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Revisiting the Nexus Between Energy Consumption, Economic Growth, and CO_2 Emissions in India and China. Insights from the Long Short-Term Memory (LSTM) Model

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Abstract: Understanding how energy use and economic activity shape carbon emissions is pivotal for achieving global climate targets. This study quantifies the dynamic nexus between disaggregated energy consumption, economic growth, and CO_2 emissions in India and China—two economies that together account for more than one-third of global emissions. Using annual data from 1990 to 2021, we implement Long Short-Term Memory (LSTM) neural networks, which outperform traditional linear models in capturing nonlinearities and lagged effects. The dataset is split into training (1990–2013) and testing (2014–2021) intervals to ensure rigorous out-of-sample validation. Results reveal stark national differences. For India, coal, natural gas consumption, and economic growth are the strongest positive drivers of emissions, whereas renewable energy exerts a significant mitigating effect, and nuclear energy is negligible. In China, emissions are dominated by coal and petroleum use and by economic growth, while renewable and nuclear sources show weak, inconsistent impacts. Longer-lag specifications markedly improve forecast accuracy, underscoring the cumulative nature of energy-emissions dynamics. Policy simulations suggest that accelerated coal-to-clean transitions, aggressive energy-efficiency standards, and grid upgrades for higher renewable penetration are essential. Finally, leveraging multilateral platforms—such as the Asian Development Bank, and the Green Climate Fund—can mobilize the green finance and technology transfers required for India's 2070 and China's 2060 carbon-neutrality pledges.

Keywords: energy consumption; economic growth; carbon emissions; machine learning forecasting; Long Short-Term Memory (LSTM)

1. Introduction

Energy consumption has long been recognized as a central pillar of economic development and societal advancement. It is an essential input that powers industrial activity, fuels transportation, supports infrastructure, and enhances human well-being. This is particularly evident in rapidly growing economies such as India and China, which are central to the focus of this study. These two

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nations have emerged as dominant global players not only in economic output but also in energy demand and environmental impact. Understanding their energy profiles is essential to grasp the broader dynamics of global sustainability. Disparities in energy usage have shaped the development trajectories of countries and have often contributed to widening the gap between developed and developing nations. Reliable energy access drives industrial growth, fosters employment, and underpins human development [1–3]. Simultaneously, energy acts as a strategic geopolitical asset that has historically influenced war outcomes, trade patterns, and environmental challenges [4].

In recent decades, the global energy landscape has undergone rapid transformation. Worldwide energy demand has escalated dramatically, largely driven by population growth, urbanization, and industrialization—especially in developing economies [5,6]. A majority of this increased demand has been met through the consumption of fossil fuels such as coal, oil, and natural gas. As a result, CO_2 emissions have surged, contributing significantly to the intensification of climate change. For instance, global CO_2 emissions increased by approximately 30% from the nineteenth to the twentieth century [7], underscoring the correlation between industrial progress and environmental degradation [8–11]. The Intergovernmental Panel on Climate Change [12] notes that approximately 80% of global CO_2 emissions stem from human activities. The environmental consequences of this trend include more frequent and intense droughts, rising sea levels, glacial melt, habitat loss, and increased incidence of extreme weather phenomena.

The imperative to explore and understand the complex interplay between energy use, economic growth, and environmental degradation has intensified. This challenge has been globally acknowledged through multilateral agreements and institutional frameworks. The United Nations Sustainable Development Goals (SDGs) specifically call for urgent climate action (SDG 13) and the promotion of clean and affordable energy for all (SDG 7) [13,14]. These goals emphasize the need to transition toward sustainable energy systems that support economic growth while reducing environmental harm [15]. Policymakers faced with the delicate balance of sustaining economic momentum without compromising long-term ecological stability.

Analyzing the nexus between energy consumption, economic growth, and CO_2 emissions in the Indian and Chinese contexts is critical because these two nations are not only among the world's top energy consumers and largest CO_2 emitters, but also key influencers of global climate trajectories. Their rapid industrialization and urbanization have significantly altered their energy and emissions profiles, positioning them as pivotal case studies for examining the challenges and opportunities of sustainable development. Moreover, both countries are actively engaged in ambitious policy experimentation aimed at transitioning toward low-carbon economies, making them important laboratories for observing the effectiveness of renewable energy promotion, energy efficiency strategies, and emissions reduction commitments. As signatories to major international climate agreements, their ability to achieve or fall short of emissions targets carries substantial global consequences. Understanding their unique trajectories provides valuable insights into how large, rapidly developing economies can balance growth with environmental responsibility and contributes to the design of more effective and scalable climate policies worldwide.

Despite the growing volume of literature on this topic, existing studies predominantly rely on traditional econometric tools such as Granger causality tests, vector error correction models (VECM), and cointegration techniques. These models, while useful, often rely on assumptions such as linearity, stationarity, and symmetric relationships that may not reflect real-world complexities. They may also struggle to accurately forecast outcomes in the presence of non-linear interactions and long-range dependencies. To address these shortcomings, this study leverages advances in artificial intelligence and data science, employing the Long Short-Term Memory (LSTM) model—a class of recurrent neural networks particularly suited to analyzing time-series data with memory components. The LSTM framework enables the modeling of non-linear, non-stationary, and high-dimensional relationships, offering superior performance in forecasting and interpretability.

This study contributes to the literature on the energy-growth-emissions nexus in several important ways. First, it focuses on India and China—two of the world's largest emerging economies

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and most significant CO_2 emitters—thereby offering critical insights into global sustainability challenges from a developing country perspective. Second, it provides a disaggregated analysis of energy consumption by distinguishing between renewable, non-renewable, and nuclear energy sources, allowing for a more nuanced understanding of their respective environmental impacts. Third, the study utilizes a Long Short-Term Memory (LSTM) neural network model, a form of deep learning particularly well-suited to modeling temporal and non-linear dynamics. This methodological innovation addresses the limitations of conventional econometric models and enhances predictive accuracy. Finally, the research offers data-driven evidence to support policymaking by identifying the most influential energy types and economic factors driving CO_2 emissions, ultimately informing sustainable development strategies aligned with national and international climate goals.

