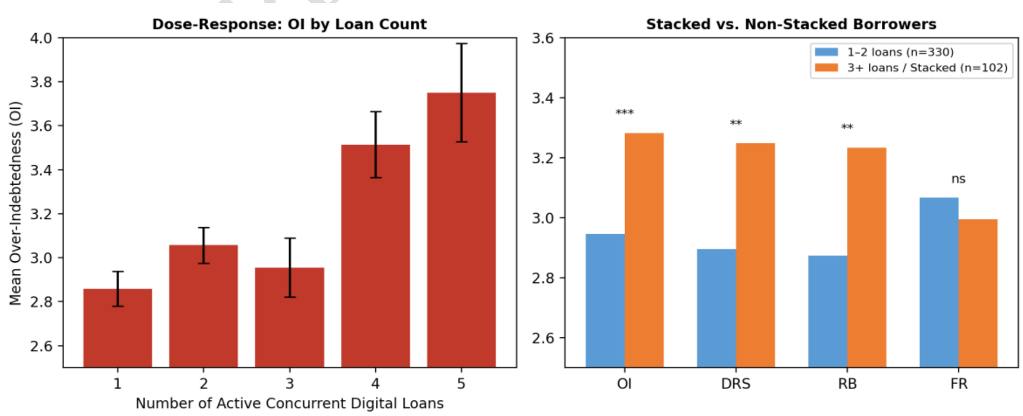

Figure 2: Dose-Response Relationship and Stacked vs. Non-Stacked Group Comparison

8.5 Mediation Analysis

A Sobel test confirms that Over-Indebtedness mediates the relationship between loan stacking and Financial Resilience. The path from Active Digital Loans to Over-Indebtedness was significant (a = 0.202, SE = 0.044, $p < .001$), as was the path from Over-Indebtedness to Financial Resilience controlling for stacking (b = –0.320, SE = 0.046, $p < .001$), yielding a significant indirect effect (ab = –0.065, Sobel z = –3.62, $p < .001$). The total effect of stacking on resilience was non-significant (c = –0.055, p = .251), and the direct effect controlling for the mediator was likewise non-significant (c′ = 0.009, p = .845) — an indirect-only mediation pattern: stacking's harm to resilience is real and statistically confirmed but operates entirely through the over-indebtedness pathway rather than being detectable in a simple bivariate comparison. This explains why Table 5's direct group comparison on FR alone did not reach significance despite the confirmed underlying mechanism and supports H5.

8.6 What Predicts Stacking? Digital Credit Usage and Literacy

Table 6
Binary Logistic Regression Predicting Loan-Stacking Status

Predictor	*B*	*SE*	*z*	*p*	OR	95% CI for OR
FLA	-0.172	0.140	-1.23	0.219	0.84	[0.64, 1.11]
DCU	0.501	0.137	3.65	< .001	1.65	[1.26, 2.16]
PCC	-0.102	0.129	-0.79	0.429	0.90	[0.70, 1.16]
FL	-0.158	0.122	-1.29	0.196	0.85	[0.67, 1.09]

Note. DV = 1 (Stacked, ≥ 3 active loans), 0 (non-stacked). N = 432. Digital Credit Usage intensity is the only significant predictor of stacking status; FinTech Lending Accessibility, Perceived Credit Convenience, and Financial Literacy are not significant in this model, supporting H6 specifically (usage drives stacking) while indicating stacking risk is not simply a function of low financial literacy.

Digital Credit Usage intensity significantly predicts the odds of falling into the stacked group (OR = 1.65, $p < .001$): each one-standard-deviation increase in usage intensity increases the odds of holding three or more concurrent loans by 65%. Notably, Financial Literacy does not significantly predict stacking status itself (p = .196), even though it significantly predicts Over-Indebtedness once stacking has occurred (Table 3). This distinction is substantively important: financial literacy appears to help borrowers manage the consequences of concurrent credit exposure rather than preventing the accumulation of that exposure in the first place — a finding discussed further in Section 9.

