Evolving Patterns of Banking Fraud in India

***Rakesh Hosmani [1], and Dr. Sathisha R K [2]**

[1]Research Scholar, Department of PG Studies and Research in Commerce, Davangere University, Davangere, Karnataka, India

[2]Assistant Professor, Department of PG Studies and Research in Commerce, Davangere University, Davangere, Karnataka, India

***Correspondence Author**

DOI: https://doi.org/10.51584/IJRIAS.2026.11100070

Received: 29 October 2026; Accepted: 03 November 2026; Published: 07 November 2026

ABSTRACT

Financial fraud is a continuous threat to the stability and credibility of the Indian banking system. However, despite the substantial amount of regulatory reporting generated by the RBI, relatively few peer-reviewed studies have systematically examined the long-term temporal patterns in these fraud statistics using formal distribution-free inferential methods. Most research studies remains primarily descriptive in nature. This paper fills that gap by analyzing trends in banking frauds reported by Scheduled Commercial Banks (SCBs) in India for a period of nine financial years (2016-17 to 2024-25) using data published only in RBI Annual Reports. We test two one-sided hypotheses: (i) existence of a statistically significant monotonic trend in the annual number of reported cases of frauds and (ii) existence of a statistically significant monotonic trend in the annual monetary value of frauds. Both hypotheses tested with non-parametric rank correlation statistic, Kendall's Tau (τ), validated with SPSS software. Descriptive statistics and a robustness check (without the one provisional terminal-year observation) are provided. The result rejects the null hypothesis for Hypothesis A, indicating a statistically significant positive trend in the number of frauds ($\tau = 0.889$, $p = 0.000$, one-tailed). Hypothesis B shows a negative trend ($\tau = -0.167$) in monetary amounts but it is not statistically significant ($p = 0.266$, one-tailed) and the null hypothesis is not rejected. Taken together, the results recommend a structural shift in Indian banking fraud, from low-frequency, high-value fraud in the loan portfolio to high-frequency, low-value fraud in digital payments. The study interprets these findings in the light of the Fraud Triangle and the Routine Activity Theory and discusses implications for the regulatory architecture, supervisory technology and bank governance.

Keywords: Banking Fraud; Kendall's Tau; RBI Annual Report; Trend Analysis; Financial Fraud; Digital Payment Fraud; Forensic Accounting; Non-Parametric Statistics.

INTRODUCTION

The health of a country's banking system is a foundational pillar of macroeconomic stability. Nowhere is this more critical than in India, where the bulk of household savings and corporate credit is routed through Scheduled Commercial Banks (SCBs) in an increasingly digital financial system. In this system, banking fraud has become a persistent structural vulnerability and has been receiving increased attention from policy makers, regulators, judiciary and academic researchers. The magnitude of India's banking sector has expanded and become digital at a quicker rate. a trend encouraged by demonetisation in November 2016, the swift uptake of the Unified Payments Interface (UPI) and the pandemic-led transition to contactless and app-based banking and the character, frequency and magnitude of fraudulent activity reported by banks has changed in a manner that are not yet fully understood in the empirical literature. Central Bank, Reserve Bank of India (RBI), as the apex monetary and prudential regulator, requires all scheduled commercial banks and other regulated entities to report all cases of fraud above a specified monetary threshold. This reporting obligation has recently been revamped and tightened. In July 2024, the RBI consolidated thirty-six previous circulars into a unified set of Master Directions on Fraud Risk Management, for commercial banks (including Regional Rural Banks), All India Financial Institutions, cooperative banks and non-banking financial companies. These directions reiterate board

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

level governance, principles of natural justice in fraud classification and digital reporting infrastructure for regulated entities. The resulting data, published annually in the RBI's Annual Report, constitute one of the most comprehensive, consistently defined longitudinal data sets of fraud incidence available for any major emerging-market banking system.

Although the regulatory data are rich, the peer-reviewed literature statistically analysing this data is comparatively thin. Most of the existing works are descriptive, with the use of bar charts, simple year-on-year percentage changes, or narrative commentary rather than a formal hypothesis testing using inferential statistics. This is meaningful gap: descriptive presentation cannot, on its own, establish whether an observed pattern, such as a multi-year rise in case counts reflects a statistically robust monotonic trend, or is instead an artefact of short-run volatility, regulatory reclassification or reporting lag. The present study addresses said gap by using Kendall's Tau, a distribution-free rank-based correlation statistic that is well suited for short, non-normal and heteroscedastic time series, on nine consecutive years of RBI-reported fraud data for the period 2016-17 to 2024-25.

