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DIGITAL PAYMENTS AND FRAUD CONNECTION: INSIGHTS FROM THE INDIAN ECONOMY

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Abstract

In the dynamic world of digital transactions in India, the symbiotic relationship between convenience and vulnerability has become increasingly apparent. This study aims to know how digital payment and fraud connect in Indian economy. The primary objective of this study is to know the relationship between financial fraud with digital payment infrastructures, value of digital payments, and volume of digital payment. The data is collected through RBI's official quarterly reports from September 2022 to May 2023. The collected time series data for all the variables has been analyzed for descriptive statistics. These series were tested for stationarity using Augmented Dickey–Fuller test (ADF - unit root test), Correlogram, and time series chart. The correlation and regression analysis has been performed on this time series data using SPSS and EViews software. From the correlation results this study reveals that there is no significant correlation between value and volume of fraud with payment infrastructure, value of digital payment, and volume of digital payment. The value of UPI transactions has a significant negative impact on digital payment fraud, indicating a potential protective effect.

Keywords: *Digital Payments, Financial Frauds, Payment Infrastructures, Relationship.*

INTRODUCTION

The evolution of digital payments in India is quite fascinating. It's like watching a technological revolution unfold. Let's rewind to the early 2000s when the concept of digital payments was in its infancy. Credit and debit cards were gaining popularity, but widespread adoption was still a distant dream. Then came the game-changer: the Unified Payments Interface (UPI). Launched in 2016, UPI revolutionized digital payments by providing a seamless, real-time platform for transferring money between bank accounts using smartphones. Demonetization in 2016 acted as a catalyst, prompting a surge in digital transactions as people sought alternative payment methods. Mobile wallets like Paytm and digital payment services like Google Pay and PhonePe capitalized on this opportunity, offering user-friendly interfaces and cashback incentives. The government's push for financial inclusion through schemes like Jan Dhan Yojana and the introduction of Aadhaar-enabled payments further fueled the growth of digital transactions. The rise of affordable smartphones and improving internet infrastructure also played a pivotal role, making digital payments accessible even in rural areas. Fast forward to recent times, and the landscape is dotted with innovations like contactless payments, biometric authentication, and the integration of digital payments in various sectors, from retail to transportation. The regulatory framework has adapted to accommodate these changes, ensuring security and promoting healthy competition among service providers. India's digital payments evolution is a prime example of how a combination of technological innovation, government initiatives, and changing consumer behaviors can transform an entire economic ecosystem. It's not just about transactions; it's about redefining the way a nation interacts with money.

With great technological advancements come inevitable challenges, and unfortunately, digital payment fraud is one of them. As digital transactions in India soared, so did the sophistication of fraudulent activities. Phishing attacks, where individuals are tricked into revealing sensitive information like passwords or credit card details, have become increasingly prevalent. Cybercriminals have adapted to new technologies, exploiting vulnerabilities in mobile apps and online platforms. Simultaneously, identity theft and account takeover fraud have also witnessed a surge. As more personal information is shared online, criminals find creative ways to use this data for unauthorized transactions. Despite efforts to enhance security measures, there's a constant cat-and-mouse game between fraudsters and cybersecurity experts. Social engineering techniques, malware attacks, and even advanced tactics like SIM swapping contribute to the rising numbers of digital payment fraud cases. To tackle this, a collaborative approach is essential. It involves continuous education for users to recognize and avoid phishing attempts, robust cybersecurity measures implemented by service providers, and a proactive stance from law enforcement agencies. India's regulatory bodies have been working on strengthening the cybersecurity framework, emphasizing the importance of multi-factor authentication and other security protocols. However, the dynamic nature of cyber threats requires a constant evolution of strategies to stay ahead of the curve. As the digital landscape evolves, so must our awareness and security measures. It's a shared responsibility to make digital transactions not only convenient but also secure for everyone involved.

In the dynamic landscape of digital transactions in India, the symbiotic relationship between convenience and vulnerability has become increasingly apparent. As the nation embraces the efficiency of digital payments, a parallel narrative unfolds - one marked by the growing threat of fraud. This exploration delves into the complex connection between the burgeoning realm of digital payments and the escalating challenges of fraud within the Indian economy.

LITERATURE REVIEW

(Jerath, 2022) analysed the digital payment in India. The study found that digital payments in India have experienced exponential growth. The researcher also stated that the government and RBI have made consistent efforts to improve payment infrastructure. (Verma et al., 2023) examined the relationship between digital payment and cyber-attacks, including online fraud. They stated that as more individuals opt for digital payments, the potential for cyber-attacks such as online fraud increases. They found that increase in digital payment leads to rise in cyber-attacks and lack of knowledge and infrastructure contribute to cybercrime. (Fernandes, 2013) studied the increase in electronic payment systems and the corresponding rise in electronic frauds. The study found that e-payment frauds are increasing with the growth of e-business and preventive measures and fraud detection techniques are necessary to minimize frauds. (Adigwe, 2012) identified the types of frauds associated with electronic payment and suggests measures to control them. The researcher stated that payment fraud is pervasive and requires constant attention and safeguarding. Moreover the researcher suggested that best practice organizations should employ a two-pronged approach to combat fraud. (Setor et al., 2021) examined the relationship between digital payment transactions and corruption in developing countries. They found that the digital payment transactions reduce corruption in developing countries. (Shree et al., 2021) focused on factors influencing the choice of payment methods and consumer perceptions of digital payments. They found that the public perception can catalyze digitization of payments. They also found that the customers prioritize convenience over online fraud experience.

