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FINANCIAL FRAUDS IN VEHICLE FINANCE COMPANIES: A SECONDARY-DATA ANALYTICS STUDY WITH REFERENCE TO TELANGANA STATE, INDIA

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Abstract

Purpose – This study examines the scale, structure and drivers of financial fraud that affects vehicle finance companies (VFCs) in Telangana, one of India's fastest-growing vehicle markets and, according to official crime statistics, the state with the highest incidence of cyber-enabled fraud. It asks how national lending-fraud patterns, state-level economic-offence trends and borrower grievances against non-banking finance companies (NBFCs) combine to shape the fraud-risk environment in which VFCs operate.

Design/methodology/approach – The paper builds four secondary datasets from Reserve Bank of India (RBI) and National Crime Records Bureau (NCRB) publications covering 2004-05 to 2024-25. It applies log-linear trend estimation, compound growth analysis, a Chow structural-break test, Spearman and Pearson correlation (including first differences), the Mann–Whitney U test, log–log elasticity estimation, Lorenz–Gini concentration analysis, and chi-square tests with Cramér's V. These results are integrated with a document-based typology of vehicle-finance fraud grounded in the fraud triangle, fraud diamond and routine activity theories.

Findings – Reported bank frauds grew at a trend rate of 10.3% a year, with a statistically significant break after 2017-18 ($F = 12.99$, $p < 0.001$), when annual growth in incidence rose from about 5.8% to 29.8%. Loan-related (advances) frauds accounted for 90.8% of the cumulative ₹5.77 lakh crore lost over two decades, despite being fewer than half of all cases. In Telangana, economic offences rose 3.4-fold and cyber crimes 10.1-fold between 2019 and 2024;

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the two series move almost in lockstep ($r = 0.97$ on first differences, $p < 0.01$), and the state's share of India's cyber crimes climbed from 6.0% to 26.7%. Fraud value in the state is highly concentrated (Gini ≈ 0.84): about 3.5% of cases account for an estimated 69% of the value. Complaints about loans and advances made up 68.7% of complaints against NBFCs received by the RBI Ombudsman in 2024-25, up from 56.4% two years earlier ($z = 34.9$, $p < 0.001$).

Research limitations/implications – Public statistics do not separate frauds against VFCs from other lending frauds at the state level; the findings therefore describe the fraud-risk environment rather than firm-level losses. The paper sets out a primary-data agenda to close this gap.

Practical implications – VFCs in Telangana need a two-tier control architecture: automated, high-volume screening for low-value identity, document and digital-channel frauds, and intensive, investigation-led oversight for the small number of high-value insider, dealer and collusive frauds that account for most losses.

Originality/value – To the authors' knowledge, this is the first study to triangulate RBI fraud statistics, NCRB state crime data and RBI Ombudsman grievance data to characterise fraud risk for vehicle financiers in a single Indian state, and to map that evidence to a theory-based fraud typology specific to vehicle lending.

Keywords: financial fraud; vehicle finance; non-banking financial companies; Telangana; fraud triangle; cyber fraud; fraud risk management; data analytics

JEL classification: G21, G23, G28, K42

Paper type: Research paper

1. Introduction

Vehicle finance sits at the centre of India's retail credit system. It funds the two-wheelers that carry most of the country's daily commuters, the cars that signal rising household incomes, and the commercial vehicles, tractors and three-wheelers that sustain small businesses and agricultural livelihoods. NBFCs dominate this segment. Crisil Ratings (2025) projects that NBFC vehicle-loan assets under management (AUM) will grow 16–17% a year to reach about ₹11 lakh crore by March 2027, with used-vehicle loans growing faster than new-vehicle loans (a compound rate of about 15% against 11% between FY2020 and FY2025). Rapid expansion

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of this kind widens the customer base to thinner-file borrowers, multiplies the number of dealers, field agents and digital touchpoints involved in each loan, and therefore enlarges the surface on which fraud can occur.

Telangana offers a sharp lens on this problem. The state's transport department reported 1.72 crore registered vehicles in February 2025, roughly one vehicle for every two residents, with about 2,000 new registrations every day; two-wheelers make up about 70% of the fleet (Siasat, 2025). Hyderabad's position as a technology and services hub has expanded both formal credit demand and digital payment adoption. At the same time, NCRB data place Telangana first among Indian states for cyber crime, with 27,230 cases in 2024 and a rate above 70 cases per lakh population (NCRB, 2026; The420.in, 2026). Economic offences registered in the state rose from 11,465 in 2019 to 39,127 in 2024. These two facts — a large, credit-dependent vehicle market and an exceptionally high fraud incidence — make Telangana a natural setting in which to study fraud risk for vehicle financiers.

Fraud damages VFCs in several ways. Direct losses arise when loans are disbursed against forged identities, inflated invoices or vehicles that do not exist. Indirect losses arise through higher credit costs, legal and repossession expenses, regulatory penalties and the erosion of customer trust when borrowers are themselves defrauded by people impersonating lenders or recovery agents. The RBI has responded by issuing dedicated Master Directions on fraud risk management for NBFCs (RBI, 2024a), which require board-approved fraud policies, early-warning signal (EWS) frameworks, data analytics and timely reporting. Yet the academic literature on Indian financial fraud remains concentrated on scheduled commercial banks and large corporate frauds (Gupta & Gupta, 2015; Singh et al., 2016). Retail asset finance, and vehicle finance in particular, has received little systematic attention, and state-level analysis is almost absent.

This study addresses that gap. It has four objectives: (i) to measure long-run trends and structural shifts in lending-related fraud in India, which form the background against which VFC fraud risk evolves; (ii) to analyse the growth, co-movement and concentration of economic and cyber fraud in Telangana; (iii) to assess what grievance data reveal about the conduct and fraud-adjacent risks of NBFC lending; and (iv) to develop a theory-based typology of vehicle-finance frauds, with red flags and controls, that VFCs operating in Telangana can use. The study relies entirely on published secondary data, and it states clearly where those data stop short of measuring VFC-specific losses.

The paper makes three contributions. Empirically, it assembles and tests a multi-source dataset that links national, state and sectoral indicators, and it shows that fraud risk in this setting is characterised by accelerating incidence, a decoupling of case counts from rupee value, and extreme concentration of value in a few large cases. Conceptually, it extends the fraud triangle and fraud diamond to the specific actors of vehicle lending — borrowers, dealers, field

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executives, recovery agents and outside impersonators — and combines them with routine activity theory to explain why digital channels shift the location of fraud. Practically, it translates the statistical findings into a two-tier control model aligned with the RBI's 2024 directions.

