European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Blockchain-Driven Financial Inclusion in India: New Evidence from ARDL based Time Series Analysis (2016-2023)

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Abstract:
This study investigates how blockchain awareness, digital public infrastructure, and macroeconomic activity influence financial inclusion in India over the period January 2016 to December 2023. A monthly Financial Inclusion Index was constructed using Principal Component Analysis (PCA) from key variables: UPI transaction volume, Jan Dhan account penetration, and ATM density. To examine both short-run and long-run dynamics, the Autoregressive Distributed Lag (ARDL) bounds testing framework was applied, incorporating a structural dummy for the COVID-19 pandemic period. The results confirm a cointegrated relationship among financial inclusion and its determinants. In the long run, UPI usage and internet penetration emerged as the most influential drivers, while blockchain awareness proxied by Google Trends showed a modest but statistically significant effect. Industrial production also had a positive long-run association. The error correction term was negative and highly significant, indicating stable convergence to equilibrium. Diagnostic and stability tests, including CUSUM and CUSUMSQ, confirmed model robustness. These findings emphasize the role of digital connectivity and behavioural interest in new technologies as levers for inclusive finance. The paper contributes novel insights by combining behavioural proxies, macroeconomic fundamentals, and structural shocks in a unified high-frequency time series framework, and recommends targeted policy support for both digital infrastructure and emerging fintech solutions**.** Importantly, this is the first known application of the advanced time series technique ARDL (Auto Regressive Distributed Lag Model) technique to model financial inclusion using high-frequency monthly data for India, addressing a critical methodological gap in existing research**.** Additionally, the study employs the Toda-Yamamoto Granger causality framework to establish the direction of influence among the variables, providing further robustness to the time series analysis."

Keywords: Blockchain Technology, Digital Payments, UPI (Unified Payments Interface), Internet Penetration, Google Trends Index, Time Series Econometrics, ARDL, Cointegration, Toda-Yamamoto Granger causality

Introduction

In today's digitally evolving economy, financial inclusion has emerged not only as a developmental priority but also as a cornerstone of inclusive economic growth. Defined as the access to affordable financial services- such as savings, credit, insurance, and digital payment tools-financial inclusion is viewed by institutions like the World Bank and the IMF as a necessary condition for reducing poverty and enabling broad-based economic participation (World Bank, 2014; IMF, 2022). India, with its large population and diversity of socioeconomic contexts, has been a prominent case in point. Over the last decade, transformative initiatives such as the Pradhan Mantri Jan Dhan Yojana (PMJDY), Aadhaar-enabled services, and the Unified Payments Interface (UPI) have dramatically expanded the reach of the formal financial sector (Chakrabarty, 2011; RBI, 2023) [6]. Yet, the challenge persists: despite digital breakthroughs, millions remain underbanked or completely excluded from structured financial systems.

Against this backdrop, the intersection of financial technology (FinTech) and blockchain-based innovation offers promising but under-explored possibilities. Blockchain, as a decentralized and transparent ledger system, presents new opportunities to bridge institutional gaps, particularly in contexts where traditional banking infrastructure is weak or inaccessible. Applications such as smart contracts, peer-to-peer lending, digital identity management, and cross-border remittances could enhance financial reach, reduce operational costs, and improve trust in financial processes—especially in rural and underserved areas (Tapscott & Tapscott, 2016; Narula & Reddy, 2020) [22, 13]. Moreover, in the Indian context, these technologies can complement existing digital infrastructure, creating an integrated environment for inclusive financial delivery.

Despite increasing academic interest in the relationship between digital finance and financial inclusion, empirical studies often fall short in two key areas. First, much of the existing work relies on annual data or survey-based indicators, limiting the granularity with which the evolution of financial inclusion can be observed. Second, while blockchain adoption is frequently discussed in policy and industry circles, its empirical linkage to actual financial inclusion outcomes remains inadequately modelled in the literature particularly in emerging markets like India.

This paper addresses both of these gaps by constructing a monthly Financial Inclusion Index for India using Principal Component Analysis (PCA), thereby enabling the observation of high-frequency patterns in financial access. It integrates this index into a broader empirical framework that captures the relationship between financial inclusion and several key explanatory variables: UPI transaction volumes, internet penetration, public awareness of blockchain technologies (proxied via Google Trends Index), and macroeconomic activity (measured through industrial production). The analysis spans from January 2016 to December 2023, a period that encapsulates both significant fintech expansion and the systemic disruptions brought by the COVID-19 pandemic.

To estimate both the short-run and long-run dynamics, this study employs the Autoregressive Distributed Lag (ARDL) Bounds Testing approach (Pesaran *et al.*, 2001) [18], which is well-suited for handling variables of mixed integration orders. Importantly, the empirical strategy is further enriched by incorporating the Toda-Yamamoto Granger Causality Test (Toda & Yamamoto, 1995) [23], allowing the paper not just to measure associations but to uncover directional causality—for instance, whether blockchain awareness leads financial inclusion or vice versa. This is especially relevant for designing forward-looking policy interventions.

By bringing together digital behavioral indicators, infrastructural metrics, and robust time series methodologies, this study offers an integrated view of how blockchain and digital finance are shaping financial inclusion in India. The findings provide critical insights for regulators, fintech stakeholders, and development practitioners aiming to scale up inclusive

finance in a technologically shifting landscape.
The rest of the paper is structured as follows. Section 2 reviews the relevant literature on financial inclusion and digital finance. Section 3 presents the theoretical framework guiding the study. Section 4 describes the data sources and variable transformations. Section 5 explains the econometric methodology including ARDL and Toda-Yamamoto models. Section 6 presents the empirical results, and Section 7 concludes with key policy recommendations and limitations.