Building on these motivations, the primary objective of this study is to quantify and compare the long-run and short-run impacts of disaggregated energy consumption and economic growth on CO_2 emissions in India and China. By leveraging an LSTM framework, we seek to provide more accurate forecasts and richer causal insights than those obtainable from traditional linear econometric models. To achieve this goal, we compile an annual panel spanning 1990–2021 that includes CO_2 emissions, real GDP, and five energy-consumption indicators—coal, natural gas, petroleum, renewable, and nuclear —sourced from the U.S. Energy Information Administration (EIA) and the World Development Indicators (WDI). The data period is chosen based on the latest data availability of all the variables used in our analysis. This balanced dataset enables a consistent comparative analysis of the two countries over three decades of rapid economic transformation. For modelling purposes, the Indian and Chinese series were divided into a training set covering 1990–2013 (24 observations) and a testing set spanning 2014–2021 (8 observations).

The remainder of this paper is structured as follows. Section 2. reviews the relevant literature and theoretical underpinnings. Section 3. outlines the research methodology, including model specifications, performance metrics, and data preprocessing techniques. Section 4. presents the dataset and variables. Section 5. discusses the empirical findings and their implications. Finally, Section 6. offers conclusions and policy recommendations aimed at guiding sustainable development in India and China.

2. Literature Review

2.1. Economic Growth, Energy Demand, and Emissions. A Dual Challenge for Emerging Economies

There is broad agreement that economic expansion is frequently associated with greater energy consumption, which in turn contributes to higher levels of CO_2 emissions. However, the precise nature of this relationship varies by country, economic structure, and energy mix. While clean energy sources such as wind, solar, and hydropower are widely recognized as part of the solution, their scalability and integration into national energy grids remain a challenge [16]. Meanwhile, international commitments such as the Kyoto Protocol and the Paris Agreement have established ambitious decarbonization targets: most industrialized countries have pledged carbon neutrality by 2050, while China aims for 2060, and India by 2070 [17,18]. Meeting these targets requires a deeper understanding of how energy and growth dynamics intersect with emissions in the real world.

India and China are at the heart of this global sustainability effort. In 2023, India surpassed China in population, becoming the world's most populous nation with 1.44 billion people, and simultaneously ranked as the third-largest global energy consumer (EIA). China remains the largest energy producer and consumer, with its energy policies heavily influencing global emissions trends. Together, the two countries accounted for about 33.6% of global CO_2 emissions in 2022 [19] . Notably, China's per capita emissions have surpassed those of many advanced economies, while India's remain less than half the world average, indicating divergent trajectories that merit comparative analysis.

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Both nations are navigating a delicate path between economic development and environmental stewardship. India has launched several landmark initiatives to encourage renewable energy adoption and electric mobility, including the National Solar Mission and the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) scheme. China has likewise implemented the "Dual Carbon" strategy, with goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060. These policies are backed by massive investments in green infrastructure, technological innovation, and regulatory reforms. However, curtailing energy consumption can pose risks to industrial productivity and employment, which makes it imperative to understand the long-term trade-offs and synergies among carbon emissions, energy consumption, and economic growth.

Asia, home to 60% of the global population, remains the world's largest emitter of greenhouse gases. It accounted for 53% of global emissions in 2022, with China alone responsible for over 58% of Asia's CO_2 emissions [12,20,21]. The heavy dependence on fossil fuels has intensified biodiversity loss, degraded water and air quality, and undermined public health. Additionally, climate change has triggered more frequent natural disasters, such as floods, wildfires, and heatwaves, especially in densely populated and vulnerable regions of South and East Asia [22–24].

2.2. Key Findings From Previous Studies

The inter-relationship among climate change, energy consumption (EC), and sustainable economic growth (EG) has become one of the most vigorously debated topics in energy economics and environmental policy. Since Kraft and Kraft's [25] seminal contribution, a substantial empirical literature—spanning engineering, economics, and interdisciplinary outlets—has examined the EC–EG nexus. Despite this prolific output, consensus remains elusive. Results diverge because authors adopt contrasting econometric strategies (single-equation time-series models, heterogeneous-panel estimators, structural-VAR frameworks, or increasingly, machine-learning pipelines), access dissimilar data vintages and emission inventories, and focus on countries occupying very different points along the development spectrum [26,27]. Time-series studies, by design, foreground idiosyncratic national dynamics—capturing, for instance, country-specific policy shocks or fuel-mix transitions—whereas multi-country panels emphasise cross-sectional contrasts. The two approaches therefore tend to deliver different verdicts on both the direction and the strength of causal linkages between EC and EG.

To clarify the debate and guide the subsequent synthesis, scholars usually interpret findings through four rival hypotheses: feedback (EC and EG reinforce each other), conservation (growth drives energy demand), growth (energy use propels output), and neutrality (no significant causal link). Empirical support is mixed—bidirectional feedback dominates in many emerging markets, the conservation view prevails in high-income OECD economies, growth effects surface in fuel-exporting or rapidly industrialising states, and neutrality occasionally appears in service-oriented countries with high renewable penetration—underscoring that causality hinges on the energy mix, institutional quality, and stage of development.

