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Examining the role of artificial intelligence, financial innovation, and green energy transition in enhancing environmental quality

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ABSTRACT

The growth of emerging economies has led to heightened environmental challenges, underscoring the importance of implementing sustainable technologies and clean energy transitions to alleviate the ecological consequences. Hence, this study explores the roles of Artificial Intelligence (AI), Financial Innovation (FI), and Green Energy Transition (GET) in improving environmental quality in emerging economies. The results are robust using advanced econometric techniques that account for cross-sectional dependence, heterogeneity, unit roots, and cointegration. We test short- and long-run relationships using the cross-sectional augmented autoregressive distributed lag (CS-ARDL) model and validate the results using feasible generalized least squares (FGLS) estimators. The findings indicated the roles of AI (−0.029), FI (−0.071), and GET (−0.144) in decreasing the ecological footprint and enhancing environmental quality. However, economic growth (0.337) contributes to an increased ecological footprint. These findings highlight that sustainable technologies, FIs, and clean energy transitions are necessary to address environmental issues and sustainable economic growth. These findings provide policymakers with valuable insights into the sustainable development of emerging economies.

1. Introduction

The current challenge for emerging economies is balancing growth and environmental sustainability. The rapid industrialization of these nations presents substantial challenges related to their ecological footprints[1] (EFs), which are frequently compounded by heightened resource utilization and increased carbon emissions. The multifaceted connection between economic growth and environmental stewardship requires strategies that facilitate growth while safeguarding the ecological systems. This intricate balance demands innovative solutions that promote sustainable development without compromising the natural environment (Alaali & Naser, 2020). Within this framework, three pivotal strategies have emerged as crucial for enhancing environmental quality while

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[1] EF is a measure of the biologically productive area required to sustain a population's consumption and absorb its wastes, reflecting overall environmental impact.

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concurrently fostering sustainable economic development: Artificial Intelligence (AI), Financial Innovation[2] (FI), and Green Energy Transition[3] (GET). The utilization of AI holds promise, given its capacity to revolutionize resource management practices and optimize energy efficiency in emerging economies. AI helps reduce waste and improves energy consumption patterns by optimizing processes and automating tasks. Moreover, adopting AI-powered technologies helps build smarter energy grids that facilitate the incorporation of renewable energy while reducing reliance on fossil fuels. By enabling technological adaptation, carbon emissions are reduced, and economic resilience is reinforced by creating new job opportunities in the technology field. Moreover, the application of AI-powered solutions in environmental monitoring enhances adherence to current environmental legislation, guaranteeing that industries follow clean practices (Khajeh Naeeni, 2023; Khajeh Naeeni & Nouhi, 2023; Zhao & Gómez Fariñas, 2023).

FI is a critical driver of resource mobilization, which is vital for sustainable development. This role of FI is particularly important in emerging economies that encounter restrictions on conventional financing mechanisms and are often poorly equipped for the transition to a green economy. Furthermore, FI's contribution to promoting financial inclusion unlocks access to funding for sustainable initiatives for underserved populations, fostering broader involvement in the green economy (Vergara & Agudo, 2021; Wang et al., 2025; Úbeda et al., 2023). Moreover, integrating sustainability principles into financial decision-making frameworks mitigates environmental risks and bolsters the long-term viability of investment portfolios (Busch et al., 2016; Zhang et al., 2025). The role of GET is key to curbing EF in emerging economies. The transition to renewable energy sources allows countries to reduce their dependence on fossil fuels and greenhouse gas emissions. Additionally, the adoption of green technologies aids in improving energy security and resilience to climate change-related disturbances, thus supporting sustainable economic development (Yang et al., 2024; Zhang & Kong, 2022). The convergence of AI, FI, and GET offers unique prospects for emerging economies to enhance their environmental conditions and foster economic expansion. By strategically leveraging these technological advancements, these nations effectively confront the obstacles inherent in industrialization processes and lay the groundwork for a sustainable development trajectory.