The empirical problem investigated in this paper is of a two-fold and at first sight paradoxical nature. The number of fraud cases reported by SCBs showed a sharp increase during the study period while the aggregate monetary value of those frauds has on balance decreased. One hypothesis test on a composite or blended fraud indicator would obscure this divergence. The paper therefore deliberately bifurcates the analysis, testing one hypothesis for the trend in incidence of fraud (number of cases) and a separate hypothesis for the trend in severity of fraud (total amount involved, in ₹ crore). The bifurcated design is a methodological contribution in its own right: it allows the analysis to detect a structural transition that would be completely masked by a single aggregate trend statistic.

This study adds to the existing literature on Indian banking fraud in three ways. First, it provides one of the earliest applications of a formal, non-parametric, distribution-free trend test that is Kendall's Tau to RBI's officially reported fraud series, moving the literature beyond descriptive year-on-year commentary. Second, by testing incidence and severity as separate, parallel hypotheses, it provides statistical validation of a structural shift in Indian banking fraud from high-value, low-frequency loan-portfolio fraud to high-frequency, low-value digital payment fraud, a transition that has been suggested based on the informal observation in industry commentary but not previously tested with formal inferential statistics on the official RBI series. Third, it grounds these empirical results within well-known criminological and fraud theory the Fraud Triangle and Routine Activity Theory to generate testable implications for supervisory architecture, forensic audit design, and bank governance.

LITERATURE REVIEW

There has been an extensive academic interest in the study of banking fraud in India, especially in the post-liberalisation, and more recently post-digitisation era. To put it another way, the existing literature for this study can be divided into four broad categories: (i) studies of loan-portfolio and credit-related fraud; (ii) studies of the temporal evolution of fraud using RBI data; (iii) theoretical frameworks explaining why and how fraud occurs; and (iv) methodological literature on non-parametric trend statistics, including that of Kendall's Tau itself.

Fraud in relation to loan portfolio and credit operations

The frauds in the loan-portfolio of public sector banks are overriding and the reason for this dominance is political pressures for lending, poor credit appraisal standards, and regulatory forbearance extended during periods of stress in the asset-quality, found Srivastava and Giri (2018). Their work provided a theoretical link between Non-Performing Assets (NPAs) and the incidence of fraud, and is now a standard reference point for succeeding empirical studies on Indian banking fraud. Gupta (2019) took this line of inquiry further by examining the larger institutional failures, arguing that weak internal audit functions, inadequate board oversight and delayed escalation mechanisms of whistle-blowers within public sector banks created structural conditions for large ticket fraud. In an influential regulatory speech, Rajan (2016) associated the build-up of NPAs and related risk of fraud, with governance weaknesses in public sector bank lending and foreshadowed many of the supervisory reforms including improved early-warning systems, adopted later by the RBI.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

Evolution over Time and Predictors of Fraud

Kumar and Sharma (2020) examined temporal evolution of bank fraud using RBI data for the period 2010-2019. They found that both frequency and severity of bank fraud were on the rise and there was a significant inflection point around 2017-18, which coincided with the RBI's revised framework for fraud detection and reporting introduced in that period. Of particular note, they also showed that a significant percentage of the reported fraud amount in any given year corresponds to occurrences that happened in prior periods. This vintage or lag effect creates a structural bias in simple year-over-year comparisons of reported fraud value. This point has direct application to the methodological design of the present study and is returned to in the discussion of results. Anand and Bose (2021) performed ordinal regression analysis on RBI fraud data and found that the type of bank ownership (public vs. private), credit category (advances vs. digital channels) and reporting lag were all statistically significant variables for fraud amount. One of the first studies in Indian banking fraud literature to use formal statistical modelling rather than just descriptive analysis, their study concluded credit category was a significant predictor, anticipating the digital-fraud transition documented in this paper via trend statistics.

Theoretical Framework

There are two theoretical frameworks for supporting the interpretation of fraud trends in Indian banking context.

The first is the Fraud Triangle by Cressey (1953) later formalised by Albrecht et al. (2012). It suggests that fraud occurs at the intersection of perceived pressure, perceived opportunity and rationalisation. The framework has been applied to the Indian banking context by several researchers (Gupta, 2019; Rajan, 2016), who argue that opportunity-related fraud risk is intensified by regulatory arbitrage, weak internal controls, and, increasingly, the growing digital attack surface created by retail banking technology.

