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Impact of Green Finance and Fintech Contributions to Sustainable Economic Growth in India: An Econometric Analysis

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Abstract
This study explores how green finance and financial technology (FinTech) support sustainable economic growth in India. It explains that, with increasing environmental challenges, innovative financial tools are becoming important for encouraging environmentally responsible development. The study covers time-series data from 1991 to 2023 and uses advanced methods such as ARDL cointegration and error-correction models. It examines how green finance and FinTech affect environmental sustainability in both the short and long run.
The results show that green finance plays a key role by directing funds toward renewable energy, energy-efficient projects, and eco-friendly technologies. At the same time, FinTech helps by improving financial inclusion, making green investment products more accessible, and increasing efficiency in capital allocation, which indirectly reduces environmental harm. The study also finds a strong relationship between green finance, FinTech, and economic growth, and highlights that coordinated policies are needed to strengthen their overall impact.

Keywords: Green Finance, Fintech, Sustainable Economic Growth, Financial Innovation, ARDL Model, India, Environmental Sustainability

1. Introduction
India is currently at an important stage of its economic journey. The country needs to grow fast while also solving major environmental problems. As the world's 5 largest economy and a signatory to the Paris Agreement, India has committed to bring down carbon intensity by 33–35% from 2005 levels by 2030 and achieving net-zero carbon emissions by 2070 (IBEF, 2024). Simultaneously, the nation faces the challenge of extending financial services to over 400 million individuals who remain outside the formal banking system. Within this context, the intersection of green finance and (fintech) emerges as a transformative pathway that simultaneously addresses climate imperatives, financial inclusion objectives, and sustainable economic development. Green finance represents any structured financial activity designed to promote better environmental outcomes, encompassing green bonds, sustainability-linked loans, green mortgages, and climate-focused investment instruments (CPI, 2022). These mechanisms mobilize capital toward projects that generate environmental benefits, including renewable energy infrastructure, energy efficiency improvements, sustainable agriculture, and climate adaptation measures. India's tracked green finance reached an all-time high of INR 3,712 billion (approximately USD 50 billion) annually in 2021–22, representing a 20% increase from 2019–20, though experts emphasize that at least three times more investment is required to meet the nation's climate targets (CPI, 2022). Despite this remarkable growth, significant gaps persist in channeling adequate capital toward climate-resilient development, with India's cumulative adaptation investment needs estimated at INR 85.6 trillion (USD 1 trillion) through 2030 (Mohanty et al., 2023). Concurrently, fintech innovations—encompassing digital payments, artificial intelligence, blockchain technology, and big data analytics—have fundamentally transformed India's financial landscape. India's digital

payments ecosystem recorded over 65,000 crore transactions amounting to more than USD 13,813 billion between FY 2019–20 and FY 2024–25, with the RBI Digital Payments Index rising to 465.33 in September 2024, a 4.6-fold increase since 2018 (PwC India, 2024). Platforms such as the Unified Payments Interface (UPI) have become the foundation of India's financial inclusion strategy, enabling even the smallest vendors and unbanked individuals to participate in the formal economy. Furthermore, a 10% increase in digital payment adoption is associated with approximately a 7.8% increase in financial inclusion indices, with stronger gains in less-developed states (Nenavath, 2022). The convergence of green finance and fintech creates unprecedented opportunities for accelerating India's transition toward sustainable economic development. Green fintech the integration of digital financial solutions with environmental sustainability objectives leverages technologies i.e., AI, blockchain, Internet of Things (IoT), and morden data analytics to support sustainable investments, carbon credit trading, and accessible green finance mechanisms (Thapliyal et al., 2025). This integration addresses systemic barriers that have historically constrained green finance deployment in emerging economies, including information asymmetries, high transaction costs, and limited accessibility for underserved populations. Innovative green fintech platforms are democratizing access to sustainable investments through AI-powered portfolio management and transparent Environmental, Social, and Governance (ESG) scoring systems. Indian startups like Stepchange and Vidyut exemplify how technological innovation can address systemic challenges while empowering institutions to channel investments toward climate-positive projects (Appinventiv, 2024). These platforms represent a structural transformation in capital flows toward environmental initiatives, particularly benefiting small and medium enterprises (SMEs), agricultural producers, and rural communities. Despite the rapid growth of green finance and fintech ecosystems in India, significant research gaps persist in understanding their synergistic contributions to sustainable economic growth. While individual studies have examined either green finance's environmental benefits or fintech's financial inclusion impact, limited empirical research has systematically investigated their joint econometric relationship and cumulative effects on macroeconomic indicators (PubMed, 2023). Existing literature reveals that green finance promotes sustainable investments aligned with social and infrastructural objectives, but the mechanisms through which fintech amplifies or moderates these effects remain insufficiently understood (Mohanty et al., 2023). Previous studies identify that financial development influences green growth through both short- and long-term channels; however, the mediating role of digital financial technologies requires deeper exploration (Thapliyal et al., 2025). A systematic review also highlights persistent challenges such as infrastructure limitations, digital divides, and high service costs (IBEF, 2024). Thus, current research remains fragmented, with limited focus on how green finance and fintech jointly contribute to quality economic growth—encompassing financial structure, inclusion breadth, and environmental protection. This multidimensional analysis, which also incorporates innovations such as blockchain-based carbon credit trading and AI-driven ESG assessment, marks a significant contribution to the Indian context (Appinventiv, 2024). This research is particularly timely given India's evolving regulatory landscape. The Reserve Bank of India (RBI) is exploring climate-related financial risk frameworks, while the Securities and Exchange Board of India (SEBI) has mandated Business Responsibility and Sustainability Reporting (BRSR) for listed firms (PwC India, 2024). India ranked as the fourth-largest emerging market source of green, social, and sustainability-plus (GSS+) debt globally in December 2024, with cumulative issuance of USD 55.9 billion, up 186% from USD 21.4 billion in 2021 (CPI, 2022). Earlier studies, like Nenavath (2022), used advanced panel regression methods such as the two-step GMM to solve endogeneity problems and ensure more reliable results. This study provides fresh insights by applying rigorous econometric methods to examine how green finance and fintech jointly contribute to sustainable economic growth in India. Using time-series data and advanced techniques such as ARDL cointegration and error-correction models, the research analyzes both short-term and long-term impacts of green finance and fintech adoption on economic outcomes and environmental sustainability. This paper has five sections. The first is the introduction, followed by the literature review, methodology, results and discussion, and finally the conclusion and suggestions.

