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Assessing the economic impact of climate risk on green and low-carbon transformation

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Introduction: Limate risk poses significant challenges to sustainable development, particularly in the context of transitioning to green and low-carbon economies. The complexity of these interactions makes it difficult to devise strategies that effectively balance competing priorities, such as economic growth, environmental protection, and social inclusion. To bridge this gap, we propose a novel framework that integrates the Integrated Green Transition Model (IGTM) and the Sustainable Transition Optimization Framework (STOF).

Methods: IGTM employs agent-based modeling and network dynamics to simulate the cascading impacts of green policies on energy systems and socio-economic outcomes, while STOF leverages advanced optimization and machine learning techniques to balance economic growth, emission reductions, and social equity under diverse scenarios.

Results: By synthesizing these approaches, our study provides actionable insights into the economic impact of climate risk and offers robust strategies for optimizing investments in renewable energy and policy interventions. The results highlight the necessity of aligning technological innovation, governance, and public engagement to accelerate the green transformation while minimizing economic disruptions.

Discussion: Fostering international cooperation and sharing best practices across nations will be pivotal in overcoming global climate challenges and ensuring a just transition for all. This research underscores the urgency of implementing integrated solutions to safeguard a sustainable and equitable future. Unlike traditional models, IGTM simulates the cascading impacts of green policies on energy and socio-economic systems, while STOF uses machine learning to balance growth, emissions, and equity. This integrated approach enables precise climate risk assessment and guides renewable energy investments and policy decisions.

KEYWORDS

climate risk, green transformation, low-carbon economy, policy optimization, renewable energy

1 Introduction

The transition to a green and low-carbon economy has become an essential global priority in mitigating the adverse effects of climate change (Angelopoulos et al., 2023). This transformation is fraught with ecopnomic challenges and uncertainties associated with climate risks, including physical risks such as extreme weather events and transition risks related to shifts in policies, technologies, and market preferences (Shen and Kwok, 2023). Understanding the economic impact of these risks is crucial not only for developing effective climate policies but also for enabling a just and efficient transformation to sustainpable systems (Yin et al., 2023). Assessing these impacts offers insights into optimizing resource allocation (Jin et al., 2023), minimizing financial instability, and fostering global cooperation in achieving decarbonization goals (Yu et al., 2023). By leveraging advanced analytical frameworks and methodologies, this research aims to bridge the gap between economic modeling and the practical implementation of green strategies, thereby enhancing resilience and adaptability in the face of climate risks (Durairaj and Mohan, 2022).

In early approaches to assessing climate risk, traditional economic models based on symbolic reasoning and structured knowledge representation were widely adopted (Zhou et al., 2020). Integrated Assessment Models (IAMs), such as the Dynamic Integrated Climate-Economy (DICE) model, relied on mathematical equations and rule-based frameworks to simulate the interaction between economic systems and climate variables (Hou et al., 2022). These models provided valuable insights into long-term climate-economic dynamics, such as the cost-benefit trade-offs of mitigation policies and the economic consequences of global warming (Dudukcu et al., 2022). Their reliance on simplified assumptions and static representations of complex systems limited their ability to account for nonlinear feedback loops and uncertainties inherent in climate risks (Amalou et al., 2022). Symbolic models often struggled to capture the heterogeneity of regional and sectoral impacts, thus constraining their applicability to real-world scenarios (Kumari and Singh, 2022). Despite these limitations, traditional models laid the foundation for integrating climate risks into economic planning.

With the advent of data-driven and machine learning (ML) techniques, researchers have developed more sophisticated tools for analyzing the economic implications of climate risk (Gruver et al., 2023). By leveraging large datasets on climate variables, economic indicators (Cheong et al., 2024), and energy systems, ML models can identify patterns and correlations that are difficult to discern using traditional approaches (Chandra et al., 2021). Supervised learning algorithms have been applied to predict the financial losses associated with extreme weather events, while clustering methods have been used to classify regions based on their vulnerability to climate risks (Wang X. et al., 2024). These approaches offer greater flexibility and scalability, enabling more granular assessments of climate-economic interactions (Jin et al., 2022). They often rely on extensive and high-quality data, which may not be available for all regions or sectors (Fan et al., 2021). The black-box nature of many ML models poses challenges for interpretability and policy implementation, as stakeholders require transparent and actionable insights to inform decision-making.

The rise of deep learning and pre-trained models has further advanced the study of climate risk and its economic impact, offering unprecedented capabilities in processing complex and high-dimensional data (Lindemann et al., 2021). Techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to analyze spatial and temporal patterns in climate and economic data (Ren et al., 2024d), while transformer-based models have facilitated the integration of multimodal inputs, including textual, numerical, and geospatial information (Zheng and Chen, 2021). These methods allow for more dynamic and adaptive modeling of climate-economic systems, capturing the interplay between diverse factors such as policy changes, technological advancements, and market responses (Wang et al., 2021b). The high computational requirements and data dependencies of deep learning models remain significant challenges. The interpretability and trustworthiness of these models must be improved to ensure their practical utility in policy and investment contexts (Altan and Karasu, 2021).

This study makes several key contributions to the field of climate risk and green economic transformation. We introduce the Integrated Green Transition Model (IGTM), which employs agent-based modeling and network dynamics to simulate the cascading impacts of green policies on energy systems and socio-economic outcomes (Wen et al., 2021). We propose the Sustainable Transition Optimization Framework (STOF), leveraging machine learning and advanced optimization techniques to balance economic growth, emission reductions, and social equity across diverse scenarios. Unlike traditional economic models, which often fail to capture the dynamic and nonlinear interactions in climate-economic systems, our framework integrates multi-layered feedback mechanisms to enhance predictive accuracy and policy relevance (Xiao et al., 2021). By synthesizing these approaches, this study provides actionable insights for optimizing investments in renewable energy, designing effective policy interventions, and ensuring a just transition to a sustainable economy.