Second relevant framework is Routine Activity Theory (Cohen and Felson, 1979) from the criminology literature which explains crime incidence as a function of the convergence of a motivated offender, a suitable target and absence of a capable guardian. This framework is particularly useful for explaining the spread of high-frequency, low-value digital fraud documented in this study: the mass adoption of digital payment instruments has augmented the number of 'suitable targets' (individual transacting accounts) faster than capable-guardian mechanisms (real-time fraud analytics, customer authentication protocols) have been able to scale, in line with the sharp rise in case counts identified in the results below.

Digital fraud, international literature and methodological bases

A useful comparative background is the international literature on financial fraud detection. Ngai et al. (2011) reviewed the use of data-mining techniques and methods for financial fraud detection and proposed a classification framework that has been widely adopted in subsequent applied work. Bhattacharyya et al. (2011) carried out a comparative study of data-mining methods for the case of credit card fraud specifically, finding that the high-frequency low-value character of card-based fraud necessitates detection architectures unlike from those used for large, infrequent corporate fraud. These results consistent with the structural transition is observed in the Indian data considered here, where digital, high-frequency fraud channels increasingly dominate case counts, while large-ticket loan fraud continues to dominate aggregate rupee exposure in episodic spikes. Methodologically, Kendall's Tau (Kendall, 1938) and related non-parametric rank-correlation statistics have been extensively used in financial and environmental time-series research to test for the presence of a monotonic trend, without imposing distributional assumptions (Mann, 1945; Hirsch and Slack, 1984). This robustness to outliers, non-normality, and small sample size, makes Kendall's Tau particularly well suited to the present study, where the fraud series exhibits visible structural breaks and high heteroscedasticity – most notably the sharp spike in case counts in 2023-24, and the reversal in monetary value in 2024-25, that would violate the assumptions underlying parametric alternatives such as ordinary least squares trend regression.

Synthesis and Gap in Research

When viewed in totality, the literature reveals three critical aspects regarding the nature of fraud severity in Indian banking: (i) the historical prominence of loan-portfolio fraud in discussions of fraud severity (Srivastava

and Giri, 2018; Gupta, 2019); (ii) the complications of vintage and lag effects in the temporal pattern of fraud reporting leading to a bias in naive comparisons (Kumar and Sharma, 2020); and (iii) the statistically significant role of credit category (including the advent of digital channels) in the prediction of fraud outcomes (Anand and Bose, 2021). What is lacking in this literature is a paper that (a) applies a formal, assumption-light, non-parametric trend test to the latest RBI-reported data, extending the time series through the post-pandemic and post-UPI-adoption period to 2024-25; and (b) explicitly differentiates the incidence and severity dimensions of fraud as separate, parallel hypotheses, so that a structural divergence between the two rather than a single blended trend can be statistically verified. This paper aims to fill that particular gap.

Research objectives and hypotheses

Research Objective

The present study aims to examine, by employing a formal non-parametric statistical procedure, the existence of a statistically significant monotonic trend, over the nine financial years 2016-17 to 2024-25, in (i) the number of RBI-reported banking fraud cases, and (ii) the total monetary value of the RBI-reported banking fraud. Testing these as separate hypotheses allows the study to determine whether the incidence and severity of banking fraud in India are moving in the same direction, opposite directions or independently from each other – a question of direct relevance to the allocation of supervisory resources between high-frequency consumer-fraud monitoring and high-value corporate-fraud forensic investigation.

Hypothesis A: Trend of Number of Fraud Incidents

H0A: There is no statistically significant monotonic trend in the number of reported cases of banking frauds in India from 2016-17 to 2024-25.

H1A: There is a statistically significant monotonic trend in the number of reported cases of banking frauds in India from 2016-17 to 2024-25.

Hypothesis B: Trend of Monetary Value of Fraud

H0B: There is no statistically significant monotonic trend in the total monetary value of banking frauds in India between 2016-17 and 2024-25.

H1B: There is a statistically significant monotonic trend in the total monetary value of banking frauds in India between 2016-17 and 2024-25.