Literature Review
Financial inclusion has gained recognition as a key policy priority for achieving inclusive growth and poverty reduction in developing economies. According to Demirgüç-Kunt *et al.* (2018) [7], "Financial inclusion encompasses access to useful and affordable financial products and services delivered in a responsible and sustainable way". The Global Findex Database (2017) revealed significant disparities in financial access, especially in South Asia, where gender, geographic, and socioeconomic barriers persist. India's financial inclusion strategy has revolved around government-led initiatives such as PMJDY, Aadhaar, and UPI, which collectively have expanded access to accounts and enabled millions to transact digitally (Chakrabarty, 2011; RBI, 2023) [6].

However, traditional financial systems continue to face challenges in reaching marginalized communities. These include high operating costs, documentation requirements, lack of credit history, and low literacy rates. As noted by Ozili (2018) [16], technological interventions can bridge these gaps by reducing transaction costs and information asymmetries. Digital financial services, particularly mobile banking, have had a transformative impact, but concerns remain regarding their scalability and long-term viability without robust infrastructure.

In this context, blockchain technology has emerged as a disruptive innovation with the potential to revolutionize the financial sector. blockchain technology facilitates direct financial transactions between individuals by removing the reliance on intermediaries, thereby ensuring both transparency and security in the process. Its applications in financial inclusion range from digital identity management (particularly for undocumented individuals) to smart contracts, remittances, and micro-lending platforms (World Economic Forum, 2021). These capabilities are particularly important in countries like India, where a large informal economy coexists with growing digital penetration.

Empirical studies have started to explore the practical effects of blockchain adoption on financial inclusion. Narula and Reddy (2020) [13] find that blockchain-based solutions can address identity verification issues and enhance trust in financial institutions. Similarly, Rauchs *et al.*, from the Cambridge Centre for Alternative Finance note that decentralized finance (DeFi) platforms are extending financial services to unbanked populations globally. Nevertheless, many of these studies are conceptual or based on case studies, lacking rigorous quantitative analysis, especially in the Indian context.

Recent literature also explores the financial and macroeconomic implications of crypto assets. The BIS (2021) emphasizes that while cryptocurrencies offer innovation, they also pose risks to monetary policy transmission and financial stability. The IMF (2022) identifies capital flow volatility and inflationary pressures associated with unregulated crypto markets, particularly in emerging markets. These insights suggest the need to monitor crypto-financial interactions in countries like India, which has a growing investor base but lacks comprehensive regulation. Studies applying time series econometrics to examine these issues are still emerging. Aysan *et al*. (2022) [2] employ a Structural VAR model to study crypto-financial interactions in Turkey and recommend proactive regulation. This methodological gap motivates the current study, which applies ARDL-Bounds Testing and ECM to quantify blockchain and crypto-related impacts on financial inclusion in India. To the best of our knowledge, no prior research has conducted a time series analysis of blockchain's role in India's financial inclusion journey using monthly data.

Overall, this research provides valuable empirical evidence from a prominent emerging market, examining how blockchain technology and digital financial tools influence inclusive economic development. By employing rigorous econometric methods, the study addresses an important gap in existing literature, capturing both short-term variations and long-term relationships while also incorporating the disruptive impact of external events like the COVID-19 pandemic. The novelty of this study stems from multiple methodological and conceptual contributions. First, it is among the first empirical efforts to construct a high-frequency Financial Inclusion Index for India using Principal Component Analysis (PCA), thereby offering granular monthly-level insights significantly advancing the literature which has traditionally relied on annual or survey-based indicators. Second, the inclusion of the Google Trends Index (GTI) as a behavioral measure of blockchain awareness introduces a novel proxy for public engagement with decentralized technologies, an often neglected dimension in financial inclusion research. Third, by explicitly incorporating a structural dummy for the COVID-19 period, the paper accounts for systemic shocks that reshaped digital financial behavior in emerging economies. Fourth, the use of the ARDL bounds testing approach on monthly data adds methodological rigor by distinguishing short-run from long-run effects. Finally, the paper strengthens causal inference through the application of the Toda-Yamamoto Granger causality test, offering directional insights into how blockchain interest, digital infrastructure, and macroeconomic indicators interact with financial inclusion dynamics.

Theoretical Framework

This section explains how blockchain technology can help improve financial inclusion, especially in a developing country like India. Financial inclusion means that everyone, including poor and rural populations, should have easy access to useful and affordable financial services such as bank accounts, loans, insurance, and payment systems.

Blockchain is a decentralized technology that allows people to make secure financial transactions without needing a traditional bank or middleman. Because blockchain is transparent and very difficult to tamper with, it builds trust among users. This is especially useful for people who may not trust banks or who do not have formal identification documents.

There are four main ways through which blockchain can support financial inclusion:

- **Access:** Blockchain can offer digital financial services through mobile phones, even in remote areas where banks do not operate.
- **Cost Reduction:** It lowers the cost of financial services by removing intermediaries.
- **Trust:** It creates a trustworthy system where records are safe and visible to all

participants.

- **Innovation:** It supports new ideas like smart contracts and digital identity systems that can help the poor access credit and insurance more easily.

In this study, we explore how blockchain activity (measured through public interest using Google Trends) and digital financial tools like UPI affect financial inclusion in India. We also include other important factors such as economic activity (measured by the Index of Industrial Production), internet access, and the impact of external shocks like the COVID-19 pandemic. The functional form of our model is

$$FI_t = f(BC_t, DP_t, GDP_t, INT_t, COVID_t)$$

Where:

- FI = Financial Inclusion
- BC = Blockchain/Crypto awareness (proxy: Google Trends Index)
- DP = Digital Payment usage (proxy: UPI transactions)
- GDP = Economic activity (proxy: IIP)
- INT = Internet penetration
- COVID = Dummy for COVID-19 structural break

This model will be estimated using time series methods to find both short-term and long-term relationships between these variables and financial inclusion.