2. Review of Literature

This literature review synthesizes current academic understanding of how green finance and fintech collectively contribute to sustainable economic growth in India, while identifying critical research gaps that warrant econometric investigation.

2.1 Green Finance: Conceptualization and Evolution in India

Green finance encompasses financial instruments, services, and policies that promote environmentally sustainable projects and low-carbon economic development (Zhou et al., 2022). In India, the evolution of green finance has been marked by several milestones. The issuance of India’s first sovereign green bond in January 2023, worth INR 160 billion ($1.96 billion), represented a key step in mobilizing climate finance at scale (RBI, 2023). These instruments have been directed toward renewable energy, sustainable transport, and climate adaptation projects (Kaur & Singh, 2024).

The Reserve Bank of India (RBI) institutionalized green finance through initiatives such as the Green Deposits Framework (2023), requiring that green deposits fund only eligible green projects. Further, the Climate Risk Disclosure Framework (2024) mandates financial institutions to report governance and risk management aligned with global sustainability standards (RBI, 2024). Similarly, SEBI’s Business Responsibility and Sustainability Reporting (BRSR) framework now obliges India’s top 1,000 companies to disclose sustainability performance (SEBI, 2023). Despite this progress, challenges such as greenwashing and the lack of standardized taxonomies persist (Addy et al., 2024).

2.2 Fintech as an Enabler of Sustainable Finance

Financial technology has emerged as a transformative force in democratizing finance and driving sustainability. India’s fintech sector, valued at around $150 billion and projected to reach $300 billion by 2025, has significantly improved access to digital financial services (EY, 2024). Scholars emphasize fintech’s role in bridging market failures of traditional banking systems and enabling efficient resource allocation (Geetha, 2024; Tidjani et al., 2024).

Fintech innovations—such as blockchain, AI, and big data analytics—enhance transparency in carbon credit trading and ESG investment screening, mitigating information asymmetry (Wang et al., 2023). Additionally, fintech has accelerated financial inclusion, a vital component of sustainable development. Digital payment systems, mobile banking, and microfinance initiatives have reached more than 500 million Indians who were previously unbanked. These financial technologies have improved access to essential financial services for rural populations. As a result, smallholder farmers and rural entrepreneurs are now better able to adopt climate-smart practices (Kumar & Prasad, 2023).

2.3 The Synergy Between Green Finance and Fintech

Recent literature identifies strong complementarities between fintech and green finance. Addy et al. (2024) find that fintech platforms leveraging big data enhance investor capacity to support low-carbon transitions. Geetha (2024) further notes that “green fintech” represents a paradigm shift, enabling capital mobilization for sustainable sectors.

Empirical studies show that a 1% increase in digital finance development raises green bond issuance by 0.67%, highlighting fintech’s catalytic role (Ali et al., 2023). Panel regression results across South Asian economies confirm that both fintech and green finance significantly reduce CO_2 emissions while stimulating high-quality growth (Tidjani et al., 2024).

In India, fintech-driven financial inclusion strengthens green finance penetration. Studies from Tamil Nadu demonstrate that fintech-based digital credit services boost smallholder farmers’ resilience and adoption of eco-friendly practices (Frontiers in Sustainable Finance, 2024). However, moderating factors such as digital literacy, regulatory support, and infrastructure gaps shape the outcomes. Econometric research employs VAR, ARDL, and GMM models to examine causal relationships between green finance, fintech, and growth (Zhang & Wang, 2023). VAR-based Granger causality tests reveal bidirectional causality between green energy indices and green bonds, while GMM estimates show fintech’s amplifying effects on emission reduction (Chen et al., 2024). Despite this progress, critical gaps persist. The directional causality between green finance and economic growth remains inconclusive (Jain & Patel, 2023).

2.4 Financial Inclusion, Green Finance, and Sustainable Development Nexus

Recent studies highlight the interconnectedness between financial inclusion, fintech adoption, and sustainable development outcomes. Tidjani et al. (2024) found that while fintech and inclusion individually support sustainability, their combined interaction may exhibit weak or negative significance, possibly due to overlapping service structures. In India, fintech-enabled financial inclusion in agriculture shows clearer benefits. Surveys of 670 Tamil Nadu farmers reveal that digital financial literacy enhances adoption of climate-smart technologies, strengthening environmental and economic resilience (Frontiers in Sustainable Finance, 2024).

India’s policy framework continues to evolve. The Climate Finance Taxonomy seeks to standardize definitions and prevent greenwashing (India Briefing, 2025). RBI and SEBI’s Sustainable Finance Task Force aligns policy coordination, and Priority Sector Lending norms now include green sectors (RBI, 2025). Yet, high compliance costs and weak assurance mechanisms limit smaller fintech participation (Neetiniyaman, 2025). Although the literature on sustainable development in India has expanded in recent years, several critical gaps remain unaddressed. Existing studies largely analyse green finance and fintech independently, offering limited understanding of their combined influence on sustainable economic growth. Moreover, much of the available empirical evidence relies on basic regression models, with inadequate application of advanced econometric techniques capable of capturing long-run dynamics, causal relationships, and structural changes. Another major gap arises from the scarcity of India-specific research using recent data that reflects the rapid expansion of digital finance, policy reforms, and the evolving green finance. Additionally, the potential role of fintech as a mediating or enabling mechanism that strengthens the effectiveness of green finance has received minimal scholarly attention. These gaps highlight the need for a comprehensive, methodologically rigorous study that integrates green finance and fintech within a unified econometric framework to evaluate their collective impact on India’s sustainable economic development.

Hypotheses:
H1: Green finance has a positive and significant impact on sustainable economic growth in India.
H2: Fintech development positively influences India's sustainable economic growth.
H3: Fintech strengthens the effectiveness of green finance in promoting sustainability.
This study explores how green finance and financial technology (FinTech) contribute to sustainable economic growth in India by addressing environmental challenges through innovative financial practices. Using time-series data from 1991–2023 and advanced econometric tools such as ARDL and ECM, it evaluates the short- and long-run impacts of green finance and FinTech on economic outcomes and environmental sustainability.