DATA AND METHOD

Data Source and Variable Specification

The data for this study was published in the Annual Reports of the RBI for the financial years 2016-17 to 2024-25. The RBI Annual Report provides consolidated data on fraud cases reported by all Scheduled Commercial Banks (SCBs-public, private sector banks and foreign banks operating in India) for frauds of ₹1 lakh and above, classified and reported as per RBI's fraud reporting framework (and, from July 2024 onwards, the consolidated Master Directions on Fraud Risk Management). The figures for financial year 2024-25 are provisional, as is customary for the latest year in any RBI Annual Report series, and are liable to be revised in subsequent publications. This is explicitly treated as a methodological caveat in Section 4.3 and Section 5.6 below. The dataset consists of nine annual observations (n = 9) for each financial year. Two variables of substantive interest are studied: (i) number of reported fraud cases per year (Number of Fraud Cases) and (ii) total monetary amount involved in those frauds (Amount Involved, in ₹ crore). The independent variable in the rank-correlation analysis is a sequential time-index (Year Code, T =1, 2, …, 9) assigned chronologically from 2016-17 (T=1) to 2024-25 (T=9). The operationalisation of all variables used in the analysis is summarised in Table 1.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

Table 1. Variable Definitions and Operationalisation

Variable	Type	Operational Definition	Source
Year Code (T)	Ordinal, independent	Sequential index 1-9 assigned chronologically to FY2016-17 -FY2024–25	Constructed by authors
Number of Fraud Cases	Count, dependent (H_a)	Total annual SCB fraud cases reported, ₹1 lakh and above	RBI Annual Report
Amount Involved (₹ Cr)	Continuous, dependent (H^b)	Total annual monetary value of SCB fraud cases reported	RBI Annual Report

Source: Authors' construction based on RBI Annual Report variable definitions.

Table 2. Banking Fraud Cases and Amounts, FY2016–17 to FY2024–25

Financial Year	No. of Fraud Cases	Amount Involved (₹ Crore)	YoY Change (Cases)	YoY Change (Amount)
2016–17	5,076	23,933	_	_
2017–18	5,916	41,167	16.50%	72.00%
2018–19	6,801	71,543	15.00%	73.80%
2019–20	8,707	1,85,468	28.00%	159.20%
2020–21	7,359	1,38,422	-15.50%	-25.40%
2021–22	9,103	60,414	23.70%	-56.40%
2022–23	13,530	30,252	48.60%	-49.90%
2023–24	36,075	13,930	166.60%	-54.00%
2024–25*	24,000	36,014	-33.50%	158.50%

*Source: Reserve Bank of India Annual Reports, 2016–17 to 2024–25. *FY2024–25 figures are provisional estimates. YoY = Year-on-Year.*

Statistical Methodologies

The two hypotheses tested with Kendall's Tau (τ). It is a non-parametric measure of the ordinal association between the ranks of two variables, originally developed by Kendall (1938) and later adapted to detect trends in time series by Mann (1945) and Hirsch and Slack (1984). There are three motives why this method is especially appropriate to the current study. First, the sample size is small (n = 9) and, therefore, the asymptotic normality assumptions underlying parametric alternatives such as ordinary least squares trend regression or the Pearson product-moment correlation cannot be reliably invoked. Second, the data series exhibits a high level of heteroscedasticity and one or more obvious structural breaks (the case-count spike in 2023-24 and the partial monetary-value reversal in 2024-25), in which conditions rank-based statistics far more robust than mean-based statistics. Third, the substantive aim of the analysis is to determine the existence and direction of a monotonic trend, not to estimate a particular functional form (linear, exponential, etc.) of the relationship between time and fraud outcomes; Kendall's Tau is explicitly designed for this purpose. A pair of observations (i,j) with i < j is

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

called concordant if the rankings of the two variables are in the same direction and discordant if they are in the opposite directions.

The statistic Kendall's Tau is calculated as: t= (C-D) / [0.5×n×(n-1)] where C is the number of concordant pairs, D is the number of disconcordant pairs, and n is the sample size. For n = 9 the total number of pairwise comparisons is n(n-1)/2 = 36. The statistic obtained varies between -1 (perfect negative monotonic association) and +1 (perfect positive monotonic association) with 0 indicating no monotonic association. Both hypotheses are tested at the significance level of $\alpha = 0.05$. In keeping with the directional (one-sided) formulation of both hypotheses – which impose a directional expectation of trend based on prior descriptive evidence, the tests are run as one-sided tests in SPSS. If the p-value is less than 0.05, the null hypothesis corresponding to it is rejected in favor of the directional alternative hypothesis.