The convergence of AI, FI, and GET fosters economic development and is consistent with the goal of sustainable environmental viability. This study aims to illuminate the interplay between technological innovations and ecological conditions in emerging economies using EFs as a proxy for assessing environmental sustainability. The aim is to capture a broader perspective of how emerging countries are appropriating technological capacity to combat environmental degradation. This study's contribution combines AI, FI, and GET under a single framework, thus assessing their combined effects on environmental quality. To explain the process at work, this study applies the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) approach to investigate the short- and long-run associations between variables (Chudik & Pesaran, 2015). The robustness of the findings was substantiated through diagnostic evaluations, including assessments of cross-sectional dependence, heterogeneity, unit roots, and cointegration tests. Additional corroboration of the results was obtained by applying feasible generalized least squares (FGLS) estimators (Hansen, 2007). These findings offer substantial insights into the interplay between technological progress and industrial expansion, providing policymakers with empirically grounded suggestions for reconciling economic initiatives with environmental imperatives. These results are relevant for decision-makers and stakeholders in emerging nations as they navigate the complexities of sustainable development.

The remainder of this paper is organized as follows. Section 2 introduces the data and methodology, Section 3 presents the results, and Section 4 provides conclusions and policy recommendations.

2. Empirical model, estimation techniques, and data

This study constructs a comprehensive framework to evaluate the causal relationship between AI, FI, GET, economic growth (GDP), and EF. To this end, we construct a multivariate estimation model.

$$EF = f\ (AI, FI, GET, GDP) \tag{1}$$

where EF represents the ecological footprint, and AI shows the development level of artificial intelligence. FI indicates financial innovation and GET represents green energy transition. The control variable was GDP, which indicates economic development. We took the logarithmic form of the above variables to reduce the heteroscedasticity problem. Thus, we generated the following equation:

$$ln\ EF_{i,t} = \beta_0 + \beta_1\ ln\ AI_{i,t} + \beta_2\ ln\ FI_{i,t} + \beta_3 GET_{i,t} + \beta_4\ ln\ GDP_{i,t} + \varepsilon_{i,t} \tag{2}$$

In the above equation, the parameters β_1 to β_4 measure the impact of the AI, FI, GET, and GDP on the EF. $\varepsilon_{i,t}$ is the error term. In addition, i and t in the subscript represent the sample country and time. Before estimating long-run coefficients, conducting panel diagnostic tests, such as cross-sectional dependence, heterogeneity, and unit root tests, is essential for understanding the data and selecting suitable estimation methods.

The estimation techniques begin with cross-sectional dependence (CD). The Breusch and Pagan (1980) and Pesaran (2004) tests are suitable for heterogeneous and non-stationary panels. These tests are also applied to the residuals to ensure their robustness. Panel heterogeneity refers to systematic differences across individual units in panel data, which compromise the reliability of empirical

[2] FI is the development and application of new financial products, services, or processes that enhance the efficiency and resilience of the financial system.

[3] GET is the shift from fossil-based energy sources to renewable and low-carbon alternatives, aimed at reducing environmental degradation and promoting sustainability.

estimates if not addressed (Bonhomme & Manresa, 2015). To address these issues, we applied Blomquist and Westerlund (2013) slope homogeneity test, which accounts for autocorrelation, heteroscedasticity, CD, and individual-specific effects. While traditional first-generation unit root tests, such as those by Im et al. (2003), Levin et al. (2002), and Breitung (2000), do not address the CD. We used more advanced second-generation cross-sectionally augmented IPS (CIPS) and cross-sectionally augmented Dickey (CADF) tests (Pesaran, 2007). This method is robust to CD and incorporates the averages of the lagged and first differences of the cross sections, as shown in Equation (3).

$$\Delta Y_{it} = \theta_i + \theta_i Y_{i,t-1} + \theta_i \overline{Y}_{t-1} + \sum_{j=0}^{p} \theta_{ij} \Delta \overline{Y_{t-j}} + \sum_{j=0}^{p} \theta_{ij} \Delta Y_{i,t-j} + \varepsilon_{it} \tag{3}$$