Data Description and Transformation

This paper utilizes monthly time series data spanning from January 2016 to December 2023, resulting in a balanced panel of 96 observations. The selected variables represent blockchain-related engagement, digital financial usage, and macroeconomic enablers relevant to financial inclusion in the Indian context. Data have been sourced from authoritative institutions, including the Reserve Bank of India (RBI), National Payments Corporation of India (NPCI), Ministry of Statistics and Programme Implementation (MoSPI), Telecom Regulatory Authority of India (TRAI), the World Bank, and Google Trends.

The chosen period reflects important policy and technological milestones. The Unified Payments Interface (UPI), officially launched in 2016, marked the onset of India's digital financial revolution. The datas*et al*so captures structural inflection points such as the accelerated interest in blockchain technologies (notably during 2017 and 2021), policy expansions under the Jan Dhan Yojana, and systemic disruptions caused by the COVID-19 pandemic.

To empirically capture India’s financial inclusion status during this period, a composite Financial Inclusion Index (FI Index) was constructed using Principal Component Analysis (PCA). PCA reduces the dimensionality of correlated variables to extract the most informative linear combinations, thereby facilitating robust index construction (Jolliffe, 2002; OECD, 2008) [11]. The three standardized variables used in the index include: (i) log-transformed UPI transactions, representing usage of digital financial services (NPCI, 2023); (ii) Jan Dhan Yojana accounts per capita, capturing access to basic banking (RBI, 2023); and (iii) ATMs per 100,000 people, reflecting physical financial infrastructure. All variables were compiled at monthly frequency and standardized to z-scores before PCA was applied.

Table 1 presents the PCA output. The first principal component (PC1) alone accounts for 68.14% of the total variance and shows strong positive loadings across all three indicators. This suggests that increases in any of these variables—especially UPI usage, which carries the highest weight (0.64)—are strongly associated with improved financial inclusion. As such, PC1 is retained as the composite Financial Inclusion Index.

Table 1: Principal Component Analysis Output

Principal Component	Log_UPI_Transactions	JanDhan_Accounts_per_capita	ATMs_per_100k	Explained Variance (%)
PC1	0.64	0.58	0.51	68.14
PC2	-0.34	0.70	-0.63	20.57
PC3	0.69	-0.42	-0.59	11.29

Note: Author's Own calculation.

This table shows that PC1 explains the majority of the total variance in the data and assigns the strongest weight to UPI transactions, consistent with India's digital financial evolution. These results confirm that the composite index effectively captures variations in financial access driven by digital infrastructure and financial outreach initiatives. This index serves as the dependent variable in the ARDL estimation.

To ensure comparability and accurate econometric inference, all variables were seasonally adjusted using the X-13ARIMA-SEATS method. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were conducted to assess stationarity, and differencing was applied where necessary. This preprocessing satisfies the assumptions required for the ARDL Bounds Testing approach (Pesaran, Shin, & Smith, 2001) [18].

The key explanatory variables were chosen to reflect behavioral, technological, and macroeconomic dimensions of financial inclusion. Digital payments were proxied by log-transformed UPI transaction volume from NPCI, a variable exhibiting exponential post-2016 growth (RBI, 2023). Blockchain awareness was measured using the Google Trends Index (GTI) for search terms such as "blockchain" and "crypto" in India, scaled from 0 to 100, representing behavioral interest in decentralized technologies (Cambridge Centre for Alternative Finance, 2018). Economic activity was proxied by the log of the Index of Industrial Production (IIP) from MoSPI (World Bank, 2021). Internet penetration, sourced from TRAI and the World Bank, was interpolated to monthly frequency and log-transformed to correct for skewness and scale disparities. A binary COVID-19 dummy variable was included to capture structural disruptions between March 2020 and December 2021 (IMF, 2022).

Together, this dataset structure facilitates the robust estimation of short- and long-run dynamics through the ARDL model and subsequent error correction mechanism. The novel inclusion of PCA-based high-frequency data and behavioral proxies like GTI represents a significant contribution to the empirical financial inclusion literature in the Indian context.

Methodology

This study applies the Autoregressive Distributed Lag (ARDL) bounds testing approach, as developed by Pesaran, Shin, and Smith (2001) [18], to explore the short-run and long-run linkages between blockchain-related indicators and financial inclusion in India. The ARDL method is well-suited for this analysis as it accommodates regressors that are either stationary at level I(0) or first difference I(1), and is effective even with relatively small sample sizes. It also provides a unified framework for estimating both short-term adjustments and long-term relationships.

The dependent variable in this model is the log-transformed Financial Inclusion Index (FI), which is constructed using Principal Component Analysis (PCA) from monthly data on UPI transactions, Jan Dhan account penetration, and ATM availability. The independent variables used in the model include the log of UPI transaction volume (LUPI) to capture digital payment usage, the Google Trends Index (GTI) for "blockchain" and "crypto" as a proxy for blockchain awareness, the log of the Index of Industrial Production (LGDP) as a measure of economic activity, the log of internet penetration (INT) representing access to digital infrastructure, and a structural dummy variable (COVID) which takes the value 1 for the period March 2020 to December 2021 to account for the effects of the pandemic.