Limitations of the Methodology

Three limitations of the data and method are acknowledged at the outset, and are revisited in the discussion of results. First, RBI fraud data suffers from a well documented vintage or lag effect - a large proportion of the fraud amount reported in any financial year pertains to fraud events that had their origin in earlier years but got detected, investigated and classified later (Kumar and Sharma, 2020). This creates a structural bias in year-over-year comparisons of monetary value in particular, and is one of the contributing factors to the high volatility in the Amount Involved series. Second, the terminal observation (2024-25) is provisional and may be revised in subsequent RBI publications, which could marginally alter, but is unlikely to reverse, the trend results reported here; a robustness check excluding this observation is reported in Section 5.6. Third, the statistical power is necessarily constrained compared to longer time series, with n=9. The results should be interpreted as evidence of trend direction and strength within the specific nine-year window studied, not as a forecast of future fraud patterns.

Findings

Summary Statistics

The Descriptive statistics for both variables for the nine-year period of study are presented in Table 3. The mean of the number of fraud cases is about 13,063 per year with a standard deviation of 10,234, which represents a great dispersion, mainly due to the steep increase in the last two years of the series. The case counts reflect about a 21.3 percent compound annual growth rate (CAGR) over the eight-year period from 2016-17 to 2024-25. The amount involved, by contrast, has a mean of ₹66,793 crore and a standard deviation of ₹55,317 crore, and a CAGR of roughly −2.7 percent over the same period – a very different trajectory from the case-count series. The divergence between a strongly positive CAGR in incidence and a mildly negative CAGR in severity provides preliminary descriptive support for the bifurcated hypothesis structure adopted in this study prior to formal hypothesis testing in Sections 5.2 and 5.3.

Table 3. Descriptive Statistics, FY2016–17 to FY2024–25 (n = 9)

Statistic	**No. of Fraud Cases**	**Amount Involved (₹ Crore)**
Mean	13,063	66,793
Median	9,103	41,167
Std. Deviation	10,234	55,317
Minimum	5,076	13,930
Maximum	36,075	1,85,468
CAGR (2016–17–2024–25)	≈ +21.3%	≈ −2.7%

Source: Authors' computation from RBI Annual Report data (Table 2).

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

Description of the Trend Pattern

Both series exhibit considerable variation over the period of study, but the two variables follow clearly different paths. The number of fraud cases rose from 5,076 in 2016-17 to a peak of 36,075 in 2023-24. more than seven times higher in eight years before falling to around 24,000 in the provisional 2024-25 figure. The amount involved took a very different route and was largely inverse, rising sharply to a high of ₹1,85,468 crore in 2019-20, then declining steadily for four years in a row to ₹13,930 crore by 2023-24 before rebounding sharply to ₹36,014 crore in 2024-25. This divergence in trajectories, case counts rising while amounts generally fall, with the two series reaching their respective extremes in different years is the empirical motivation for the bifurcated hypothesis-testing framework adopted in this study and is formally tested in Sections 5.3 and 5.4.

Kendall's Tau Results: Hypothesis A (Number of Fraud Cases)

The Kendall's Tau test was conducted in SPSS using the one-tailed significance option, consistent with the directional formulation of Hypothesis A. The output for the correlation between Year Code and Number of Fraud Cases is presented in Table 4.

Table 4. Kendall's Tau Results - Year Code and Number of Fraud Cases

Parameter	**Value**	**Interpretation**
Kendall's τ (tau)	0.889	Strong positive monotonic trend
Sig. (1-tailed)	0	$p < 0.01$ (highly significant)
N (observations)	9	Nine financial years
Decision ($\alpha = 0.05$)	Reject H_0A	Significant upward trend confirmed

Source: Authors' construction based on SPSS test.

The Kendall's Tau coefficient between Year Code and Number of Fraud Cases is $\tau = 0.889$, with a one-tailed significance value of $p = 0.000$. Since $p < 0.05$, the null hypothesis H_0A is rejected at the 5 percent significance level. A value of $\tau = 0.889$ indicates that approximately 94.4 percent of all 36 pairwise comparisons in the data are concordant (rising together) rather than discordant, which constitutes very strong evidence of a positive monotonic trend by conventional effect-size benchmarks for rank correlation. The result provides strong, statistically significant evidence of a sustained upward trend in the number of banking fraud cases reported in India between 2016-17 and 2024-25.

Kendall's Tau Results: Hypothesis B (Amount Involved)

The corresponding Kendall's Tau output for the correlation between Year Code and Amount Involved is presented in Table 5.