Finally, the CIPS statistics were expressed as follows:

$$\text{CIPS} = \frac{1}{N} \sum_{i=1}^{n} CADF_i \tag{4}$$

This study applied a panel cointegration test of the residual-based Westerlund and Edgerton (2007) error correction model (ECM) to assess the long-term association between EF and its key drivers. It differs from the methods advocated by Pedroni (2004) and Kao (1999) because of their greater robustness and ability to address the challenges of CD and slope heterogeneity. The methodological approach delineated by (Westerlund & Edgerton, 2007) employs a quartet of statistical assessments. These comprise two group statistics, G_t and G_a, which investigate the occurrence of cointegration in at least one cross-sectional entity, and two panel statistics, P_t and P_a, which substantiate the cointegration across the entire panel dataset. This systematic analytical framework thoroughly examined the intricate relationships between the study variables. The analytical framework of this study employed the CS-ARDL approach, as explained by Chudik and Pesaran (2015), allowing us to investigate the long-run coefficients related to the EF function. This methodology is favored because it can efficiently handle common problems in panel data, such as CD, slope heterogeneity, and endogeneity (Nghiem et al., 2023). Furthermore, the robustness of the CS-ARDL approach for variables with mixed-order integration makes it particularly appropriate for the datasets used in this study. Equation (5) describes the CS-ARDL model:

$$\Delta X_{i,t} = \delta_i + \sum_{j=1}^{p} \delta_{ij} \Delta X_{i,t-j} + \sum_{j=1}^{p} \delta'_{ij} IV_{s,i,t-j} + \sum_{j=0}^{1} \delta'_{ij} \Delta \overline{CS}_{i,t-j} + \varepsilon_{i,t} \tag{5}$$

In addition, this study incorporates the feasible generalized least squares (FGLS) methodology, as outlined by Hansen (2007), to complement the CS-ARDL estimation technique and the robustness of long-term findings. The efficacy of the FGLS approach in addressing CD is well documented, and it is adept at managing correlations that coincide or occur over time among various cross-sections. This methodological combination was intended to provide a robust framework for the analysis conducted in this study.

2.1. Data and preliminary analysis

This analysis used annual data from 2000 to 2023 to cover 16 emerging countries. The countries considered included Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, India, Mexico, Malaysia, Peru, the Philippines, Poland, Thailand, Turkey, and South Africa. The selection of the study duration and countries was based purely on the availability of relevant data. The dependent variable, EF, was measured as a proxy for environmental degradation. Ecological footprints signify the (global hectares per capita) measured by the aggregate of cropland, forestry land, fishing ground, built-up land, grazing land, and carbon footprint. Data on ecological footprints

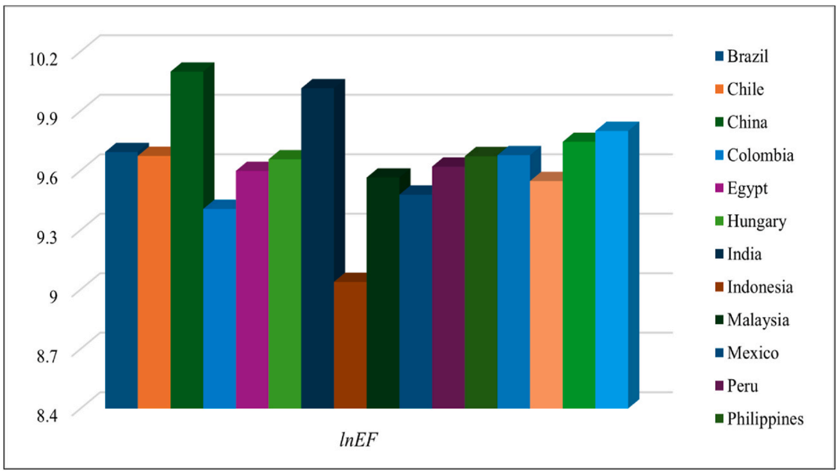

Fig. 1. EF in emerging economies, Source (GFN, 2024):

were retrieved from the Global Footprint Network database ([GFN, 2024]). Fig. 1 illustrates the ecological footprint of emerging economies from 2000 to 2023. It presents the EF across selected emerging economies. Variations in EF values indicate differences in environmental impact, with some countries exhibiting higher footprints. The data highlight notable disparities in resource consumption and environmental sustainability across sample countries ([GFN, 2024]). AI has rapidly advanced across markets and applications, making its measurement more challenging. Some studies, such as Wang et al. (2023), use AI-related patents as indicators of technological innovation, whereas others, such as Li et al. (2023), rely on robot application data to assess AI's impact of AI on resource efficiency.