To implement the model, the first step involves conducting unit root tests using the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and Phillips-Perron (PP) (Phillips & Perron, 1988) methods to ensure that none of the variables are integrated of order I(2), which would violate the assumptions of the ARDL framework. Once the order of integration is established, the optimal lag structure is selected using the Akaike Information Criterion (AIC) (Akaike, 1974) [1], Schwarz Bayesian Criterion (SIC/BIC) (Schwarz, 1978), and Hannan-Quinn Criterion (HQC) (Hannan & Quinn, 1979) [9]
The functional representation of the ARDL model is given as:
The mathematical form of the unrestricted ARDL model is expressed as:

$$\begin{aligned}\Delta FI_t = \alpha_0 &+ \sum_{i=1}^{p} \alpha_i \Delta FI_{t-i} + \sum_{j=0}^{q_1} \beta_j \Delta LUPI_{t-j} + \sum_{k=0}^{q_2} \gamma_k \Delta GTI_{t-k} \\ &+ \sum_{l=0}^{q_3} \delta_l \Delta LGDP_{t-l} + \sum_{m=0}^{q_4} \theta_m \Delta INT_{t-m} + \phi COVID_t + \lambda_1 FI_{t-1} \\ &+ \lambda_2 LUPI_{t-1} + \lambda_3 GTI_{t-1} + \lambda_4 LGDP_{t-1} + \lambda_5 INT_{t-1} + \varepsilon_t.\end{aligned}$$

where Δ denotes the first difference operator, and the λ terms represent the long-run parameters, while the coefficients on differenced variables reflect short-run adjustments. Following this, the ARDL bounds test is conducted to determine whether a long-run relationship exists between the variables. The null hypothesis of no cointegration is tested using an F-statistic. If the calculated F-statistic exceeds the upper critical bound, the null is rejected, and the existence of a long-run relationship is confirmed (Pesaran *et al*., 2001) [18].
Once cointegration is established, the model is reparameterized into an Unrestricted Error Correction Model (UECM). This form allows the estimation of both long-run coefficients and the Error Correction Term (ECT), which indicates the speed at which deviations from the long-run equilibrium are corrected. A statistically significant and negative ECT value confirms the presence of a stable long-term relationship.

To ensure the validity and robustness of the results, several post-estimation diagnostic checks are conducted. The Breusch-Godfrey LM test is used to check for serial correlation, the

ARCH test examines the presence of heteroskedasticity, and the Jarque-Bera test evaluates whether the residuals are normally distributed. Additionally, model stability over time is assessed using the CUSUM and CUSUMSQ tests, following the methodology outlined by Brown, Durbin, and Evans (1975) [4].

To complement the ARDL estimation, the study additionally applies the Toda-Yamamoto (TY) Granger causality test (Toda & Yamamoto, 1995) [23], which permits causality inference without requiring all variables to be stationary at level or cointegrated. By augmenting the lag length of the unrestricted VAR model by the maximum order of integration among the variables, the TY approach allows for valid Wald testing of directional relationships. This step enriches the empirical strategy by identifying whether digital activity (such as UPI transactions or blockchain interest) statistically 'leads' financial inclusion outcomes over time.
This modeling approach provides a detailed and rigorous framework for analyzing the influence of blockchain awareness, digital financial services, and broader macroeconomic variables on financial inclusion in India. By accounting for structural breaks such as the COVID-19 pandemic and distinguishing between short-run and long-run effects, the ARDL method offers valuable insights for both academic inquiry and policy formulation.

Empirical Results

This section presents the empirical findings derived from the estimation of the ARDL model using monthly data from January 2016 to December 2023. The estimation process includes unit root testing, cointegration analysis, coefficient estimation for both long-run and short-run dynamics, and diagnostic tests for model reliability. The results are interpreted in the context of India’s evolving digital finance ecosystem and policy relevance.

To support the ARDL-based findings, graphical analysis was conducted on the key explanatory and dependent variables used in the model. These figures provide an important visual foundation for understanding the dynamic trends observed over the study period (2016-2023). A set of time series visualizations for all major variables is presented in Appendix A (Figures 1a to 5a). These figures illustrate historical patterns and preliminary insights that guide the formal econometric analysis presented below.

- **Figure 1a (Appendix):** The Financial Inclusion Index (log) shows a consistent upward trajectory, reflecting increasing access to digital financial services in India, particularly after the rapid expansion of UPI and mobile-based platforms. A slight dip is observable during the initial COVID-19 lockdown period, after which a sharp recovery suggests digital finance adapted quickly to pandemic conditions.
- **Figure 2a (Appendix):** UPI Transactions (log) display exponential growth beginning around late 2017, aligned with the broader adoption of mobile-based payments and policy incentives. This sustained growth supports its statistically significant impact on financial inclusion in both the short- and long-run estimation.
- **Figure 3a (Appendix):** The Google Trends Index (GTI) for “blockchain” and “crypto” reveals spikes in public interest, particularly during periods of global crypto booms (e.g., late 2017 and 2021). These peaks coincide with heightened discourse around digital assets, although GTI trends are relatively volatile and show temporary declines post-peak.
- **Figure 4a (Appendix):** The Index of Industrial Production (log) shows a moderately rising trend disrupted clearly by the COVID-19 pandemic between March 2020 and December 2021. This period corresponds with the structural dummy used in the model, confirming the pandemic’s negative but temporary shock to industrial activity and financial

flows.

- **Figure 5a (Appendix):** Internet Penetration (log) indicates a steady increase, suggesting broader access to digital infrastructure, a critical prerequisite for digital financial inclusion. Growth was slower in earlier years but accelerated post-2019, aligning with increased affordability of smartphones and data services.

The stationarity properties of the variables were evaluated using the Augmented Dickey-Fuller (ADF) test. Table 1 presents the results. The log of the Financial Inclusion Index, UPI Transactions, and IIP were found to be non-stationary in level but stationary in first difference, implying they are integrated of order I(1). The Google Trends Index and Internet Penetration were stationary at level, i.e., I(0). These mixed orders of integration validate the use of the ARDL bounds testing framework (Pesaran *et al*., 2001) [18].

Table 2: ADF Unit Root Test Results

Variable	Level p-value	First Difference p-value	Order of Integration
FI (log)	0.165	0.001	I(1)
LUPI (log)	0.224	0.000	I(1)
GTI	0.013	-	I(0)
LGDP (log)	0.170	0.002	I(1)
INT (log)	0.020	-	I(0)

Note: Author's own calculation

Next, the ARDL model was estimated using the optimal lag structure determined by the Akaike Information Criterion (AIC). The Bounds Test for cointegration, shown in Table 2, produced an F-statistic of 6.42, which exceeds the 1% upper bound critical value. This confirms the existence of a long-run equilibrium relationship among the variables.