Given the limitations of traditional, machine learning, and deep learning methods, we propose a hybrid framework that combines the strengths of these approaches while addressing their weaknesses. Our method integrates IAMs with ML-based tools to enhance the accuracy and granularity of economic impact assessments. By leveraging transfer learning and ensemble modeling techniques, our approach ensures adaptability to different regions and sectors, while maintaining a balance between interpretability and predictive power. Our framework incorporates scenario analysis and stress testing to evaluate the resilience of green and low-carbon strategies under varying climate risk conditions. This integrated approach enables policymakers and stakeholders to make informed decisions, thereby accelerating the transition to a sustainable and resilient economy.

- The hybrid integration of IAMs and ML enhances the precision and scalability of economic impact assessments, bridging the gap between theory and practice.
- The proposed approach demonstrates high versatility in addressing regional, sectoral, and policy-specific challenges, ensuring wide applicability.

- Empirical results highlight the effectiveness of this framework in guiding investments and policy measures, fostering a balanced and inclusive green transition.

2 Related work

2.1 Climate risk and economic vulnerability

The relationship between climate risk and economic systems has been extensively studied due to the increasing frequency and intensity of climate-related events (Wang et al., 2021a). Climate risks, including physical risks such as extreme weather events, rising sea levels, and prolonged droughts, as well as transition risks arising from policy changes and market shifts toward sustainability, impose significant economic burdens (Ruan et al., 2021). Research indicates that physical climate risks directly disrupt economic activities by damaging infrastructure, reducing agricultural productivity, and displacing populations (Moskolaï et al., 2021). These risks can undermine economic stability through supply chain disruptions and increased costs of insurance and capital (Widiputra et al., 2021). Transition risks, manifest in the form of stranded assets in carbon-intensive sectors, shifts in investment flows, and regulatory costs associated with achieving decarbonization goals. From a macroeconomic perspective, climate risks have been shown to reduce GDP growth, amplify income inequality, and increase financial market volatility (Ren et al., 2024e). Empirical studies leveraging econometric models and scenario analysis suggest that economies highly dependent on fossil fuels or those with limited adaptive capacity are particularly vulnerable (Ren et al., 2024c). At the microeconomic level, climate risks affect firm performance through operational disruptions, changes in consumer preferences, and heightened regulatory scrutiny (Said and Dindar, 2024). Quantifying these impacts remains a critical challenge, as it requires integrating climate projections with economic modeling (Dindar, 2022). Recent advances in integrated assessment models (IAMs) have contributed to this effort, providing frameworks for estimating the economic costs of climate risks under various mitigation and adaptation scenarios. Despite these developments, more granular studies are needed to assess sector-specific and regional impacts, particularly in developing countries that are disproportionately affected by climate change (Ren et al., 2024b).

2.2 Green transformation and economic resilience

The transition toward a green and low-carbon economy is increasingly viewed as a critical pathway for enhancing economic resilience in the face of climate risks (Wu et al., 2022). Green transformation involves the adoption of renewable energy, energy efficiency technologies, and sustainable practices across industries to decouple economic growth from carbon emissions (Morid et al., 2021). Empirical evidence suggests that investments in green technologies and infrastructure can yield substantial economic benefits, including job creation, enhanced energy security, and long-term cost savings (Das et al., 2023). Studies on renewable energy deployment have highlighted its potential to stabilize energy prices, reduce dependency on imported fuels, and stimulate innovation in adjacent sectors. Policymakers have increasingly relied on cost-benefit analysis and lifecycle assessments to justify these measures, emphasizing their long-term economic returns despite short-term adjustment costs (Wang S. et al., 2024). The uneven distribution of costs and benefits remains a concern. Workers in carbon-intensive sectors and communities reliant on fossil fuel revenues often face economic displacement during the transition. Just transition frameworks, which aim to ensure equitable economic outcomes, have been proposed as solutions to these challenges, emphasizing social dialogue, reskilling programs, and targeted support for affected regions (Ren et al., 2024a). Research has also explored the role of financial systems in facilitating green transformation. Green finance instruments, such as green bonds and climate funds, have been shown to mobilize the capital needed for large-scale sustainability projects (Wang Z. et al., 2024). Central banks and financial regulators are increasingly incorporating climate risks into stress testing and monetary policy to safeguard economic stability during the transition. Despite these advancements, significant barriers persist, including the misalignment of short-term market incentives with long-term climate goals and the limited availability of data to assess the financial risks associated with climate change.

2.3 Low-carbon strategies and economic optimization

Low-carbon transformation strategies are central to mitigating the economic impacts of climate risk while fostering sustainable growth (Xu et al., 2020). These strategies encompass a broad range of measures, including the adoption of carbon-neutral technologies, circular economy practices, and nature-based solutions (Karevan and Suykens, 2020). Studies on carbon-neutral technologies, such as carbon capture and storage (CCS) and hydrogen energy systems, have demonstrated their potential to reduce emissions without compromising industrial output (Yang and Wang, 2021). Circular economy models, which prioritize resource efficiency and waste minimization, have been shown to enhance economic competitiveness while reducing environmental degradation. Economic optimization models have been employed to evaluate the cost-effectiveness of low-carbon strategies under various scenarios (Zhang et al., 2024). Computable general equilibrium (CGE) models and dynamic stochastic general equilibrium (DSGE) models have been used to analyze the trade-offs between economic growth and emission reductions (Chen et al., 2024). These models indicate that proactive investments in low-carbon technologies can minimize the economic costs of climate policies while maximizing co-benefits such as improved public health and ecosystem services. Sectoral analyses have also highlighted the differential impacts of low-carbon strategies, with energy-intensive industries facing higher transition costs compared to service-oriented sectors (Ren et al., 2024e). The role of innovation and technological diffusion in accelerating low-carbon transformation has been a key area of focus. Research has emphasized the importance of fostering collaborative innovation ecosystems involving governments, private enterprises, and research institutions to drive technological breakthroughs and scale their adoption. Challenges such as financing gaps, technological uncertainties, and policy inconsistencies continue to impede progress. Addressing these barriers requires integrated policy frameworks that align economic incentives with climate objectives, ensuring that low-carbon transformation contributes to both economic sustainability and climate resilience.