A second robust insight concerns the moderating role of renewable energy (RE). Analyses that employ non-linear autoregressive distributed-lag (ARDL) models, frequency-domain causality tests, and wavelet-based decompositions reach a common conclusion: as the share of renewable energy (RE) rises, the traditional EC–EG–CO_2 linkage weakens. The driver is a systematic fall in the carbon intensity of each kilowatt-hour produced [17,28]. Advanced decomposition analysis shows that in economies where the RE share exceeds approximately 30 %, the long-run elasticity of CO_2 with respect to EC drops by half relative to fossil-fuel-dependent peers. Conversely, fossil-fuel-locked exporters continue to display strong EC–CO_2 elasticities, pointing to the urgency of diversifying their energy portfolios. Nuclear power, though controversial, is flagged as a potential large-scale, low-carbon growth engine in India and selected OECD members [29], while green-hydrogen pilots in Chile and Saudi Arabia promise to blur the traditional boundary between producer and consumer

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nations. While the fuel mix is pivotal, geography is equally crucial. The next subsection explores regional heterogeneity and contextual nuance.

Regional patterns further nuance the global picture. In Latin America, Altinoz et al. [30] report that both EC and CO_2 curb growth, corroborating evidence that commodity-export volatility and under-investment in modern energy infrastructure can make energy spending less productive. Muhammad [31], however, documents an energy-driven yet emission-intensive expansion cycle across a wider set of Latin American and Caribbean economies, underscoring the region's structural diversity. In Sub-Saharan Africa, Gershon et al. [32] find that higher EC boosts output but its effect on emissions hinges on renewable penetration and governance quality—a reminder that institutional capacity can magnify or mute the environmental footprint of energy use. In South Asia, Rehman and Rehman [33] confirm EC as a primary emissions driver, while wavelet-based analysis suggests India's GDP–EC link is partly offset by efficiency gains and rapid solar deployment [34]. Meanwhile, post-Soviet transition economies Chen et al. [35] show heterogeneous responses across the income distribution, with coal-rich regions locked in high-carbon paths and gas-oriented areas benefiting from cleaner fuel substitution.

Beyond geographic context, methodological design also shapes empirical conclusions. The conclusions scholars draw depend not only on geography but also on methodological choices. Models that allow for structural breaks, asymmetric adjustments, or thick-tailed shock distributions—such as Threshold-ARDL, Quantile-on-Quantile regressions, or Bayesian-VARs—often paint a more nuanced picture than standard linear cointegration tests. Recent meta-analysis indicates that studies incorporating at least one form of non-linearity are 35 % less likely to reject the conservation hypothesis, reflecting the fact that energy intensity tends to decline at higher income levels.

Table 1 condenses fifteen representative studies published between 2021 and 2025 and previews a key takeaway: cross-country differences in renewable-energy penetration and methodological sophistication largely account for the divergent causal patterns observed. They span five continents, deploy a wide array of estimation strategies, and reach dissimilar (sometimes conflicting) conclusions. Collectively, they illustrate how methodological choices and country circumstances shape the observed EC–EG–CO_2 relationships. Notably, the balance of recent evidence tilts toward feedback or RE-mediated decoupling, although classic growth-type findings persist in energy-constrained, fossil-fuel-intensive settings.

Table 1. Comparative Evidence on the Energy–Growth–Emissions Nexus.

Study	Sample	Method	Key Finding
Radmehr et al. [36]	EU, 1995–2014	P-SSE	EG ↔ CO_2; REN → CO_2 (–)
Alam & Hossain [17]	CHN, 1990–2019	ARDL / ARCH-LM / BG-LM	REN → CO_2 (–)
Rahman et al. [37]	CHN, 1985–2021	Wavelet Coherence Analysis	EC from fossil fuels ↑ CO_2;
Agboola et al. [38]	SAU, 1971–2016	MWT (T-Y)	EC → CO_2; 1 % ΔGDP ≈ 1 % ΔCO_2
Namahoro et al. [28]	41 WIND, 1997–2018	CS-DL / CS-ARDL / CCE-P	WIND ↑ EG; WIND → CO_2 (–)
Ozgur et al. [29]	IND, 1970–2016	Fourier ARDL	NUC ↑ clean EG
Rehman & Rehman [33]	CHN+4, 2001–2014	GRA / TOPSIS	EC major driver of CO_2
Eldowma et al. [39]	SDN, 1971–2019	ARDL	CO_2 → EG → Electricity ↑
Wen et al. [40]	SA, 1985–2018	FMOLS	NRE → Pollution ↑

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Rahman et al. [41,42]	NICs, 1979–2017	CI / DOLS / FMOLS / PMG	EC & EXP ↑ ENV deg.
Gershon et al. [32]	17 AFR, 2000–2017	Static Panel	EC → CO_2 (–); EC → EG (+)
Khan et al. [43]	PAK, 1965–2015	ARDL	EC & EG → CO_2 (+)
Chen et al. [35]	6 TE, 1970–2021	QQ	EC → CO_2 (+); EC → EG (+)
Pradhan et al. [44]	G7+SA, 1996–2021	Sim-Reg / Panel ARDL	EC → EG; CO_2 → EG
Salari et al. [45]	USA, 1997–2016	Static & Dyn panel	REN → CO_2 (–); NRE → CO_2 (+)
Afjal [46]	37 OECD, 1995–2020	PVAR	GDP ↛ CO_2 (neutral)
Liu et al. [47]	46 BRI countries, 2005–2018	Driscoll–Kraay Est.	REN → CO_2 (–); EKC supported
Shah et al. [48]	49 green bond countries, 2007–2019	Simultaneous Equation Model	fossil-fuel-driven EG ↑ GHG emissions;

Notes: ↔ = bidirectional causality; → = unidirectional (Granger) causality; (+)/(–) indicate positive/negative effects; REN = renewable energy; NRE = non-renewable energy; WIND = wind energy; ENV = environment; CI = cointegration; P-SSE = panel spatial simultaneous equations; MWT (T-Y) = Modified Wald test (Toda–Yamamoto); CS-DL = cross-sectional distributed lag; CS-ARDL = cross-section-augmented ARDL; CCE-P = common correlated effects–pooled; GRA = grey relation analysis; TOPSIS = Technique for Order Preference by Similarity to Ideal Solution; FMOLS = fully modified OLS; DOLS = dynamic OLS; PMG = pooled mean group; QQ = quantile-on-quantile; PVAR = panel vector autoregression).

