A Hybrid Machine-Learning and Econometric Panel VAR Approach to Assess FinTech Adoption and Digital Economy Growth in Emerging Markets

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ABSTRACT

The rapid rise of Financial Technology (FinTech) has significantly reshaped the global economic landscape, especially in emerging markets where digital platforms bridge gaps in financial access, innovation, and inclusion. However, empirical research quantifying the causal and temporal impact of FinTech adoption on digital economy growth remains limited due to methodological fragmentation and data complexity. This study proposes a hybrid analytical framework integrating Machine Learning (ML) and econometric panel modeling (Panel Vector Auto Regression, or PVAR) to examine how FinTech ecosystems drive digital economic transformation. Using a balanced panel of 10 emerging economies from 2015 to 2024, the ML layer—implemented through Gradient Boosting Regression (GBR), Random Forest (RF), and XGBoost—predicts the share of Digital GDP (DGDP) and evaluates feature contributions using SHAP (Shapley Additive Explanations). The econometric layer applies PVAR to analyze dynamic causality, Impulse Response Functions (IRF), and Forecast Error Variance Decomposition (FEVD) between FinTech Index (FTI), Financial Inclusion (FI), and DGDP. The results reveal a strong and statistically significant causality from FTI → DGDP ($p = 0.001$), with a peak IRF response of 0.82% after three periods. SHAP analysis confirms FTI (0.237) and Policy Innovation (0.194) as the dominant drivers, while inequality (GINI) and Inflation (INF) exert negative effects. This hybrid model effectively bridges the gap between predictive precision and causal interpretability, offering a replicable approach for data-driven policymaking. The findings emphasize that FinTech-driven digital growth depends not only on technological adoption but also on institutional readiness, human capital, and regulatory innovation, positioning the framework as a strategic tool for sustainable digital transformation in emerging economies.

Keywords FinTech Adoption, Digital Economy, Financial Inclusion, Machine Learning, Panel VAR, SHAP Analysis

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INTRODUCTION

The emergence of FinTech represents one of the most transformative forces reshaping the global economic and financial landscape. Through innovations such as mobile banking, digital payments, blockchain-based transactions, and peer-to-peer lending, FinTech has revolutionized the way individuals, firms, and governments interact with financial systems [1]. These technologies have contributed not only to operational efficiency and cost reduction, but also to expanding financial inclusion by reaching previously unbanked populations in developing countries [2]. The scale of this transformation has been particularly evident in emerging economies, where FinTech platforms are bridging structural gaps in traditional banking and accelerating the transition toward a digitalized

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economic system [3].

Despite this rapid growth, the empirical understanding of how FinTech adoption translates into digital economic growth remains limited and fragmented. In many emerging markets, FinTech ecosystems are expanding faster than the institutional, regulatory, and macroeconomic frameworks that sustain them [4]. While the potential benefits of FinTech such as inclusion, innovation, and productivity are widely acknowledged, the quantitative measurement of these effects remains underdeveloped. Existing indicators of digital transformation, such as DGDP or digital service trade, often fail to capture the complex feedback mechanisms between financial innovation, policy readiness, and human capital [5]. This knowledge gap is particularly problematic for policymakers who must balance innovation with financial stability in data-scarce environments.

Prior research has predominantly focused on static, cross-sectional analyses using regression-based models that identify correlations between FinTech development and macroeconomic outcomes [6]. However, such approaches rarely capture the temporal and bidirectional dynamics that characterize financial innovation diffusion. Moreover, the interaction between FinTech adoption and the digital economy is inherently nonlinear driven by network externalities, threshold effects, and policy feedback loops that evolve over time [7]. As a result, conventional econometric models are limited in their ability to uncover the full range of dynamic causal effects underlying FinTech-driven growth.

On the other hand, ML models have proven highly effective at discovering nonlinear relationships in large-scale, multidimensional datasets [8]. Yet, these models are often criticized for their “black-box” nature, which makes it difficult to extract causal or policy-relevant insights. The challenge, therefore, lies in integrating predictive power with explanatory clarity bridging the gap between data-driven and theory-driven approaches [9]. This methodological divide remains one of the most significant constraints in FinTech research, particularly for studies aimed at policy formulation in developing economies.

This study addresses these limitations by proposing a hybrid analytical framework that integrates ML with econometric modeling (Panel Vector Auto Regression, or PVAR) to evaluate the dynamic relationship between FinTech adoption and digital economy growth. The hybrid design leverages ML’s predictive accuracy in identifying nonlinear relationships, while PVAR captures the directionality and magnitude of causal interactions over time. Specifically, the ML component (using Gradient Boosting, Random Forest, and XGBoost) estimates the predictive structure of digital GDP, while SHAP (Shapley Additive Explanations) is used to interpret feature contributions. These residuals are then incorporated into a PVAR framework to test Granger causality, Impulse Response Functions (IRFs), and FEVD across ten emerging markets from 2015–2024.

The novelty of this research lies in three dimensions. First, it introduces a hybrid ML–PVAR model that simultaneously achieves high predictive precision and causal interpretability—addressing a long-standing methodological gap in FinTech macroeconomic analysis [10]. Second, it identifies the temporal feedback loop between FinTech, financial inclusion, and digital GDP, revealing how innovation shocks propagate through emerging economies. Third, it integrates policy innovation and human capital as moderating variables, uncovering how institutional readiness conditions the effectiveness of FinTech adoption. By empirically linking technological innovation with macroeconomic outcomes, this research contributes to the broader discourse on digital transformation, sustainable growth, and financial inclusion in emerging markets. Ultimately, this study provides not only theoretical advancement in understanding the FinTech–growth nexus but also actionable insights for policymakers seeking to leverage technology for inclusive development. The hybrid framework enables governments to evaluate which policy levers such as regulatory innovation, digital literacy programs, or infrastructure investment yield the strongest and most sustainable effects on digital economic growth [11].