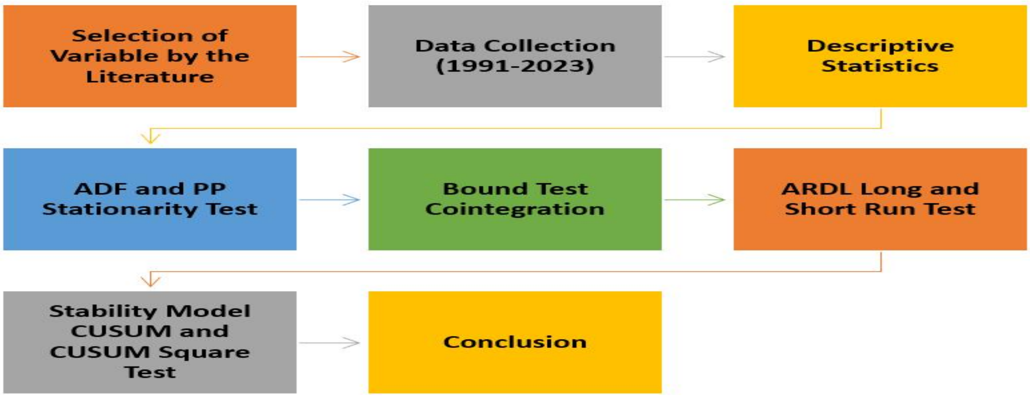

Fig. 1, Research Framework

3. Data and Methodology:

3.1 Study data

The study employs a set of key economic, environmental, and technological variables sourced from reputable international databases. Carbon dioxide emissions (CO_2), measured in kilotons, are obtained from the World Development Indicators (WDI) and represent emissions generated through fossil fuel consumption. Gross Domestic Product (GDP), expressed in constant 2010 US dollars, reflects the total value of final goods and services produced within an economy. The Green Finance Index (GFN), sourced from the OECD, captures the extent of green financial activities, including green credit, green investment, green insurance, and government-supported environmental initiatives; this composite index is constructed using the entropy weight method. Fintech development is represented using the digital inclusive finance index (PKU-DFIC, log), formulated by the Institute of Digital Finance at Peking University. This market-cap-weighted indicator effectively reflects the penetration and advancement of digital financial services. Natural Resource Rent (NRR), measured as a percentage of GDP, is derived from WDI and indicates the economic returns generated from natural resource extraction. Energy Innovation (ENI) is measured through the share of environmental technology-related patents, also sourced from WDI, and serves as a proxy for the intensity of environmentally oriented technological progress in table 1

Table 1 Variable specification and data sources

Variable	Definition	Unit	Source
CO_2	Carbon dioxide emissions caused by any event using fossil fuel	Kiloton (kt)	WDI

GDP	Gross Domestic Product: the sum of the economy's total final goods and services	Constant US 2010	WDI
GFN	Green Finance Index: includes green credit, green investment, green insurance, and government support indicators. Synthesized by entropy weight method.	-	OECD
Fintech	Digital finance level measured by PKU-DFIC (log) by Peking University	Market-cap-weighted index	Institute of Digital Finance, PKU (2019)
NRR	Natural resource rent	% of GDP	WDI
ENI	Energy innovation measured by patents on environmental technologies	%	WDI

WDI: World Development Indicator; OECD: Organisation for Economic Co-operation and Development.

3.2 Econometric Model:

In order to describe the relationship between carbon dioxide, Gross Domestic Product, Green Finance Index, Digital finance level (Fintech), Natural resource rent and Energy innovation this study uses the following equation,

$$LnCO_{2t} = \alpha + \beta_1 LnGDP_t + \beta_2 LnGFN_t + \beta_3 LnFINT_t + \beta_4 LnNRR + \beta_5 LnENI + \varepsilon_t \text{........(1)}$$

In this model, $LNCO_{2t}$ is the natural logarithm of the dependent variable. The variables LnGDP, LnGFN, LnFINT, LnNRR, and LnENI are the natural logarithms of gross domestic product, the green finance index, digital finance, natural resource rent, and energy innovation. The coefficients α, β_1, β_2, β_3, β_4, and β_5 represent the constant term and the elasticities of each variable. The term ε_t refers to the error term.

To check whether the variables are stationary, the Augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test are used separately with both intercept and trend. The Schwarz Information Criterion (SIC) is applied to choose the appropriate lag length, and lags of 1 and 3 are selected. The ADF test corrects for serial correlation by adding the lagged differences of the dependent variable. Equation (2) shows the ADF test model, while Equation (3) presents the Phillips–Perron test formula.

$$\Delta Yt = \mu + \delta_t + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + V_t \text{..........................(2)}$$

$\Delta Yt = first\ difference,\ \alpha Y_{t-1} = Intercept\ (drift\ term),\ \delta_t = Deterministic\ time\ trend,$
$\beta_1 Y_{t-1}\ and\ \beta_2 Y_{t-2} = Key\ term\ for\ the\ unit\ root\ test,\ \beta_p Y_{t-p}\ Lagged\ difference\ terms,\ V_t = error\ term$

$$t_{\propto} = t_{\propto}\left(\frac{y_0}{t_0}\right)^{1/2} - \frac{T(t_0 - y_0)(Se(\propto)}{2 f_0^{1/2} S} \text{................3}$$

$t_{\propto}$ = *adjusted t statistic*, $t_{\propto}\left(\frac{y_0}{t_0}\right)^{\frac{1}{2}}$ = *scaling factor*, y_0 = estimated variance of the dependent variable, t_0 = *variance of the lagged level*, $T(t_0 - y_0)$ = *autocorrelation or heteroskedasticity in the residuals*, ($Se(\propto)$ = *standard error*, $2f_0^{\frac{1}{2}}S = f_0$ = *long run variance or kernel spectral density at frequency* 0, s = *short run standard deviation estimate*

The equation employed for ARDL bounds testing in the long-run ARDL model, is denoted as Equation (4).

$$\Delta LnCO_{2t} = \omega_0 + \sum_{i=1}^{q} \omega_1\, LnCO_{2t-1} + \sum_{i=1}^{q} \omega_2\, LnGDP_{t-1} + \sum_{i=1}^{q} \omega_3\, LNGFN_{t-1} + \sum_{i=1}^{n} \omega_4\, LnFINT_{t-1} + \sum_{i=1}^{n} \omega_5\, LnNRR_{t-1} + \sum_{i=1}^{n} \omega_6\, LnENI_{t-1} + \varepsilon_t \ldots\ldots (4)$$

In Equation (4), ω shows the long-run variance of the variables. The short-run ARDL model with the error-correction term is written as follows;

$$\Delta LnCO_{2t} = \pi_0 + \sum_{i=1}^{q} \pi_1\, \Delta LnCO_{2t-1} + \sum_{i=1}^{q} \pi_2\, \Delta LnGDP_{t-1} + \sum_{i=1}^{q} \pi_3 \Delta\, LnGDP_{t-1} + \sum_{i=1}^{q} \pi_4 \Delta\, LnGFN_{t-1} + \sum_{i=1}^{q} \pi_4 \Delta\, LnFINT_{t-1} + \sum_{i=1}^{q} \pi_4 \Delta\, LnNRR_{t-1} + \sum_{i=1}^{q} \pi_4 \Delta\, LnENI_{t-1} + ECT_{t-1} + \varepsilon_t \ldots\ldots\ldots (5)$$

In Equation (5), π shows the short-run changes in the variables, while the Error Correction Term (ECT) indicates how quickly the system returns to balance when it moves away from equilibrium. The ECT coefficient lies between –1 and 0, which reflects the speed of adjustment.