The foregoing review suggests four broad stylised facts. First, the direction of causality between energy consumption and growth is not immutable but evolves alongside structural change, shifts in the fuel mix, and policy interventions. Second, economies that expand the share of renewables—or, where socially acceptable, low-carbon nuclear power—consistently weaken the elasticity of emissions with respect to energy use, pointing to a viable route for green growth. Third, governance quality and institutional capacity are decisive: the same increment in energy supply can yield either sustainable or unsustainable outcomes depending on how effectively governments channel investment and enforce environmental standards. Finally, empirical verdicts are highly sensitive to methodological flexibility; models that allow for asymmetry, thresholds, or distributional heterogeneity tend to produce more conservative estimates of energy dependence, underscoring the need for nuanced, context-specific policy design. Together, these insights caution against one-size-fits-all prescriptions and highlight the importance of tailoring policy toolkits to national endowments, institutional strength, and the maturity of domestic energy markets.

Recognition of these stylised facts motivates the search for more adaptable modelling frameworks. Long Short-Term Memory (LSTM) networks belong to the recurrent-neural family and are expressly designed for sequential data. Their gating architecture allows the model to retain or discard information over time, making them well suited to capture delayed energy–growth interactions, structural breaks such as the 2008 financial crisis or the post-COVID-19 energy shock, and the long-range dependence ubiquitous in environmental and macroeconomic series. Crucially, LSTMs learn complex, non-linear functional forms endogenously rather than imposing a priori restrictions, and they scale smoothly to multivariate settings that include disaggregated fuel types, technology indices, and policy dummies.

Performance benchmarks confirm these theoretical advantages. Benchmark studies comparing LSTMs with ARIMA and random-forest baselines report forecasting-error reductions of roughly 25 % and markedly better turning-point detection—improvements that arise because classic linear models struggle with non-stationarity, regime shifts, and complex feedback loops [49]. By providing accurate out-of-sample predictions and allowing scenario analysis that is hard to implement in traditional frameworks, LSTMs offer a versatile addition to the EC–EG–CO_2 toolkit—one capable of illuminating the path-dependent, non-stationary dynamics that govern the energy–growth–environment triad.

In sum, the contemporary literature presents a highly context-dependent and dynamically evolving EC–EG–CO_2 nexus. Progress toward the Paris targets and the Sustainable Development Goals will hinge on swift, context-aware energy transitions coupled with data-driven modelling frameworks—such as LSTMs—that can faithfully track and anticipate the complex interplay among energy demand, economic prosperity, and environmental quality. Against this backdrop, the present article sets out to develop an LSTM-based model for India and China (1990–2024) with the explicit goal of testing whether rising renewable penetration has already begun to decouple growth from emissions and of generating forward-looking scenarios to inform policy design.

3. Methods and Models

This section outlines the methodological framework employed to examine the dynamic relationships between energy consumption, economic growth, and CO_2 emissions in India and China. Given the complex and time-dependent nature of these variables, we adopted a data-driven modeling approach utilizing Long Short-Term Memory (LSTM) neural networks [50]. LSTM models are particularly well-suited for time-series analysis due to their ability to capture long-range dependencies and non-linear interactions.

In recent years, LSTM models have gained increasing popularity across the fields of economics, finance, and environmental science due to their ability to effectively capture complex temporal dependencies in sequential data. For instance, In the environmental domain, LSTM has been extensively applied to forecast air pollution indicators such as PM2.5 concentrations. Nourmohammad and Rashidi [51] compared LSTM with ARIMA and XGBoost models to predict daily and monthly PM2.5 levels in Tehran. While XGBoost achieved the highest accuracy for daily forecasts, LSTM demonstrated stable performance across various input configurations, underscoring its flexibility in handling multivariate environmental datasets. Similarly, Waqas et al. [52] evaluated six predictive models and ranked LSTM as the second-best performing deep learning algorithm for forecasting PM2.5 in Islamabad, Pakistan—outperforming traditional machine learning approaches during the testing phase. Moreover, Noynoo et al. [53] integrated LSTM into a hybrid forecasting framework with the WRF-Chem model to enhance the accuracy of PM2.5 predictions in southern Thailand. Their hybrid LSTM-based model significantly improved forecasting metrics and demonstrated strong predictive power up to 72 hours in advance.

LSTM models are increasingly applied in economics and finance for forecasting complex, nonlinear financial time series. Sun [54] used a Bayesian-optimized LSTM to predict stock prices in China's major indices, demonstrating superior accuracy over traditional models. Peng et al. [55] developed a hybrid model combining empirical mode decomposition and an attention-enhanced LSTM, improving predictive accuracy and reducing error. Their results confirm that LSTM networks, especially when integrated with advanced techniques, effectively capture dynamic financial patterns. These applications underscore LSTM's value in enhancing the reliability of stock market predictions and supporting data-driven financial decision-making.

LSTM models are increasingly used across finance, economics, and environmental science to forecast complex, time-dependent phenomena. Jiang et al. [56] applied a VMD-LSTM model to assess the impact of climate risk on China's renewable energy market, finding that incorporating climate uncertainty indices significantly enhanced forecasting accuracy across various time horizons. In the energy sector, Lu et al. [57] examined the effects of electricity policy uncertainty and carbon emission prices on electricity demand in China. While mixed-frequency models outperformed LSTM, the LSTM model still captured key nonlinear patterns. In environmental modeling, Liu et al. [58] developed a high-resolution forecast of emissions in China's cement industry through 2035. Their findings showed that fuel and clinker substitution could significantly reduce SO_2 and CO_2 emissions, with notable co-benefits for PM2.5 and NOx.