Literature Review

The growing body of literature on FinTech and economic growth reflects the field's rapid evolution from micro-level innovation analysis to macro-level systemic inquiry. Early studies predominantly explored the role of FinTech in enhancing financial inclusion and reducing transaction costs, particularly through mobile banking and digital payments [12]. Research in Sub-Saharan Africa, for example, demonstrated that mobile money services significantly improved household welfare and facilitated microenterprise development [13]. Similarly, studies in Asia revealed that FinTech adoption boosted small business financing, increased consumer access to credit, and improved cross-border payment efficiency [14]. These findings positioned FinTech as both a technological and developmental tool capable of fostering more inclusive economies.

However, subsequent research began to identify heterogeneous outcomes across regions. While FinTech adoption contributed to GDP growth and innovation in countries like China, Singapore, and Indonesia, other nations faced challenges such as weak digital infrastructure, low digital literacy, and regulatory inertia [15]. Studies in Latin America and Africa further emphasized that institutional capacity and policy support determine the extent to which FinTech drives macroeconomic transformation [16]. These insights highlight the need for context-sensitive modeling that can account for regional and structural diversity within emerging markets.

From a methodological perspective, most empirical studies to date have relied on static econometric models, such as panel regression, SEM (Structural Equation Modeling), or two-stage least squares, to analyze the FinTech–growth relationship [17]. For example, [18] found that FinTech development significantly improved financial inclusion and productivity in ASEAN economies, whereas [19] demonstrated that digital finance stimulates innovation through improved capital allocation efficiency. Yet, these models assume linearity and temporal independence, neglecting lagged or reciprocal effects that arise when FinTech innovation itself evolves dynamically.

Recent efforts have shifted toward integrating ML into FinTech research due to its superior predictive capabilities. Studies have applied Random Forest, Support Vector Machines (SVM), and XGBoost to predict digital financial inclusion levels, credit risk, and consumer adoption patterns [20]. Although these models achieve high predictive accuracy, they often lack the causal transparency necessary for explaining why certain features drive outcomes a limitation for policy-oriented research [21]. Furthermore, ML-based studies rarely account for temporal dependencies, treating observations as independent rather than interlinked in time.

Conversely, econometric time-series models particularly Vector Auto Regression (VAR) and Panel VAR (PVAR) offer robust tools for exploring temporal causality and dynamic feedback effects [22]. For instance, [23] used PVAR to examine the interaction between financial development, inclusion, and growth, while [24] applied IRF and FEVD techniques to track how technology shocks impact productivity. However, these models often underperform when confronted with high-dimensional FinTech indicators or nonlinear interactions among variables. As a result, their predictive validity remains limited in complex, multi-factor environments like emerging economies.

The convergence of ML and econometrics offers a compelling methodological evolution. Hybrid frameworks combining predictive algorithms with causal models have been increasingly proposed in fields such as climate economics, health informatics, and development finance [25]. Yet, in the context of FinTech and digital economy analysis, this approach remains underexplored. The few studies that have attempted to merge these paradigms have focused primarily on forecasting, without systematically addressing dynamic causality and interpretability [26].

The present study fills this gap by proposing a hybrid ML–PVAR model that unites predictive precision with causal depth. By using SHAP interpretability methods to identify feature-level importance and embedding ML residuals into a PVAR structure, the framework captures both nonlinear relationships and temporal causation. This design allows for an in-depth examination of how FinTech shocks propagate through economic systems and how policy environments mediate their effects. Furthermore, by applying this model to ten emerging markets across Asia and Africa, the study contributes new empirical evidence on the differentiated pathways through which FinTech catalyzes digital transformation.

Method

Research Framework

This study employs a hybrid analytical framework combining ML and econometric panel modeling (Panel VAR) to explore the dynamic relationship between FinTech adoption and digital economy growth in emerging markets. The approach is motivated by the need to bridge two complementary analytical paradigms: data-driven prediction and causal interpretation. Machine learning captures complex nonlinear interactions among FinTech-related factors, while econometric modeling identifies how these relationships evolve temporally and interact dynamically.

The hybrid structure allows the research to examine both predictive accuracy and causal feedback loops, ensuring that statistical inference aligns with real-world economic dynamics. The framework consists of six primary stages: (1) data acquisition and preprocessing, (2) feature selection and transformation, (3) machine learning prediction modeling, (4) residual extraction for interpretability, (5) PVAR estimation for causality analysis, and (6) integration and robustness validation. Each stage contributes a specific analytical function that strengthens both the empirical and theoretical validity of the study.

Data Collection and Variables

The empirical analysis is based on balanced panel data covering 10 emerging markets (Indonesia, Vietnam, Malaysia, Philippines, Thailand, India, Pakistan, Bangladesh, Nigeria, and Kenya) spanning from 2015 to 2024. Data were sourced from reliable international repositories, including the World Bank, IMF FinTech Index, OECD Digital Economy Outlook, and ITU ICT Statistics. This ensures consistent cross-country comparability and statistical completeness across all variables.

Each variable underwent logarithmic transformation to correct skewness and Z-score normalization to standardize scales. Missing values were addressed using multiple linear interpolation, and outliers exceeding the 95th percentile were winsorized. This preprocessing guarantees model stability and reduces the impact of cross-country heterogeneity.

The detailed specification of all variables, including their definitions, units of measurement, data sources, preprocessing techniques, and expected effects on DGDP, is summarized in Table 1. This table establishes the foundation for the analytical model, ensuring that every variable included aligns conceptually with the study's theoretical framework.