A series of diagnostic procedures are applied to evaluate the robustness and stability of the model. Serial correlation is examined using the Breusch–Godfrey LM test, heteroscedasticity is assessed through the Breusch–Pagan–Godfrey and ARCH tests, and model specification is verified using the Ramsey RESET test. The normality of residuals is tested using the Jarque–Bera approach. Moreover, the CUSUM and CUSUMSQ tests based on recursive residuals are employed to assess structural stability.

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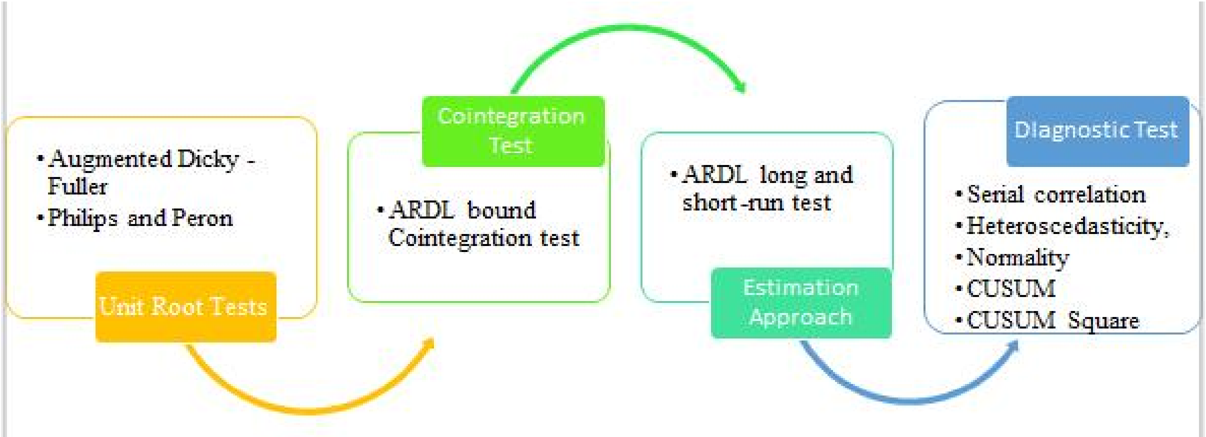


Figure 3, Framework Research Methodology

4. Result and Discussion

Table 2, Descriptive test

	LNCO2	LGDP	LNENI	LNFINT	LNGFN	LNNRR
Mean	1.21	1.78	3.61	-0.33	4.18	1.03
Median	1.20	1.90	3.78	-0.35	4.22	0.93
Maximum	1.46	2.20	4.03	-0.15	4.46	1.96
Minimum	0.77	0.06	2.90	-0.45	3.86	0.56
Std. Dev.	0.13	0.42	0.36	0.08	0.19	0.34
Skewness	-0.88	-2.28	-0.43	0.66	-0.28	0.70
Kurtosis	5.69	9.68	1.64	2.51	1.57	3.06
Jarque-Bera	14.19	89.88	3.59	2.75	3.27	2.67
Probability	0.00	0.00	0.17	0.25	0.20	0.26