3 Methods

3.1 Overview

The transition to green and low-carbon development has become a global imperative, driven by the need to mitigate climate change, ensure energy security, and achieve sustainable economic growth. This section outlines the framework and approach for studying and advancing the green and low-carbon transformation. It describes the key challenges, the dynamic interplay of technological innovation, policy frameworks, and socio-economic factors, and introduces the methodologies and models used in this research. The green and low-carbon transformation encompasses systemic changes in energy systems, industrial processes, and consumption patterns. These changes are guided by ambitious global commitments such as the Paris Agreement, which aims to limit global warming to well below 2°C above pre-industrial levels. Key aspects of this transition include decarbonizing energy generation, improving energy efficiency, promoting circular economy principles, and leveraging digitalization to optimize resource utilization.

In Preliminaries provides a rigorous formalization of the challenges associated with this transformation. This includes the quantification of carbon emissions, the dynamics of renewable energy integration, and the trade-offs between economic development and environmental goals. It highlights the need for a multi-level framework to capture the interactions between technological, economic, and regulatory dimensions. In Integrated Green Transition Model (IGTM), a novel approach for analyzing and predicting the impacts of green and low-carbon policies and technologies. The model incorporates agent-based simulations and network dynamics to explore the cascading effects of green interventions on energy systems, industrial networks, and socio-economic outcomes. In the Sustainable Transition Optimization Framework (STOF), which is designed to optimize decision-making under uncertainty. STOF integrates machine learning and scenario analysis to address critical challenges, such as balancing investment in renewable infrastructure with the risks of technological obsolescence and fostering public engagement for behavior change.

3.2 Preliminaries

The green and low-carbon transformation addresses the urgent need to mitigate the adverse effects of climate change while fostering sustainable development. This section formalizes the challenges inherent in this transformation and establishes a mathematical framework for analyzing the interplay of environmental, economic, and technological dimensions. We consider decarbonization goals, energy transitions, and economic trade-offs as the foundation for this formalization.

The total carbon emissions C from an economy can be expressed as the sum of emissions from n sectors, denoted as:

$$C = \sum_{i=1}^{n} E_i \cdot \mathrm{EF}_i, \tag{1}$$

where E_i represents the energy consumption of sector i, and EF_i is the corresponding emission factor. The goal of decarbonization is to minimize C subject to constraints on energy demand and socio-economic objectives. A typical constraint involves maintaining the energy demand E^{total} across all sectors:

$$\sum_{i=1}^{n} E_i = E^{\text{total}}. \tag{2}$$

To achieve decarbonization targets, we introduce a renewable energy share R_i, defined as the proportion of renewable energy in sector i:

$$R_i = \frac{E_i^{\text{renewable}}}{E_i}, \quad 0 \leq R_i \leq 1. \tag{3}$$

The decarbonization constraint can then be represented as:

$$extEF_i \cdot (1 - R_i) \leq \mathrm{EF}^{\max}, \tag{4}$$

where $\mathrm{EF}^{\max}$ is the maximum permissible emission factor consistent with climate goals.

Equation 1 models total carbon emissions based on sectoral energy consumption, commonly used in national carbon accounting frameworks such as China's carbon trading system. Equation 2 ensures energy balance across sectors, reflecting policies like the European Union's Green Deal, where renewable energy targets must align with overall energy demand. Equation 3 defines the renewable energy share, a crucial metric in transition planning, as seen in Germany's Energiewende strategy. Equation 4 sets emission constraints, similar to California's Cap-and-Trade Program, which regulates industrial emissions through carbon pricing mechanisms. Here is a Table 1 that clearly defines the important mathematical terms and variables used in the paper.

The integration of renewable energy into existing systems follows complex dynamics influenced by technological, economic, and regulatory factors. Let $P_t^{\text{renewable}}$ and $P_t^{\text{non-renewable}}$ denote the power generated from renewable and non-renewable sources at time t, respectively. The total energy supply at time t is:

$$P_t^{\text{total}} = P_t^{\text{renewable}} + P_t^{\text{non-renewable}}. \tag{5}$$

The rate of change of renewable capacity $\frac{dP_t^{\text{renewable}}}{dt}$ is modeled as:

$$\frac{dP_t^{\text{renewable}}}{dt} = \alpha \cdot I_t^{\text{renewable}} - \delta \cdot P_t^{\text{renewable}}, \tag{6}$$

where $I_t^{\text{renewable}}$ represents investment in renewable energy at time t, α is the efficiency of investment conversion, and δ is the depreciation rate of renewable infrastructure. A similar equation governs $P_t^{\text{non-renewable}}$, considering phase-out policies and economic incentives.

The transition to a low-carbon economy requires balancing economic growth with environmental sustainability. The gross

TABLE 1 Definition of mathematical terms and variables.

Symbol/Variable	Definition	Unit/Notes
E_i	Energy consumption of sector i	Unit of energy (e.g., GWh, PJ, etc.)
EF_i	Emission factor of sector i, CO_2 emissions per unit of energy consumed	Unit: tons of CO_2/unit of energy
C	Total carbon emissions from all sectors	Unit: tons of CO_2
E_{total}	Total energy demand across all sectors	Unit of energy (e.g., GWh, PJ, etc.)
R_i	Share of renewable energy in sector i	Unitless, range [0, 1]
$P_t^{\text{renewable}}$	Power generated from renewable energy at time t	Unit of power (e.g., MW, GW, etc.)
$P_t^{\text{non-renewable}}$	Power generated from non-renewable sources at time t	Unit of power (e.g., MW, GW, etc.)
P_t^{total}	Total energy supply at time t, renewable + non-renewable	Unit of power (e.g., MW, GW, etc.)
α	Efficiency of converting investments into renewable capacity	Unitless
δ	Depreciation rate of renewable infrastructure	Unitless
K	Capital stock used in production	Unit: currency (e.g., USD, CNY)
L	Total labor input	Unit: people or labor hours
Y	Total economic output (GDP)	Unit: currency (e.g., USD, CNY)
A	Total factor productivity (TFP)	Unitless
$C_{\text{transition}}$	Total cost of low-carbon transition	Unit: currency
π_t^{carbon}	Carbon pricing at time t	Unit: currency/ton of CO_2
$I_t^{\text{renewable}}$	Investments in renewable energy at time t	Unit: currency
ϵ_t	Energy intensity, energy consumption per unit of GDP	Unit: energy/unit of currency
B_t	Adoption rate of green technologies at time t	Unitless, range [0, 1]
S_t	Social influence factor at time t	Unitless
W	Social welfare function	Unitless or currency