Industrial robots are considered a more precise metric for AI development than patents because robots are widely integrated into production, reflecting the practical adoption and maturity of AI technologies. In this study, industrial robot installations sourced from the International Federation of Robotics (IFR, 2024) represented AI development as an independent variable. Fig. 2 illustrates the development of AI in emerging economies. This highlights the overall trend of increasing AI development, with notable fluctuations. Furthermore, financial innovation (FI) is measured by research and development expenditure and intensity (value-added) in the financial sector, following Beck et al. (2016) and (Bernier & Plouffe, 2019). Data were obtained from the Analytical Business Enterprise Research and Development (ANBERD) database (OECD, 2024). Fig. 3 illustrates the FI levels in emerging economies from 2000 to 2023, showing the varying levels of financial advancement among countries. GET is measured in terms of nuclear, hydro, and other renewable energy use (% of total energy). Data were collected from the BP Statistical Review of World Energy (BP, 2024). Fig. 4 illustrates the GET growth trend from 2000 to 2023 in emerging economies. The steady upward trajectory indicates the increasing adoption of green energy sources over time, with a notable acceleration in the early 2000s followed by a more gradual rise in recent years. This trend reflects a broader shift toward sustainable energy practices in these economies (BP, 2024). Economic growth (GDP) represents the gross domestic product (GDP) per capita. Data were extracted from the World Bank (WDI, 2024). Fig. 5 illustrates GDP, which represents economic growth in emerging economies. It steadily increased over time, reflecting consistent economic expansion during this period. Table 1 presents the variables used in this study.

Table 2 summarizes the descriptive statistics of the study variables. *lnEF* had a mean of 9.643, with moderate variability, whereas *lnAI* showed higher variability, with a mean of 2.859. *lnFI* and *lnGET* exhibit low variability with means of 4.527 and 4.170, respectively. *lnGDP* has a mean value of 8.551, with moderate variability. These statistics indicate a range of variations across the variables, supporting their suitability for the panel data analysis. Table 3 presents the pairwise correlation matrix for the variables. The pairwise correlation matrix helps to assess the strength and direction of the linear relationships between the variables. The *lnEF* had weak and statistically insignificant correlations with the other variables. *lnAI* is negatively correlated with *lnGET* and *lnGDP*, which is significant at the 1 % level. *lnGET* has a strong positive correlation with *lnGDP*, which is significant at the 1 % level. AI exhibits a significant negative correlation with GET (−0.532) and GDP (−0.422), suggesting that higher AI levels may be associated with lower economic growth and GET in emerging economies than in developed ones. This finding implies a potential trade-off between AI adoption and sustainable economic development.

3. Results and discussion

Table 4 reports the results of the CD test using Breusch and Pagan (1980) and Pesaran (2004). All variables showed significant results, with p-values of 0.000, indicating a strong CD at the 1 % significance level. It suggests that the variables were highly interconnected across the cross-section of the dataset. Table 5 presents the results of the slope homogeneity test, with the Tilde (Delta) and

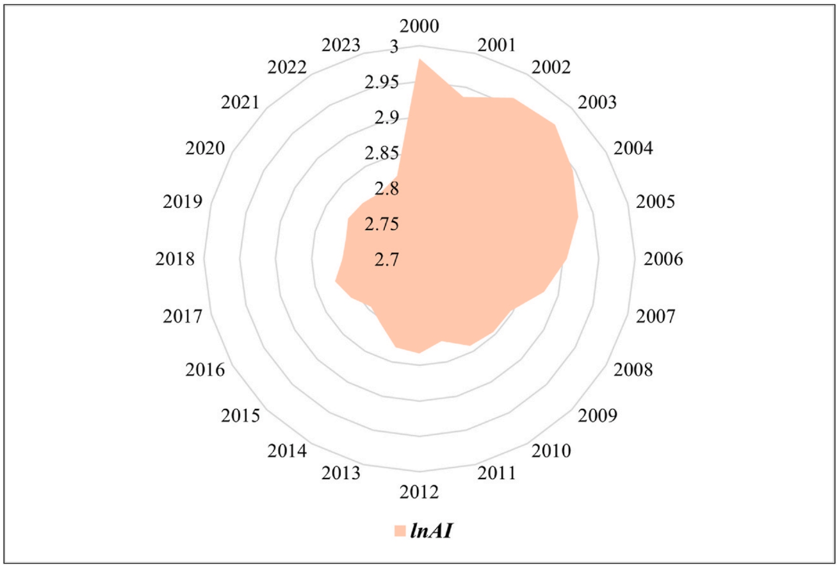

Fig. 2. AI in emerging economies, Source (IFR, 2024):