As the digitalization of financial transactions accelerates in the Indian economy, a critical examination of the relationship between digital payments and financial fraud becomes imperative. Despite the growing significance of this intersection, there exists a noticeable research gap in comprehensively understanding the nuanced dynamics, contributing factors, and the evolving landscape of fraud within the context of digital payments in India. This research endeavors to bridge this gap by offering in-depth insights into the multifaceted relationship between digital payment systems and the value and volume of financial fraud, shedding light on unexplored facets and paving the way for informed strategies and policies.

Research Methodology

The primary objective of this study is to know the relationship between digital payments transactions and financial fraud. Here the value and volume of fraud are used as proxy of financial fraud, volume and value of IMPS, NEFT, and UPI transactions are used as proxy of digital payment transactions and number of ATM & CRM, Cards, and UPI QR are used as proxy of payment infrastructures. The data is collected through RBI's official quarterly reports from September 2022 to May 2023. The collected time series data for all the variables has been analyzed for descriptive statistics. These series were tested for stationarity using Augmented Dickey–Fuller test (ADF - unit root test), Correlogram, and time series chart. The volume of NEFT and IMPS are stationary at level, the volume of UPI, number of ATM & CRM, number of Cards, and number of UPI QR became stationary at first difference. The value of NEFT is stationary at level and value of IMPS, UPI and Value & volume of fraud became stationary at first difference. The correlation and regression analysis has been performed on this time series data using SPSS and EViews software.

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HYPOTHESES FOR TESTING

H_{01}: There is no significant relationship of value and volume of fraud with payment infrastructures, value of digital payments, and volume of digital payments.

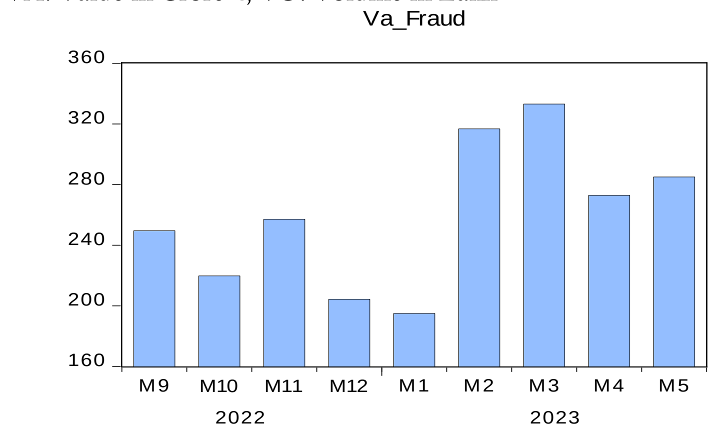
H_{01}: There is no significant impact of payment infrastructures, value of digital payments, and volume of digital payments on value and volume of fraud.

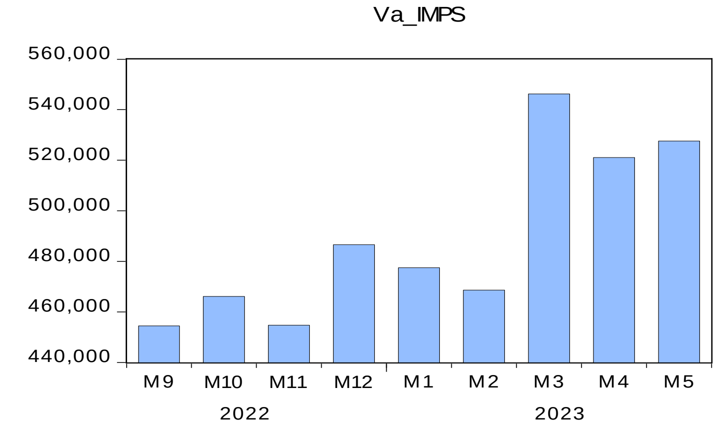
DATA ANALYSIS

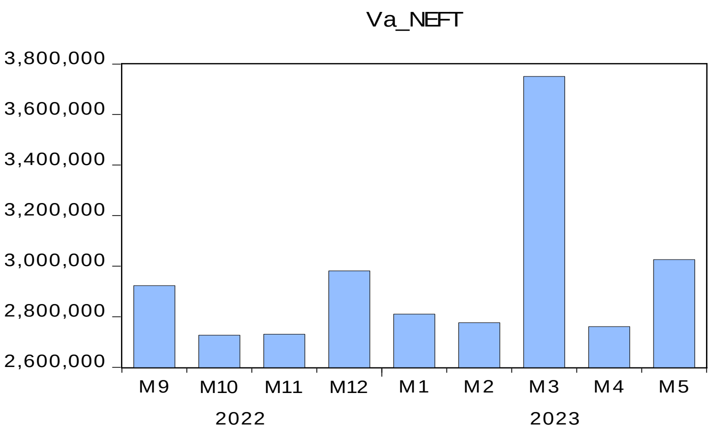
Table 1: Descriptive Statistics of Selected Variables under Study