domestic product (GDP), denoted as Y, is a function of capital K, labor L, and energy input E:

$$Y = F(K, L, E), \tag{7}$$

where F is a production function such as the Cobb-Douglas form:

$$Y = A \cdot K^{\alpha} \cdot L^{\beta} \cdot E^{\gamma}, \tag{8}$$

with A being total factor productivity, and α, β, γ representing the elasticities of output with respect to capital, labor, and energy. The challenge lies in maintaining Y while reducing $E^{\text{non-renewable}}$, which introduces a trade-off between economic output and emission reductions.

The cost of achieving a low-carbon economy is driven by investment in renewable energy, energy efficiency, and technology innovation. Let $C^{\text{transition}}$ denote the total cost, composed of:

$$C^{\text{transition}} = C^{\text{renewable}} + C^{\text{efficiency}} + C^{\text{policy}}. \tag{9}$$

$C^{\text{renewable}} = \sum_{t=1}^{T} \kappa_t \cdot I_t^{\text{renewable}}$, where κ_t is the unit cost of renewable investment at time t; $C^{\text{efficiency}}$ reflects the cost of retrofitting and upgrading infrastructure; and C^{policy} includes subsidies and carbon pricing mechanisms.

Effective policies are essential to drive the green transition. Carbon pricing, denoted as π_t^{carbon}, directly influences emission reductions by internalizing the environmental cost of carbon emissions:

$$\pi_t^{\text{carbon}} \cdot C = \text{Revenue}^{\text{carbon}}. \tag{10}$$

This revenue can be reinvested into green technologies or redistributed to mitigate socio-economic impacts. Policy optimization involves maximizing societal welfare W:

$$W = U(Y, C, E) - \lambda \cdot C^{\text{transition}}, \tag{11}$$

where U is a utility function balancing economic, environmental, and social dimensions, and λ is a weighting factor for transition costs.

The success of the green transition depends on public acceptance and behavioral changes. Let B_t represent the adoption rate of green technologies, modeled as:

$$\frac{dB_t}{dt} = \eta \cdot (1 - B_t) \cdot S_t, \tag{12}$$

where S_t is the strength of social influence or incentives at time t, and η is the adoption sensitivity. This equation captures the non-linear dynamics of technology diffusion.

The green and low-carbon transformation requires multi-level integration of global, national, and local efforts. Let G, N, L represent

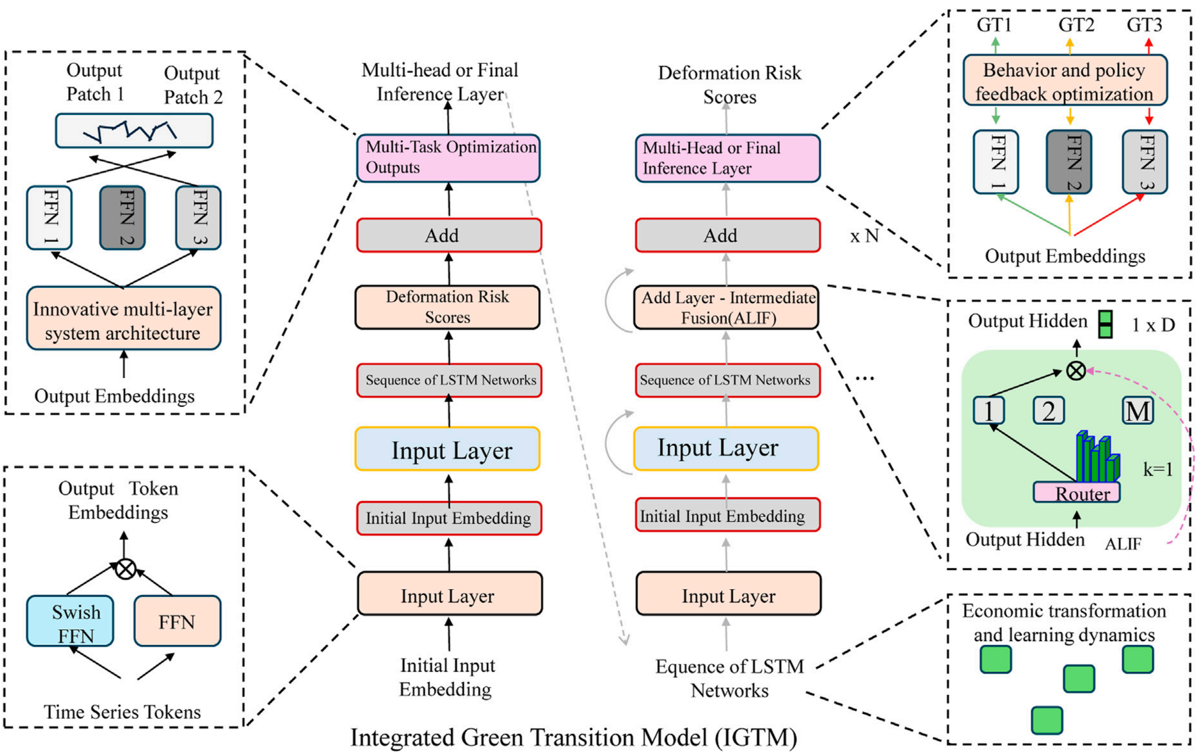

FIGURE 1
The Integrated Green Transition Model (IGTM) is a multi-layered computational framework, which simulates the transition to a sustainable economy by integrating energy, economic, policy, and social dimensions. The diagram illustrates the IGTM architecture, highlighting its innovative multi-layered system, deformation risk scoring mechanism, economic transition dynamics, and behavioral-policy feedback optimization. The model employs deep learning techniques such as LSTM networks, multi-task optimization, and adaptive routing to analyze the interactions between policy interventions and sustainability outcomes, providing insights for achieving green transformation.