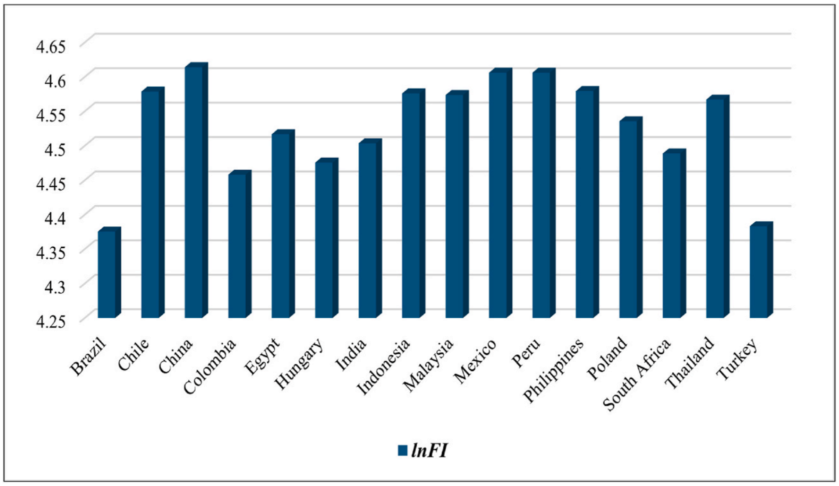

Fig. 3. FI in emerging economies, Source (OECD, 2024):

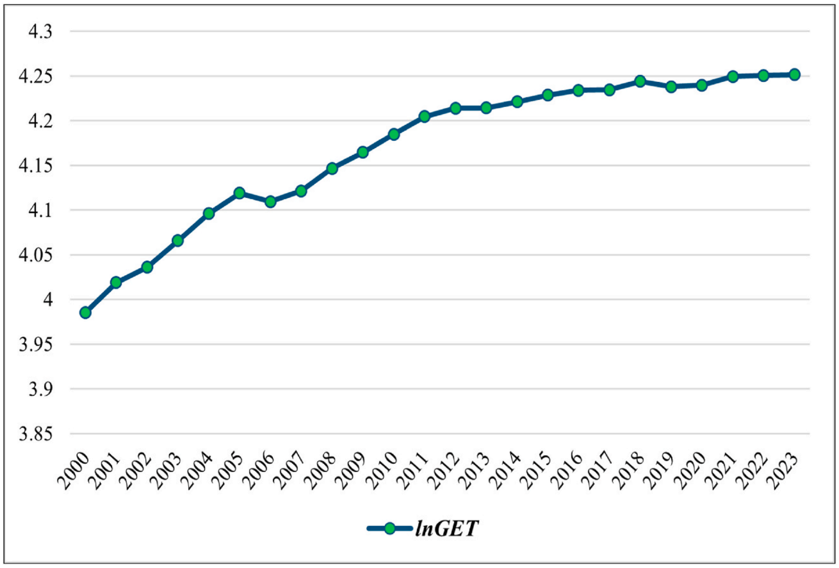

Fig. 4. GET in emerging economies, Source (BP, 2024):

Adjusted Tilde (Delta) statistics showing significance at the 1 % level. It indicated that the slopes were not homogeneous across the variables, suggesting variability in their relationships.

Table 6 presents the unit root test results, showing the CIPS and CADF test statistics for each variable at level *1(0)* and first difference *1(1)*. For most variables, the CADF test results indicate stationarity at the 1 % significance level, except for *lnEF* and *lnGET*, where the results are non-stationary at level *1(0)* but become stationary at first differences *1(1)*. It suggests that the variables become stationary after differencing, which is important for subsequent time series analyses. Table 7 presents the results of the panel cointegration tests. The G_t and P_t tests were significant at the 1 % level, indicating a long-term relationship between the variables.