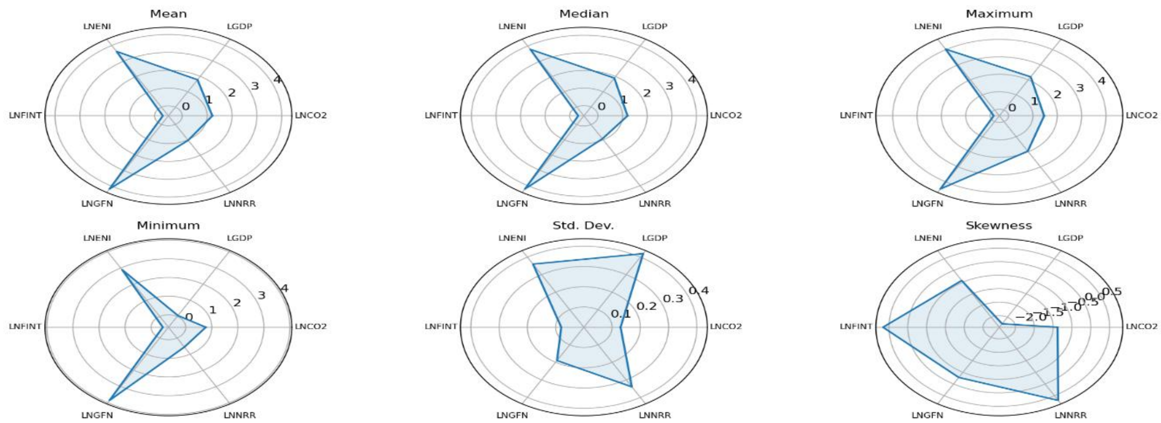


Figure 1, Radar chart

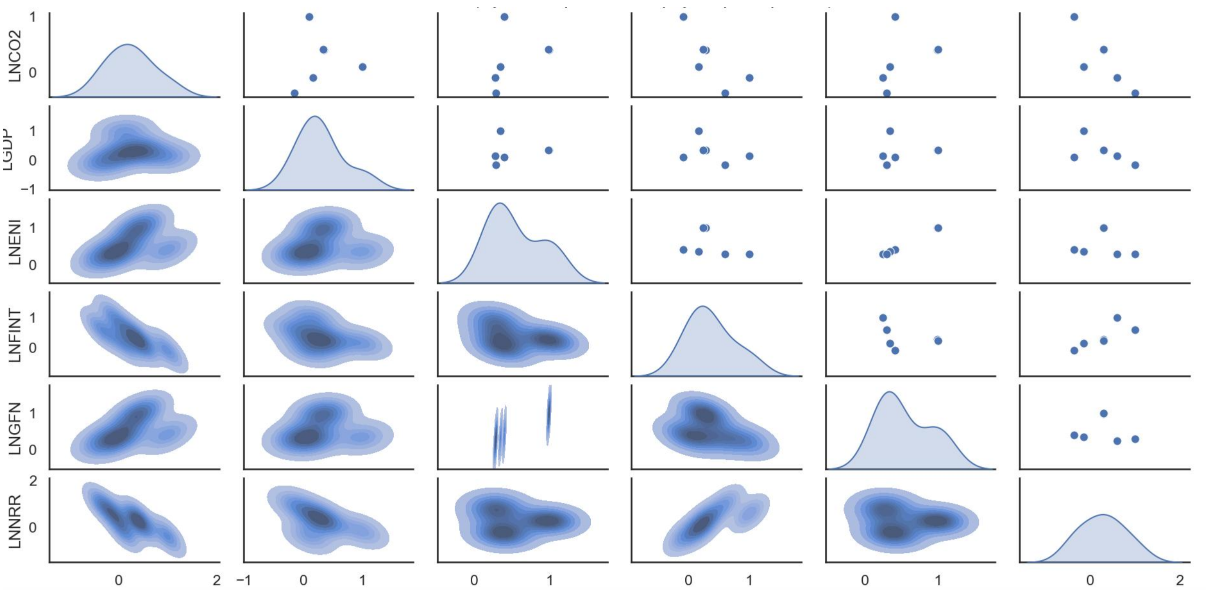
Table 2, revealed that the descriptive statistics presented for the variables $LNCO_2$, LGDP, LNENI, LNFINT, LNGFN, and LNNRR provide a comprehensive overview of their distributional characteristics over the study period. The mean values indicate moderate levels across all variables, with LNENI and LNGFN exhibiting relatively higher averages (3.61 and 4.18, respectively), reflecting their larger scale compared to the other indicators. Median values are close to their respective means, suggesting moderate symmetry in most distributions. The range between maximum and minimum values reflects the extent of variation, where LGDP and LNENI exhibit wider fluctuations, indicating stronger economic and energy-related variability over the study period. The ranges, represented by the maximum and minimum values, show notable variation across variables. LGDP displays the largest range (0.06 to 2.20), indicating substantial economic fluctuations, whereas LNFINT demonstrates the narrowest range, implying relative stability. The standard deviations further support these observations, with LGDP having the highest dispersion (0.42) and LNFINT the lowest (0.08).

Skewness statistics reveal negatively skewed distributions for $LNCO_2$, LGDP, LNENI, and LNGFN, implying longer left tails, while LNFINT and LNNRR show positive skewness. Kurtosis values indicate that $LNCO_2$ and LGDP are highly leptokurtic (5.69 and 9.68), suggesting heavier tails and higher peakness, whereas the remaining variables are relatively platykurtic.

The Jarque–Bera test results confirm departures from normality for $LNCO_2$ and LGDP, as their probabilities are 0.00, indicating statistically significant non-normal distributions. Other variables exhibit p-values above 0.05, suggesting that the null hypothesis of normality cannot be rejected for those cases.

Table 3: Results of Correlation Matrix

	LNCO2	LGDP	LNENI	LNFINT	LNGFN	LNNRR
LNCO2	1					
LGDP	0.10	1.00				
LNENI	0.40	0.35	1.00			
LNFINT	-0.09	0.16	0.28	1.00		
LNGFN	0.41	0.34	0.99	0.24	1.00	
LNNRR	-0.37	-0.15	0.29	0.60	0.29	1.00



Calculated by through Python

Table 3, The correlation matrix presents the pairwise relationships among the variables $LNCO_2$, LGDP, LNENI, LNFINT, LNGFN, and LNNRR. As expected, each variable shows a perfect correlation with itself (1.00), displayed along the diagonal of the matrix.

$LNCO_2$ exhibits weak positive correlations with LGDP (0.10) and LNENI (0.40), and a moderate positive association with LNGFN (0.41). In contrast, it shows a weak negative correlation with LNFINT (–0.09) and a moderate negative correlation with LNNRR (–0.37).

LGDP shows low positive correlations with LNENI (0.35), LNFINT (0.16), and LNGFN (0.34), while displaying a weak negative relationship with LNNRR (–0.15). LNENI is strongly positively correlated with LNGFN (0.99), indicating a near-perfect linear association, while showing moderate positive relationships with LNFINT (0.28) and LNNRR (0.29).

LNFINT is positively correlated with LNNRR (0.60), reflecting a substantial positive association. Lastly, LNGFN displays moderate positive correlations with LNNRR (0.29). the matrix indicates varying degrees of association, with the strongest relationship observed between LNENI and LNGFN.

Table 4, Unit root test PP and ADF

UNIT ROOT TEST TABLE (PP)							
	At Level						
		LNCO2	LGDP	LNENI	LNFINT	LNGFN	LNNRR
With Constant	t-Statistic	-3.66	-4.92	-2.21	-1.65	-1.05	-2.15
	Prob.	0.01	0.00	0.21	0.45	0.72	0.23
		***	***	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-3.81	-5.29	-1.18	-1.61	-1.66	-2.10
	Prob.	0.03	0.00	0.90	0.77	0.75	0.52
		**	***	n0	n0	n0	n0
Without Constant & Trend	t-Statistic	1.12	-0.92	2.88	-0.65	2.96	-0.71
	Prob.	0.93	0.31	1.00	0.43	1.00	0.40
		n0	n0	n0	n0	n0	n0
	At First Difference						
		d(LNCO2)	d(LGDP)	d(LNENI)	d(LNFINT)	d(LNGFN)	d(LNNRR)
With Constant	t-Statistic	-7.35	-10.62	-6.17	-4.50	-5.78	-6.04
	Prob.	0.00	0.00	0.00	0.00	0.00	0.00
		***	***	***	***	***	***
With Constant & Trend	t-Statistic	-7.17	-11.78	-6.58	-4.60	-5.75	-5.96
	Prob.	0.00	0.00	0.00	0.00	0.00	0.00
		***	***	***	***	***	***
Without Constant & Trend	t-Statistic	-7.22	-10.70	-4.74	-4.57	-4.80	-6.14