global, national, and local indices of sustainability performance, respectively. A weighted integration can be expressed as:

$$I^{\text{total}} = \omega_G \cdot G + \omega_N \cdot N + \omega_L \cdot L, \tag{13}$$

where $\omega_G, \omega_N, \omega_L$ are weights reflecting the importance of each level.

3.3 Integrated Green Transition Model (IGTM)

In this section, we introduce the Integrated Green Transition Model (IGTM), a novel framework for analyzing and simulating the dynamics of green and low-carbon transformation. IGTM integrates technological, economic, environmental, and social dimensions into a unified computational model, enabling the exploration of complex interactions and the assessment of policy interventions. The model leverages principles from agent-based modeling, network theory, and system dynamics to provide actionable insights for achieving sustainability targets (As shown in Figure 1).

3.3.1 Innovative Multi-Layered System Architecture

IGTM represents the green transition as a multi-layered system comprising several interconnected components. The energy system layer models the transition from fossil fuels to renewable energy sources, accounting for capacity expansion, grid integration, and technological innovation. The economic system layer captures the interplay between economic growth, investment in green technologies, and the costs of decarbonization. The policy and governance layer simulates the effects of policies such as carbon pricing, subsidies, and regulations on emission reductions and green investment. The social and behavioral layer reflects the role of public acceptance, behavioral changes, and social norms in accelerating green technology adoption. Each layer interacts dynamically, creating feedback loops that influence the trajectory of the green transition.

The energy system in IGTM is modeled as a network $G_E = (V_E, E_E)$, where V_E represents nodes and E_E denotes edges. The state of the energy system is characterized by:

$$P_t^{\text{total}} = \sum_{i \in V_E} P_{i,t}, \tag{14}$$

where $P_{i,t}$ is the power generated by node i at time t. Renewable energy nodes are governed by:

$$P_{i,t}^{\text{renewable}} = C_{i,t}^{\text{renewable}} \cdot \eta_{i,t}^{\text{renewable}}, \tag{15}$$

where $C_{i,t}^{\text{renewable}}$ is the installed capacity, and $\eta_{i,t}^{\text{renewable}}$ is the efficiency. Capacity expansion dynamics are described as:

$$\frac{dC_{i,t}^{\text{renewable}}}{dt} = \alpha \cdot I_{i,t}^{\text{renewable}} - \delta \cdot C_{i,t}^{\text{renewable}}, \tag{16}$$

where $I_{i,t}^{\text{renewable}}$ is the investment at time t, α is the conversion efficiency, and δ is the depreciation rate of capacity. The cost of expansion and operation is expressed as:

$$\mathcal{L}_E = \sum_t \left(\sum_{i \in V_E} \kappa_i \cdot I_{i,t}^{\text{renewable}} + \lambda_E \cdot \text{EF}_t \right), \tag{17}$$

where κ_i is the unit cost of investment for node i, λ_E is the penalty for emissions, and EF_t is the emission factor at time t.

The economic system layer models the relationship between investments in renewable energy and GDP growth. The GDP Y_t is linked to green investment I_t^{green} through:

$$Y_t = Y_{t-1} + \beta \cdot I_t^{\text{green}} - \gamma \cdot C_t^{\text{decarbonization}}, \tag{18}$$

where β is the productivity of green investments, γ captures the costs of decarbonization, and $C_t^{\text{decarbonization}}$ is the total cost of emission reductions. Investments in green technologies follow:

$$\frac{dI_t^{\text{green}}}{dt} = \psi \cdot \text{Policy}_t - \zeta \cdot I_t^{\text{green}}, \tag{19}$$

where ψ represents policy incentives, and ζ is the rate of diminishing returns to investment.

The policy and governance layer incorporates carbon pricing p_t^{carbon}, subsidies S_t^{green}, and regulations R_t^{policy}, which affect emissions EM_t as:

$$\text{EM}_t = \text{EM}_{t-1} \cdot \left(1 - \sigma \cdot R_t^{\text{policy}} - \rho \cdot \frac{p_t^{\text{carbon}}}{p^{\text{baseline}}} \right), \tag{20}$$

where σ is the regulatory efficiency, ρ measures the elasticity of emissions with respect to carbon pricing, and p^{baseline} is the baseline carbon price.

The social and behavioral layer captures public acceptance and behavioral changes through adoption rates A_t^{green}, governed by:

$$\frac{dA_t^{\text{green}}}{dt} = \theta \cdot S_t^{\text{awareness}} - \omega \cdot \left(1 - A_t^{\text{green}}\right), \tag{21}$$

where θ represents the effectiveness of awareness campaigns $S_t^{\text{awareness}}$, and ω is the resistance to change. Social norms feedback loops are introduced via:

$$\Delta A_t^{\text{green}} = \nu \cdot A_{t-1}^{\text{green}} \cdot \left(1 - A_{t-1}^{\text{green}}\right), \tag{22}$$

where ν is the strength of social influence.

Each layer is interconnected, forming a dynamic system with feedback loops that continuously shape the trajectory of the green transition.