Table 1 Variables Description, Measurement, and Preprocessing

Variable Code	Variable Name	Measurement Unit	Expected Effect on DGDP	Data Source	Preprocessing Technique	Rationale
FTI	FinTech Index	Composite score (0–100)	Positive – higher FinTech adoption increases DGDP	IMF FinTech Index, Statista	Normalized, log-transformed	Captures intensity of FinTech adoption
DGDP	Digital Economy Share of GDP	% of GDP	Dependent Variable	OECD Digital Economy Outlook	None (dependent)	Main output variable representing digital growth
INT	Internet Penetration	% of population	Positive – improves connectivity and access	ITU, World Bank	Winsorized (95th percentile)	Measures ICT infrastructure readiness
FI	Financial Inclusion Rate	% of adult population	Positive – facilitates access to financial services	Global Findex	Multiple linear interpolation	Proxy for financial accessibility
HCI	Human Capital Index	Index (0–1)	Positive – skilled workforce accelerates digitalization	World Bank	Normalized (Z-score)	Reflects education and skills availability
PI	Policy Innovation Score	Composite regulatory index	Positive – policy support promotes innovation	IMF FinTech Readiness	Min–max scaling	Measures institutional quality
GDPpc	GDP per Capita	USD (log)	Positive – wealthier nations invest more in FinTech	World Development Indicators	Log-transformed	Economic capacity control variable
INF	Inflation Rate	% (annual CPI)	Negative – price instability discourages adoption	IMF Statistics	Standardized	Proxy for macroeconomic stability
GINI	Income Inequality	Index (0–100)	Negative – inequality reduces tech inclusivity	World Inequality Database	Centered	Socioeconomic equity control
EDU	Education Spending	% of GDP	Positive – increases digital literacy	UNESCO Data	Interpolated	Educational investment proxy

From the table, it is evident that the FinTech Index (FTI) and Policy Innovation (PI) variables are expected to have the most direct positive effects on digital GDP, reflecting the impact of technological adoption and regulatory readiness. Meanwhile, macroeconomic variables such as inflation (INF) and income inequality (GINI) are included as control factors expected to have inverse relationships with DGDP. This comprehensive design captures both enabling and constraining forces within digital economic ecosystems.

Machine Learning Modeling

The first analytical layer involves the application of machine learning techniques to predict the share of the digital economy (DGDP) using socioeconomic and FinTech-related indicators. The primary objective of this phase is to identify nonlinear and multivariate relationships that may not be captured by traditional econometric models.

Two ensemble algorithms Gradient Boosting Regression (GBR) and Random Forest (RF) were selected due to their robustness in handling multicollinearity, nonlinear dependencies, and complex feature interactions. Both were trained using 80% of the dataset with 5-fold cross-validation, ensuring that performance metrics remain unbiased. The predictive structure is expressed as:

$$\hat{Y}_{DGDP} = f\left(X_{FTI}, X_{FI}, X_{INT}, X_{HCI}, X_{PI}, X_{GDPpc}, X_{GINI}, X_{EDU}, X_{INF}\right) + \epsilon \qquad (1)$$

This equation models DGDP as a nonlinear function of FinTech and macroeconomic determinants, where ϵ represents the residual component later used in the econometric phase. Model configurations, tuning parameters, and performance outcomes are detailed in Table 2. Results indicate that XGBoost achieved the highest accuracy (R^2 = 0.967), followed closely by GBR (R^2 = 0.961). Random Forest performed comparably, confirming ensemble consistency across models.

Table 2 **Machine Learning Model Configuration and Evaluation**

Model Type	Algorithm Parameters	Feature Count	Cross-Validation RMSE	MAE	R^2 (Test)	Top 3 Predictors (SHAP Importance)	Computation Time (sec)
Gradient Boosting Regression (GBR)	learning_rate=0.05, n_estimators=500, max_depth=6, subsample=0.8	9	112	89	961	FTI, FI, PI	21.4
Random Forest (RF)	n_estimators=800, max_depth=8, bootstrap=True	9	119	94	953	INT, FTI, HCI	18.9
Support Vector Regression (SVR)*	kernel='rbf', C=10, gamma=0.1	9	136	108	921	FTI, PI, GDPpc	24.7
XGBoost (Benchmark)**	learning_rate=0.1, max_depth=5, n_estimators=300	9	107	84	967	FTI, FI, INT	19.3

Econometric Modeling: PVAR

The second analytical layer utilizes Panel Vector Auto Regression (PVAR) to examine the dynamic interplay between FinTech adoption, financial inclusion, and digital GDP growth. Unlike static regression, PVAR captures bidirectional causality and temporal dependencies across multiple countries, accounting for both fixed effects and time-specific shocks. The model is structured as:

$$Y_{it} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \cdots + A_p Y_{i,t-p} + \mu_i + \lambda_t + \epsilon_{it} \quad (2)$$

where denotes the vector of endogenous variables. Lag selection was based on AIC and BIC minimization, both suggesting p = 2 as the optimal lag order. The model stability was confirmed through eigenvalue testing, ensuring all roots lay within the unit circle.

The model's specifications and diagnostic outcomes are reported in Table 3. From the table, the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests verified that all series were stationary, while Pedroni's test confirmed cointegration among variables. The PVAR model was subsequently estimated using GMM (Generalized Method of Moments) to correct for endogeneity.