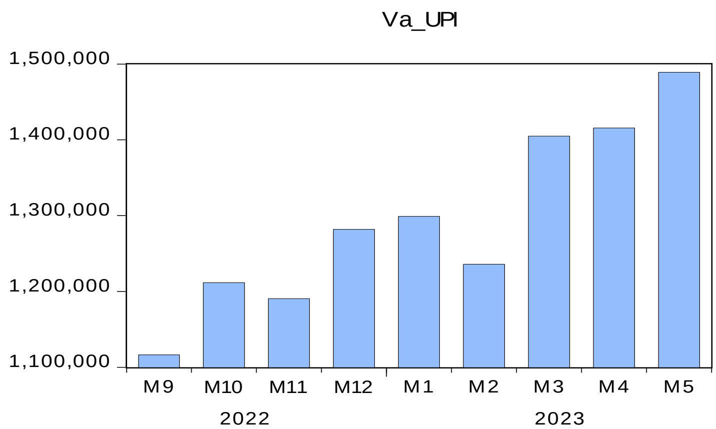
	VA_FRAUD	VA_NEFT	VA_IMPS	VA_UPI	VO_FRAUD	VO_IMPS	VO_NEFT	VO_UPI
Mean	259.2143	2942932.	489193.9	1293900.	1.888298	4789.696	4756.783	79697.76
Median	257.0429	2810180.	477491.5	1281971.	1.793570	4824.590	4798.310	78288.95
Maximum	333.0123	3750569.	546234.7	1489145.	2.291570	5015.490	5469.057	94151.85
Minimum	194.9630	2726827.	454451.3	1116438.	1.536220	4478.132	4332.454	67808.00
Std. Dev.	47.96296	322371.7	33983.22	121305.5	0.280203	183.3732	335.4235	8556.678
Skewness	0.141118	1.958126	0.569869	0.235055	0.220288	-0.347969	0.815059	0.360462
Kurtosis	1.850116	5.623683	1.807319	1.939842	1.648728	1.900612	3.443809	2.003609
Jarque-Bera	0.525709	8.332780	1.020559	0.504352	0.757516	0.634869	1.070343	0.567197
Probability	0.768854	0.015508	0.600328	0.777108	0.684711	0.728014	0.585569	0.753069
Sum	2332.929	26486390	4402745.	11645096	16.99468	43107.27	42811.05	717279.9
Sum Sq. Dev.	18403.56	8.31E+11	9.24E+09	1.18E+11	0.628111	269005.7	900071.6	5.86E+08
Observations	9	9	9	9	9	9	9	9

VA: Value in Crore ₹, VO: Volume in Lakh









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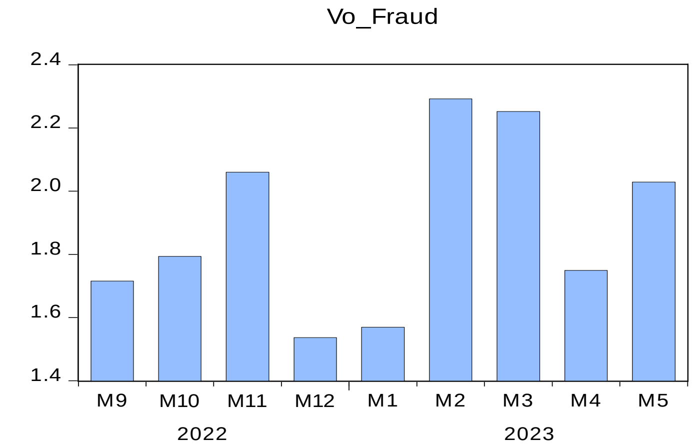
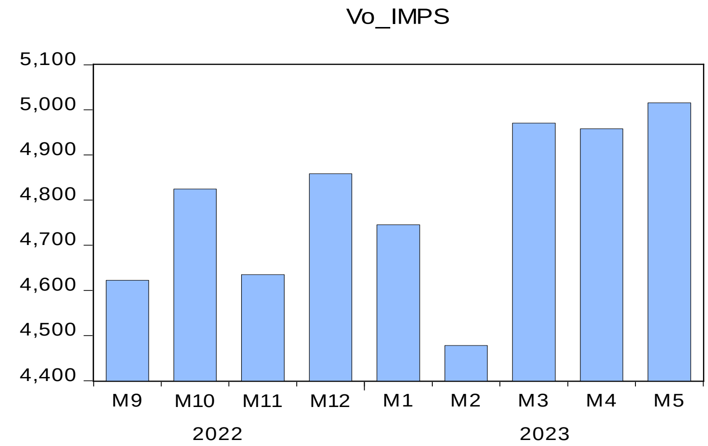
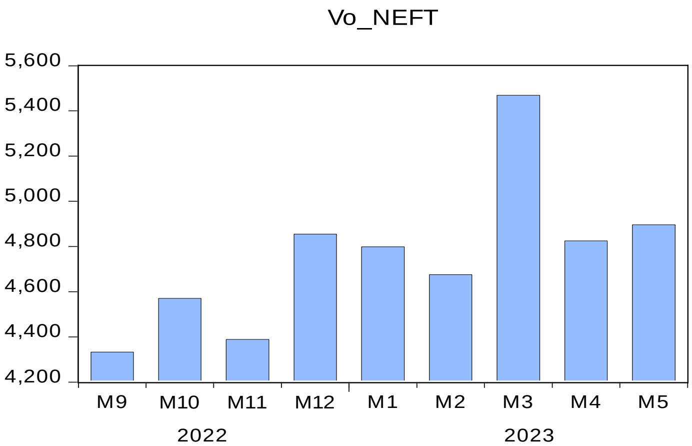
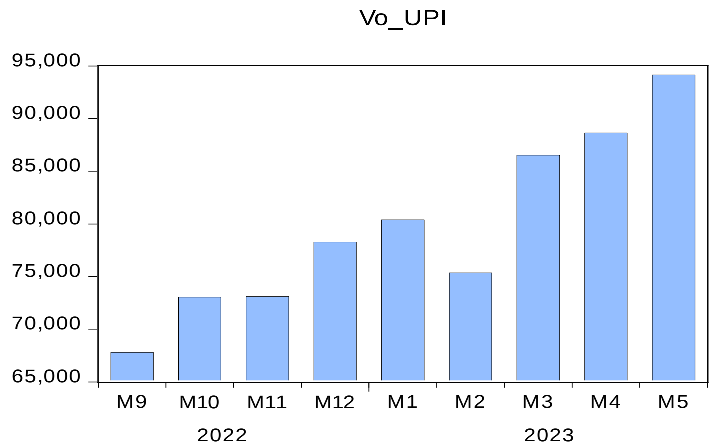