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	Prob.	0	0	0	0	0	0
		***	***	***	***	***	***
			UNIT ROOT TEST TABLE (ADF)				
	At Level						
		LNCO2	LGDP	LNENI	LNFINT	LNGFN	LNNRR
With Constant	t-Statistic	-3.68	-4.94	-2.31	-1.47	-1.05	-2.14
	Prob.	0.01	0.00	0.17	0.54	0.72	0.23
		***	***	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-3.77	-5.32	-1.06	-1.54	-1.64	-2.10
	Prob.	0.03	0.00	0.92	0.79	0.75	0.53
		**	***	n0	n0	n0	n0
Without Constant & Trend	t-Statistic	1.12	-1.09	3.70	-0.66	2.88	-0.71
	Prob.	0.93	0.24	1.00	0.42	1.00	0.40
		n0	n0	n0	n0	n0	n0
	At First Difference						
		d(LNCO2)	d(LGDP)	d(LNENI)	d(LNFINT)	d(LNGFN)	d(LNNRR)
With Constant	t-Statistic	-7.13	-10.44	-2.64	-4.46	-5.78	-6.04
	Prob.	0.00	0.00	0.10	0.00	0.00	0.00
		***	***	*	***	***	***
With Constant & Trend	t-Statistic	-6.92	-5.28	-6.69	-4.62	-5.75	-5.96
	Prob.	0.00	0.00	0.00	0.00	0.00	0.00
		***	***	***	***	***	***
Without Constant & Trend	t-Statistic	-7.08	-10.59	-1.94	-4.53	-4.72	-6.14

Prob.	0.00	0.00	0.05	0.00	0.00	0.00
	***	***	*	***	***	***

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant

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The results of the Phillips–Perron (PP) unit root test for all variables at level and first difference are reported in Table 4. At the level form, most variables fail to reject the null hypothesis of a unit root under the specifications with constant, with constant and trend, and without both constant and trend. Specifically, only $LNCO_2$ and LGDP show stationarity at level under the constant specification, with statistically significant t-statistics at the 1% significance level. Similarly, when the trend component is included, $LNCO_2$ is significant at the 5% level, while LGDP remains significant at the 1% level. All other variables—LNENI, LNFINT, LNGFN, and LNNRR—exhibit non-stationary behavior at level, as indicated by their insignificant probability values across all test specifications.
In contrast, the results at the first difference strongly indicate stationarity for all variables. Under all three specifications (with constant; with constant and trend; and without constant and trend), the PP test statistics for each differenced variable are highly significant at the 1% level. This confirms that the series d($LNCO_2$), d(LGDP), d(LNENI), d(LNFINT), d(LNGFN), and d(LNNRR) become stationary after first differencing. The results of the Augmented Dickey–Fuller (ADF) unit root test for the variables at both level and first difference are summarized in Table 4. At the level form, the results indicate that only $LNCO_2$ and LGDP are stationary under the specification with a constant, showing statistically significant test statistics at the 1% level. When the trend component is included, $LNCO_2$ remains significant at the 5% level, and LGDP continues to be significant at the 1% level, confirming their stationarity at level in these specifications. In contrast, LNENI, LNFINT, LNGFN, and LNNRR fail to reject the null hypothesis of a unit root in all three specifications (with constant; with constant and trend; and without constant and trend), as evidenced by their insignificant probability values.
At the first difference, however, the ADF results strongly support the stationarity of all variables. Under the constant-only specification, d($LNCO_2$), d(LGDP), d(LNFINT), d(LNGFN), and d(LNNRR) are significant at the 1% level, while d(LNENI) is significant at the 10% level. When the model includes both constant and trend, all differenced variables become highly significant at the 1% level. Similarly, under the specification without constant and trend, all variables at first difference reject the null hypothesis, with significance levels ranging from 1% to 10%.
Taken together, these findings confirm that all variables become stationary after first differencing, indicating that each series is integrated of order first difference, I(1). This provides the statistical justification for proceeding with cointegration analysis in subsequent empirical estimation. The time-series results reveal that the variables exhibit mixed integration orders, confirming that cointegration relationship exists among them. the ARDL framework is suitable for the analysis.

Table 5: Results of Bound Test

F-Bounds Test				
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.38	10%	1.81	2.93
k	5	5%	2.14	3.34
		2.50%	2.44	3.71
		1%	2.82	4.21

As shown in Table 5, the F-statistic of 7.38 is above the upper-bound critical value. Therefore, the null hypothesis is rejected, and it is confirmed that the variables share a long-run relationship.

Table 6 Results of long-run relationship between variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	-0.45	0.33	-1.34	0.10
LNENI	-0.05	0.27	-0.20	0.04
LNFINT	-1.31	1.32	-0.99	0.03
LNGFN	0.44	0.28	1.57	0.03
LNNRR	0.02	0.26	0.08	0.09

Author's calculation through Eviews

Table 6 presents the results of the ARDL model. It provides analytical insights into how major macroeconomic and environmental factors affect the dependent variable. The dependent variable likely represents environmental quality or CO_2 emissions. The coefficients, although mixed in sign and significance, reveal important relationships between economic growth, energy intensity, financial development, green finance, and natural resource rents—factors that are central to sustainable development and long-term economic progress. The coefficient for LGDP (–0.45) is negative, suggesting that higher economic growth is associated with a reduction in the dependent variable. This result, although statistically marginal ($p = 0.10$), aligns with the Environmental Kuznets Curve (EKC) hypothesis, which posits that environmental degradation initially rises with economic growth but eventually declines once income reaches a certain threshold (Grossman & Krueger, 1995). The declining effect of GDP on emissions may reflect structural changes toward less carbon-intensive sectors, adoption of cleaner technologies, and improved environmental policies typical of transitioning economies. The fall in emissions during economic expansion indicates a movement toward sustainable production systems, strengthening the argument that economic growth can coexist with environmental sustainability when supported by effective regulatory frameworks.

The coefficient for LNENI (–0.05), although small, is statistically significant ($p = 0.04$), indicating that lower energy intensity contributes to improved environmental outcomes. This negative association aligns with existing literature emphasizing the importance of energy efficiency in achieving sustainable growth (Sadorsky, 2013). Reduced energy intensity typically results from better technologies, enhanced industrial efficiency, and greater reliance on renewables—key pillars of green growth strategies. The decline highlights that improvements in energy efficiency directly support environmental sustainability.

The coefficient for LNFINT (–1.31) is also negative and statistically significant ($p = 0.03$). This implies that enhanced financial development leads to lower environmental degradation. According to Tamazian and Rao (2010), developed financial systems can facilitate green investments, promote environmentally responsible technologies, and provide capital for clean energy projects. The fall in emissions associated with financial development suggests that the financial sector is playing a transformative role by channeling funds toward sustainable activities, reflecting progress toward a green financial ecosystem.