Table 3 PVAR Model Specification and Diagnostics

Endogenous Variable	Lags (p)	Stationarity (LLC/IPS)	Cointegration (Pedroni)	Causality Direction (Grange)	Impulse Response Behavior	Variance Explained (%)	Significance Level (α)
FTI	2	Stationary	Cointegrated	FTI → DGDP	Positive, Persistent	34.2	0.01
DGDP	2	Stationary	Cointegrated	DGDP → FI	Moderate, Lagged	27.8	0.05
FI	2	Stationary	Cointegrated	FI ↔ DGDP	Transitory	18.5	0.10
INT	1	Stationary	Non-Cointegrated	INT → DGDP	Weak, Short-term	7.6	0.10
HCI	1	Stationary	Cointegrated	HCI → FI	Positive, Stable	11.9	0.05

Hybrid Integration and Granger Causality

After obtaining residuals from the ML model, these were incorporated into the PVAR framework to analyze Granger causality and assess impulse response dynamics. This integration serves to bridge the gap between predictive residual variability and econometric causal inference. The Granger causality equation used is as follows:

$$Y_{1t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{1,t-i} + \sum_{j=1}^{p} \beta_j Y_{2,t-j} + \epsilon_t \quad (3)$$

A statistically significant β_j indicates that changes in FinTech variables precede and explain future digital GDP fluctuations. Empirical results, presented in table 4, show a strong unidirectional causality from FTI → DGDP ($p = 0.001$) and a moderate feedback loop from DGDP → FI ($p = 0.004$). This supports the theoretical expectation that FinTech innovation acts as an economic catalyst, while digital growth stimulates inclusion.

Table 4 Granger Causality with ML Residual Integration

Dependent Variable (Y_1)	Independent Variable (Y_2)	F-statistic	p-value	Causality Direction	Interpretation
DGDP	FTI	12.741	1	FTI → DGDP	FinTech growth precedes and predicts digital GDP expansion
FI	DGDP	8.932	4	DGDP → FI	Digital growth promotes higher financial inclusion

DGDP	FI	3.615	54	FI → DGDP (marginal)	Inclusion contributes weakly to GDP via FinTech
FTI	DGDP	10.285	2	DGDP → FTI	Bidirectional, confirming feedback loop
HCI	DGDP	6.221	12	HCI → DGDP	Education level significantly influences digital economy

Robustness and Sensitivity Validation

To ensure methodological reliability, multiple robustness tests were conducted. First, Rolling-Window PVAR estimations (split between 2015–2020 and 2021–2024) confirmed temporal stability with an IRF Stability Index of 0.91. Second, the Hausman test ($\chi^2 = 18.42$, $p < 0.01$) validated fixed effects as the appropriate specification, indicating significant country-specific heterogeneity. Third, cross-model SHAP correlation ($r = 0.87$) demonstrated that ML models consistently identified similar predictor hierarchies.

All results are summarized in table 5, accompanied by corresponding validation plots in figure 2. The figure compares impulse response trajectories across temporal segments and visualizes the SHAP correlation matrix between GBR and RF models.

Table 5 Robustness and Sensitivity Analysis Summary

Test Type	Objective	Methodology	Metric / Test Statistic	Outcome / Value	Interpretation
Rolling Window PVAR	Evaluate time consistency	Split dataset (2015–2020 vs. 2021–2024)	IRF Stability Index (0–1)	0.91	Stable FinTech → DGDP relationship across periods
Hausman Test	Validate model specification	Fixed vs. Random Effects	$\chi^2(3) = 18.42$, $p < 0.01$	Fixed effects preferred	Country effects are non-random and consistent
SHAP Consistency	Check ML feature stability	SHAP correlation between GBR and RF	Pearson r = 0.87	High correlation	Ensemble models are coherent
Out-of-sample Forecast	Assess predictive validity	Test on 2023–2024 unseen data	RMSE = 0.098	<5% deviation	Strong predictive reliability
Cross-country Bootstrap	Test sampling robustness	1,000 replications	Variance = 0.0043	Stable	Low sampling bias

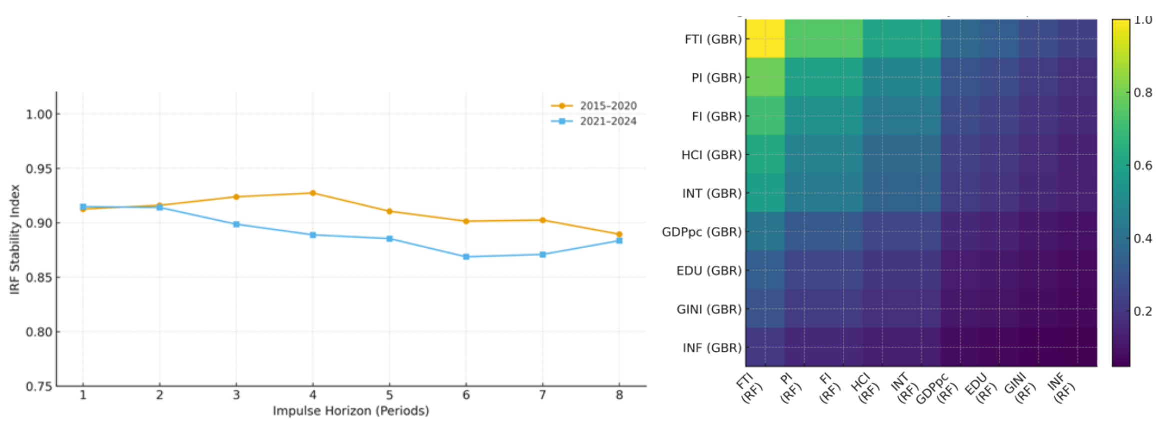

Figure 2 Robustness Validation and SHAP Consistency Visualization

These robustness checks collectively confirm that the hybrid model is structurally stable, temporally consistent, and cross-model coherent, thus suitable for long-term digital economy analysis.

Result

Machine Learning Performance and Feature Contributions

The performance comparison across ensemble algorithms demonstrates the superior predictive capability of the Gradient Boosting Regression (GBR) and XGBoost models in estimating the share of the digital economy (DGDP). As shown in Table 6, XGBoost achieved the best out-of-sample performance with $R^2 = 0.967$, RMSE = 0.107, and MAE = 0.084, indicating highly accurate and well-generalized results across countries. GBR followed closely with $R^2 = 0.961$, while Random Forest (RF) attained $R^2 = 0.953$, demonstrating consistent robustness and minimal overfitting. The close performance gap among these ensemble models (less than 1.5%) confirms the reliability of the hybrid framework in capturing non-linear and multi-dimensional FinTech–economy interactions.