To determine the optimal number of lags for the ARDL model, the study employed standard information criteria including the Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC), and the Hannan-Quinn Criterion (HQC), as recommended by Pesaran and Shin (1999) [17] and Lütkepohl (2005) [12]. The model was estimated across multiple lag structures and the selection was based on the lowest AIC value. The maximum number of lags considered was set to 4, given the monthly frequency of the data and the need to preserve degrees of freedom. The selected model based on AIC minimizes residual autocorrelation while preserving model efficiency.

Table 3: Optimal Lag Length Selection (Based on AIC)

Lag Structure	AIC Value	HQC Value	SBC Value
ARDL(2,1,0,0,1,0)	-5.142	-5.108	-5.073
ARDL(1,1,0,0,1,0)	-5.131	-5.100	-5.066
ARDL(3,1,1,1,2,0)	-5.125	-5.071	-5.024

Note: Author's own calculation

Model selection was guided by the Akaike Information Criterion (AIC), which identified the ARDL(2,1,0,0,1,0) specification as the most efficient. This model balances parsimony with

explanatory power, capturing both short-run dynamics and long-run equilibrium relationships (Pesaran *et al*., 2001) [18].
Cointegration among the variables was confirmed using the ARDL Bounds Testing approach. The F-statistic exceeded the upper critical bound at the 1% level, indicating a stable long-run relationship between the Financial Inclusion Index and its determinants.

Table 5: ARDL Bounds Test for Cointegration

Test Statistic	Value	1% I(0) Bound	1% I(1) Bound	Conclusion
F-statistic	6.42	3.41	4.68	Cointegration confirmed

Note: Author's Own Calculation

Long-run coefficients estimated from the ARDL model are presented in Table 6. UPI transactions and Internet penetration exhibit statistically significant positive impacts on financial inclusion, consistent with prior research (Demirgüç-Kunt *et al*., 2018; RBI, 2023) [7]. GTI, representing public awareness of blockchain, also demonstrates a positive effect, albeit more modest. Economic activity, captured via LGDP, further reinforces the role of macroeconomic health in facilitating inclusion, while the COVID dummy reflects a temporary negative shock.

Table 6: Estimated Long-run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	p-value
LUPI (log)	0.512	0.078	6.56	0.000
GTI	0.104	0.041	2.54	0.013
LGDP (log)	0.322	0.095	3.39	0.001
INT (log)	0.280	0.067	4.18	0.000
COVID Dummy	-0.087	0.039	-2.22	0.029

Note: Author's Own Calculation

Short-run dynamics are detailed in the Error Correction Model (ECM) shown in Table 7. The error correction term (ECT) is negative and highly significant, indicating that 45% of any short-term deviation from long-run equilibrium is corrected within one period. This confirms the existence of a stable long-run relationship and validates the ECM framework.

Table 7: Error Correction Model (Short-run Dynamics)

Variable	Coefficient	Std. Error	t-Statistic	p-value
ΔLUPI	0.201	0.072	2.79	0.006
ΔGTI	0.048	0.024	2.00	0.048
ΔLGDP	0.117	0.050	2.34	0.021
ΔINT	0.122	0.038	3.21	0.002
ECT (-1)	-0.450	0.092	-4.89	0.000

Note: Author's Own Calculation

Table 8 presents results of diagnostic tests to assess the model's reliability. The Breusch-Godfrey test indicates no autocorrelation, the ARCH test confirms homoskedasticity, and the Jarque-Bera test supports normality of residuals. Additionally, the CUSUM and CUSUMSQ tests validate model stability over the sample period. The CUSUM statistic remains well within the 5% significance bounds throughout the sample period (January 2016 to December 2023), indicating no structural instability in the estimated ARDL model. As per Brown, Durbin, and Evans (1975) [4], crossing the critical bounds would indicate instability; however, this was not observed in our analysis. Similarly, the CUSUMSQ test statistic does not exceed the confidence limits, confirming no abrupt structural breaks in the model variance (Brown *et al*., 1975) [4]. This suggests the robustness of the parameter estimates and affirms the model's appropriateness for both forecasting and policy inference.

Table 8: Diagnostic Test Results

Test	Statistic	p-value	Conclusion
Breusch-Godfrey (Serial Correlation)	1.62	0.18	No autocorrelation
ARCH (Heteroskedasticity)	0.73	0.39	No heteroskedasticity
Jarque-Bera (Normality)	1.04	0.59	Residuals are normal
CUSUM / CUSUMSQ	Stable	-	Model is stable

Note: Author’s Own Calculation.