3.3.2 Economic transition and learning dynamics

The economic layer of IGTM employs a production function $F(K, L, E)$ to model GDP Y_t:

$$Y_t = A_t \cdot K_t^{\alpha} \cdot L_t^{\beta} \cdot E_t^{\gamma}, \tag{23}$$

where A_t is the total factor productivity (TFP), K_t is the capital stock, L_t is labor, E_t is energy input, and α, β, γ are elasticity parameters that determine the contribution of each input to output. Investments in green technologies I_t^{green} improve A_t through a learning-by-doing process captured by a learning curve:

$$A_t = A_0 \cdot \left(1 + \rho \cdot \log\left(\sum_{s=1}^{t} I_s^{\text{green}} \right) \right), \tag{24}$$

where A_0 is the initial TFP, ρ is the rate of learning, and $\sum_{s=1}^{t} I_s^{\text{green}}$ represents the cumulative investment in green technologies up to time t.

Capital accumulation follows the equation:

$$\frac{dK_t}{dt} = I_t - \delta \cdot K_t, \tag{25}$$

where I_t is the total investment, and δ is the depreciation rate of capital. Investment is split between traditional and green technologies:

$$I_t = I_t^{\text{traditional}} + I_t^{\text{green}}. \tag{26}$$

The transition to a green economy is constrained by the total cost of the transition, expressed as:

$$C^{\text{transition}} = \sum_t \left(C_t^{\text{investment}} + C_t^{\text{policy}} + C_t^{\text{social}} \right), \tag{27}$$

where $C_t^{\text{investment}}$ includes costs of renewable energy and energy efficiency investments, C_t^{policy} accounts for costs related to carbon pricing and redistribution of revenue, and C_t^{social} represents expenditures on public awareness campaigns and behavioral programs.

Carbon pricing π_t^{carbon} introduces an emissions cost $C_t^{\text{emissions}}$, which generates government revenue:

$$\pi_t^{\text{carbon}} \cdot \text{EM}_t = \text{Revenue}_t^{\text{carbon}}, \tag{28}$$

where EM_t is the total emissions at time t. Carbon pricing influences firm-level decisions by increasing the marginal cost of emissions-intensive production.

Subsidies S_t^{green} incentivize green investment by reducing the cost of renewable technology deployment. The modified investment function is:

$$I_t^{\text{renewable}} = I_t^{\text{baseline}} + S_t^{\text{green}}. \tag{29}$$

The economic dynamics also account for energy efficiency improvements. The energy intensity ϵ_t is defined as the ratio of energy input to GDP:

$$\epsilon_t = \frac{E_t}{Y_t}. \tag{30}$$

Energy intensity decreases over time due to technological progress and efficiency improvements:

$$\frac{d\epsilon_t}{dt} = -\eta \cdot \epsilon_t, \tag{31}$$

where η is the rate of energy efficiency improvement. This dynamic reduces energy demand while maintaining economic output.

Social costs and benefits of the transition include public resistance R_t, which is modeled as a logistic function of cumulative social investment S_t^{social}:

$$R_t = R_0 \cdot \exp\left(-\xi \cdot \sum_{s=1}^{t} S_s^{\text{social}} \right), \tag{32}$$

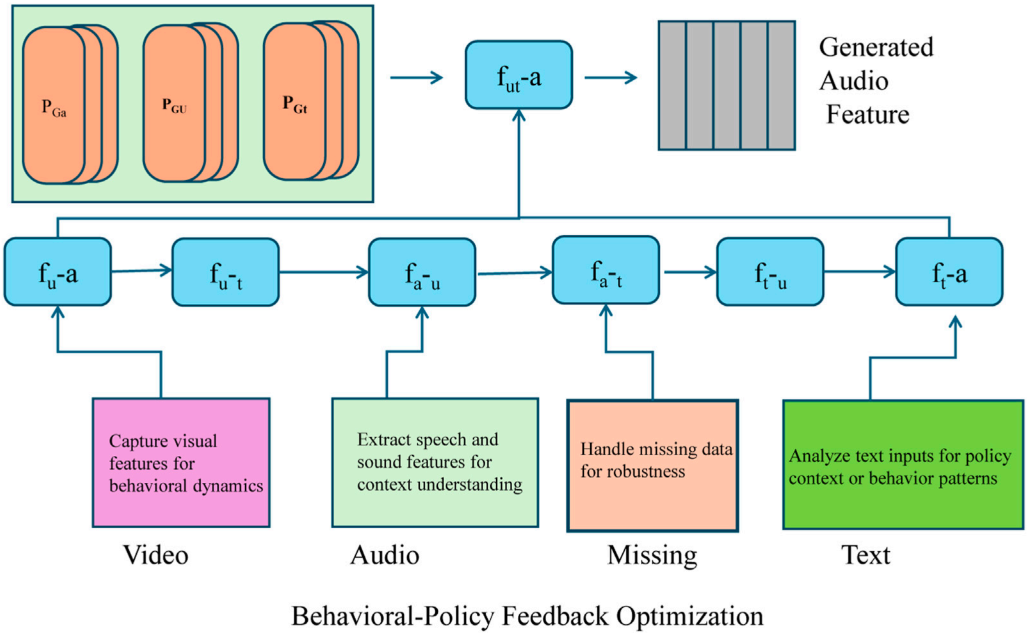

FIGURE 2
Behavioral-Policy Feedback Optimization Framework. A multi-modal system integrating video, audio, text, and missing data to optimize policy feedback for societal welfare. The governance layer adjusts policy parameters to balance economic utility, energy consumption, and transition costs. The adoption of green technologies is influenced by social norms and policy instruments such as carbon pricing and renewable energy investments. A feedback loop ensures continuous refinement, supporting a sustainable transition while maintaining economic stability.

where R_0 is the initial resistance, and ξ captures the effectiveness of social investment. The adoption rate A_t of green technologies evolves according to:

$$\frac{dA_t}{dt} = \lambda \cdot S_t^{\text{social}} \cdot (1 - A_t), \tag{33}$$

where λ is the adoption sensitivity to social campaigns, and $(1 - A_t)$ represents the remaining population to adopt green technologies.