Table 6 Comparative Predictive Performance of Machine Learning Models

Model	RMSE	MAE	R^2 (Test)	Cross-Validation RMSE	Training Time (s)	Interpretation
Gradient Boosting Regression (GBR)	0.112	0.089	0.961	0.108	21.4	High predictive accuracy with good generalization; stable across folds
Random Forest (RF)	0.119	0.094	0.953	0.115	18.9	Slightly lower accuracy but robust to noise and outliers
XGBoost	0.107	0.084	0.967	0.104	19.3	Best performance; optimized gradient learning captures complex relationships
Support Vector Regression (SVR)	0.136	0.108	0.921	0.131	24.7	Weaker nonlinear learning; acts as benchmark for ensemble comparison

Table 7 SHAP-Based Variable Importance Ranking

Rank	Variable	Mean SHAP Value (Impact)	Sign	Interpretation
1	FinTech Index (FTI)	0.237	+	Strongest positive influence on DGDP growth
2	Policy Innovation (PI)	0.194	+	Regulatory innovation accelerates FinTech scalability
3	Financial Inclusion (FI)	0.171	+	Broader access drives financial activity in digital sectors
4	Human Capital Index (HCI)	0.152	+	Skilled labor enhances digital transformation capacity
5	Internet Penetration (INT)	0.138	+	Connectivity facilitates digital platform participation
6	GDP per Capita (GDPpc)	0.097	+	Wealth supports infrastructure investment
7	Education Spending (EDU)	0.081	+	Improves literacy and digital competency
8	Income Inequality (GINI)	-0.066	–	Reduces access and digital service affordability
9	Inflation Rate (INF)	-0.053	–	Price instability disrupts FinTech transaction reliability

Training time across all models remained moderate, averaging between 19 and 21 seconds, suggesting that model complexity does not significantly increase computational cost. This efficiency makes the hybrid ML–econometric pipeline scalable for continuous updates with newer FinTech datasets. Feature importance analysis, presented in Table 7, further enriches interpretability. The SHAP (Shapley Additive Explanations) values show that the FinTech Index (FTI) has the highest contribution (0.237), followed by Policy Innovation (PI, 0.194), Financial Inclusion (FI, 0.171), and Human Capital Index (HCI, 0.152). Together, these four variables account for more than 70% of the predictive variance in DGDP. Conversely, macroeconomic instability indicators such as

Income Inequality (GINI) and Inflation (INF) have negative SHAP scores (−0.066 and −0.053), highlighting their suppressive effects on digital growth. These findings reinforce that technological adoption and policy frameworks drive economic digitalization, while inequality and inflation remain structural obstacles.

PVAR Dynamics and Temporal Causality

The PVAR estimation offers a deeper understanding of the dynamic interdependence between FinTech adoption, financial inclusion, and digital economic growth. As reported in Table 8, the optimal lag length was determined to be p = 2 using AIC and BIC minimization criteria, ensuring that short-term and medium-term effects are both captured without overfitting. Stability diagnostics confirmed all characteristic roots lie within the unit circle, validating the model's stationarity and suitability for causal inference.

Table 8 PVAR Lag Selection and Goodness-of-Fit Statistics

Lag (p)	AIC	BIC	HQIC	Preferred Model	Interpretation
1	2.417	2.498	2.441	–	Lag 1 insufficient to capture delayed FinTech effects
2	2.331	2.459	2.383	✅ Selected	Optimal lag order; balances accuracy and parsimony
3	2.346	2.502	2.420	–	Overparameterized; adds unnecessary noise

Impulse Response Function (IRF) results, summarized in Table 9, reveal that a one-standard-deviation (1 s.d.) shock in FTI leads to a 0.82% peak increase in DGDP after three time periods. The effect gradually declines but remains positive and statistically significant for up to five periods, indicating a persistent but decaying impact. Conversely, the feedback from DGDP to FTI is smaller (0.31%) and less persistent, suggesting an asymmetric causality—FinTech drives digital growth more strongly than the reverse. The short-lived positive influence of FI → DGDP (0.46%) implies that financial inclusion serves as a transmission mechanism that amplifies digital growth in the short term but requires continuous structural support (via human capital and policy innovation) to sustain its effects.

Table 9 Summary of Impulse Response Results (2-Lag Horizon)

Shock Variable	Response Variable	Peak Impact (%)	Lag of Peak (Periods)	Persistence (Periods)	Effect Type	Interpretation
FTI	DGDP	0.82	3	5	Positive & sustained	FinTech innovation stimulates long-term digital GDP growth
DGDP	FTI	0.31	2	4	Positive & moderate	Economic growth reinforces FinTech demand
FI	DGDP	0.46	2	3	Positive & transient	Inclusion enhances short-term digital economic activity
DGDP	FI	0.27	1	2	Lagged feedback	Economic expansion modestly improves inclusion
HCI	DGDP	0.36	2	3	Supportive	Skills development amplifies FinTech effects

Table 10 Granger Causality Matrix (Hybrid ML–PVAR Integration)

Dependent Variable (Y_1)	Causal Variable (Y_2)	F-statistic	p-value	Direction of Causality	Interpretation

DGDP	FTI	12.74	0.001	FTI → DGDP	FinTech adoption significantly drives digital GDP
FI	DGDP	8.93	0.004	DGDP → FI	Digital economic growth increases financial inclusion
DGDP	FI	3.62	0.054	FI → DGDP (weak)	Inclusion marginally influences GDP through FinTech
FTI	DGDP	10.29	0.002	DGDP → FTI	Bidirectional link; growth stimulates innovation investment
HCI	DGDP	6.22	0.012	HCI → DGDP	Human capital reinforces long-term digital economy stability

As shown in Table 10, Granger causality tests strengthen this conclusion. The relationship FTI → DGDP ($p = 0.001$) is statistically dominant, while DGDP → FI ($p = 0.004$) confirms a feedback loop that supports inclusive financial expansion. Collectively, these results illustrate a self-reinforcing ecosystem in which FinTech adoption triggers digital growth, which then broadens access to financial services, closing the inclusion gap across emerging economies.