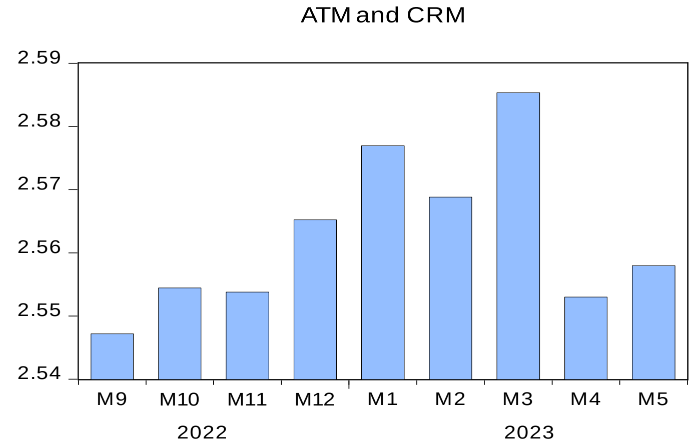
The descriptive statistics table provides a comprehensive overview of selected variables, offering insights into the central tendencies and distributions of financial transactions in the study. The mean values serve as key indicators, revealing the average levels across various parameters. Notably, the mean values for Value of Fraud (VA_FRAUD), Value of NEFT transactions (VA_NEFT), Value of IMPS transactions (VA_IMPS), and Value of UPI transactions (VA_UPI) provide a snapshot of the typical monetary magnitudes involved, with averages of ₹259.21 Crore, ₹2,942,932.0 Lakh, ₹489,193.9 Crore, and ₹1,293,900.0 Crore, respectively. The standard deviations highlight the extent of variability around these means, signifying the degree of dispersion in the data. Additionally, other statistical measures such as skewness, kurtosis, and Jarque-Bera statistics offer insights into the shape and normality of the distributions. The table, with its focus on both value and volume metrics, lays a foundation for a nuanced understanding of the financial landscape under examination.

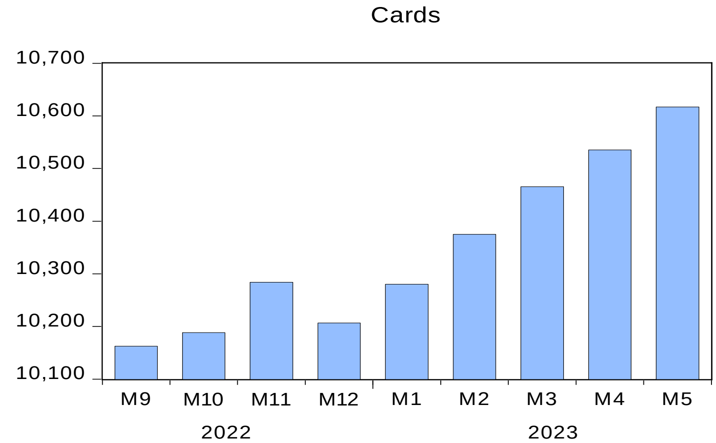
Table 2: Descriptive Statistics of Selected Variables under Study