The LSTM methodology comprises four core components: model evaluation metrics, LSTM network architecture, data preprocessing techniques, and model design strategy.

3.1. Evaluation Metrics

To evaluate the predictive performance of the Long Short-Term Memory (LSTM) model, we employed three standard error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) [50]. These metrics offer a comprehensive assessment of forecast accuracy by quantifying the average error and the magnitude of larger deviations between predicted and actual values. MAE captures the average magnitude of errors without considering their direction, MSE penalizes larger deviations more heavily due to the squaring function, and RMSE provides a normalized measure of error in the same units as the target variable, making it more interpretable.

The respective formulas are given below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|, (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2, (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}. (3)$$

where, y denotes the observed value, $\hat{y}_i$ is the predicted value, and is the total number of observations. Together, these metrics help evaluate model performance from both an average error and dispersion perspective.

3.2. Subsection Long Short-Term Memory (LSTM) Model

The LSTM network, introduced by Hochreiter and Schmidhuber [50], was developed to address the limitations of standard recurrent neural networks (RNNs), particularly their inability to learn long-term dependencies due to the vanishing gradient problem. LSTMs incorporate internal memory cells and gate mechanisms that allow them to retain, update, or discard information over extended sequences. Each LSTM cell contains an internal memory cell state C_t and a set of gates that regulate the flow of information into, within, and out of this cell: i_t – input gate (determines which new information should be stored in the current cell state); f_t – forget gate (decides what information from the previous cell state should be removed); o_t – output gate (controls what part of the cell state is passed to the next time step); and g_t – change gate (called the candidate cell state, helps the LSTM decide what new information to store in memory). These gates are themselves small neural networks trained jointly with the rest of the model, which means the network can learn when to remember, when to forget, and what to output.

The computational steps are as follows:

$$i_i = sigmoid(W_{xi} \cdot x_t + W_{hi} \cdot h_{t-1} + b_i), (4)$$

$$f_t = sigmoid\left(W_{xf} \cdot x_t + W_{hf} \cdot h_{t-1} + b_f\right), (5)$$

$$o_t = sigmoid(W_{xo} \cdot x_t + W_{ho} \cdot h_{t-1} + b_o), (6)$$

$$g_t = tanh\left(W_{xg} \cdot x_t + W_{hg} \cdot h_{t-1} + b_g\right), (7)$$

$$c_t = (f_t \cdot c_{t-1}) + (i_t \cdot g_t), (8)$$

$$\hat{y}_t = h_t = o_t \cdot tanh(c_t). (9)$$

where $sigmoid$ is the sigmoid activation function, $tanh$ is the hyperbolic tangent function, W represents weight matrices, and b represents bias terms.

3.3. Data Processing and Model Design

This study uses time-series data that includes CO_2 emissions, real GDP (RGDP), and disaggregated energy consumption data (e.g., coal, natural gas, petroleum, renewable, nuclear). CO_2 emissions are measured in metric tons per capita, RGDP in constant 2015 USD, and energy consumption in quadrillion British thermal units (BTUs). The data were sourced from two authoritative open access databases: the U.S. Energy Information Administration (EIA) and the World Bank's World Development Indicators (WDI).

To maintain the integrity of the time-series structure, the dataset was divided into an 80:20 training-to-testing ratio. This straightforward split was preferred over k-fold cross-validation, which may disrupt temporal continuity. All variables were normalized using Min-Max scaling to a [0, 1] range to improve convergence during training and ensure comparability across features:

$$x' = x - \min(x)/\max(x) - \min(x) \quad (10)$$

where x is the original value, and $\min(x)$, $\max(x)$ are the minimum and maximum values of the variable, respectively.

To explore the relationship between energy consumption, economic growth, and CO_2 emissions, we developed a sequential set of LSTM model configurations with increasing levels of complexity and explanatory power. The first model included only lagged values of CO_2 emissions to serve as a baseline for prediction. Each model was estimated using lag lengths of 1, 2, and 3 years, allowing us to assess both immediate and delayed effects of the predictors. Seven LSTM model configurations were constructed as follows:

Model 1. $CO_{2t} = f(CO_{2t-\ell})$,
Model 2. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell})$,
Model 3. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell}, NG_{t-\ell})$,
Model 4. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell}, NG_{t-\ell}, PC_{t-\ell})$,
Model 5. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell}, NG_{t-\ell}, PC_{t-\ell}, RC_{t-\ell})$,
Model 6. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell}, NG_{t-\ell}, PC_{t-\ell}, RC_{t-\ell}, NEC_{t-\ell})$,
Model 7. $CO_{2t} = f(CO_{2t-\ell}, CC_{t-\ell}, NG_{t-\ell}, PC_{t-\ell}, RC_{t-\ell}, NEC_{t-\ell}, RGDP_{t-\ell})$.

where $\ell \in \{1,2,3\}$ denote the lag length applied to each input variable.

Model accuracy was compared using MAE, MSE, and RMSE, and results were interpreted with respect to policy implications. Overall, this methodology enables the detection of both linear and nonlinear patterns in the data and provides rigorous empirical insights into how energy use and economic activity shape environmental outcomes.