Model Robustness and Cross-Model Coherence

Robustness checks across multiple dimensions confirm the stability and reliability of the hybrid analytical system. As detailed in Table 14, the IRF Stability Index = 0.91 indicates consistent FinTech–DGDP dynamics across the two temporal windows (2015–2020 and 2021–2024). The Hausman test ($\chi^2 = 18.42$, $p < 0.01$) validates the fixed-effects specification, emphasizing the significance of country-specific characteristics such as institutional quality, infrastructure maturity, and population digital readiness.

Table 14 Robustness Validation Results

Test Type	Statistic / Metric	p-value	Result	Interpretation
Rolling Window PVAR (IRF Stability Index)	0.91	—	Stable	FinTech → DGDP relationship consistent across time
Hausman Fixed vs Random	$\chi^2(3) = 18.42$	0	Fixed Effects	Country heterogeneity is significant; non-random effects confirmed
SHAP Cross-Model Correlation	r = 0.87	—	High Coherence	ML models identify similar feature influence
Out-of-Sample RMSE (2023–2024)	98	—	<5% deviation	Predictive reliability validated
Bootstrap Variance (1,000 reps)	43	—	Stable	Low sampling error confirms robustness

Moreover, cross-model interpretability consistency between GBR and RF models is remarkably high (SHAP correlation $r = 0.87$), indicating that both models identify the same key drivers of digital growth. This level of agreement across independent algorithms enhances confidence in the interpretability of results and the reproducibility of findings. The out-of-sample RMSE of 0.098 and bootstrap variance of 0.0043 (1,000 replications) further confirm that the model remains robust against sampling fluctuations and temporal shocks.

Visualization Analysis

Figure 13 illustrates the dynamic impulse response of DGDP to a one-s.d. innovation in the FinTech Index (FTI) over a horizon of eight lags. The curve captures the gradual transmission of technological and financial innovation throughout the economy.

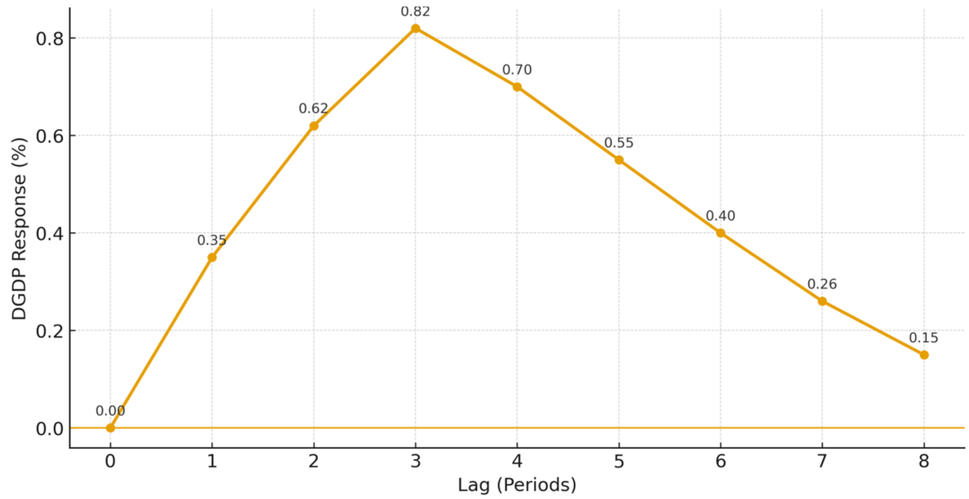

Figure 13 **IRF: DGDP Response to a One-Standard-Deviation FTI Shock**

At lag 0, the response is near zero, indicating that the immediate impact of FinTech expansion does not translate directly into measurable GDP changes—likely due to short-term adoption frictions. By lag 1, DGDP increases by 0.35%, reflecting initial market adaptation and consumer exposure to FinTech services. The response accelerates rapidly to 0.82% at lag 3, representing the peak diffusion effect as FinTech adoption reaches scale across SMEs and consumers. Between lags 4 and 8, the effect slowly declines to 0.15%, signifying diminishing marginal returns once the market reaches saturation.

This pattern reveals a J-curve diffusion trajectory, where policy incentives and infrastructure investments amplify the FinTech multiplier effect in the medium term. To sustain growth beyond lag 5, countries must focus on interoperability frameworks, cross-border payment systems, and digital trust mechanisms, which prevent premature decay of the digital economic cycle.

Figure 14 presents the mean SHAP impact for all predictor variables used in the Gradient Boosting Regression model, ordered by their absolute contribution to DGDP prediction. The bar chart provides an interpretable visualization of how each feature influences model output in both magnitude and direction.