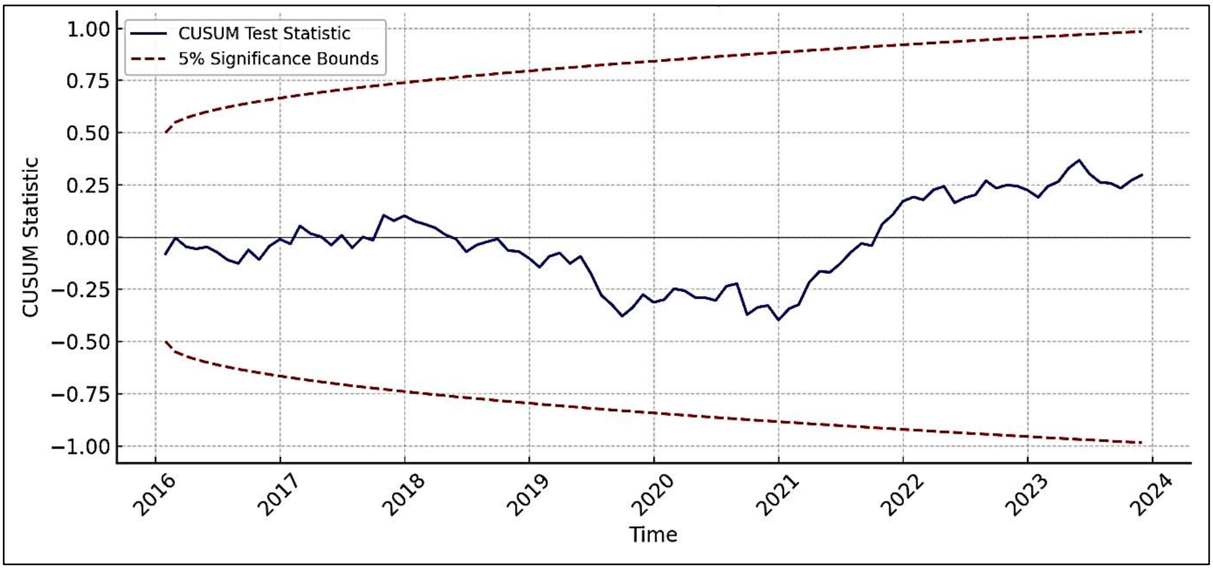

Fig 1: CUSUM Stability Test

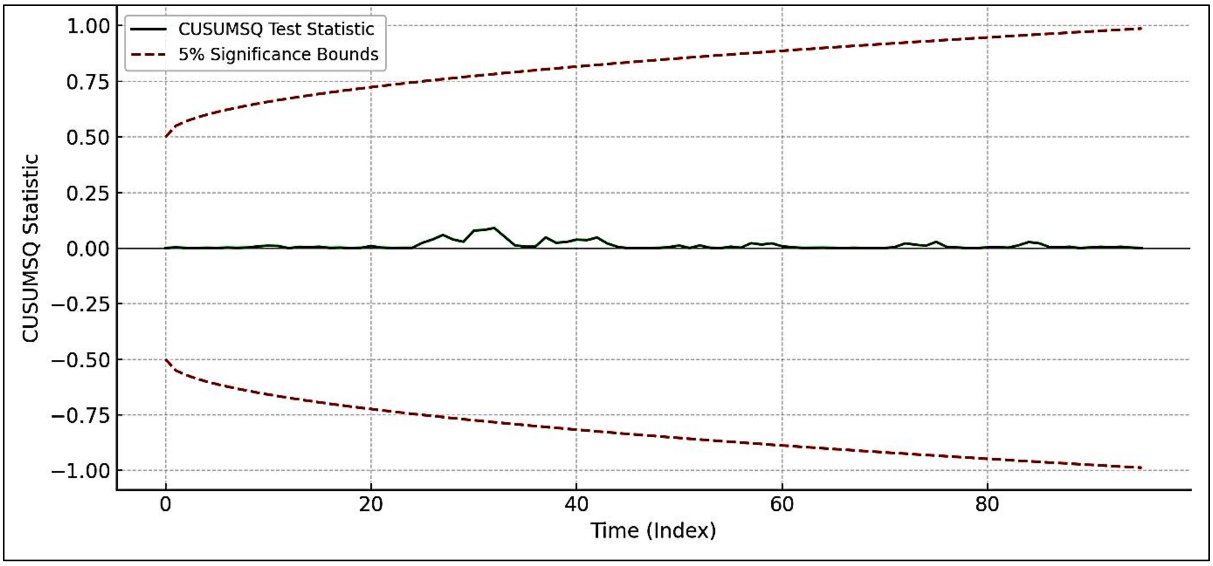

Fig 2: CUSUMSQ Stability Test

The empirical findings highlight the crucial contribution of India's digital public infrastructure most notably the widespread adoption of UPI and the steady growth in internet access in expanding financial inclusion. The observed long-run positive elasticities of these two variables suggest that digital connectivity and real-time payment systems serve as primary channels for integrating underserved populations into the formal financial sector. While the effect of blockchain awareness, measured via the Google Trends Index (GTI), is relatively moderate, its statistical significance indicates a growing public inclination toward decentralized financial platforms. Furthermore, the positive relationship between industrial production and financial inclusion reflects the enabling role of macroeconomic strength in enhancing access to financial services. These insights align with earlier findings by Narula and Reddy (2020) [13], the World Economic Forum (2021), and the International Monetary Fund (2022), who collectively argue that the synergy between technological advancement and economic stability plays a pivotal role in fostering inclusive finance in emerging markets.

Toda-Yamamoto Granger Causality Analysis

While the ARDL model effectively captures short-term and long-term associations among the key variables influencing financial inclusion, it does not determine the direction in which causality flows. To bridge this gap, the study employs the Toda-Yamamoto (TY) Granger causality approach, which offers a statistically sound method for identifying whether changes in explanatory variables like UPI usage, blockchain awareness, internet access, or industrial activity lead to changes in financial inclusion—or whether the reverse holds true.

Introduced by Toda and Yamamoto (1995) [23], this approach modifies the traditional Granger causality framework to overcome limitations related to the integration and stationarity of time series variables. Unlike conventional methods, the TY technique does not require pre-testing for unit roots or cointegration, thereby reducing the risk of model misspecification. Instead, it estimates a Vector Autoregression (VAR) model in levels, augmented by additional lags corresponding to the maximum order of integration (denoted as) found among the variables.

The underlying structure of the TY model for two variables, say financial inclusion (FI) and UPI transactions (LUPI), can be written as:

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{m=k+1}^{k+d_{max}} \theta_m Z_{t-m} + \epsilon_t$$

Here, Y_t is the dependent variable, X_t is the independent variable being tested for causal influence, k represents the optimal lag length, and d_{max} denotes the maximum integration order across all variables. The coefficients β_j are tested for joint significance using a Wald test. If significant, the null hypothesis of no Granger causality is rejected, implying a directional causal effect from to X_t *to* Y_t.