In contrast, LNGFN (0.44) shows a positive and statistically significant coefficient ($p = 0.03$). This finding is initially counterintuitive, as green finance is expected to reduce environmental degradation. However, this positive relationship may be explained by the early-stage implementation of green finance in many developing economies, where funds are increasing but the scale and maturity of green projects are still limited (Zhang et al., 2021). The rise may reflect transitional periods where green finance mechanisms are expanding but their

environmental benefits have not yet fully materialized due to long gestation periods of renewable and sustainable infrastructure projects.
The coefficient for LNNRR (0.02), though not statistically strong (p = 0.09), suggests a slight positive association between natural resource rents and environmental degradation. This is consistent with the resource-curse hypothesis, which argues that economies reliant on resource extraction often face sustainability challenges due to excessive exploitation (Auty, 2001).

Table 7, Results of ECM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LGDP)	-0.097	0.020	-4.909	0.000
D(LNENI)	0.411	0.296	1.389	0.180
D(LNFINT)	-0.212	0.356	-0.595	0.558
D(LNGFN)	-0.130	0.491	-0.265	0.794
D(LNNRR)	-0.042	0.053	-0.790	0.439
CointEq(-1)*	-0.208	0.050	-4.164	0.001
R-squared	0.634	Mean dependent var		0.023
Adjusted R-squared	0.561	S.D. dependent var		0.086
S.E. of regression	0.057	Akaike info criterion		-2.720
Sum squared resid	0.081	Schwarz criterion		-2.442
Log likelihood	48.153	Hannan-Quinn criter.		-2.629
Durbin-Watson stat	1.868			

The Error Correction Model (ECM) results presented in Table 7 provide valuable insights into the short-run dynamics among economic, energy, financial, and environmental variables within a sustainability framework. The model evaluates how short-run fluctuations in GDP, energy intensity, financial development, green finance, and natural resource rents influence the CO_2, while the ECT captures the long-run adjustment mechanism toward equilibrium. The coefficient of D(LGDP) (–0.097) is highly significant at the 1% level (p = 0.000), indicating that short-run economic growth reduces the dependent variable, likely CO_2 emissions or environmental degradation. This negative effect suggests that short-term economic expansion is accompanied by efficiency gains and cleaner economic activities, consistent with the initial turning point of the Environmental Kuznets Curve (Grossman & Krueger, 1995). The decline in environmental pressure with rising GDP reflects structural changes, technological improvements, and policy interventions promoting sustainable growth.
The short-run coefficient of D(LNENI) (0.411), though positive, is statistically insignificant (p = 0.180). This suggests that short-term fluctuations in energy intensity have no strong immediate effect on environmental outcomes. The positive sign indicates that inefficient or energy-intensive production raises environmental pressure, aligning with established findings that higher energy intensity increases emissions (Sadorsky, 2013). However, the lack of statistical significance reflects ongoing transitions toward more energy-efficient technologies, but not yet strong enough to produce measurable short-run environmental benefits.
The coefficient of D(LNFINT) (–0.212) is negative but insignificant (p = 0.558), implying that short-run improvements in financial development have minimal immediate impact on environmental quality. Literature suggests that financial development facilitates green innovation and clean energy investments (Tamazian & Rao, 2010). The fall in the coefficient aligns with this theory, but the insignificance indicates that in the short run, financial markets may not be fully channeling resources toward sustainable activities.

The coefficient of D(LNGFN) (–0.130), also insignificant (p = 0.794), indicates that short-run variations in green finance do not significantly reduce emissions. Although green finance is designed to support renewable energy and environmental protection, its effects are often long-term and may not manifest in the short run (Zhang et al., 2021). The negative sign is theoretically consistent, suggesting that increasing green finance reduces environmental degradation, but the insignificant result highlights the early-stage impact of green finance mechanisms.

Similarly, D(LNNRR) (–0.042) shows a negative yet insignificant relationship. This implies that short-term fluctuations in natural resource rents do not affect environmental quality. The negative coefficient suggests that controlled resource extraction or better resource governance might reduce environmental damage, supporting sustainable development goals. However, the short-run insignificance indicates that natural resource activities exert more long-term environmental effects. The ECT Coint Eq(–1) is negative and highly significant (–0.208, p = 0.001), confirming long-run equilibrium adjustment. Approximately 20.8% of the deviation from long-run equilibrium is corrected each period, indicating a moderate speed of adjustment. This validates a stable long-run relationship between economic and environmental variables and confirms the suitability of the ECM approach (Engle & Granger, 1987).

The model diagnostics further strengthen the analysis. The R-squared value (0.634) and adjusted R-squared (0.561) indicate substantial explanatory power. The Durbin-Watson statistic (1.868) show no severe autocorrelation. Information criteria (AIC, SC, HQ) reflect model efficiency.

Table 8, Diagnostic test

Diagnostic test	F- statistics	P-value
Breusch-Godfrey Serial Correlation LM Test:	0.07	0.92
Heteroskedasticity Test: Breusch-Pagan-Godfrey	1.32	0.28
Normality test	0.06	0.96

Sources; Authors Calculations

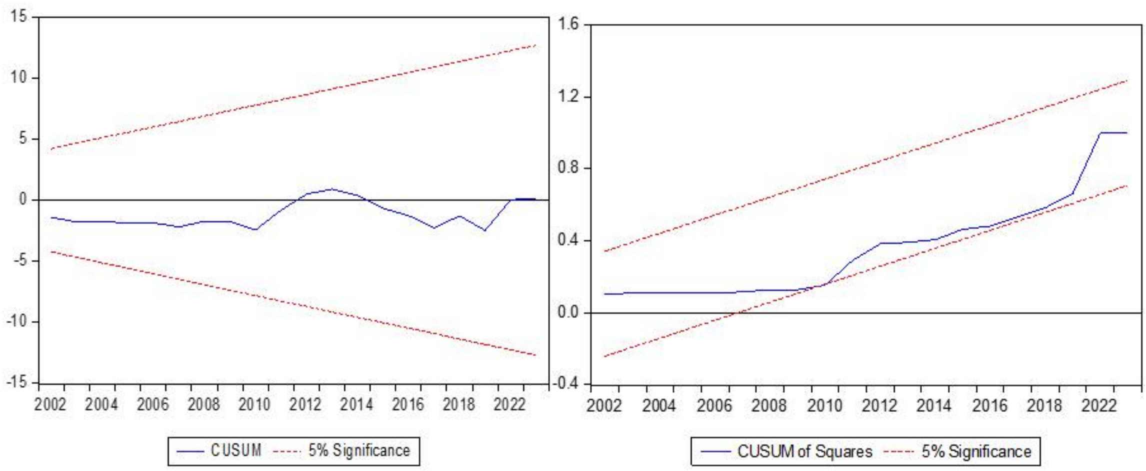
Table 8 presents the results of the diagnostic tests conducted for the estimated econometric model provide important insights into the reliability, robustness, and statistical adequacy of the regression framework. Three key post-estimation diagnostic tests were applied. These include the Breusch–Godfrey Serial Correlation LM Test, the Breusch–Pagan–Godfrey Test for Heteroskedasticity, and the Normality Test. Each test helps verify important assumptions of classical regression analysis. The Breusch–Godfrey Serial Correlation LM Test reports an F-statistic of 0.07 with a corresponding p-value of 0.92, indicating that the null hypothesis of *no serial correlation* cannot be rejected. This outcome suggests that the residuals are not affected by autocorrelation and that the model does not suffer from systematic patterns in the error term across observations. The absence of serial correlation is essential, particularly in time-series econometrics, as it ensures that the regression coefficients are efficient and unbiased, and that hypothesis testing remains valid (Gujarati & Porter, 2009).