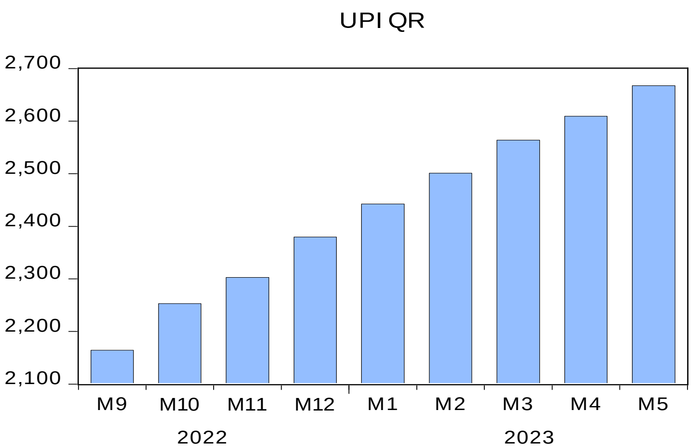
	WALLETS	UPI_QR	CARDS	ATM_AND_CRM
Mean	13307.11	2431.499	10345.99	2.562509
Median	13335.10	2442.342	10283.92	2.557960
Maximum	13509.02	2667.571	10616.74	2.585340
Minimum	13106.33	2164.298	10162.40	2.547180
Std. Dev.	117.9829	170.3392	162.1937	0.012570
Skewness	-0.057325	-0.150402	0.466534	0.628378
Kurtosis	2.550527	1.806974	1.834464	2.199953
Jarque-Bera	0.080689	0.567673	0.835909	0.832317
Probability	0.960458	0.752890	0.658392	0.659576
Sum	119763.9	21883.49	93113.95	23.06258
Sum Sq. Dev.	111359.6	232123.6	210454.3	0.001264

Observations	9	9	9	9

VA: Value in Crore ₹, VO: Volume in Lakh







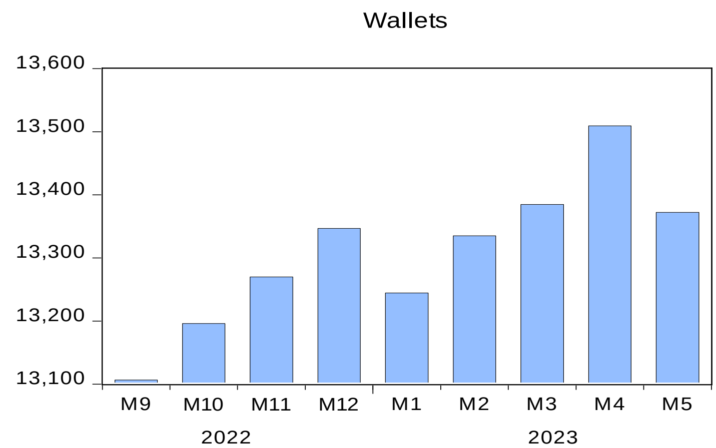


Table 2 presents descriptive statistics for selected variables under study, focusing on four categories: WALLETS, UPI_QR, CARDS, and ATM_AND_CRM. The mean values provide an average perspective, revealing that WALLETS have an average of 13,307.11 Lakh transactions, UPI_QR has 2,431.499 Lakh transactions, CARDS show an average of 10,345.99 Lakh transactions, and ATM_AND_CRM has an average of 2.562509 transactions. The standard deviations indicate the extent of variability around these means, with WALLETS having the lowest variability (117.9829) and CARDS showing the highest (162.1937). Skewness and kurtosis values offer insights into the shape of the distribution, indicating whether it is symmetric or skewed. Notably, all skewness values are close to zero, suggesting a relatively symmetrical distribution, while kurtosis values indicate slightly heavier tails. The Jarque-Bera tests further confirm the normality of the distributions, with high p-values supporting the hypothesis of normality. The sums and sum squared deviations provide aggregate information, summarizing the total volume and variability across observations. Overall, the table offers a detailed overview of the central tendencies, variabilities, and distribution shapes for the examined variables.

Table 3: Correlation Analysis

		Vo_IMPS	Vo_NEFT	Vo_UPI	Va_IMPS	Va_NEFT	Va_UPI	Cards	Wallets	ATM & CRM	UPI QR	Vo_Fraud	Va_Fraud
Vo_IMPS	Pearson Correlation	1	.658	.797*	.831**	.473	.812**	.562	.549	.148	.560	-.152	.046
	Sig. (2-tailed)		.054	.010	.005	.199	.008	.115	.126	.704	.117	.697	.906
	N	9	9	9	9	9	9	9	9	9	9	9	9
Vo_NEFT	Pearson Correlation	.658	1	.716*	.887**	.824**	.759*	.569	.622	.787*	.707*	.288	.441