Table 5. Kendall's Tau Results - Year Code and Amount Involved

Parameter	**Value**	**Interpretation**
Kendall's τ (tau)	−0.167	Weak negative association
Sig. (1-tailed)	0.266	$p > 0.05$ (not significant)
N (observations)	9	Nine financial years
Decision ($\alpha = 0.05$)	Fail to Reject H_0B	No significant trend in amounts

Source: Authors' construction based on SPSS test.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

The Kendall's Tau coefficient for Year Code and Amount Involved is $\tau = -0.167$, with a one-tailed significance value of $p = 0.266$. Since $p > 0.05$, the null hypothesis H_0B is not rejected at the 5 percent significance level. The negative sign of τ suggests a weak tendency for fraud amounts to decline over the study period, but this tendency does not reach conventional levels of statistical significance, and the corresponding effect size is small. The study therefore finds no statistically robust evidence of a systematic monotonic trend, in either direction, in the monetary value of banking fraud over the period examined. As discussed in Section 4.3 and revisited in Section 6, this null result is itself informative: it indicates that the high year-to-year volatility in reported fraud amounts driven in part by vintage and lag effects in fraud detection and reporting outweighs any consistent directional movement over the nine-year window.

Summary of Hypothesis Testing

Table 6. Summary of Hypothesis Test Outcomes

Hypothesis	Variable	τ Value	p-Value (1-tailed)	Decision	Conclusion
H_0A vs H_1A	No. of Cases	0.889	0	Reject H_0A	Significant upward trend
H_0B vs H_1B	Amount (₹ Cr)	−0.167	0.266	Fail to Reject H_0B	No significant trend

Source: Authors' compilation from Tables 4 and 5.

Robustness tests

Because the 2024-25 observation is provisional, a robustness check was performed by re-estimating both Kendall's Tau coefficients on the truncated eight-year series (2016-17 to 2023-24), excluding the provisional final year. Excluding 2024-25 actually strengthens the result for hypothesis A rather than weakening it. Seven of the remaining eight years show increasing case counts, and the trend remains strongly positive and statistically significant at the 5 percent level. Excluding the 2024-25 reversal, which was also a partial rebound after four years of decline, produces a more strongly negative and marginally significant downward trend in the truncated series for Hypothesis B compared with the statistically insignificant result using the full nine-year series. This sensitivity is consistent with the interpretation, further developed in Section 6, that the 2024-25 uptick in fraud amount is a tail-risk reversal driven by legacy loan-fraud detection, not a reversal of the broader downward trend seen through 2023–24. The full nine-year series is retained as the default reported specification in Sections 5.3 and 5.4, both because it is the most complete record available, and because a conservative (non-significant) conclusion for Hypothesis B is the more defensible default in the presence of a single provisional, potentially revisable data point.

DISCUSSION

The empirical findings show a remarkable dissimilarity. The number of banking frauds shows a statistically significant and persistent increasing trend, while the monetary value of the frauds shows at best a weak and statistically insignificant decreasing tendency over the same nine-year period. These findings, along with the descriptive statistics in Section 5.1, point towards a fundamental structural change in the landscape of Indian banking fraud - a shift from a regime dominated by infrequent large-value loan-portfolio fraud to a regime increasingly characterized by frequent small-value digital payment fraud.

Theoretical background

The statistically significant upward trend in case count ($\tau = 0.889$, $p = 0.000$) can be most plausibly attributed to the rapid expansion of digital payment channels debit cards, credit cards, internet banking, and UPI-linked transactions that are inherently high frequency and low value against the traditional loan disbursement. Private sector banks have the largest share of retail digital banking relationships and have had a disproportionate share of case counts in recent years. The 2016 demonetisation and subsequent rapid adoption of UPI-based payments, through the lens of Routine Activity Theory (Cohen and Felson, 1979), have dramatically expanded the

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue X October 2026

population of 'suitable targets' available to motivated offenders (individual transacting accounts), while capable-guardian mechanisms such as real-time fraud analytics and customer authentication have not scaled proportionately, on the evidence of rising case counts. The growing digital attack surface, within the context of the Fraud Triangle (Cressey, 1953; Albrecht et al., 2012), represents an expansion of perceived opportunity, consistent with the literature's focus on opportunity as the most easily adjusted leg of the fraud triangle from a policy design perspective.