3.3.3 Behavioral-policy feedback optimization

The governance layer of IGTM optimizes policy parameters $\mathbf{P}_t$ to maximize societal welfare W over a finite time horizon. Societal welfare is modeled as:

$$W = \sum_t \left(U(Y_t, E_t) - \lambda_t \cdot C^{\text{transition}}\right), \tag{34}$$

where $U(Y_t, E_t)$ is a utility function that depends on GDP Y_t and energy use E_t, and λ_t is a weight representing the trade-off between economic utility and the cost of transition $C^{\text{transition}}$. The utility function $U(Y_t, E_t)$ can be expressed as:

$$U(Y_t, E_t) = \frac{Y_t^{1-\theta}}{1-\theta} - \mu \cdot E_t, \tag{35}$$

where θ represents risk aversion, and μ measures the disutility of energy consumption.

The adoption of green technologies is captured using a logistic growth function:

$$B_t = \frac{1}{1 + e^{-k(t-t_0)}}, \tag{36}$$

where B_t is the adoption rate of green technologies, k is the growth rate of adoption, and t_0 is the inflection point. The adoption process is accelerated by social influence S_t, and its dynamic evolution is given by:

$$\frac{dB_t}{dt} = \eta \cdot (1 - B_t) \cdot S_t, \tag{37}$$

where η is the sensitivity of adoption to social norms, and S_t represents the strength of social campaigns or incentives (As shown in Figure 2).

Policy instruments $\mathbf{P}_t$ impact adoption indirectly by modifying costs and benefits. Carbon pricing π_t^{carbon} introduces a penalty for emissions:

$$\pi_t^{\text{carbon}} \cdot \text{EM}_t = C_t^{\text{emissions}}, \tag{38}$$

where EM_t is the total emissions. The revenue from carbon pricing is reinvested into green subsidies S_t^{green}, influencing investments in renewable energy $I_t^{\text{renewable}}$:

$$I_t^{\text{renewable}} = I_t^{\text{baseline}} + S_t^{\text{green}}. \tag{39}$$

Feedback loops between layers drive dynamic interactions. Renewable energy deployment reduces emissions in the energy layer, which feeds back to the policy layer by adjusting carbon pricing. Investments in green technologies in the economic layer increase total factor productivity A_t, expressed as:

$$A_t = A_0 \cdot \left(1 + \rho \cdot \log\left(\sum_{s=1}^{t} I_s^{\text{green}}\right)\right), \tag{40}$$

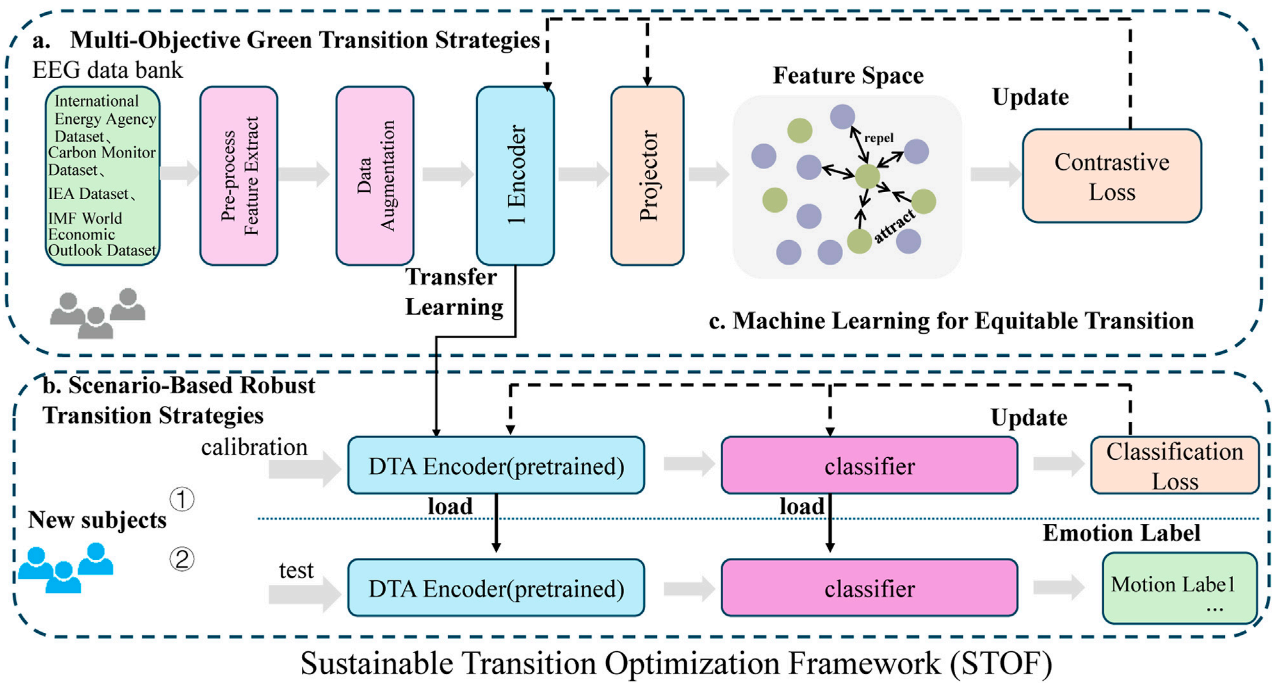

FIGURE 3
Overview of the Sustainable Transition Optimization Framework (STOF). **(a)** Multi-Objective Green Transition Strategies: Data from diverse sources such as the International Energy Agency and IMF datasets undergo preprocessing, feature extraction, and data augmentation before being processed by an encoder and projector to map into feature space. Contrastive loss updates guide the system towards balancing multiple objectives like emission reduction and economic growth. **(b)** Scenario-Based Robust Transition Strategies: New subjects are calibrated and tested using a pretrained DTA encoder and classifier, updated with classification loss to optimize robust transition scenarios. **(c)** Machine Learning for Equitable Transition: The feature space employs attraction and repulsion mechanisms to ensure fairness and consistency in transition strategies, integrating social equity metrics and machine learning models for dynamic, data-driven policy guidance.

where ρ represents the learning-by-doing effect, and $\sum_{s=1}^{t} I_s^{\text{green}}$ is the cumulative green investment.