	Sig. (2-tailed)	.054		.030	.001	.006	.018	.110	.074	.012	.033	.452	.235
	N	9	9	9	9	9	9	9	9	9	9	9	9
Vo_UPI	Pearson Correlation	.797*	.716*	1	.906**	.396	.997**	.908**	.795*	.323	.934**	.175	.358
	Sig. (2-tailed)	.010	.030		.001	.291	.000	.001	.010	.397	.000	.653	.345
	N	9	9	9	9	9	9	9	9	9	9	9	9
Va_IMPS	Pearson Correlation	.831**	.887**	.906**	1	.700*	.925**	.815**	.756*	.451	.835**	.267	.512
	Sig. (2-tailed)	.005	.001	.001		.036	.000	.007	.019	.223	.005	.487	.159
	N	9	9	9	9	9	9	9	9	9	9	9	9
Va_NEFT	Pearson Correlation	.473	.824**	.396	.700*	1	.434	.321	.238	.643	.342	.387	.528
	Sig. (2-tailed)	.199	.006	.291	.036		.244	.400	.537	.062	.367	.303	.144
	N	9	9	9	9	9	9	9	9	9	9	9	9
Va_UPI	Pearson Correlation	.812**	.759*	.997**	.925**	.434	1	.894**	.804**	.366	.934**	.187	.367
	Sig. (2-tailed)	.008	.018	.000	.000	.244		.001	.009	.333	.000	.630	.331
	N	9	9	9	9	9	9	9	9	9	9	9	9
Cards	Pearson Correlation	.562	.569	.908**	.815**	.321	.894**	1	.792*	.196	.937**	.476	.644
	Sig. (2-tailed)	.115	.110	.001	.007	.400	.001		.011	.614	.000	.195	.061
	N	9	9	9	9	9	9	9	9	9	9	9	9
Wallets	Pearson Correlation	.549	.622	.795*	.756*	.238	.804**	.792*	1	.273	.864**	.248	.443
	Sig. (2-tailed)	.126	.074	.010	.019	.537	.009	.011		.478	.003	.520	.232
	N	9	9	9	9	9	9	9	9	9	9	9	9
ATM and CRM	Pearson Correlation	.148	.787*	.323	.451	.643	.366	.196	.273	1	.430	.280	.251
	Sig. (2-tailed)	.704	.012	.397	.223	.062	.333	.614	.478		.247	.465	.514
	N	9	9	9	9	9	9	9	9	9	9	9	9
UPI QR	Pearson Correlation	.560	.707*	.934**	.835**	.342	.934**	.937**	.864**	.430	1	.368	.526
	Sig. (2-tailed)	.117	.033	.000	.005	.367	.000	.000	.003	.247		.330	.146
	N	9	9	9	9	9	9	9	9	9	9	9	9
Vo_Fraud	Pearson Correlation	-.152	.288	.175	.267	.387	.187	.476	.248	.280	.368	1	.899**
	Sig. (2-tailed)	.697	.452	.653	.487	.303	.630	.195	.520	.465	.330		.001
	N	9	9	9	9	9	9	9	9	9	9	9	9
Va_Fraud	Pearson Correlation	.046	.441	.358	.512	.528	.367	.644	.443	.251	.526	.899**	1
	Sig. (2-tailed)	.906	.235	.345	.159	.144	.331	.061	.232	.514	.146	.001	
	N	9	9	9	9	9	9	9	9	9	9	9	9
*. Correlation is significant at the 0.05 level (2-tailed).													
**. Correlation is significant at the 0.01 level (2-tailed).													

The correlation analysis indicates that the data does not reveal any significant correlation between the volume of fraud and the value of fraud concerning key variables such as payment infrastructure, the overall value of digital payments, and the volume of digital transactions. This implies that the occurrence and magnitude of fraud within the digital payment landscape in India are not overtly influenced by the scale or extent of the payment infrastructure in place. Additionally, the absence of a discernible correlation with the overall value and volume of digital payments suggests that the prevalence of fraud is not inherently tied to the sheer magnitude of transactions within the digital ecosystem. This nuanced finding prompts a deeper exploration into the specific factors or vulnerabilities that might contribute to instances of fraud, diverging from conventional assumptions about direct correlations with transactional volumes or infrastructure scale. As the study unfolds, it aims to unravel the intricate layers of this relationship, offering a more granular understanding of the dynamics between digital payments and financial fraud in the Indian economic context.

Table 4: Regression results for impact of volume of digital payment transactions on digital payment fraud

Dependent Variable: VA_FRAUD
Method: Least Squares
Date: 07/16/23 Time: 11:21
Sample (adjusted): 2021M06 2023M05
Included observations: 8 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	26.62924	33.71389	0.78986	0.47380
VO_IMPS	-0.14684	0.25894	-0.56710	0.60100
VO_NEFT	0.11809	0.06976	1.69283	0.16570
VO_UPI	-0.00707	0.01187	-0.59578	0.58340

R-squared	0.598507	Mean dependent var	4.446719
Adjusted R-squared	0.297387	S.D. dependent var	58.35002
S.E. of regression	48.91016	Akaike info criterion	10.9247
Sum squared resid	9568.816	Schwarz criterion	10.96442
Log likelihood	-39.6988	Hannan-Quinn criter.	10.6568
F-statistic	1.987604	Durbin-Watson stat	1.409272
Prob(F-statistic)	0.258124		

VA: Value in Crore ₹, VO: Volume in Lakh

The regression analysis explores the impact of the volume of digital payment transactions on digital payment fraud (Dependent Variable: VA_FRAUD). The model includes three independent variables: VO_IMPS, VO_NEFT, and VO_UPI, representing the volume of IMPS, NEFT, and UPI transactions, respectively. The coefficients indicate the estimated impact of each variable on digital payment fraud. The constant term (C) is 26.62924, suggesting that when all independent variables are zero, the predicted digital payment fraud is 26.63. However, none of the independent variables (VO_IMPS, VO_NEFT, VO_UPI) show statistically significant coefficients, as their p-values are above conventional significance levels (0.05). The R-squared value is 0.5985, indicating that approximately 59.85% of the variability in digital payment fraud can be explained by the model. The adjusted R-squared adjusts for the number of predictors and is 0.2974. The standard error of the regression is 48.91016, representing the average deviation of the observed values from the predicted values. The F-statistic is 1.9876 with a p-value of 0.2581, suggesting that the overall model may not be statistically significant. The Durbin-Watson statistic checks for autocorrelation, and a value of 1.4093 indicates a lack of strong correlation in the residuals. In summary, while the model explains a significant portion of the variance, the individual variables fail to reach statistical significance, indicating that the volume of digital payment transactions may not have a significant impact on digital payment fraud in this analysis.