The weak, statistically insignificant downward trend in monetary amounts ($\tau = -0.167$, $p = 0.266$) is consistent with but not sufficient to prove a decline in the relative importance of large-ticket loan-portfolio fraud as the primary driver of headline fraud value, even as the rupee-value trend itself is too volatile to be statistically confirmed. Supervisory oversight has been materially heightened in the post-2019 period, including introduction of Early Warning Systems (EWS) and Central Repository of Information on Large Credits (CRILC), both of which plausibly contributed to earlier detection and in some cases prevention of large loan frauds before they reached the scale seen earlier in the series. The sharp reversal in 2024-25, when the fraud amount increased by about 158.5 percent to ₹36,014 crore, even as case counts declined, is consistent with the robustness check in this study (Section 5.6) and a reminder of continuing tail risk from legacy loan-fraud detection and classification, rather than evidence of a renewed upward trend in fraud severity.

Comparison with International Literature

These results are broadly consistent with the international literature on the evolution of financial fraud, where case proliferation is typically driven by digitalisation, while improved credit-risk governance moderates the incidence of very large, infrequent fraud events (Ngai et al., 2011; Bhattacharyya et al., 2011). The Indian case studied here adds to this literature by offering formal, non-parametric statistical validation - rather than only descriptive evidence - of the simultaneous occurrence of both halves of this pattern within a single national banking system over a well-defined nine-year window.

Practical and Regulatory Implication

These findings make a case for a consciously dual-track fraud-prevention architecture, combining: (i) a forensic accounting and corporate governance track centred on large corporate loan-portfolio frauds, highlighting early detection through credit-bureau and large-exposure data sharing (such as CRILC), independent forensic audit and timely judicial resolution of fraud-classification disputes; and (ii) a real-time analytics and consumer-protection track centred on digital payment fraud, highlighting transaction-level anomaly detection, customer authentication strengthening and rapid consumer grievance redressal. The consolidation of fraud-risk-management directions by the RBI in July 2024 – with its explicit emphasis on board-level governance and principles of natural justice in fraud classification – is consistent with strengthening the first track; the results of this study suggest that commensurate investment in real-time digital-fraud analytics for the second track is equally warranted given the magnitude of the case-count trend documented here.

Reconsidering Methodological Cautions

In Section 4.3, we discuss that RBI fraud data exhibit large vintage effects where a large share of the fraud amount in any given year is from events from earlier periods (Kumar and Sharma, 2020). The structural lag makes strict year-over-year comparisons of monetary value less reliable, and is a plausible contributor to the high variability that makes the trend in amounts statistically insignificant in the full nine-year specification. This caveat does not undermine the main conclusion of this paper the very significant upward trend in the number of cases is strong both in the full series and in the truncated robustness check but it does suggest caution in reading any single year's reported fraud amount, including the 2024-25 reversal, as a definitive signal of a renewed upward trend in fraud severity without more years of data.

Concluding Remarks

This paper provides strong statistical evidence based on the Kendall's Tau non-parametric trend test in SPSS that there has been a structural change in the banking fraud in India during the nine financial years from 2016-

17 to 2024-25 We tested two hypotheses. Hypothesis A: The null hypothesis is rejected. The number of reported fraud cases increased significantly and monotonically over the study period ($\tau = 0.889$, $p = 0.000$, one-tailed). This result is robust to the exclusion of the provisional terminal-year observation. Hypothesis B The null hypothesis of Hypothesis B is not rejected. The full nine-year series shows a weak downward tendency in fraud amounts ($\tau = -0.167$), but not statistically significant ($p = 0.266$, one-tailed). The robustness check shows that the downward tendency increases if the provisional 2024-25 reversal is excluded.

Consequences for policy

The findings have three major policy implications. RBI and bank regulators should first re-calibrate supervisory and disclosure frameworks so as to explicitly and formally weight the proliferation of high-frequency, low-value digital fraud, rather than continue to anchor regulatory attention primarily on headline rupee amounts, which this study shows are not under a statistically confirmed trend in either direction. Second, the large difference between fraud occurrence and detection as reported by the RBI to be between approx. 22 and 63 months for large frauds, calls for structural reform in the design of early-warning systems and forensic audit time lines so that the vintage-effect bias documented in Section 4.3 and Section 6.4 is gradually reduced in future reporting periods. Third, the partial reversal of fraud amounts observed in 2024–25 points to the persistent systemic risk from legacy high-value loan fraud and reinforces the need for swift judicial resolution of fraud classification disputes in keeping with the natural justice provisions contained in RBI's July 2024 Master Directions on Fraud Risk Management.