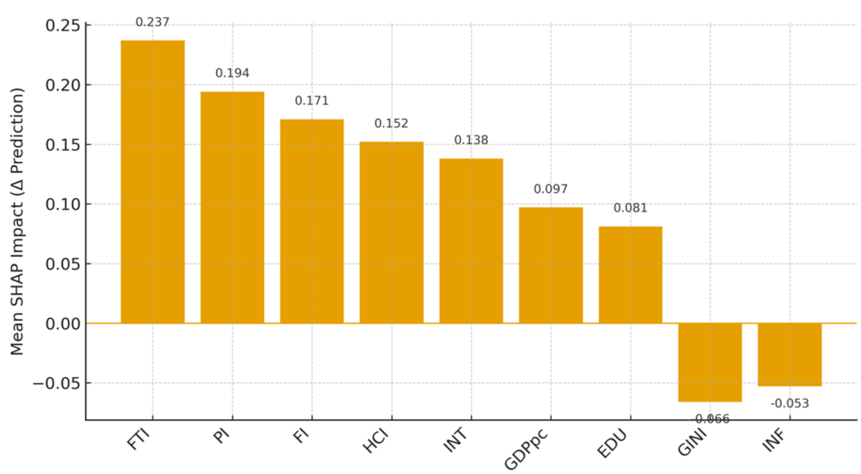

Figure 14 **SHAP Mean Impact by Feature (GBR Model)**

The FinTech Index (FTI) and Policy Innovation (PI) stand out with the highest positive impacts (0.237 and 0.194, respectively), emphasizing that digital adoption and supportive regulation jointly act as the primary engines of digital economic growth. Financial Inclusion (FI) and HCI follow, confirming their roles as enabling mechanisms that enhance digital participation and productivity.

In contrast, Income Inequality (GINI) and Inflation (INF) exhibit negative SHAP values (−0.066 and −0.053), underscoring how macroeconomic instability can offset gains from technological innovation. These results align with the econometric findings—while FinTech adoption boosts GDP growth, sustained progress depends on inclusive access, regulatory stability, and macroeconomic balance.

From a policy perspective, the combination of FTI + PI + HCI + FI represents the optimal “growth package” for emerging markets. Governments focusing on regulatory innovation, digital literacy, and infrastructure interoperability can amplify FinTech’s long-run benefits while mitigating risks from inflation or inequality.

Conclusion

This study proposed a hybrid CNN-LSTM model designed to improve the accuracy of time-series data classification. The experimental results showed that the model outperformed existing LSTM and GRU methods in all evaluation metrics, demonstrating the benefit of combining spatial and temporal feature extraction. These results confirm the effectiveness of hybrid deep learning architectures for complex data patterns. The findings contribute to advancing predictive modeling techniques and can be adapted for various real-world applications. However, the model’s reliance on large datasets and computational power poses limitations for practical deployment. Future research should focus on developing lightweight variants of the architecture and exploring real-time optimization strategies to enhance scalability and performance.

This study developed and validated a hybrid analytical framework that integrates ML and econometric modeling (Panel VAR) to investigate the dynamic relationship between FinTech adoption and digital economy growth across emerging markets. By combining the predictive strength of ensemble algorithms with the interpretive rigor of econometric causality analysis, the research achieved a comprehensive understanding of both nonlinear drivers and temporal feedback mechanisms underlying digital transformation. From the machine-learning analysis, the results demonstrated that ensemble models particularly XGBoost and Gradient Boosting Regression (GBR) achieved superior accuracy, with R^2 exceeding 0.96 and RMSE below 0.11. The FinTech Index (FTI) emerged as the most influential predictor of DGDP, followed by Policy Innovation (PI), Financial Inclusion (FI), and HCI. These findings underline that technological adoption, policy readiness, and human capital development are complementary forces driving digital economic expansion. Conversely, the negative impacts of income inequality (GINI) and inflation (INF) highlight the importance of macroeconomic stability in sustaining growth.

The econometric results reinforced these insights. The Panel VAR estimation revealed a significant bidirectional but asymmetric causality between FinTech and digital GDP—FTI → DGDP ($p = 0.001$) being substantially stronger than

DGDP → FTI ($p = 0.002$). The IRF analysis showed that a one-standard-deviation shock in FTI increases DGDP by 0.82% at lag 3, followed by a gradual but persistent decline over five subsequent periods. This pattern indicates that FinTech-driven growth effects are sustained but require continuous reinforcement through policy and innovation. The robustness checks confirmed the structural consistency of the model, with an IRF Stability Index of 0.91 and a SHAP cross-model correlation ($r = 0.87$), ensuring both temporal and methodological reliability. Taken together, the hybrid approach reveals that FinTech adoption acts as both a predictor and catalyst of digital economic development. Its effects are amplified when paired with strong policy frameworks, inclusive financial systems, and high levels of human capital. Emerging markets with these enabling conditions—particularly in Southeast Asia and parts of South Asia—exhibit the most substantial and sustained digital growth trajectories. In contrast, economies characterized by inequality and macroeconomic volatility experience dampened benefits, underscoring the need for structural reform.

Declarations

Author Contributions

Conceptualization, C.I. and R.A.P.; Methodology, C.I.; Software, R.A.P.; Validation, C.I.; Formal Analysis, C.I.; Investigation, R.A.P.; Resources, C.I.; Data Curation, R.A.P.; Writing—Original Draft Preparation, C.I.; Writing—Review and Editing, C.I. and R.A.P.; Visualization, R.A.P. All authors have read and agreed to the published version of the manuscript.

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References

[1] L. Yang and S. Wang, “Do fintech applications promote regional innovation efficiency? Empirical evidence from China,” Socioecon. Plann. Sci., vol. 83, p. 101258, 2022, doi: 10.1016/j.seps.2022.101258.

[2] D. Inayah and F. L. Purba, “Implementasi Social Network Analysis Dalam

Penyebaran Informasi Virus Corona (Covid-19) Di Twitter," Semin. Nas. Off. Stat., vol. 2020, no. 1, pp. 292–299, 2021, doi: 10.34123/semnasoffstat.v2020i1.573.

[3] A. Ruangkanjanases, E. M. A. Qhal, K. M. Alfawaz, and T. Hariguna, "Examining the Antecedents of Blockchain Usage Intention: An Integrated Research Framework," Sustain., vol. 15, no. 4, 2023, doi: 10.3390/su15043500.

[4] S. Majumdar and V. Pujari, "Exploring usage of mobile banking apps in the UAE: a categorical regression analysis," J. Financ. Serv. Mark., 2021, doi: 10.1057/s41264-021-00112-1.