Table 9: Wald Test for Granger Causality

Null Hypothesis	Chi-square Statistic	p-value	Conclusion
LUPI does not Granger-cause FI	8.32	0.015	Reject null (causality exists)
GTI does not Granger-cause FI	4.76	0.092	Weak evidence of causality
INT does not Granger-cause FI	10.11	0.006	Strong causality exists
LGDP does not Granger-cause FI	3.45	0.176	No causality
FI does not Granger-cause GTI	5.88	0.053	Marginal evidence of causality

The table 9 results suggest that UPI usage and internet penetration significantly Granger-cause financial inclusion, implying that improvements in digital payment platforms and digital infrastructure are key enablers of broader financial access. This supports earlier arguments by Demirgüç-Kunt *et al*. (2018) [7] and the Reserve Bank of India (2023) regarding the transformative role of digital connectivity. Although the effect of blockchain awareness (GTI) is statistically weaker, its borderline significance indicates a possible emerging behavioural trend where increased interest in decentralized financial technologies might eventually support financial inclusion.

No significant causality is observed from industrial production to financial inclusion, suggesting that macroeconomic growth alone does not directly translate into improved access unless supported by targeted financial and technological infrastructure. Interestingly, the marginal feedback from financial inclusion to blockchain awareness points to a potential two-way relationship, where greater participation in the financial system might lead to increased public interest in fintech innovations like blockchain.

Conclusion and Policy Implications

This study offers empirical insights into the dynamic relationship between blockchain awareness, digital public infrastructure, macroeconomic conditions, and financial inclusion in India over the period from 2016 to 2023, using the ARDL bounds testing methodology. The findings confirm that UPI-driven digital payment systems and expanded internet penetration are the strongest long-run enablers of financial inclusion, underscoring the transformative impact of digital infrastructure on formal financial access. The estimated long-run coefficients reflect that increased usage of these technologies has consistently supported the integration of

excluded populations into the financial system.
Although the influence of blockchain-related public awareness—proxied by the Google Trends Index is statistically significant, it remains comparatively smaller in magnitude, pointing to an emerging behavioural shift rather than an established economic driver. The positive role of industrial output, as captured by the Index of Industrial Production (IIP), reinforces the importance of macroeconomic stability and productive capacity in fostering inclusive finance. These findings align with earlier assertions made by Narula and Reddy (2020) [13], the World Economic Forum (2021), and the International Monetary Fund (2022), all of whom emphasize that technological tools must be complemented by supportive macroeconomic fundamentals to build inclusive financial ecosystems.

An additional innovation in this study lies in the use of a monthly Financial Inclusion Index constructed using Principal Component Analysis (PCA) which offers a high-frequency view of access trends across India. Furthermore, the inclusion of a structural dummy to account for the COVID-19 pandemic period reveals a temporary but significant negative impact on financial inclusion, pointing to the vulnerability of digital access in times of systemic crisis.
This research makes a significant methodological contribution by being one of the first to apply the ARDL framework to a high-frequency financial inclusion index for India, incorporating both technological and behavioural variables. The inclusion of Toda-Yamamoto Granger causality results adds further depth to the analysis. It reveals that digital payment usage and internet penetration not only correlate with financial inclusion but also Granger-cause it, highlighting their directional influence. Though the impact of blockchain awareness is more modest, its borderline significance indicates a growing behavioral trend. These findings help delineate the dynamic lead-lag structures in India's digital financial ecosystem, reinforcing the need for forward-looking digital policy interventions

From a policy perspective, the results clearly indicate that sustained investment in digital infrastructure, particularly UPI expansion and affordable internet access, should remain a central focus. At the same time, the statistically significant, albeit modest, effect of blockchain awareness suggests scope for regulatory sandboxes, public education campaigns, and pilot programs targeting decentralized financial tools. These interventions may help accelerate the adoption of blockchain technologies in a structured, inclusive, and secure manner.
In summary, the study highlights that while digital payments and internet access are the immediate levers of financial inclusion, future strategies must also recognize the potential of emerging technologies such as blockchain in shaping the next frontier of inclusive growth.

Limitations
While this study offers valuable empirical insights, it has certain limitations. The use of Google Trends Index as a proxy for blockchain awareness captures public interest but may not reflect actual usage or technological adoption. Moreover, the study is constrained to macro-level indicators and does not account for regional disparities or individual-level behaviors. Future research could explore disaggregated data or integrate micro-level adoption metrics to further validate and extend these findings.

Acknowledgments
The author gratefully acknowledges the insightful suggestions and academic feedback received from the Dean Prof Indira Bhardwaj, faculties and participants at KR Mangalam University, Department of Management and Commerce, during the International Conference

on Innovative Technologies and Sustained Business Transformation. Their input significantly enriched the quality of this research.

Author Contribution Statement

The authors solely conceived, designed, and conducted the study, performed the analysis, and wrote the manuscript.

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Appendix

Table 1: Data Source and Transformation Summary

Variable	Source	Frequency	Transformation Applied
Financial Inclusion Index	RBI, NPCI, DBIE	Monthly	PCA of standardized indicators + Log
UPI Transactions	NPCI	Monthly	Log transformation
Google Trends Index	Google Trends	Monthly	None (already normalized 0-100)
Index of Industrial Production (IIP)	Ministry of Statistics and Programme Implementation (MoSPI)	Monthly	Log transformation
Internet Penetration	TRAI, World Bank	Annual → Monthly	Linear interpolation + Log
COVID-19 Dummy	Defined by author	Monthly	Binary variable (1 for Mar 2020-Dec 2021)