Table 5: Regression results for impact of total value of digital payment transactions on digital payment fraud

Dependent Variable: VA_FRAUD
Method: Least Squares
Date: 07/16/23 Time: 11:21

Sample (adjusted): 2021M06 2023M05

Included observations: 8 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-78.7280	310.7726	-0.2533	0.8125
VA_IMPS	0.0019	0.0014	1.3217	0.2568
VA_NEFT	0.0000	0.0001	0.3888	0.7172
VA_UPI	-0.0012	0.0004	-3.0594	0.0377
R-squared	0.712476	Mean dependent var	4.446719	
Adjusted R-squared	0.496834	S.D. dependent var	58.35002	
S.E. of regression	41.39014	Akaike info criterion	10.59082	
Sum squared resid	6852.574	Schwarz criterion	10.63054	
Log likelihood	-38.36326	Hannan-Quinn criter.	10.32291	
F-statistic	3.303966	Durbin-Watson stat	1.957629	
Prob(F-statistic)	0.13924			

VA: Value in Crore ₹, VO: Volume in Lakh

The regression analysis explores the impact of the total value of digital payment transactions on digital payment fraud (VA_FRAUD). The coefficients associated with the variables provide insights into their individual contributions to the dependent variable. The intercept term (C) of -78.7280 suggests a negative constant impact, although it is not statistically significant (t-Statistic: -0.2533, Prob.: 0.8125). Among the transaction types, only VA_UPI exhibits statistical significance, with a coefficient of -0.0012 and a t-Statistic of -3.0594 (Prob.: 0.0377), indicating a negative relationship with digital payment fraud. The R-squared value of 0.712476 suggests that approximately 71.25% of the variability in digital payment fraud can be explained by the included variables. The adjusted R-squared, however, is 0.496834, reflecting the adjustment for the number of predictors. The F-statistic of 3.303966 is associated with a p-value of 0.13924, suggesting that the overall model may not be statistically significant. The Durbin-Watson statistic of 1.957629 indicates the absence of strong autocorrelation. In summary, the analysis indicates that while VA_UPI has a significant negative impact on digital payment fraud, the overall model may require further refinement or additional variables to enhance its explanatory power.

Table 6: Regression results for impact of digital payment infrastructures on amount of digital payment fraud

Dependent Variable: VA_FRAUD

Method: Least Squares

Date: 07/16/23 Time: 11:21

Sample (adjusted): 2021M06 2023M05

Included observations: 8 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-23.5931	206.4297	-0.1143	0.9162
ATM	1467.1410	2528.6210	0.5802	0.6025
CARDS	0.6944	0.5769	1.2037	0.3150
WALLETS	0.1749	0.3275	0.5341	0.6303
UPI_QR	-0.3050	3.0104	-0.1013	0.9257
R-squared	0.433098	Mean dependent var	4.446719	
Adjusted R-squared	-0.322771	S.D. dependent var	58.35002	
S.E. of regression	67.10941	Akaike info criterion	11.5197	
Sum squared resid	13511.02	Schwarz criterion	11.56935	
Log likelihood	-41.07879	Hannan-Quinn criter.	11.18482	
F-statistic	0.57298	Durbin-Watson stat	2.58019	

Prob(F-statistic)	0.70413

VA: Value in Crore ₹, VO: Volume in Lakh

The regression analysis aims to explore the impact of digital payment infrastructures, including ATM, CARDS, WALLETS, and UPI_QR, on the amount of digital payment fraud (Dependent Variable: VA_FRAUD). The coefficients associated with each infrastructure variable represent the estimated change in the amount of digital payment fraud for a one-unit change in the respective infrastructure, holding other variables constant. However, the coefficients for ATM, CARDS, WALLETS, and UPI_QR are not statistically significant, as indicated by their t-Statistics and associated probabilities. This implies that, based on the current sample and adjusted dates, there is insufficient evidence to conclude that these individual digital payment infrastructures have a significant impact on digital payment fraud. The R-squared value of 0.433098 suggests that the model explains 43.31% of the variance in digital payment fraud, but the negative Adjusted R-squared indicates that the model may not be well-specified. The F-statistic and its associated probability suggest that the overall model is not statistically significant. The Durbin-Watson statistic of 2.58019 indicates the presence of potential autocorrelation. In summary, based on the provided regression results, the examined digital payment infrastructures do not appear to have a significant impact on the amount of digital payment fraud in the specified time period and sample.

Table 7: Implications of the Study

Sr. No.	Section	Implication
1	Theory	The study challenges the existing theoretical understanding by suggesting that the volume of digital payment transactions may not be a decisive factor in predicting digital payment fraud. This prompts a reevaluation of current theoretical frameworks related to the connection between digital payments and fraud in the Indian economy.
2	Practice	The findings have practical implications for stakeholders in the digital payment ecosystem, emphasizing the need to reconsider the reliance on specific payment infrastructures as predictors of fraud. Businesses and financial institutions may need to adopt a more nuanced approach to fraud prevention, focusing on the protective impact of UPI transactions and exploring additional variables for a comprehensive risk mitigation strategy.
3	Policy	Policymakers can use the study's results to inform regulatory measures and policies related to digital payments and fraud prevention. The recognition of UPI transactions as having a negative impact on fraud suggests the importance of supporting and promoting secure digital payment methods. Policymakers may also consider incentivizing the implementation of advanced security measures in the industry.
4	Future Research	This study can be extended to Investigate whether the impact of digital payment infrastructures on fraud varies across different regions or demographics, offering a more nuanced understanding. Further study can be conducted by incorporating other factors such as user behavior, security protocols, or regional variations that might contribute to digital payment fraud.