The rest of the paper is organised as follows. Section 2 describes the institutional and regulatory context. Section 3 reviews the literature and develops the hypotheses. Section 4 explains the data and methods. Section 5 presents the results, and Section 6 discusses them. Section 7 draws out policy and managerial implications, Section 8 notes limitations and future research, and Section 9 concludes.

2. Institutional and Regulatory Context

2.1 The vehicle finance business model

A vehicle loan is a secured retail loan in which the lender's security is a hypothecation charge over a movable asset. Under Section 51 of the Motor Vehicles Act, 1988, the charge is endorsed on the registration certificate (RC), and it can be removed only on the financier's no-objection certificate. In practice the loan cycle passes through several hands: a dealer or direct selling agent sources the customer; a credit or field verification officer checks identity, residence, income and the vehicle invoice; the lender disburses funds, usually to the dealer; the RTO records the hypothecation; and collection and, if necessary, repossession follow over the loan tenure. Every hand-off is a control point, and every control point is a potential point of failure. Used-vehicle and commercial-vehicle loans add further risk because valuation is subjective and the asset may already carry an undisclosed charge.

2.2 The regulatory framework

Most VFCs in India are NBFCs registered with and supervised by the RBI. Three strands of regulation bear directly on fraud. First, the Master Direction on Fraud Risk Management in NBFCs (RBI, 2024a) requires a board-approved fraud risk policy, a senior-level committee to oversee fraud risk, an EWS framework, adherence to natural justice before an account is classified as fraudulent, and reporting of frauds to the RBI and, where warranted, to law enforcement. Second, the RBI's fair-practices and outsourcing norms govern how loans are sourced and how recovery agents conduct themselves, an area that generates many borrower complaints. Third, the RBI's digital lending regulations govern lending through apps and lending service providers and are intended to curb the impersonation and data-misuse frauds that grew rapidly after 2020. Grievances that lenders do not resolve can be escalated to the Reserve Bank – Integrated Ombudsman Scheme (RB-IOS), 2021, whose annual reports provide the grievance data analysed in this paper.

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2.3 Telangana as the study setting

Telangana was formed in 2014 and has since become one of India's higher-income states, anchored by the Hyderabad metropolitan region. Its vehicle fleet is large and growing, and its rural districts depend heavily on tractor and two-wheeler finance. Policing is organised through several commissionerates, including Hyderabad, Cyberabad and Rachakonda, alongside district police units, and the state has built specialised cyber-crime infrastructure. Higher crime registration can reflect better reporting as well as more crime, a point the discussion returns to. For VFCs, however, the relevant question is not only how much fraud is reported but what kinds of fraud are growing, how value is distributed across cases, and where in the lending cycle losses arise.

3. Literature Review and Hypotheses

3.1 Theories of fraud

The dominant explanation of why individuals commit fraud is Cressey's (1953) fraud triangle, which holds that fraud requires a non-shareable financial **pressure**, a perceived **opportunity** to commit and conceal the act, and a **rationalisation** that allows the offender to reconcile the act with a self-image of honesty. Wolfe and Hermanson (2004) added **capability** — the position, skills and personality needed to exploit an opportunity — to form the fraud diamond. Later reviews have broadened the triangle to include collusion, organisational culture and the offender's interaction with control systems (Dorminey et al., 2012; Schuchter & Levi, 2016). Economic theories complement these behavioural accounts: Becker (1968) models crime as a rational choice that weighs expected gains against the probability and severity of punishment, which implies that low detection and conviction rates raise fraud incidence.

Two further lenses are useful for lending. Information-asymmetry theory explains why lenders cannot perfectly observe borrower type or intent (Akerlof, 1970; Stiglitz & Weiss, 1981), so misrepresentation at origination is a structural risk of credit markets. Agency theory explains why employees and intermediaries, whose incentives differ from those of the lender, may collude or cut corners when monitoring is weak (Jensen & Meckling, 1976). Routine activity theory (Cohen & Felson, 1979) shifts the focus from the offender to the situation: crime occurs when a motivated offender meets a suitable target in the absence of a capable guardian. The theory is especially helpful for explaining digital fraud, because online channels multiply contacts between offenders and targets while reducing face-to-face guardianship.

3.2 Empirical evidence on financial fraud in India

Indian research on financial fraud has concentrated on banks. Singh et al. (2016) studied frauds in Indian banks and identified weak credit appraisal, poor post-disbursal monitoring, collusion between staff and borrowers, and delays in fraud classification as recurring causes, noting that

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large-value advances frauds dominated losses. Gupta and Gupta (2015) found that Indian managers perceived corporate fraud as rising and attributed it to weak enforcement, governance failures and the pressure to meet targets. Reurink (2018), reviewing the international literature, classified financial fraud into financial-statement fraud, fraudulent financial mis-selling and fraudulent investment schemes, and emphasised that the social cost of fraud lies largely in damage to trust. The Association of Certified Fraud Examiners' global studies consistently show that tips are the most common way frauds are detected and that losses rise with the perpetrator's seniority and the duration of the scheme (ACFE, 2024).

Evidence specific to vehicle finance is mostly found in practitioner disclosures and police reports rather than peer-reviewed studies. A widely reported example is Mahindra & Mahindra Financial Services' 2024 disclosure of a fraud of up to ₹150 crore at a branch in north-east India, which involved forged KYC documents in retail vehicle loans (Business Standard, 2024). Police reports across Indian states describe gangs that obtain vehicle loans with forged identity documents, resell financed vehicles with fake RCs, or impersonate lenders to collect fees from would-be borrowers (e.g., ETV Bharat, 2025; Telangana Today, 2025). These cases suggest that vehicle-finance fraud spans the whole loan cycle and involves internal as well as external actors, but they have not been organised into a systematic framework.

3.3 Data analytics and fraud detection

A large literature examines statistical and machine-learning approaches to fraud detection. Bolton and Hand (2002) set out the distinction between supervised methods, which learn from labelled frauds, and unsupervised methods, which flag anomalies. Ngai et al. (2011) and West and Bhattacharya (2016) review applications across credit cards, insurance, securities and lending, noting the challenges of class imbalance, concept drift and the scarcity of labelled data. The RBI's 2024 directions explicitly expect NBFCs to use data analytics in their EWS frameworks (RBI, 2024a). Understanding the macro-level shape of fraud — how fast it grows, where it concentrates and how its form changes — is a precondition for designing such systems, and that is the analytical contribution of the present study.