8.7 Boundary Condition: Is Stacking Segment-Specific or Universal?

Chi-square tests found no significant association between stacking status and geographic zone ($\chi^2(2)$ = 0.54, p = .764), occupation ($\chi^2(3)$ = 4.84, p = .184), or digital credit type ($\chi^2(3)$ = 0.44, p = .931). Stacking prevalence ranged narrowly from 21.5% (Peri-urban/Working-class) to 25.0% (Commercial/Trading

Hub) across zones, and from 14.7% (daily-wage/informal workers) to 27.6% (salaried professionals) across occupations — differences too small to reach significance at this sample size. This supports H8: loan stacking is not concentrated in any particular demographic or occupational segment but represents a usage-pattern risk that cuts uniformly across Bangalore's borrower population.

8.8 Summary of Hypotheses Testing

Table 7
Hypotheses Testing Summary

Hypothesis	Result
H1: Usage Tenure → OI (positive)	Not supported ($r = .03$, $p = .48$)
H2: Borrowing Frequency → OI (positive)	Not supported ($r = .00$, $p = .97$)
H3: Repayment Burden → FR (negative)	Not supported ($r = -.05$, $p = .34$)
H4: Loan Stacking → OI, DRS, RB (positive)	Supported ($\beta = .13–.23$, all $p < .01$)
H5: OI mediates Stacking → FR	Supported (Sobel $p < .001$, indirect-only mediation)
H6: DCU → Loan Stacking (positive)	Supported ($OR = 1.65$, $p < .001$)
H7: FL → OI (negative)	Supported ($\beta = -.148$, $p < .001$)
H8: Stacking prevalence uniform across zone/occupation/credit type	Supported (all χ^2 tests $p > .18$)

Note. OI = Over-Indebtedness; DRS = Debt Repayment Stress; RB = Repeat Borrowing; FR = Financial Resilience; DCU = Digital Credit Usage; FL = Financial Literacy.

9. Discussion of Findings

The central finding of this study is a genuine paradox, precisely stated: none of the three variables that would intuitively describe a 'long-term' relationship with fintech credit — how long a borrower has used it, how often they borrow, or what share of income they devote to repayment — predicts over-indebtedness or reduced financial resilience. What predicts both is something structurally different: the number of digital loans a borrower holds concurrently across different platforms at a single point in time. A borrower who has used fintech credit for five years, borrowing occasionally and comfortably within a modest repayment-burden ratio, shows no elevated risk. A borrower who has used it for six months but currently holds four or five simultaneous loans shows sharply elevated over-indebtedness (Figure 2) and, through that channel, reduced financial resilience.

This pattern is consistent with, and extends, the payday-lending literature's core insight (Melzer, 2011; Skiba &Tobacman, 2008) that short-tenor credit's harm operates through renewal and accumulation rather than contractual duration — but with an important fintech-specific refinement. In the single-lender payday context, the lender can see renewals. In India's multi-app fintech ecosystem, each platform's digital-footprint-based underwriting (Berg et al., 2020) operates largely in isolation from competitors' exposure data, meaning a borrower can accumulate a stacked, effectively long-term-equivalent debt position that is structurally invisible to any single lender at the point of underwriting. This is the mechanism this study labels the 'long-term debt paradox': short-tenor products, precisely because their brevity and cross-platform fragmentation make cumulative exposure hard to see, can produce persistent constraint that functions like long-term debt without ever appearing as such in any single loan's records.

The finding that Digital Credit Usage intensity — not low financial literacy — predicts who ends up stacking loans (Section 8.6) is also notable. It suggests stacking is primarily a usage-volume phenomenon (heavier users of the fintech ecosystem simply interact with more apps and platforms) rather than a knowledge-deficit phenomenon. Financial literacy's protective role, by contrast, operates downstream: it significantly reduces over-indebtedness conditional on usage and stacking levels (Table 3), suggesting literacy helps borrowers manage concurrent obligations rather than preventing them from accumulating in the first place. Finally, the absence of any significant segment concentration (Section 8.7) — stacking is roughly as prevalent among IT-corridor professionals as among informal workers, and across all four digital credit product types — reframes this risk as a design and market-structure issue rather than a vulnerable-population issue, with direct implications for how regulation should be targeted.