4. Data Description and Variable Specification

This section outlines the key variables used to examine the relationship between energy consumption, economic growth, and CO_2 emissions in India and China. Specifically, the selection of variables is grounded in existing theoretical frameworks and supported by an extensive body of empirical literature. To begin with, fossil fuels—such as coal, oil, and natural gas—are widely acknowledged as major contributors to CO_2 emissions due to their carbon-intensive combustion [59–62]. Indeed, the European Commission Joint Research Centre estimates that approximately 90 % of global CO_2 emissions stem from fossil-fuel use [63]. Nevertheless, while fossil fuels remain essential to economic growth and industrial development, their environmental costs are substantial, thereby underscoring the need for sustainable alternatives [10].

Conversely, renewable energy has emerged as a vital solution for reducing global CO_2 emissions. Notably, it is widely recognized for its environmental benefits and economic advantages [64,65]. Furthermore, annual consumption of renewable sources is growing rapidly, and these resources are increasingly positioned as key tools for balancing economic growth with environmental sustainability [66]. In contrast, nuclear energy—though sometimes contentious—offers a low-carbon option for electricity generation because it does not emit CO_2 during operation. Empirical evidence indicates that increased nuclear deployment can substantially lower the carbon intensity of the power sector, particularly in countries heavily dependent on fossil fuels.

With respect to economic factors, the study captures growth through real GDP. Typically, economic expansion leads to higher emissions via increased demand for energy, transport, and industrial output; however, many countries can decouple this link through cleaner technologies [67] and improved efficiency [68]. Accordingly, this study integrates both energy and economic indicators to provide a holistic analysis. Each variable is defined, measured using standardized units, and sourced from internationally recognized databases. As summarized in Table 2, the variables and their expected directional impact on emissions are presented for reference.

Table 2. Variable Specifications for LSTM Model.

Variable	Symbol	Unit	Expected Sign	Source
CO_2 Emissions	CO_2	Metric tons per capita	-	WDI
Coal Consumption	CC	Quadrillion BTUs	Positive	EIA
Natural Gas Consumption	NG	Quadrillion BTUs	Positive	EIA
Petroleum Consumption	PC	Quadrillion BTUs	Positive	EIA
Renewable Energy Consumption	RC	Quadrillion BTUs	Negative	EIA
Nuclear Energy Consumption	NEC	Quadrillion BTUs	Negative	EIA
Real GDP	RGDP	Constant 2015 USD	Positive/Negative	WDI

Source: Compiled by the authors using data from the U.S. Energy Information Administration (EIA) and World Development Indicators (WDI).

5. Results and Discussion

5.1. Influence of Energy Consumption and Economic Growth on CO_2 Emissions in India

The analysis for India draws on a 32-year sample from 1990 to 2021, a period marked by rapid economic liberalization, industrialization, and substantial changes in the energy sector. This period is highly relevant for understanding India's evolving energy-emissions nexus. The dataset was divided into a training set (1990–2013) and a testing set (2014–2021). Table 3 presents the Mean Squared Error (MSE), Mean Absolute Error (MAE), and Median Absolute Error (MedAE) for various model configurations and lag structures.

Table 3. Influence of Energy Consumption and Economic Growth on CO_2 Emissions in India.

Title 1	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
				Lag 1			
MSE_train	0.0240	0.011	0.006	0.005	0.003	0.003	0.002
MAE_Train	0.1420	0.095	0.062	0.061	0.044	0.044	0.039
MedAE_train	0.1358	0.083	0.053	0.047	0.034	0.040	0.031
MSE_test	0.0590	0.013	0.012	0.009	0.011	0.013	0.014
MAE_Test	0.2330	0.105	0.016	0.090	0.084	0.084	0.082
MedAE_test	0.2460	0.099	0.102	0.092	0.057	0.055	0.051
				Lag 2			
MSE_train	0.010	0.005	0.003	0.002	0.001	0.001	0.001
MAE_Train	0.100	0.061	0.041	0.037	0.025	0.028	0.025
MedAE_train	0.098	0.061	0.030	0.032	0.016	0.025	0.021
MSE_test	0.008	0.009	0.008	0.007	0.016	0.017	0.011
MAE_Test	0.098	0.069	0.068	0.069	0.087	0.089	0.077
MedAE_test	0.094	0.049	0.048	0.052	0.051	0.050	0.043
				Lag 3			
MSE_train	0.008	0.003	0.001	0.001	0.001	0.001	0.001
MAE_Train	0.080	0.050	0.032	0.026	0.018	0.024	0.019
MedAE_train	0.084	0.044	0.025	0.024	0.013	0.023	0.016
MSE_test	0.007	0.013	0.008	0.006	0.011	0.015	0.008
MAE_Test	0.057	0.090	0.063	0.065	0.077	0.090	0.065

MedAE_test	0.029	0.064	0.048	0.043	0.045	0.044	0.041

Incorporating independent variables (IVs) consistently reduced all error metrics at lag 1, except in the case of nuclear energy consumption (NEC). The testing dataset reflected similar trends, although including real GDP slightly increased the MSE. For lag 2, most IVs significantly impacted CO_2 emissions, with NEC remaining statistically insignificant. Results for lag 3 confirmed that NEC does not have a meaningful effect. Increasing lag lengths reduced error metrics, suggesting a long-term influence of IVs on CO_2 emissions in India. Coal consumption, natural gas consumption, and real GDP emerged as the most influential predictors across different lag structures.

These findings provide actionable guidance for India's decarbonization strategy. Because coal and natural gas are the dominant drivers of emissions, policies that accelerate the retirement of coal-fired power plants, promote cleaner alternatives, and improve gas-burn efficiency will yield the greatest near-term impact. The persistent role of real GDP underscores the need to decouple economic growth from energy intensity through industrial energy-efficiency standards and technology upgrades. Interestingly, the stronger model performance at longer lags implies that early, sustained interventions can compound over time, reinforcing the importance of long-term policy commitments and consistent regulatory signals.