The results of the CS-ARDL analysis in Table 8 provide a comprehensive understanding of the relationships between AI, FI, GET, GDP, and EF. Examining long- and short-term dynamics offers valuable insights into the interplay and impact of these variables on ecological sustainability. The long-range analysis demonstrated a statistically significant coefficient of −0.029 ($p < 0.05$) associated with AI. This inverse relationship implies that AI advancements correlate with a reduction in EF, suggesting that AI integration promotes efficient resource utilization and reduces environmental consequences (Chen & Xing, 2025; Han et al., 2024). This conclusion aligns with Wang et al. (2024), who argue that green innovation significantly decreases EF. Additionally, Mehmood et al. (2024) emphasized this viewpoint and highlighted the contribution of technology in reducing environmental degradation. In contrast, the FI-associated coefficient was −0.071. Nonetheless, this was not statistically significant and, thus, had a negative effect on EF. It is consistent with Destek and Sarkodie (2019), who suggested that the relationship between financial development and EF is complex.

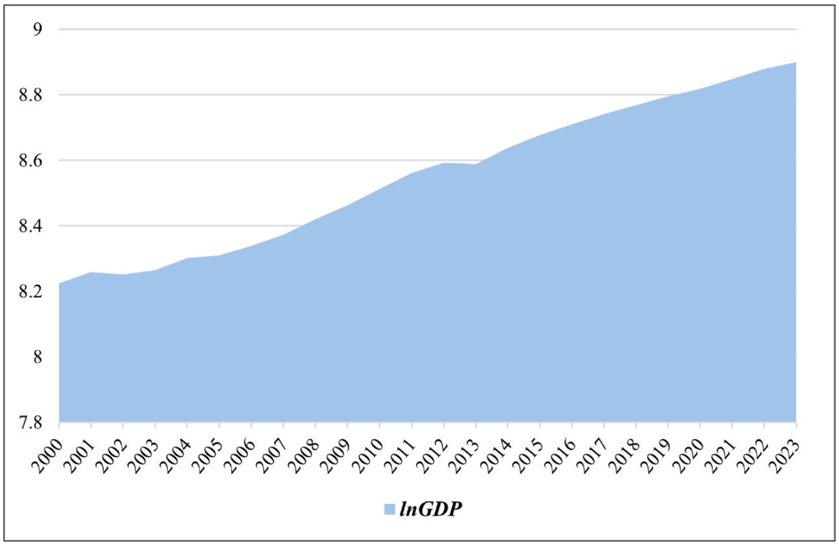

Fig. 5. GDP in emerging economies, Source (WDI, 2024):

Table 1
Data description.

Variables	Symbol	Measurement	Sources
Ecological footprints	EF	Ecological footprints (Global hectares per capita)	GFN
AI development	AI	Industrial robot installation	IFR
Financial innovation	FI	Financial sector R&D expenditures intensity	ANBERD
Green energy transition	GET	Nuclear, hydro, and other renewable energy use (% of total energy)	BP
Economic growth	GDP	GDP per capita (constant 2010 US$)	WDI

Note: GFN, Global Footprint Network; IFR, International Federation of Robotics; ANBERD, Analytical Business Enterprise Research and Development; WDI, World Development Indicators; BP, BP Statistical Review of World Energy.

Table 2
Descriptive statistics.

Variables	Obs	Mean	Std. D	Min	Max
lnEF	384	9.643	0.270	8.517	10.748
lnAI	384	2.859	0.758	0.693	3.898
lnFI	384	4.527	0.144	4.036	4.965
lnGET	384	4.170	0.138	3.720	4.445
lnGDP	384	8.551	0.676	6.481	9.619

Table 3
Pairwise correlations matrix.

Variables	*lnEF*	*lnAI*	*lnFI*	*lnGET*	*lnGDP*
lnEF	1.000				
lnAI	−0.011	1.000			
	(0.823)				
lnFI	0.076	−0.044	1.000		
	(0.139)	(0.387)			
lnGET	0.054	−0.532[a]	0.050	1.000	
	(0.293)	(0.000)	(0.328)		
lnGDP	0.015	−0.422[a]	−0.001	0.685[a]	1.000
	(0.772)	(0.000)	(0.987)	(0.000)	

Notes: [a] denotes significance level at 1 %.

Table 4
Cross-sectional dependence (CD) test.

Variables	Breusch-Pagan LM	p-value	Pesaran CD	p-value
lnEF	81268.590[a]	0.000	6.360[a]	0.000
lnAI	19048.630[a]	0.000	4.928[a]	0.000
lnFI	3789.240[a]	0.000	3.742[a]	0.000
lnGET	362.010[a]	0.000	24.280[a]	0.000
lnGDP	636.000[a]	0.000	19.238[a]	0.000

Notes: [a] denotes significance level at 1 %.