3.4 Research gap and hypotheses

The review reveals three gaps: (i) little peer-reviewed work on fraud in Indian vehicle finance or NBFC retail lending; (ii) almost no state-level analysis that links fraud statistics to the lending environment; and (iii) limited integration of quantitative evidence with fraud theory to produce actionable typologies. Drawing on the theories above, the study tests seven hypotheses.

Routine activity theory predicts that expanding credit and digital channels increase the number of offender–target contacts. Hence, **H1:** the number of reported lending-related frauds in India shows a significant positive long-run trend. Because digital adoption accelerated sharply in the

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late 2010s, **H2:** fraud incidence shows a structural break, with faster growth in the recent period. Agency and fraud-diamond theories imply that the largest frauds require insider capability and access, which are concentrated in credit (advances) operations. Hence, **H3:** the average value of advances frauds is significantly higher than that of card and internet frauds. At the state level, cyber channels provide a common vehicle for many economic offences, so **H4:** economic offences and cyber crimes in Telangana co-move positively, and **H5:** cyber crime in Telangana grows faster than the national average. Following the evidence that a few large frauds drive losses, **H6:** the value of fraud in Telangana is highly concentrated (Gini coefficient above 0.5). Finally, if lending conduct is a growing source of borrower harm, **H7:** the composition of complaints against NBFCs shifts significantly towards loans and advances over time.

4. Data and Methodology

4.1 Research design

The study uses a descriptive-analytical design based on secondary data. Firm-level fraud data for VFCs are confidential, and no public source reports frauds against VFCs in Telangana separately. The study therefore takes a triangulation approach: it combines three independent official data streams, each describing one part of the fraud-risk environment facing Telangana's vehicle financiers, and interprets them through fraud theory and documented case evidence. The approach follows the logic of convergent designs, in which agreement among independent sources strengthens inference where no single source is decisive.

4.2 Data sources

Table 1 summarises the four datasets. Dataset A is drawn from the RBI's *Report on Trend and Progress of Banking in India* (Appendix Table IV.7), which reports frauds of ₹1 lakh and above by area of operation. The series for 2004-05 to 2021-22 is taken from the 2023-24 edition (RBI, 2024b), and the series for 2022-23 to 2024-25 from the 2024-25 edition (RBI, 2025a), so that the most recent revised figures are used. The RBI notes that 2024-25 includes 122 cases worth ₹18,336 crore reported afresh for earlier years, which partly explains the jump in value in that year. Although the series covers banks, advances frauds are the closest available proxy for the lending-fraud environment in which NBFCs, including VFCs, compete for the same borrowers and use many of the same dealers and verification agencies.

Dataset B comprises NCRB *Crime in India* figures for Telangana on economic offences (cheating, forgery, fraud, criminal breach of trust and related heads) and cyber crimes for 2019–2024, together with the all-India cyber-crime totals (NCRB, 2022, 2023, 2025, 2026). Dataset C reports the distribution of Telangana's 2024 cheating, forgery and fraud cases by value of property involved. Dataset D is drawn from the RBI's *Annual Report of the Ombudsman*

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Scheme 2024-25 (RBI, 2025b) and gives complaints against NBFCs by category for 2022-23 to 2024-25. Contextual data on Telangana's vehicle fleet and NBFC vehicle-loan AUM come from the state transport department, as reported in the press, and from Crisil Ratings (2025).

Table 1. Datasets, variables and sources

Dataset	Coverage	Key variables	Source
A. Bank frauds by area of operation	India, 2004-05 to 2024-25 (21 years)	Number and amount (₹ crore) of frauds: total, advances, card/internet	RBI (2024b, 2025a), Appendix Table IV.7
B. Economic offences and cyber crime	Telangana and India, 2019–2024 (6 years)	Cases registered: economic offences, cyber crimes; India cyber total	NCRB Crime in India, 2021–2024 editions
C. Fraud cases by value	Telangana, 2024	Cheating/forgery/fraud cases in eight value classes	NCRB Crime in India 2024, as reported by IndToday (2026)
D. Complaints against NBFCs	India, 2022-23 to 2024-25	Complaints by category: loans & advances, credit cards, others	RBI (2025b)

Note: The RBI fraud series covers frauds of ₹1 lakh and above reported by banks. NCRB figures are cases registered by police. All datasets are provided in the supplementary file.

4.3 Analytical techniques

Six groups of techniques are applied. First, long-run growth is measured by the compound annual growth rate (CAGR) and by a log-linear trend model, which is more robust to the choice of end-points:

$$\ln(Y_t) = \alpha + \beta t + \varepsilon_t, \quad \text{trend growth rate} = (e^{\beta} - 1) \times 100$$

where Y_t is the number or value of frauds in year t. Second, the Chow (1960) test examines whether the trend coefficient changed after 2017-18, a date chosen *a priori* because it marks the period after demonetisation and the rapid spread of UPI and app-based lending. The F-statistic compares the residual sum of squares of the pooled model with that of the two sub-period models. Third, the association between the number and value of frauds is measured by Spearman's rank correlation for the full period and for the latest eight years, and the difference in average fraud size between advances and card/internet frauds is tested with the one-sided Mann–Whitney U test, which does not assume normality.

Fourth, for Telangana, the co-movement of economic offences and cyber crimes is measured by Pearson's correlation both in levels and in first differences, since two trending series can be correlated in levels even when unrelated. A log–log regression gives the elasticity of economic offences with respect to cyber crime, and the log-linear trend model is used to produce indicative projections for 2025 and 2026 with 95% prediction intervals. Fifth, concentration of fraud value is measured with a Lorenz curve and Gini coefficient computed from grouped data (Lorenz, 1905), using class mid-points to estimate the value in each class. Sixth, changes in the composition of NBFC complaints are tested with a chi-square test of independence, with

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Cramér's V as the effect size, and a two-proportion z-test for the change in the share of loan-related complaints. All analysis was carried out in Python (pandas, SciPy and statsmodels), and the significance level is 5% unless otherwise stated.

5. Results

5.1 Long-run trends in lending-related fraud in India

Table 2 reports descriptive statistics and trend estimates for Dataset A. Over 2004-05 to 2024-25, banks reported an average of 7,741 frauds a year (median 4,670), involving an average of ₹27,461 crore. The number of frauds grew at a CAGR of 12.1% and a log-linear trend rate of 10.3% a year ($R^2 = 0.79$, $p < 0.001$); the amount involved grew at a trend rate of 25.1% ($R^2 = 0.74$, $p < 0.001$). H1 is therefore supported. The cumulative amount involved over the 21 years was ₹5.77 lakh crore, of which ₹5.24 lakh crore (90.8%) arose from advances.