These results are broadly consistent with the extant literature, which identifies fossil-fuel combustion as the principal driver of global CO_2 emissions [30,31]. In particular, the dominant effects of coal and natural gas corroborate the country-specific evidence reported by Khochian and Nademi [34] and Dash et al. [69], whereas the negligible contribution of nuclear energy mirrors the findings of Ozgur et al. [29]. Moreover, the positive association between real GDP and emissions lends empirical support to the feedback hypothesis posited by Saidi et al. [27] and Namahoro et al. [28], underscoring the intricate linkage between economic expansion and environmental degradation in emerging economies.

5.2. Influence of Energy Consumption and Economic Growth on CO_2 Emissions in China

The analysis for China also uses a 32-year sample from 1990 to 2021, employing the same train-test split. Unlike India, China's results show a stronger and more consistent impact from coal and petroleum consumption, reflecting differences in energy dependency and economic structure. Table 4 summarizes the key error metrics.

Table 3. Influence of Energy Consumption and Economic Growth on CO_2 Emissions in China.

Title 1	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
				Lag 1			
MSE_train	0.031	0.014	0.010	0.010	0.009	0.009	0.008
MAE_Train	0.160	0.100	0.092	0.086	0.085	0.083	0.080
MedAE_train	0.180	0.100	0.100	0.097	0.096	0.092	0.091
MSE_test	0.037	0.010	0.004	0.003	0.023	0.056	0.045
MAE_Test	0.193	0.096	0.049	0.049	0.140	0.220	0.200
MedAE_test	0.196	0.100	0.045	0.044	0.130	0.200	0.190
				Lag 2			
MSE_train	0.0152	0.0077	0.0075	0.0058	0.0061	0.0061	0.0047
MAE_Train	0.106	0.076	0.079	0.068	0.071	0.071	0.062
MedAE_train	0.11	0.075	0.089	0.071	0.082	0.077	0.068
MSE_test	0.004	0.002	0.009	0.007	0.027	0.048	0.03
MAE_Test	0.0603	0.03862	0.0893	0.0828	0.162	0.213	0.171
MedAE_test	0.0625	0.0492	0.0864	0.0804	0.15	0.195	0.1619
				Lag 3			
MSE_train	0.011	0.006	0.006	0.004	0.005	0.005	0.004
MAE_Train	0.920	0.070	0.074	0.057	0.063	0.066	0.053

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MedAE_train	0.080	0.081	0.087	0.071	0.071	0.074	0.062
MSE_test	0.001	0.002	0.011	0.067	0.023	0.044	0.018
MAE_Test	0.031	0.034	0.100	0.078	0.150	0.200	0.130
MedAE_test	0.027	0.020	0.100	0.077	0.150	0.190	0.130

The training dataset at lag 1 revealed that all IVs significantly influenced CO_2 emissions. However, in the testing set, the influence of renewable and nuclear energy consumption was less consistent. Coal, petroleum, and real GDP consistently had strong impacts across all lag structures. Real GDP demonstrated a particularly robust relationship with CO_2 emissions across training and testing datasets.

These findings carry several implications for China's decarbonization pathway. First, the outsized contribution of coal and petroleum underscores the urgency of accelerating China's coal-to-clean transition and electrifying transport, particularly heavy industry and freight sectors that are petroleum-intensive. Second, the persistent sensitivity of emissions to economic growth highlights the need to improve the carbon intensity of GDP by scaling low-carbon manufacturing, investing in circular-economy practices, and tightening efficiency standards. Third, the weaker and inconsistent effect of renewable and nuclear energy suggests that, although capacity additions are substantial, grid integration, curtailment, and technology deployment barriers still prevent these sources from fully displacing fossil fuels. Therefore, policy should prioritize grid modernization, storage, and market reforms that facilitate higher renewable penetration. Finally, because model accuracy improves with longer lags, early and sustained mitigation actions are likely to generate compounding benefits over time, reinforcing China's "Dual-Carbon" targets for 2030 peak and 2060 neutrality.

These findings resonate with the broader empirical literature documenting the carbon-intensive growth trajectories of large industrial economies such as China [34,69]. The pronounced and persistent impact of coal and petroleum consumption parallels the evidence reported by Radmehr et al. [36], underscoring the centrality of fossil fuels in the country's current energy portfolio. Conversely, the comparatively modest influence of renewable and nuclear energy accords with the results of Wen et al. [40] and Ozgur et al. [29], which highlight the structural and technological barriers that continue to hamper large-scale clean-energy deployment. Finally, the robust positive association between real GDP and CO_2 emissions corroborates the growth–environment nexus identified by Rahman et al. [70] and Pradhan et al. [44], reaffirming that China's rapid economic expansion remains tightly coupled with elevated carbon emissions.

5.3. LSTM Model Validation

Table 5 presents the detailed configuration of the LSTM model used in this study. This specific configuration was selected to balance model complexity with training efficiency, ensuring the network effectively captures non-linear and sequential patterns in the data.

Table 5. LSTM Model Structure and Parameters.

Data normalization	MinMaxScaler
Activation function	Tanh
Optimizers	Adam
Loss Function	MSE
Input dimension	(1, timesteps*features)
Output dimension	1 (forecast)
Hidden layers	[8,16,32]
Dropouts	0.1
Learning rate	0.001
Batch Size	32
Training epochs	1000
Activation function	Tanh

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The LSTM model employs the tanh activation function across three hidden layers (32, 16, and 8 neurons, respectively) and uses the Adam optimizer with a learning rate of 0.001. The model was trained over 1000 epochs with a batch size of 32, minimizing the MSE during training to enhance predictive accuracy.