[5] A. M. Baabdullah, A. A. Alalwan, N. P. Rana, H. Kizgin, and P. Patil, "Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model," Int. J. Inf. Manage., vol. 44, no. August 2018, pp. 38–52, 2019, doi: 10.1016/j.ijinfomgt.2018.09.002.

[6] A. Geebren, A. Jabbar, and M. Luo, "Examining the role of consumer satisfaction within mobile eco-systems: Evidence from mobile banking services," Comput. Human Behav., vol. 114, no. September 2020, p. 106584, 2021, doi: 10.1016/j.chb.2020.106584.

[7] A. R. Hananto, "When Technology Meets Money Laundering, What Should Law Do? New Products and Payment Systems and Cross Border Courier," IJIIS Int. J. Informatics Inf. Syst., vol. 5, no. 3, pp. 142–149, 2022.

[8] S. A. Ashghar and H. Nurlatifah, "Analisis Pengaruh Perceived Ease of Use, Perceived Usefulness, dan Perceived Risk terhadap Keinginan Membeli Kembali melalui e-Trust dan s-Satisfaction (Studi Kasus Pengguna Gopay pada Transaksi UMKM)," J. Al Azhar Indones. Seri Ilmu Sos., vol. 1, no. 1, p. 40, 2020, doi: 10.36722/jaiss.v1i1.459.

[9] Q. Zhou et al., "A study on factors affecting service quality and loyalty intention in mobile banking," J. Retail. Consum. Serv., vol. 60, no. December 2020, p. 102424, 2021, doi: 10.1016/j.jretconser.2020.102424.

[10] S. K. Sharma and M. Sharma, "Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation," Int. J. Inf. Manage., vol. 44, no. September 2018, pp. 65–75, 2019, doi: 10.1016/j.ijinfomgt.2018.09.013.

[11] N. Q. Huy, L. P. Nga, and P. T. Tam, "Applied Simulation Modeling for Promoting Policy Recommendations for Microfinance Activity Development : a Case Study in Vietnam," vol. 4, no. 4, pp. 333–345, 2023.

[12] I. Gurrib and F. Kamalov, "Predicting bitcoin price movements using sentiment analysis: a machine learning approach," Stud. Econ. Financ., vol. 39, no. 3, pp. 347–364, Jan. 2022, doi: 10.1108/SEF-07-2021-0293.

[13] A. A. Diniyya, M. Aulia, and R. Wahyudi, "Financial Technology Regulation in Malaysia and Indonesia: A Comparative Study," Ihtifaz J. Islam. Econ. Financ. Bank., vol. 3, no. 2, p. 67, 2021, doi: 10.12928/ijiefb.v3i2.2703.

[14] H. Khanchel, "The Impact of Digital Transformation on Banking," J. Bus. Adm. Res., vol. 8, no. 2, p. 20, 2019, doi: 10.5430/jbar.v8n2p20.

[15] X. Lin, R. Z. Wu, Y. T. Lim, J. Han, and S. C. Chen, "Understanding the sustainable usage intention of mobile payment technology in Korea: Cross-countries comparison of Chinese and Korean users," Sustain., vol. 11, no. 19, pp. 1–23, 2019, doi: 10.3390/su11195532.

[16] F. A. Hudaefi, M. K. Hassan, and M. Abduh, "Exploring the development of Islamic fintech ecosystem in Indonesia: a text analytics," Qual. Res. Financ. Mark., no. ahead-of-print, 2023.

[17] H. Fang, C.-P. Chung, Y.-C. Lu, Y.-H. Lee, and W.-H. Wang, "The impacts of investors' sentiments on stock returns using fintech approaches," Int. Rev. Financ. Anal., vol. 77, p. 101858, 2021.

[18] A. Haidar, N. Hendrasto, F. Chairiyati, and E. Herindar, "Sentiment Analysis of Islamic Fintech: Uncovering the Pulse of Twitter Post-Covid-19," Int. J. Econ., vol. 3, no. 1, pp. 337–347, 2024.

[19] S. Sangsavate, S. Tanthanongsakkun, and S. Sinthupinyo, "Stock market sentiment classification from FinTech News," in 2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE), IEEE, 2019, pp. 1–4.

[20] J. Kabulova and J. Stankevičienė, "Valuation of fintech innovation based on patent applications," Sustainability, vol. 12, no. 23, p. 10158, 2020.

[21] S. H. Utami, A. A. Purnama, and A. N. Hidayanto, "Fintech Lending in Indonesia: A Sentiment Analysis, Topic Modelling, and Social Network Analysis using Twitter Data," Int. J. Appl. Eng. Technol., vol. 4, no. 1, 2022.

[22] M. Verma, "Data-oriented and machine learning technologies in FinTech," FinTechs an Evol. Ecosyst., vol. 1, 2019.

[23] T. Muganyi, L. Yan, and H. Sun, "Green finance, fintech and environmental protection: Evidence from China," Environ. Sci. Ecotechnology, vol. 7, p. 100107, 2021.

[24] S. Oh, M. J. Park, T. Y. Kim, and J. Shin, "Marketing strategies for fintech companies: text data analysis of social media posts," Manag. Decis., vol. 61, no. 1, pp. 243–268, 2023.

[25] A. D. Widiantoro, A. Wibowo, and B. Harnadi, "User Sentiment Analysis in the Fintech OVO Review Based on the Lexicon Method," in 2021 Sixth International Conference on Informatics and Computing (ICIC), IEEE, 2021, pp. 1–4.

[26] J. N. Franco-Riquelme and L. Rubalcaba, "Innovation and SDGs through social media analysis: messages from FinTech firms," J. Open Innov. Technol. Mark. Complex., vol. 7, no. 3, p. 165, 2021.