Table 2. Descriptive statistics and trend estimates, bank frauds in India, 2004-05 to 2024-25

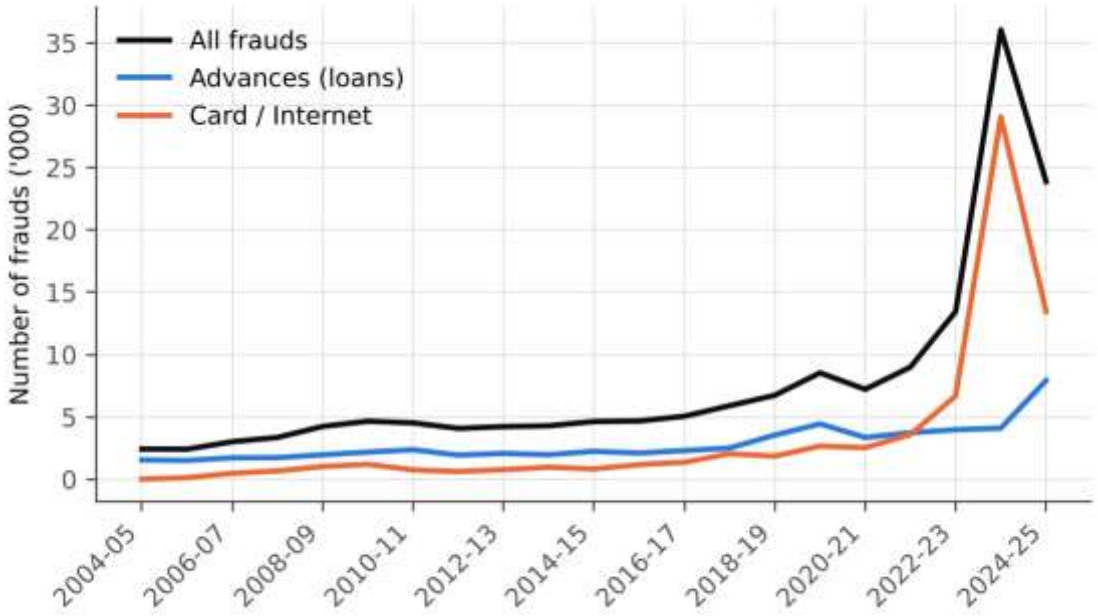
Variable	Mean	Median	SD	Trend growth (% p.a.)	R^2
Total frauds (number)	7,741	4,670	8,046	10.3***	0.79
Total amount (₹ crore)	27,461	11,261	40,599	25.1***	0.74
Advances frauds (number)	2,834	2,254	1,476	6.2***	0.81
Card/internet frauds (number)	3,436	1,191	6,589	23.2***	0.78
Avg. advances fraud (₹ lakh)	721.3	377.7	988.4	–	–
Avg. card/internet fraud (₹ lakh)	4.4	4.1	2.0	–	–
Advances share of value (%)	83.8	85.7	10.9	–	–

Note: Trend growth from $\ln(Y) = \alpha + \beta t$; *** $p < 0.001$. Source: authors' computation from RBI (2024b, 2025a).

Figure 1 shows the composition of this growth. Advances frauds grew steadily at 6.2% a year, while card and internet frauds grew almost four times as fast, at 23.2% a year, and their share of the number of frauds rose from 1.1% in 2004-05 to a peak of 80.7% in 2023-24. Figure 2 shows, however, that advances frauds have dominated value throughout: their share of the amount involved averaged 83.8% and fell below 60% only once (2017-18, when off-balance-sheet frauds of ₹16,288 crore inflated the total).

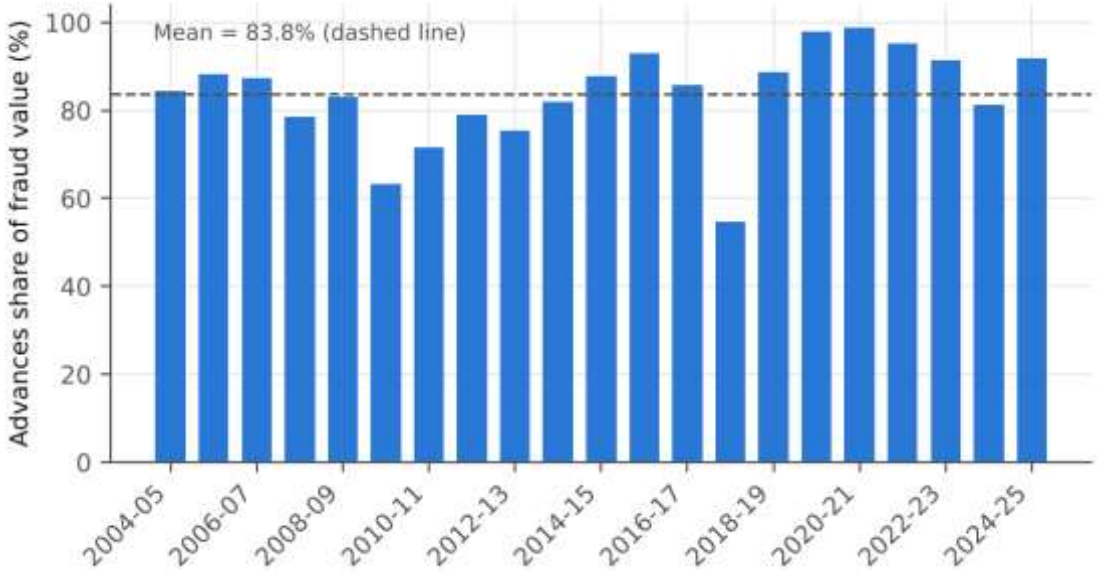
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Figure 1. Frauds reported by banks in India by number, 2004-05 to 2024-25



Source: authors' computation from RBI (2024b, 2025a). Frauds of ₹1 lakh and above.

Figure 2. Advances (loan) frauds as a share of the total value of bank frauds (%)



Source: authors' computation from RBI (2024b, 2025a).

5.2 Structural break and the decoupling of incidence from value

The Chow test confirms a structural break in the trend of fraud incidence after 2017-18 ($F(2, 17) = 12.99$, $p < 0.001$). Before the break, the number of frauds grew at 5.8% a year; from 2018-19 onwards it grew at 29.8% a year, supporting H2. Over the full period, the number and

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value of frauds are strongly rank-correlated (Spearman's $\rho = 0.80$, $p < 0.001$). Over the latest eight years, however, the correlation turns negative ($\rho = -0.64$, $p = 0.086$): the years with the most frauds were not the years with the largest losses. This decoupling is consistent with a shift in the fraud mix towards many small digital frauds, while value continues to be driven by a few large credit frauds.