Table 5
Slope homogeneity test.

Statistics	Test value	Probability
Tilde (Delta)	4.071[a]	0.000
Adjusted tilde (Delta)	4.880[a]	0.000

Notes: [a] denotes significance level at 1 %.

Table 6
Panel unit root tests.

Variables	CIPS		CADF	
	1(0)	*1(1)*	*1(0)*	*1(1)*
lnEF	−1.235	−3.784[a]	−1.547 (0.799)	−2.784[a] (0.000)
lnAI	−2.096[a]	−3.965[a]	−2.128[b] (0.060)	−3.015[a] (0.000)
lnFI	−2.277[a]	−4.182[a]	−2.374[a] (0.005)	−3.755[a] (0.000)
lnGET	−1.983	−4.155[a]	−1.836 (0.362)	−3.091[a] (0.000)
lnGDP	−1.529	−2.900[a]	−2.235[b] (0.023)	−2.801[a] (0.000)

Notes: [a] and [b] denote significance levels at 1 % and 5 %, respectively.

Table 7
Panel cointegration test.

Estimates	Value	Z-value	P-value
G_t	−4.427[a]	−7.915	0.000
G_a	−14.143	0.689	0.754
P_t	−16.017[a]	−6.550	0.000
P_a	−10.579	0.834	0.798

Notes: [a] denotes significance level at 1 %.

Table 8
CS-ARDL results.

Variables	Coefficient	Standard error	Z-value	P-value
Long Run				
lnAI	−0.029[b]	0.013	−2.070	0.038
lnFI	−0.071	0.054	−1.330	0.184
lnGET	−0.144[b]	0.073	−1.960	0.050
lnGDP	0.337[a]	0.112	3.000	0.003
Short Run				
lnAI	−0.028[b]	0.013	−2.120	0.034
lnFI	−0.063	0.049	−1.280	0.202
lnGET	−0.139[b]	0.060	−2.290	0.022
lnGDP	0.356[a]	0.123	2.890	0.004
ECM	−1.047[a]	0.077	−13.500	0.000

Notes: [a] and [b] denote significance levels at 1 % and 5 %, respectively.

Aldhaen and Braendle (2025) explore accreditation's role in FI and business sustainability, which indicates that accreditation significantly enhances business sustainability, with notable growth in financial inflows post-accreditation.

The GET variable coefficient of −0.144 was statistically significant at the 5 % significance level. This finding suggests a negative correlation between increased utilization of renewable energy sources and EF. This relationship corroborates the conclusions of Gayen et al. (2024), underscoring the crucial role of transitioning to renewable energy in reducing the environmental impact. Furthermore

(Qamruzzaman & Karim, 2024), corroborated this conclusion by demonstrating that green energy initiatives mitigate environmental degradation and stimulate economic activities. Our findings underscore the pivotal role of GET in advancing the Sustainable Development Goals (SDGs) 7 and 13. By promoting renewable energy sources, GET directly contributes to SDG 7's targets, such as ensuring universal access to modern energy services and increasing the share of renewable energy in the global energy mix (Bai et al., 2023; Khalfaoui et al., 2022). Additionally, adopting GET aligns with the objectives of SDG 13 by mitigating the impact of climate change by reducing greenhouse gas emissions. This synergy between the GET and SDGs highlights the critical importance of sustainable energy solutions for achieving global sustainability targets (Majeed et al., 2021; Xiaoman et al., 2021; Xu et al., 2023). Conversely, the variable representing economic growth exhibited a positive coefficient of 0.337, which was statistically significant at the 1 % level. This finding suggests that higher GDP per capita is associated with an increased EF. This outcome aligns with the Environmental Kuznets Curve (EKC) hypothesis, which postulates that environmental degradation initially intensifies with economic growth but subsequently diminishes at higher income levels. Supporting this perspective, Destek and Sinha (2020) documented a similar correlation, noting that economic growth contributes to an elevated EF, which is mainly attributed to the consumption of non-renewable energy sources.