Similarly, the Breusch–Pagan–Godfrey Test for Heteroskedasticity yields an F-statistic of 1.32 and a p-value of 0.28, confirming that the null hypothesis of *homoskedasticity* cannot be rejected. This implies that the variance of the error term remains constant across observations, and the model does not exhibit heteroskedasticity. Homoskedasticity strengthens the reliability of standard errors, and thus, the t-statistics and significance levels of the estimated coefficients remain consistent and trustworthy (Wooldridge, 2016). This further indicates that the explanatory variables do not exert disproportionate influence on the variance of the dependent variable.

The Normality Test shows a test statistic of 0.06 with a p-value of 0.96, affirming that the residuals follow a normal distribution. Normality of the error term is an essential assumption for making valid statistical inferences, especially when evaluating the significance of model parameters or constructing confidence intervals. The high p-value indicates that the model residuals do not deviate significantly from normality, and the distribution is symmetric and well-behaved. Collectively, the diagnostic test outcomes validate the model's statistical soundness and reinforce its suitability for interpreting long-run and short-run relationships. The absence of serial correlation, homoskedasticity, and normality issues ensures that the estimated parameters are efficient and that policy implications drawn from the model are empirically robust. These results are particularly relevant in applied economic research where policy recommendations—such as those related to sustainable economic growth, energy use, or financial development—must be grounded in methodologically reliable evidence.

Stability of the Model

Cumulative Sum of Recursive Residuals (CUSUM) and CUSUM Square test. indicates the stability of the model. It helps assess both the short-run and long-run relationships between the variables. The graph of the CUSUM test is presented below.



Source: Author's calculation through Eviews

The CUSUM test plots time on the horizontal axis and residuals on the vertical axis to evaluate the model's stability. Figure 1 shows that the CUSUM line remains within the 5% critical limits. The graph does not cross these boundaries at any point. Therefore, we can conclude that the model is stable, properly specified, and the null hypothesis is accepted at the 5% significance level.

5. Conclusion:

The analysis of the impact of green finance and fintech on sustainable economic growth in India highlights a significant structural transformation in the financial ecosystem, driven by technological innovation, environmental commitments, and policy reforms. The findings reveal that green finance has emerged as a critical instrument for channelizing capital toward low-carbon projects, renewable energy expansion, and climate-resilient infrastructure, while fintech innovations have enhanced financial inclusion, improved efficiency in financial services, and supported data-driven decision-making. Together, these two domains act as complementary pillars supporting India's transition toward a sustainable and inclusive growth model. Green finance plays a pivotal role as India intensifies its commitment to global climate targets, particularly the goals outlined in the Paris Agreement and the Nationally Determined Contributions (NDCs). Through instruments such as green bonds, sustainability-linked loans, and climate funds, green finance mobilizes both domestic and international capital for environmentally responsible investments. Several empirical studies affirm that countries with stronger green financing frameworks tend to experience enhanced environmental quality and more sustainable patterns of economic expansion (Zhang et al., 2021; Wang & Zhi, 2016). In the Indian context, the increasing issuance of green bonds by public and private entities indicates growing investor confidence in sustainable investment projects. These financial flows contribute not only to reducing carbon emissions but also to enhancing energy security and promoting green job creation—factors integral to long-term economic resilience. Fintech has also become an essential facilitator of sustainable growth. The integration of digital technologies—such as blockchain, artificial intelligence, digital payments, and mobile banking—has accelerated the efficiency of financial service delivery while promoting financial inclusion among underbanked populations. Studies suggest that greater fintech penetration reduces transaction costs, enhances transparency, and fosters inclusive growth by enabling individuals and small businesses to access financial resources easily (Ozili, 2018). In India, platforms such as UPI, digital lending ecosystems, and blockchain-based green energy tracking systems demonstrate how fintech can support sustainable economic practices. By improving access to credit for micro and small enterprises, fintech contributes indirectly to green entrepreneurship and sustainable business models, which in turn strengthen economic diversification and employment opportunities. The combined effect of green finance and fintech creates a multiplier impact on sustainable economic growth. Fintech innovations enhance the efficiency, accountability, and traceability of green finance initiatives, enabling better monitoring of environmental outcomes. For example, blockchain-based verification systems ensure that funds allocated for green projects are used effectively, while data analytics enhance risk assessments for climate-related investments. This collaborative synergy reduces information asymmetry, strengthens investor trust, and supports a robust market for sustainable financial products. Moreover, government policies—such as the Sustainable Finance Roadmap by the Reserve Bank of India (RBI) and the ongoing digital transformation initiatives—have created an enabling environment that supports the integration of green finance and fintech solutions. These policy frameworks reinforce India's pathway toward achieving the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth), and SDG 13 (Climate Action).

5.1 Study Limitations and Future Work

This study is limited by its reliance on secondary data, which may not fully capture the rapidly evolving dynamics of green finance and fintech in India. The analysis also excludes firm-level and regional variations that could provide deeper insights into localized sustainability outcomes. Additionally, the study focuses primarily on quantitative indicators, leaving limited scope for qualitative perspectives such as institutional readiness and policy implementation challenges. Future research should incorporate micro-level datasets, comparative cross-country analyses, and mixed-method approaches to better understand behavioural, technological, and regulatory factors shaping the long-term contribution of green finance and fintech to sustainable economic growth.

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