The Mann–Whitney test confirms that the average size of an advances fraud is significantly larger than that of a card or internet fraud ($U = 441$, $p < 0.001$), supporting H3. In every one of the 21 years, the average advances fraud was larger than the average digital fraud; the median of the annual average fraud size was about ₹3.8 crore for advances, against about ₹4 lakh for card and internet frauds.

5.3 Economic offences and cyber crime in Telangana

Table 3 and Figure 3 present the Telangana series. Economic offences rose from 11,465 cases in 2019 to 39,127 in 2024, a 3.4-fold increase and a CAGR of 27.8%. Cyber crimes rose from 2,691 to 27,230, a 10.1-fold increase and a CAGR of 58.9%. Both log-linear trends fit closely ($R^2 = 0.95$ and 0.96 respectively, $p < 0.001$). The two series are almost perfectly correlated in levels ($r = 0.994$, $p < 0.001$) and, more importantly, remain highly correlated in first differences ($r = 0.970$, $p = 0.006$), which indicates that year-to-year increases in cyber crime coincide with increases in economic offences and that the association is not merely a shared trend. H4 is supported. The log–log elasticity is 0.53 (SE = 0.05, $R^2 = 0.97$, $p < 0.001$): a 10% rise in cyber crime is associated with a rise of about 5.3% in economic offences.

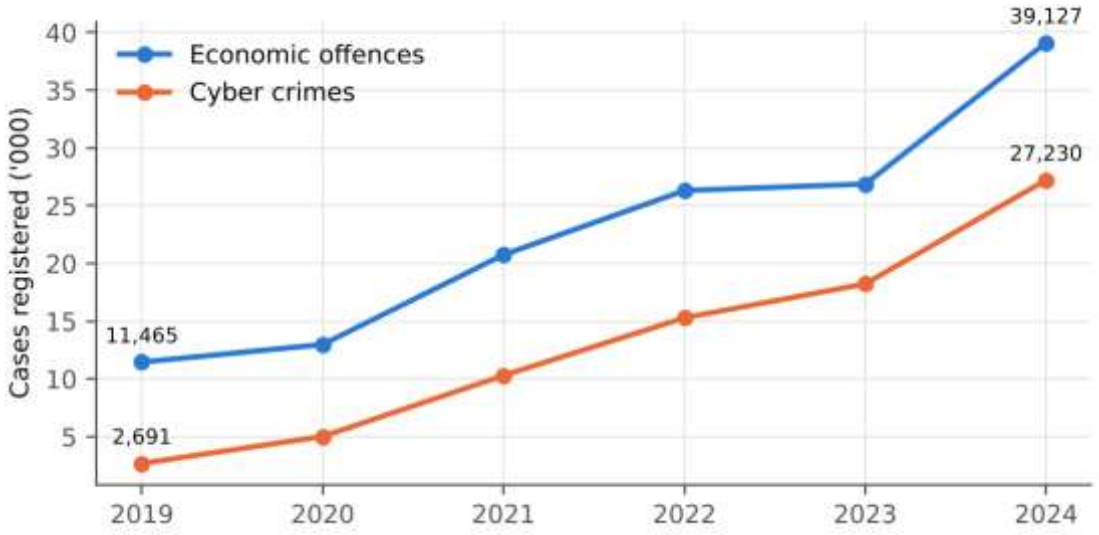
Table 3. Economic offences and cyber crime in Telangana, 2019–2024

Year	Economic offences (Telangana)	Cyber crimes (Telangana)	Cyber crimes (India)	Telangana share of India's cyber crimes (%)
2019	11,465	2,691	44,546	6.0
2020	12,985	5,024	50,035	10.0
2021	20,759	10,303	52,974	19.4
2022	26,321	15,297	65,893	23.2
2023	26,881	18,236	86,420	21.1
2024	39,127	27,230	1,01,928	26.7
CAGR 2019–24 (%)	27.8	58.9	18.0	–
Trend growth (% p.a.)	27.7***	57.2***	18.7***	–

Note: *** $p < 0.001$. Sources: NCRB Crime in India (2021–2024 editions), as compiled from Telangana Today (2022), Business Standard (2023), IndToday (2026) and The420.in (2026); authors' computation.

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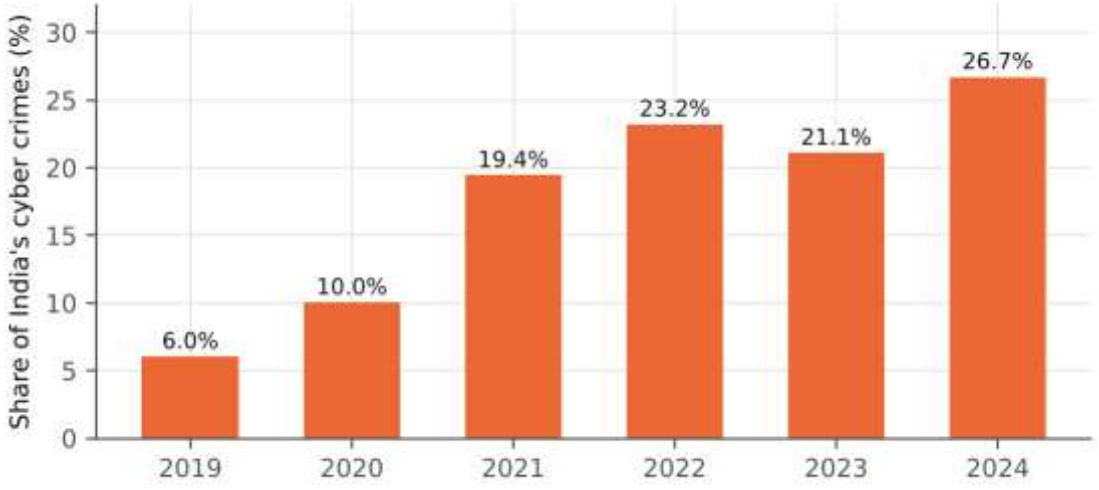
Figure 3. Economic offences and cyber crimes registered in Telangana, 2019–2024



Source: as for Table 3.

Telangana's cyber crimes grew three times faster than the national total (trend growth of 57.2% against 18.7%), supporting H5. As Figure 4 shows, the state's share of India's cyber crimes rose from 6.0% in 2019 to 26.7% in 2024, even though it holds less than 3% of India's population. Indicative projections from the trend models suggest about 49,000 economic offences (95% prediction interval: 32,000–76,000) and about 49,000 cyber crimes (23,000–105,000) in 2025. The width of these intervals, based on only six observations, means the projections should be read as a signal of direction rather than as forecasts.