In the short run, the coefficients for AI, FI, GET, and GDP show signs and significance levels similar to those in the long run. The short-run coefficient for AI was −0.028, indicating that immediate advancements in AI were still correlated with a reduction in EF. This is consistent with Wang et al. (2024), who suggested that data-driven technologies foster more sustainable practices. The short-run coefficient for GET is −0.139, further highlighting the immediate ecological benefits of transitioning to green energy, aligning with (Gasparatos et al., 2017; Ullah et al., 2025), who emphasize the role of GET in promoting environmental sustainability. The short-run coefficient for GDP is 0.356, reinforcing the long-run observation that economic growth tends to increase the EF. This persistent relationship highlights the need for policies that balance economic growth with sustainable practices.

These findings have profound implications, suggesting that economic growth exacerbates environmental degradation without intentional intervention. The ECM results confirm the stability and long-run equilibrium, with significant error terms correcting for deviations over time. The FGLS results in Table 9 align with the CS-ARDL findings, reinforcing key insights. A 1 % increase in AI reduced EF by 0.005 %, consistent with the significant negative relationship in the CS-ARDL model. The FI showed an EF reduction of 0.023 %, although CS-ARDL found this relationship insignificant. GET reduced the EF by 0.018 %, supporting the significant negative association identified in the CS-ARDL model. Conversely, GDP increased EF by 0.207 %, which is consistent with the CS-ARDL results. These findings highlight the roles of AI, FI, and GET in mitigating EF, while acknowledging the environmental challenges of economic growth.

4. Conclusion

This study illuminates the intricate interplay between AI, FI, and GET and their cumulative impact on the environmental conditions of emerging economies. The findings reveal that AI and GET substantially influence the reduction in EF, thus fostering progress toward environmental sustainability. However, the effects of FI demonstrate variability depending on the analytical approach used, indicating the need for additional research in this domain. The link between economic growth and EF amplification underscores the significant environmental repercussions of industrial expansion. This observation highlights the critical need for policy frameworks that effectively synthesize technological progress using sustainable energy approaches to mitigate the adverse ecological consequences of economic prosperity. In response to these findings, this study advocates a comprehensive strategy that leverages the benefits of AI, FI, and GET while simultaneously addressing the challenges posed by rapid industrialization. Consequently, this analysis yielded several pivotal policy recommendations for sustainable development.

Policymakers should prioritize the integration of AI and GET into environmental strategies. These technological elements have considerable potential to mitigate EF and foster sustainability. Achieving this goal necessitates the strategic allocation of resources toward research and development endeavors, emphasizing AI technologies such as machine learning algorithms for predictive maintenance and energy management systems (e.g., Google DeepMind's applications), which enhance energy efficiency and augment environmental monitoring capabilities. The widespread implementation of renewable energy sources such as solar photovoltaic installations and wind energy farms is crucial for achieving this goal. In addition, it is imperative to examine the interplay between economic expansion and environmental deterioration, as illustrated by the positive correlation between GDP growth and EF intensification. Policymakers should implement sustainable practices to reduce the ecological consequences of industrial development. These practices should include promoting clean industries and enforcing circular economy models. Although FI offers specific opportunities for beneficial outcomes, the effects of such innovations are inconsistent; thus, careful regulation is required to ensure their

Table 9
FGLS results.

Variables	Coefficient	Std. errs.	Z-value	P-value
lnAI	−0.005[a]	0.004	−11.050	0.000
lnFI	−0.023[a]	0.003	−6.080	0.000
lnGET	−0.018[a]	0.003	−5.860	0.000
lnGDP	0.207[a]	0.010	20.510	0.000
Constant	0.091[a]	0.014	6.510	0.000

Notes: [a] denotes significance level at 1 %.

alignment with sustainability goals and avert any exacerbation of environmental degradation. An integrated and holistic approach is vital to combining the innovative capabilities of AI, the transformative characteristics of GET, and the strategic implementation of sustainable financial innovations. By adopting these comprehensive strategies, policymakers can facilitate long-term sustainability and significantly reduce the adverse environmental effects of economic development, thereby establishing a sustainable and resilient future for emerging economies.

CRediT author statement

Abdul Majeed: Conceptualization, Investigation, Resources, Writing – original draft.
Yuantao Xie: Data curation, Software, Methodology, Writing – original draft.
Chongyan Gao: Data curation, Software, Methodology, Writing – original draft.
Anna Min Du: Investigation, Project administration, Supervision, Validation, Writing – review & editing.
Muniba: Data curation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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