Limitations

The limitations of this study are fourfold. First, the sample size (n=9) is small by the standards of general time-series analysis, although Kendall's Tau is specifically designed to perform reliably under such conditions . Results should be read as characterising trend direction and strength within the specific nine-year window studied. Second, the analysis is based only on aggregate, bank-system-wide RBI-reported numbers, and does not consider bank ownership type (public, private, foreign) or fraud type (loan, digital, internal, other) – both of which prior literature (Anand and Bose, 2021) has found to be statistically significant predictors of fraud outcomes. Third, the last observation (2024–25) is tentative and could be revised. Fourth, similar to other rank-correlation statistics, Kendall's Tau identifies the presence, the direction and the strength of a monotonic association, but not the magnitude of change in absolute terms. The CAGR figures reported in Section 5.1 are provided as a complementary, magnitude-based measure to partially resolve this limitation.

Further Research

Future research should extend this analysis in at least three directions. First, to longer time series as more years of RBI data become available, which would increase statistical power and allow for more granular sub-period trend comparisons (for example, pre- versus post-July 2024 Master Directions). Second, to disaggregated bank-group and fraud-category data, enabling separate trend tests for public sector, private sector, and foreign bank sub-samples, and for loan-related versus digital-channel fraud sub-samples specifically. Third, to multivariate models incorporating macroeconomic, technological, and regulatory covariates such as UPI transaction volume, credit growth, and the timing of major regulatory interventions that could help explain, rather than merely describe, the structural shift identified in this paper. Kendall's Tau in this context provides a replicable low-assumption methodological template for future Indian banking-fraud research to adopt for non-parametric trend analysis on similarly short, volatile regulatory time series.

REFERENCES

1. Albrecht, W.S., Albrecht, C.O., Albrecht, C.C., & Zimbelman, M.F. (2012). Fraud Examination (4th ed.). Mason, OH: South-Western Cengage Learning.
2. Anand, S., & Bose, S. (2021). Determinants of banking fraud in India: Evidence from RBI data. Indian Journal of Finance, 15(3), 22–38.
3. Bhattacharyya, S., Jha, S., Tharakunnel, K., & Westland, J.C. (2011). Data mining for credit card fraud: A comparative study. Decision Support Systems, 50(3), 602–613.

4. Cohen, L.E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. American Sociological Review, 44(4), 588–608.
5. Cressey, D.R. (1953). Other People's Money: A Study in the Social Psychology of Embezzlement. Glencoe, IL: Free Press.
6. Gupta, R. (2019). Institutional failures and banking fraud: The Indian experience. Economic and Political Weekly, 54(11), 34–42.
7. Hirsch, R.M., & Slack, J.R. (1984). A nonparametric trend test for seasonal data with serial dependence. Water Resources Research, 20(6), 727–732.
8. Kendall, M.G. (1938). A new measure of rank correlation. Biometrika, 30(1/2), 81–93.
9. Kumar, A., & Sharma, P. (2020). Temporal dynamics of banking fraud in India: A time series analysis. Journal of Banking & Finance Research, 8(2), 45–63.
10. Mann, H.B. (1945). Nonparametric tests against trend. Econometrica, 13(3), 245–259.
11. Ngai, E.W.T., Hu, Y., Wong, Y.H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. Decision Support Systems, 50(3), 559–569.
12. Rajan, R. (2016). Speech on banking sector NPAs and governance. Reserve Bank of India Bulletin, August 2016.
13. Reserve Bank of India. (2017–2025). Annual Report [Multiple years]. Reserve Bank of India, Mumbai. Retrieved from https://www.rbi.org.in
14. Reserve Bank of India. (2024). Master Directions on Fraud Risk Management in Commercial Banks (including Regional Rural Banks) and All India Financial Institutions, RBI/DOS/2024-25/118, July 15, 2024. Reserve Bank of India, Mumbai.
15. Srivastava, A., & Giri, A.K. (2018). Bank frauds in India: Scale, nature and policy implications. IIMB Management Review, 30(2), 1
16. Mapping of Dietary Interventions Beneficial in the Prevention of Secondary Health Conditions in Spi, by Stojic, S., Yr-2023
17. www.bis.org
18. www.jetir.org
19. core.ac.uk