Figure 4. Telangana's share of cyber crime cases registered in India (%)



Source: as for Table 3.

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5.4 Concentration of fraud value in Telangana

Table 4 shows the distribution of Telangana's 2024 cheating, forgery and fraud cases by value of property involved. Of the 27,752 cases for which a value class is recorded, 47.9% involved less than ₹1 lakh and a further 44.1% involved ₹1–10 lakh; together, 92.0% of cases fell below ₹10 lakh. Using class mid-points, these cases account for only about 20.6% of the estimated total value. In contrast, the 3.5% of cases involving ₹50 lakh or more account for about 69.0% of the estimated value. The Lorenz curve in Figure 5 bows sharply away from the line of equality, and the grouped-data Gini coefficient is 0.84, well above the 0.5 threshold specified in H6, which is therefore supported.

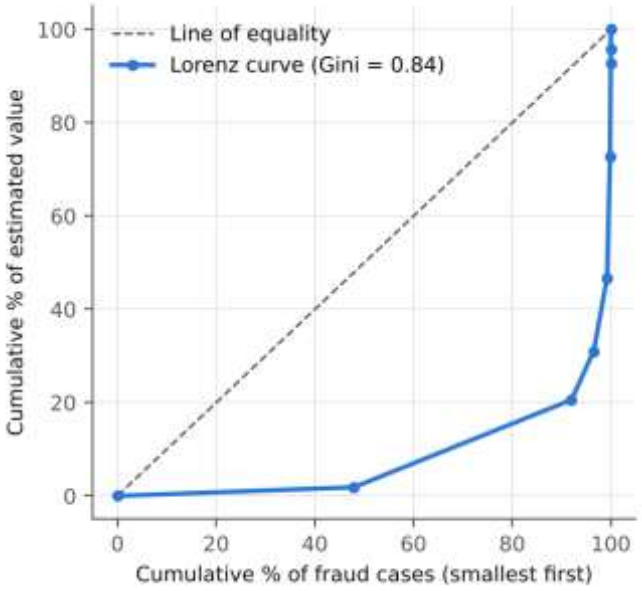
Table 4. Cheating, forgery and fraud cases in Telangana by value of property involved, 2024

Value class	Cases	% of cases	Estimated value (₹ crore)	% of estimated value
Below ₹1 lakh	13,294	47.9	66	1.9
₹1–10 lakh	12,245	44.1	673	18.8
₹10–50 lakh	1,248	4.5	374	10.4
₹50 lakh–1 crore	749	2.7	562	15.6
₹1–10 crore	170	0.6	935	26.0
₹10–25 crore	41	0.1	718	20.0
₹25–50 crore	3	<0.1	113	3.1
₹50–100 crore	2	<0.1	150	4.2
Total	27,752	100.0	3,591	100.0

Note: Estimated value = cases × class mid-point (₹0.5 lakh assumed for the lowest class). Value class is not recorded for all 38,908 cases registered under these heads. Source: NCRB Crime in India 2024 as reported by IndToday (2026); authors' computation.

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Figure 5. Lorenz curve of estimated fraud value, Telangana, 2024



Source: authors' computation from Table 4.

5.5 Complaints against NBFCs

Table 5 and Figure 6 summarise complaints against NBFCs received by the RBI Ombudsman offices. Total NBFC complaints rose from 33,072 in 2022-23 to 43,864 in 2024-25 (CAGR 15.2%), and NBFCs' share of all complaints received by the offices edged up from 14.1% to 14.8%. Complaints about loans and advances — the category that covers vehicle loans — grew much faster, at a CAGR of 27.0%, while credit-card complaints were flat and other complaints fell. The share of loans and advances in NBFC complaints rose from 56.4% to 68.7% ($z = 34.9$, $p < 0.001$). The chi-square test confirms that the composition of complaints changed significantly across the three years ($\chi^2(4) = 1{,}394.1$, $p < 0.001$), supporting H7, although Cramér's V of 0.08 indicates that the effect, while highly significant given the large sample, is modest in size.

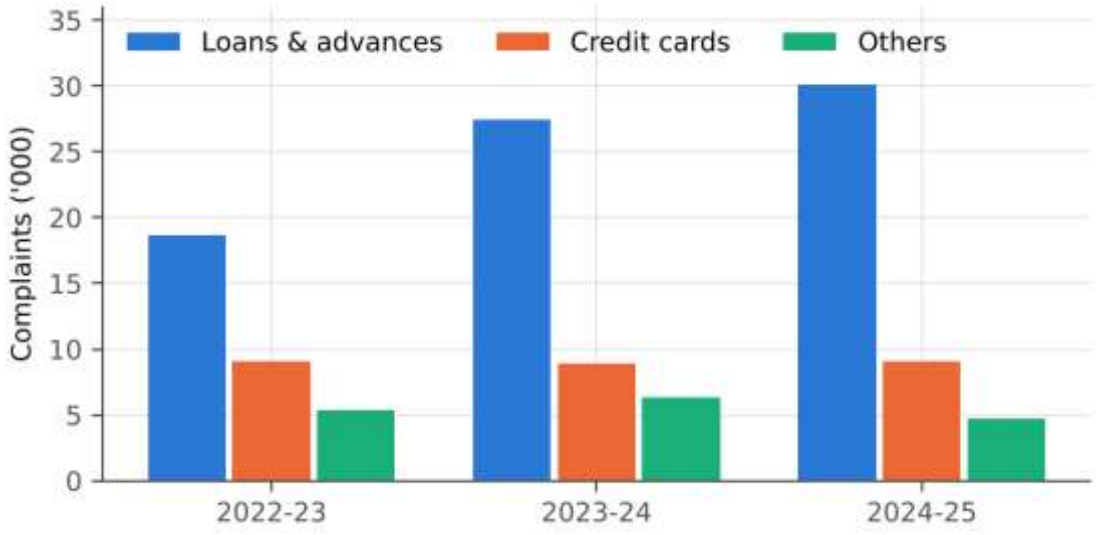
Table 5. Complaints against NBFCs received by RBI Ombudsman offices, by category

Category	2022-23	2023-24	2024-25	CAGR (%)
Loans and advances	18,657 (56.4%)	27,471 (64.3%)	30,114 (68.7%)	27.0
Credit cards	9,090 (27.5%)	8,912 (20.9%)	9,063 (20.7%)	−0.1
Others	5,325 (16.1%)	6,316 (14.8%)	4,687 (10.7%)	−6.2
Total	33,072	42,699	43,864	15.2
Test statistics	$\chi^2(4) = 1{,}394.1$, $p < 0.001$; Cramér's V = 0.08			

Source: RBI (2025b); authors' computation.