10. Implications

10.1 Theoretical Implications

This study contributes a mechanism-level decomposition that the existing fintech debt-trap literature (Yue et al., 2022; Aggarwal et al., 2024) has not attempted: rather than treating 'digital credit risk' as a single construct, it isolates concurrent cross-platform stacking as the specific, structurally distinct driver, while showing that intuitive proxies for chronicity (tenure, frequency, burden ratio) are empirically inert. It also extends the Western payday-lending rollover literature (Melzer, 2011; Skiba &Tobacman, 2008) into a fintech-specific, digital-footprint-underwriting context (Berg et al., 2020), proposing that information asymmetry between competing platforms — not merely borrower psychology — is a necessary structural condition for the paradox to occur.

10.2 Regulatory Implications

1. The finding that loan stacking, not tenure or frequency, drives over-indebtedness directly supports the case for RBI Account Aggregator-based real-time, cross-lender exposure checks specifically at the point of digital loan underwriting — closing the information gap identified in Section 5.3 as the structural precondition for stacking.

2. Because stacking prevalence is not segment-concentrated (Section 8.7), exposure-tracking requirements should apply uniformly across all digital lending NBFCs and platforms rather than being risk-tiered by borrower occupation or income bracket.
3. Since usage intensity (not low literacy) predicts stacking, disclosure and cooling-off interventions may be more effective if triggered by a borrower's real-time active-loan count across the ecosystem, rather than by static borrower risk-scoring at individual-platform level.

10.3 Lender and Product-Design Implications

1. Lenders could incorporate literacy-style guidance specifically at the point where a borrower's cross-platform active-loan count (where visible via credit bureau or Account Aggregator data) crosses three loans — the threshold at which this study's dose-response relationship shows over-indebtedness rising sharply.
2. Since financial literacy's protective effect operates downstream of stacking rather than preventing it, literacy interventions should be paired with — not substituted for — structural exposure limits.

11. Limitations of the Study

1. Loan stacking was measured via borrower self-report of active loan count rather than verified through credit bureau or Account Aggregator records; some under-reporting is possible given the topic's sensitivity.
2. The cross-sectional design cannot establish whether usage intensity causes stacking or whether both are jointly driven by an unmeasured borrower characteristic (e.g., income volatility); longitudinal or credit-bureau-linked data would strengthen causal claims.
3. The study's empirical scope is confined to Bangalore city; replication in other Indian metros with
4. Different fintech-platform density would test the generalisability of the null tenure/frequency/burden findings.
5. The stacked/non-stacked threshold (≥ 3 active loans) follows common regulatory practice but is a simplification; the dose-response analysis (Figure 2) partially addresses this by modelling the full 1–5 loan range.
6. The repayment-burden ratio was captured in banded rather than continuous form, which may understate a true continuous relationship with resilience at the margins.

12. Conclusion

This study tested whether fintech lending's short-term design nonetheless produces a long-term debt paradox—a persistent financial constraint functionally equivalent to long-term debt despite no single loan being long-tenor. The evidence is precise: three plausible 'long-term relationship' proxies — usage tenure, borrowing frequency, and repayment-burden ratio — show no significant association with over-indebtedness or financial resilience among 432 Bangalore-based digital-credit borrowers. What does predict both, with a clear statistical dose-response relationship, is concurrent loan stacking: holding three or more active digital loans across different platforms at once. Nearly a quarter of borrowers (23.6%) fall into this stacked category, and the risk is distributed uniformly across income, occupation, and geographic segments rather than concentrated among any single vulnerable group. The paradox this study documents is therefore structural rather than behavioural in origin: it is not that borrowers fail to manage any single short-term loan responsibly, but that India's fragmented, digital-footprint-based fintech underwriting architecture currently has no mechanism to make a borrower's cumulative cross-platform exposure visible to any one lender — turning a portfolio of individually short-term products into a collectively long-term constraint. Closing that visibility gap, rather than further restricting individual loan tenor or targeting specific borrower segments, is the most direct implication of this study's findings for regulators and lenders alike.

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