CONCLUSION

The analysis conducted in this study reveals no significant correlation between the value and volume of fraud and payment infrastructure, digital payment value, and digital payment volume. Regression results further support this, showing that the volume of digital payment transactions does not exert a significant influence on the occurrence of digital payment fraud, and the selected digital payment infrastructures are not substantial predictors of such fraud. However, the analysis indicates that the value of UPI transactions has a significant negative impact on digital payment fraud, suggesting that higher values of UPI transactions may have a protective effect against fraud. This finding highlights the potential effectiveness of UPI as a secure digital payment method in the Indian context. Despite these findings, the overall model's explanatory power could be enhanced by refining the current variables or incorporating additional ones. This suggests that the existing model may not fully capture all the relevant factors that influence digital payment fraud in the Indian economy. Future research should consider exploring other variables and potential predictors to develop a more comprehensive understanding of the relationship between digital payments and fraud.

REFERENCES

[1] Adigwe, P. K. (2012). Ways of Curbing Frauds Associated with Electronic Payment. AFRREV *IJAH: An International Journal of Arts and Humanities*, 1(1), 30-39.
[2] Chang, V., Di Stefano, A., Sun, Z., & Fortino, G. (2022). Digital payment fraud detection methods in digital ages and Industry 4.0. *Computers and Electrical Engineering*, *100*, 107734.
[3] Fernandes, L. (2013). Fraud in electronic payment transactions: Threats and countermeasures. *Asia Pacific Journal of Marketing*

& Management Review. ISSN, 2319, 2836.
[4] Fernandes, L. (2013). Fraud in electronic payment transactions: Threats and countermeasures. *Asia Pacific Journal of Marketing & Management Review. ISSN*, *2319*, 2836.
[5] Jerath, Dr. S. (2022). Digital Payments in India: An Analysis. In International Journal of Innovative Technology and Exploring Engineering (Vol. 11, Issue 11, pp. 47–54). *Blue Eyes Intelligence Engineering and Sciences Engineering and Sciences Publication - BEIESP*. https://doi.org/10.35940/ijitee.k9303.10111122
[6] Kolodiziev, O., Mints, A., Sidelov, P., Pleskun, I., & Lozynska, O. (2020). Automatic machine learning algorithms for fraud detection in digital payment systems. *Восточно-Европейский журнал передовых технологий*, *5*(9-107), 14-26.
[7] Lonkar, A., Dharmadhikari, S., Dharurkar, N., Patil, K., & Phadke, R. A. (2024). Tackling digital payment frauds: a study of consumer preparedness in India. *Journal of Financial Crime*.
[8] Mints, A., & Sidelov, P. (2022). Digital payment card fraud: new vectors and detection. *Digital Technologies in the Contemporary Economy: Collective Monograph/editor Žaneta Simanavičienė. ISBN 9786094880506*.
[9] Setor, T. K., Senyo, P. K., & Addo, A. (2021). Do digital payment transactions reduce corruption? Evidence from developing countries. *Telematics and informatics*, 60, 101577.
[10] Sharma, P., & Chakravarthy, N. R. (2019). Knock Of Advertisement In Digital Social Interaction: Informative Or Intrusion For Social Media Users.
[11] Shree, S., Pratap, B., Saroy, R., & Dhal, S. (2021). Digital payments and consumer experience in India: a survey based empirical study. *Journal of Banking and Financial Technology*, 5, 1-20.
[12] Verma, S., Sharma, J., Kaushik, K., & Vyas, V. (2023). Mounting Cases of Cyber-Attacks and Digital Payment. In Cybersecurity Issues, Challenges, and Solutions in the Business World (pp. 59-80). *IGI Global.*
[13] https://bfsi.economictimes.indiatimes.com/blog/the-digital-payment-revolution-paving-the-way-for-indias-financial-independence/102745245#:~:text=The%20demonetization%20drive%20in%202016,journey%20towards%20a%20cashless%20society.
[14] https://www.linkedin.com/pulse/evolution-digital-payment-systems-india-dharmendra-kumar/
[15] https://www.nic.in/blogs/digital-payments-driving-the-growth-of-digital-economy/
[16] https://timesofindia.indiatimes.com/blogs/voices/the-evolution-of-digital-payments-and-its-impact-on-consumer-spending/
[17] https://english.jagran.com/business/evolution-of-digital-payments-in-india-how-upi-transformed-digital-payment-method-future-of-upi-10098919
[18] https://pib.gov.in/FeaturesDeatils.aspx?NoteId=151350&ModuleId%20=%202
[19] https://www.wipro.com/blogs/vijay-mahadevan-iyer/a-new-generation-emerges-in-indias-evolving-payment-system/