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Figure 6. Complaints against NBFCs received by RBI Ombudsman offices, by category



Source: RBI (2025b).

5.6 Summary of hypothesis tests

Table 6. Summary of hypothesis tests

Hypothesis	Test	Key statistic	Result
H1: Positive long-run trend in fraud incidence	Log-linear OLS	$\beta \rightarrow 10.3\%$ p.a., $p < 0.001$	Supported
H2: Structural break after 2017-18	Chow test	$F = 12.99$, $p < 0.001$	Supported
H3: Advances frauds larger than card/internet frauds	Mann–Whitney U (one-sided)	$U = 441$, $p < 0.001$	Supported
H4: Economic offences and cyber crime co-move (Telangana)	Pearson r (levels, differences)	$r = 0.99$; $\Delta r = 0.97$, $p = 0.006$	Supported
H5: Telangana cyber crime grows faster than India's	Trend comparison	57.2% vs 18.7% p.a.	Supported
H6: Fraud value highly concentrated (Gini > 0.5)	Lorenz–Gini (grouped)	Gini = 0.84	Supported
H7: NBFC complaints shift towards loans and advances	χ^2 test; z-test	$\chi^2 = 1{,}394.1$; $z = 34.9$; $V = 0.08$	Supported (small effect)

5.7 A typology of vehicle-finance frauds

The statistical results describe the environment but not the mechanics of fraud within a VFC. To bridge this gap, Table 7 sets out a typology of vehicle-finance frauds organised by stage of the loan cycle. It was developed by mapping documented cases and regulatory fraud categories (RBI, 2024a) to the elements of the fraud diamond and routine activity theory, and it links each fraud type to observable red flags and to the controls that the RBI's directions and good practice

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recommend. The typology also identifies which tier of the control model proposed in Section 7 is best suited to each fraud type, based on the value and volume patterns reported above.

Table 7. Typology of vehicle-finance frauds, red flags and controls

Stage / fraud type	Typical actors and modus operandi	Dominant fraud-diamond element	Red flags	Key controls (tier)
Origination: identity and KYC fraud	Borrower or gang uses forged or borrowed Aadhaar, PAN or address proof; synthetic identities; 'benami' borrowers	Opportunity (weak verification); capability (document forgery)	Mismatched photo, mobile or address; multiple loans on one mobile or device; first EMI default	Aadhaar/CKYC e-verification, device and mobile linkage analytics, field verification audit (Tier 1)
Origination: income and invoice inflation	Dealer or DSA inflates invoice or down-payment receipt; fake salary slips or bank statements	Pressure (sales targets); rationalisation ('everyone does it')	Loan-to-value near cap; dealer-level clustering of early defaults; round-figure invoices	Invoice checks with OEM data, dealer scorecards, account-aggregator statements (Tier 1/2)
Asset: ghost and double financing	Same vehicle financed by two lenders, or loan raised on a vehicle never delivered	Opportunity (no shared charge registry check); collusion	Delay in RC endorsement; chassis or engine number reused; dealer delivery lag	Vahan hypothecation check before disbursal; RC-endorsement tracking; physical delivery verification (Tier 2)
Asset: fake NOC and hypothecation removal	Forged no-objection certificate used at RTO to clear charge; vehicle sold to third party	Capability (access to forms, intermediaries)	Charge cleared while loan outstanding; resale soon after disbursal	Digital NOC issuance integrated with Vahan; periodic RC reconciliation (Tier 2)
Servicing: collection misappropriation	Field executive collects EMIs in cash and does not deposit; issues fake receipts	Pressure (personal finances); opportunity (cash handling)	Customer disputes paid status; rising cash share; receipt-book gaps	Digital receipts, cash limits, customer SMS confirmation, rotation of collectors (Tier 1/2)
Recovery: repossession and auction fraud	Collusion in undervalued sale of repossessed vehicles; unauthorised seizure by agents	Opportunity (opaque disposal); rationalisation	Sale price far below valuation; repeated buyers; complaints of coercive recovery	Independent valuation, e-auction, agent registration and conduct monitoring (Tier 2)
Insider: branch-level embezzlement	Staff create fictitious loans or divert disbursements, often with dealers (cf. Mahindra Finance, 2024)	Capability (system access, seniority); collusion	Branch growth far above peers; disbursements to related accounts; override frequency	Maker–checker separation, override analytics, surprise audits, whistle-blower channel (Tier 2)
Digital: impersonation and advance-fee fraud	Outsiders pose as VFC staff or recovery agents via WhatsApp, Telegram or fake websites; collect 'processing fees' or EMIs	Opportunity (no capable guardian online)	Customer reports of unknown agents; fake domains or apps using brand	Brand monitoring, verified communication channels, customer awareness, rapid reporting to cyber cell (Tier 1)

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Note: Tier 1 = automated, high-volume screening of low-value cases; Tier 2 = investigation-led oversight of low-volume, high-value cases (see Section 7). Sources: authors' synthesis from RBI (2024a), Business Standard (2024), ETV Bharat (2025), Telangana Today (2025) and the literature reviewed in Section 3.

6. Discussion

The results point to three features of the fraud-risk environment that matter for VFCs in Telangana. The first is **acceleration combined with a change in form**. The structural break in fraud incidence after 2017-18 and the near-fourfold faster growth of card and internet frauds relative to advances frauds show that the fraud problem has become larger and more digital. Telangana sits at the leading edge of this shift: its cyber crimes grew roughly three times faster than the national total, and its share of all cyber crime in India more than quadrupled in five years. This pattern fits routine activity theory closely. Digital lending, UPI-based EMI collection and social-media customer contact have greatly increased the number of points at which motivated offenders can reach suitable targets, while the 'capable guardian' — a branch officer who knows the customer, or a customer who knows the agent — is often absent in remote interactions. For VFCs, this means that fraud now increasingly arises outside the loan file, for example when customers pay a fake agent or download a cloned app, and this damages trust in the lender even when the lender itself suffers no direct loss.