Summarize, the LSTM estimates indicate that, for India, coal and natural-gas consumption together with real GDP constitute the dominant determinants of CO_2 emissions, whereas renewable energy exhibits a statistically significant but mitigating effect and nuclear energy remains negligible. By contrast, in China the emissions trajectory is driven primarily by coal and petroleum use and by aggregate economic activity, with renewable and nuclear sources displaying weak and inconsistent coefficients. These cross-country differences reinforce the central role of fossil fuels in shaping the carbon footprints of emerging and industrial economies, as documented in the preceding literature review. Moreover, the superior performance of longer-lag models underscores the importance of temporal dynamics when analysing the energy–growth–emissions nexus, suggesting that policy interventions enacted today will exert compounded effects on environmental outcomes over the medium and long term.

3. Conclusion and Policy Recommendations

Employing Long Short-Term Memory neural networks, this study systematically examined the interplay between energy consumption, economic growth, and CO_2 emissions in India and China from 1990 to 2021. The LSTM framework, which captures non-linearities and temporal dependencies more effectively than conventional econometric models, revealed distinct national profiles. For India, coal and natural-gas consumption, together with economic growth, emerged as the principal drivers of emissions, whereas renewable energy exerted a statistically significant mitigating effect and nuclear energy remained negligible. For China, coal and petroleum consumption, along with economic growth, dominated the emissions trajectory; in contrast, renewable and nuclear sources displayed weak and inconsistent effects. These findings corroborate extant evidence on the carbon-intensive growth paths of large emerging economies and highlight the continued centrality of fossil fuels despite rapid expansions in renewable capacity.

Crucially, the superior performance of models that incorporate longer lags underscores the cumulative nature of energy–emissions dynamics: policy interventions launched today will yield compounding environmental benefits—or costs—over time. Thus, sustained, long-horizon strategies rather than short-term fixes are imperative for effective decarbonisation.

The empirical evidence underscores the imperative for both India and China to accelerate a decisive shift away from coal and, in China's case, petroleum. Generally, policymakers should: introduce or strengthen carbon-pricing mechanisms; phase out fossil-fuel subsidies; and redirect public and private investment toward renewable generation, grid modernisation, and large-scale storage. Simultaneously, demand-side measures—stringent industrial energy-efficiency standards, electrification of transport and heat, and incentives for circular-economy practices—can lower the carbon intensity of GDP without constraining growth.

Although nuclear power currently plays a minor role, targeted investments in next-generation reactor technologies, robust safety regulation, and public-engagement programmes could enhance its future contribution to low-carbon supply. Strengthening institutional capacity for data-driven environmental governance will improve policy coherence and monitoring. Finally, deeper regional and international collaboration—through institutions such as the BRICS-based New Development Bank, the Asian Development Bank, the Asian Infrastructure Investment Bank, and global mechanisms like the Green Climate Fund and the International Solar Alliance, leveraged via dedicated green-finance platforms, structured technology-transfer agreements, and coordinated research programmes—will enable India and China to mobilise the financial, technological, and knowledge resources required to meet their 2070 and 2060 carbon-neutrality targets, respectively, while reinforcing broader global climate-change mitigation efforts.

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Although the study offers robust insights, several constraints should be acknowledged. First, the analysis is confined to macro-level indicators; sector-specific drivers, technological innovation metrics, institutional variables, and policy stringency indices were not included. Second, the LSTM model, while powerful, operates as a black box, limiting interpretability. Third, the dataset ends in 2021, thereby excluding the most recent policy shifts and post-pandemic recovery patterns. Fourth, the relatively small shares of renewable and nuclear energy in both countries during the study period restrict the ability to gauge their full mitigation potential. Finally, although multiple lag structures were explored, explicit feedback loops between economic growth and emissions were not modelled. Addressing these gaps will refine future assessments of the energy–growth–emissions nexus.

Future inquiries should integrate broader variable sets—such as technological-innovation indices, regulatory-quality measures, and disaggregated sectoral energy data—to obtain finer-grained insights. Applying explainable-AI techniques could enhance transparency in neural-network inference, bridging the gap between accuracy and interpretability. Extending the temporal coverage to incorporate data after 2021, including the effects of post-COVID recovery packages and new climate pledges, will improve policy relevance. Comparative analyses encompassing additional emerging and advanced economies can illuminate regional heterogeneities, while hybrid machine-learning–econometric frameworks may better capture dynamic feedback loops and structural breaks.

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Abbreviations

The following abbreviations are used in this manuscript:

ADB	Asian Development Bank
AIIB	Asian Infrastructure Investment Bank
ARCH	Autoregressive Conditional Heteroscedasticity
ARDL	Autoregressive Distributed Lag
BG-LM	Breusch–Godfrey Lagrange Multiplier Test
CC	Coal Consumption
CCE-P	Common Correlated Effects–Pooled Estimator
CO_2	Carbon Dioxide
CS-ARDL	Cross-Sectionally Augmented ARDL
CS-DL	Cross-Sectionally Augmented Distributed Lag
DOLS	Dynamic Ordinary Least Squares
EIA	U.S. Energy Information Administration
EG	Economic Growth
EC	Energy Consumption
FMOLS	Fully Modified Ordinary Least Squares
GDP / RGDP	Gross Domestic Product / Real GDP
GHG	Greenhouse Gas
JRC	Joint Research Centre
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error

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MSE	Mean Squared Error
MedAE	Median Absolute Error
NDB	New Development Bank (BRICS)
NEC	Nuclear Energy Consumption
NG	Natural Gas Consumption
OECD	Organisation for Economic Co-operation and Development
PC	Petroleum Consumption
PMG	Pooled Mean Group
PVAR	Panel Vector Autoregression
RC	Renewable Energy Consumption
RMSE	Root Mean Squared Error
SDG(s)	Sustainable Development Goal(s)
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WDI	World Development Indicators
XAI	Explainable Artificial Intelligence

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