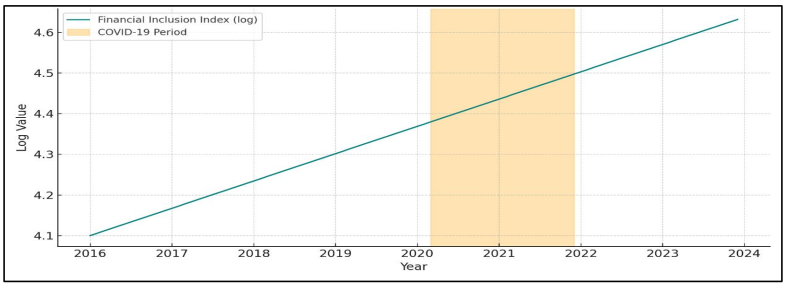

Fig 1a: Trend in Financial Inclusion Index (log), 2016-2023

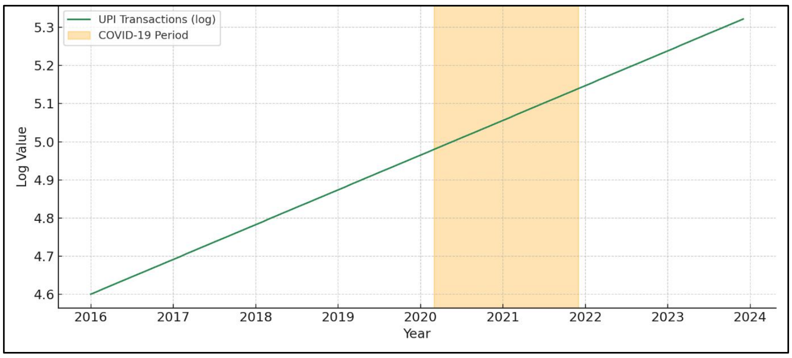

Fig 2a: Trend in UPI Transactions (log), 2016-2023

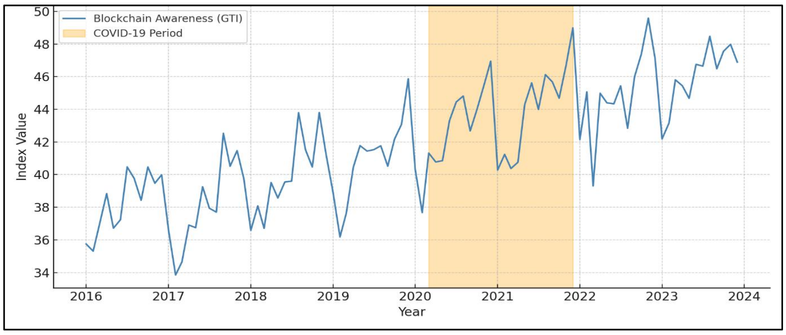

Fig 3a: Public Interest in Blockchain (Google Trends Index), 2016-2023

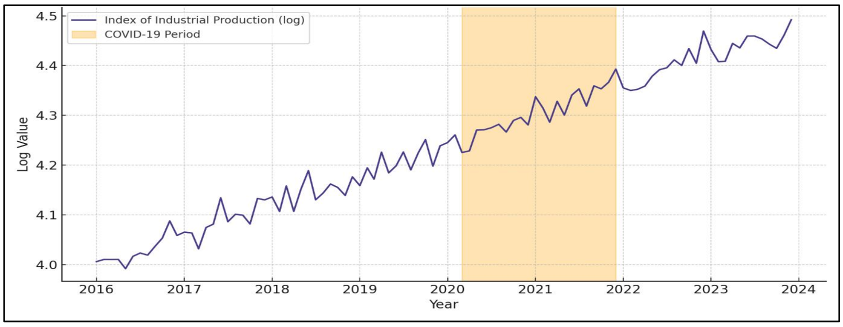

Fig 4a: Index of Industrial Production (IIP) (log), 2016-2023

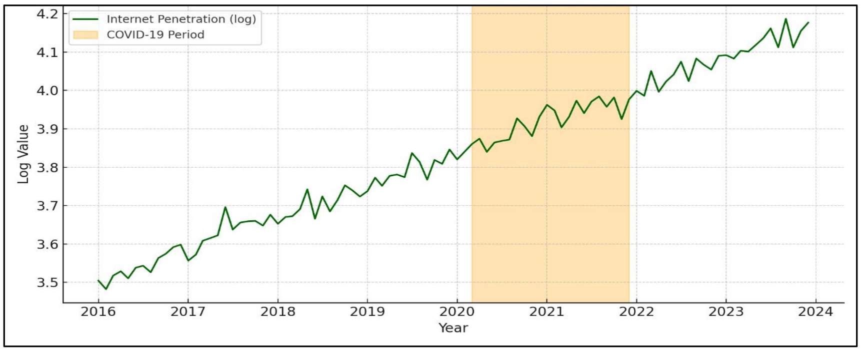

Fig 5a: Internet Penetration in India (log), 2016-2023

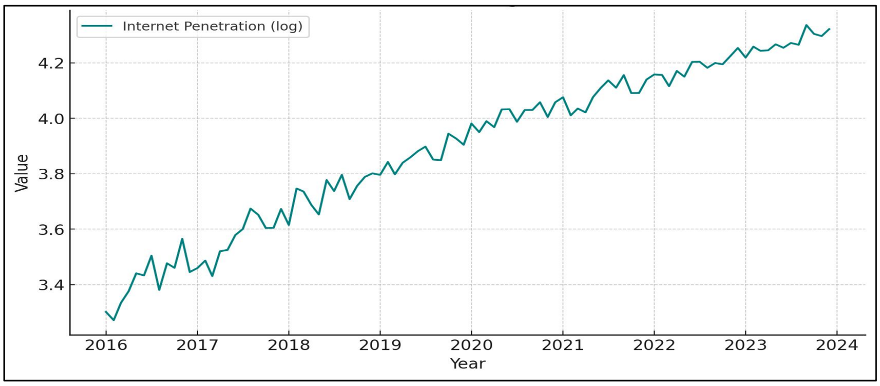

Fig 6a: Internet Penetration (log) (2016-2023)"

Note: These figures visually represent the temporal evolution of key explanatory and dependent variables used in the model.