The second feature is the **decoupling of incidence from value**, and the resulting concentration. Nationally, the rank correlation between the number and value of frauds turned negative in the latest eight years; in Telangana, fewer than 4% of fraud cases account for more than two-thirds of estimated value. These findings are consistent with the bank-fraud literature, which shows that a small number of large credit frauds drive losses (Singh et al., 2016), and with the fraud diamond's emphasis on capability: large frauds require access, authority and often collusion, which are found inside lending organisations and their dealer networks rather than among opportunistic outsiders. The practical implication is that a fraud-control strategy that counts cases will tend to focus on the many small digital frauds, while a strategy that measures losses must focus on a few insiders, dealers and organised groups. Both are necessary, but they call for different tools.

The third feature is the **growing weight of lending conduct in borrower grievances**. Complaints about loans and advances against NBFCs grew nearly twice as fast as total NBFC complaints, and their share rose by more than 12 percentage points in two years. Not every complaint involves fraud; many concern interest, charges, documentation or recovery conduct. But the grievance data matter for fraud management for two reasons. First, borrower complaints are an important early-warning source: the ACFE (2024) finds that tips are the single most common means of fraud detection, and complaints about unrecognised loans, unacknowledged payments or aggressive agents are often the first sign of identity fraud, collection misappropriation or unauthorised recovery. Second, poor conduct and fraud share

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root causes in weak supervision of intermediaries, which the agency-theory perspective identifies as the key vulnerability of a business model that depends on dealers, DSAs and outsourced agents.

The strong co-movement of economic offences and cyber crime in Telangana deserves careful interpretation. A high correlation in first differences shows that the two series rise together year by year, and the elasticity of 0.53 suggests that cyber-enabled offences make up a substantial and growing part of the state's economic crime. However, part of the rise in registered cases may reflect better reporting: Telangana has invested in cyber-crime reporting systems and police capacity, and higher registration can indicate more effective policing as well as more crime. This ambiguity does not weaken the managerial implication — whatever the balance between true incidence and reporting, VFCs operating in the state face a customer base that is heavily targeted by digital fraudsters — but it cautions against reading the state's ranking as a simple measure of criminality.

Taken together, the findings extend fraud theory in a sector-specific direction. The fraud triangle and fraud diamond explain the motivation and capability of insiders and intermediaries, who account for most of the value lost. Routine activity theory explains the growth and location of low-value, high-volume digital fraud, which accounts for most cases and much of the reputational harm. Information-asymmetry theory explains why origination fraud remains a structural risk in a market expanding towards thin-file borrowers and used vehicles. A comprehensive account of vehicle-finance fraud therefore needs all three lenses, and the typology in Table 7 shows how they combine at each stage of the loan cycle.

7. Policy and Managerial Implications

The evidence supports a **two-tier fraud-control architecture** for VFCs, aligned with the RBI's 2024 Master Direction.

- **Tier 1: automated, high-volume screening.** Because more than nine in ten fraud cases involve less than ₹10 lakh, VFCs should rely on automated controls for identity and document verification (Aadhaar-based e-KYC, CKYC look-ups, PAN validation), device and mobile-number linkage analytics to detect synthetic or repeat identities, rule-based and machine-learning anomaly scoring at origination, and real-time customer confirmation of every collection. These controls should be calibrated to minimise friction for genuine borrowers.
- **Tier 2: investigation-led oversight of high-value risk.** Because a small share of cases accounts for most of the value, VFCs should give priority to branch- and dealer-level analytics (early-default clustering, override frequency, abnormal growth), mandatory Vahan hypothecation checks before disbursal and RC-endorsement tracking after it,

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independent valuation and e-auction of repossessed vehicles, rotation of staff in sensitive roles, surprise audits and a protected whistle-blower channel.

- **Using grievance data as early-warning signals.** Complaints about unrecognised loans, missing payment credits or unknown recovery agents should feed directly into the EWS framework required by the RBI, rather than being handled only as customer-service matters.
- **Defending against brand impersonation.** VFCs should publish verified contact channels, monitor for fake apps, domains and social-media accounts that use their brand, and set up rapid reporting protocols with the Telangana cyber-crime authorities and the national cyber-crime reporting portal.

For regulators and the state government, three steps would strengthen the system. First, integrating the financier's NOC digitally with the Vahan registration system would close the forged-NOC route to clearing hypothecation. Second, the RBI and NCRB could publish fraud statistics separately for NBFC segments and by state, which would allow lenders and researchers to benchmark risk. Third, joint awareness campaigns by lenders, the transport department and the police, delivered in Telugu and through rural channels where tractor and two-wheeler loans dominate, would reduce borrowers' exposure to impersonation and advance-fee fraud.

8. Limitations and Future Research

The study has several limitations. First, and most important, no public source reports frauds against VFCs in Telangana separately. The national RBI series covers banks, the NCRB series covers all economic offences and cyber crimes, and the Ombudsman series covers NBFCs nationally. The findings therefore characterise the environment in which VFCs operate and should not be read as estimates of VFC losses. Second, NCRB data record cases registered by police and are affected by reporting behaviour and police capacity. Third, the RBI series is revised between editions, and the 2024-25 figures include frauds reported afresh for earlier years. Fourth, the Telangana series has only six annual observations, so the trend models and projections are indicative, and the value distribution relies on class mid-points. Fifth, some Telangana figures were compiled from press summaries of NCRB tables; they should be checked against the original NCRB tables before policy use.

These limitations define a clear agenda for future research. A primary survey of VFC managers, credit officers and borrowers across Telangana's districts, analysed with structural equation modelling, could test the fraud-diamond constructs directly and estimate the effect of specific controls. Access to anonymised loan-level data from one or more VFCs would allow supervised machine-learning models of origination fraud to be built and validated. Comparative studies across states with different levels of digital adoption would help separate

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true fraud incidence from reporting effects, and qualitative case studies of detected frauds would enrich the typology proposed here.

9. Conclusion

This study set out to characterise the fraud-risk environment facing vehicle finance companies in Telangana. By triangulating RBI fraud statistics, NCRB state crime data and RBI Ombudsman grievance data, it shows that lending-related fraud in India has accelerated sharply since 2017-18 and shifted towards digital channels; that loan frauds nonetheless account for about nine-tenths of rupee losses; that Telangana has become the national centre of cyber-enabled fraud, with economic offences and cyber crimes rising together; that fraud value in the state is highly concentrated in a small number of large cases; and that complaints about NBFC lending are growing faster than any other category. All seven hypotheses are supported. The paper's typology connects these patterns to the specific actors and stages of vehicle lending, and its two-tier control model offers VFCs a practical way to direct automated screening at the many small frauds and investigative effort at the few large ones. As vehicle credit continues to expand in Telangana and across India, fraud control will be central to keeping that growth sound.

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