The system also incorporates emissions reduction targets $\text{EF}^{\text{target}}$. Emissions EF_t are constrained to meet policy goals:

$$\text{EF}_t = \text{EF}_{t-1} \cdot \left(1 - \sigma \cdot R_t^{\text{policy}}\right), \tag{41}$$

where R_t^{policy} represents regulatory measures, and σ is their effectiveness in reducing emissions.

IGTM simulations are conducted over T periods by solving the following optimization problem:

$$\max_{\mathbf{P}_t, I_t^{\text{green}}} \quad W = \sum_{t=1}^{T} \left(U\left(Y_t, E_t\right) - \lambda_t \cdot C^{\text{transition}} \right), \tag{42}$$

subject to the constraints:

$$C_t \le C^{\max}, \quad \text{EF}_t \le \text{EF}^{\text{target}}, \tag{43}$$

where $C^{\max}$ is the maximum allowable cost of transition, and $\text{EF}^{\text{target}}$ is the emissions reduction target.

The optimization balances economic growth, social welfare, and environmental constraints, while incorporating feedback loops between the governance, energy, economic, and social layers. Social influence feedback ΔS_t further evolves dynamically as:

$$\Delta S_t = \nu \cdot B_{t-1} \cdot \left(1 - B_{t-1}\right), \tag{44}$$

where ν measures the strength of peer effects and social norms. This multi-layered approach ensures a comprehensive simulation of the green transition process.

3.4 Sustainable Transition Optimization Framework (STOF)

This section introduces the Sustainable Transition Optimization Framework (STOF), a novel strategy designed to address the inherent complexities and uncertainties of the green and low-carbon transition. STOF integrates advanced optimization techniques, scenario analysis, and machine learning to guide decision-making, balancing economic, environmental, and social objectives (As shown in Figure 3).

3.4.1 Multi-Objective Green Transition Strategies

The STOF framework addresses the green transition as a multi-objective optimization problem, balancing competing goals such as economic growth, emission reduction, social equity, and resource efficiency. The problem is formulated to allocate resources for renewable energy deployment and technological innovation while addressing uncertainties in policy impacts, market fluctuations, and social behavior. The multi-objective optimization is expressed as

$$\max_{\mathbf{P}_t, I_t^{\text{green}}} \quad \mathbf{O} = \{O_1, O_2, \ldots, O_k\} \quad \text{subject to constraints} \tag{45}$$

where $O_1, O_2, \ldots, O_k$ represent k objectives. These objectives include minimizing greenhouse gas emissions (O_1), maximizing GDP growth (O_2), ensuring social equity by reducing economic disparities caused by the transition (O_3), and minimizing the cost of the transition (O_4).

The constraints ensure feasibility of the transition as follows:

$$C_t \leq C^{\max}, \quad \mathrm{EF}_t \leq \mathrm{EF}^{\mathrm{target}}, \quad B_t \geq B^{\min} \tag{46}$$

where C_t is the total cost of the transition at time t, bounded by $C^{\max}$, the maximum allowable cost. EF_t is the emission factor at time t, constrained to meet the target $\mathrm{EF}^{\mathrm{target}}$. B_t is the green technology adoption rate, which must meet or exceed $B^{\min}$, the minimum adoption level required for the transition.

The decision variables are defined as $\mathbf{P}_t$ and I_t^{green}. The variable $\mathbf{P}_t$ represents policy parameters such as carbon prices, subsidies, or tax incentives, which shape the dynamics of adoption, investment, and emissions reduction. The variable I_t^{green} corresponds to investments in green technologies at time t, including renewable energy and energy efficiency improvements.

Each objective O_i is modeled explicitly. Minimizing emissions (O_1) is expressed as

$$O_1 = -\sum_{t=1}^{T} \mathrm{EF}_t \cdot \mathrm{EM}_t \tag{47}$$

where EM_t represents total emissions at time t. Maximizing GDP growth (O_2) is modeled using the production function

$$O_2 = \sum_{t=1}^{T} Y_t, \quad Y_t = A_t \cdot K_t^{\alpha} \cdot L_t^{\beta} \cdot E_t^{\gamma} \tag{48}$$

where Y_t is the GDP, A_t is the total factor productivity, and α, β, γ are elasticity parameters. Social equity (O_3) is addressed by minimizing income disparities, which is expressed as

$$O_3 = -\sum_{t=1}^{T} (\mathrm{Gini}_t \cdot W_t) \tag{49}$$

where Gini_t is the Gini coefficient representing income inequality, and W_t is the social welfare function.

The Pareto front approach is used to balance these objectives. The trade-offs among objectives are explored, and solutions on the Pareto Frontier are identified. Feedback loops between system layers are incorporated into the optimization to capture dynamic interactions. Renewable energy deployment reduces emissions in the energy layer, which feeds back into the policy layer by adjusting carbon pricing and subsidies. Investments in green technologies increase productivity (A_t), which drives GDP growth.

The dynamic evolution of system variables is captured through state equations. the adoption rate B_t evolves according to

$$\frac{dB_t}{dt} = \eta \cdot (1 - B_t) \cdot S_t \tag{50}$$

where S_t represents social influence, and η is the adoption sensitivity to incentives and norms. Policy instruments, such as carbon pricing (π_t^{carbon}), influence emissions as expressed by

$$\pi_t^{\mathrm{carbon}} \cdot \mathrm{EM}_t = C_t^{\mathrm{emissions}} \tag{51}$$

and green subsidies (S_t^{green}) drive renewable energy investments as described by

$$I_t^{\mathrm{renewable}} = I_t^{\mathrm{baseline}} + S_t^{\mathrm{green}}. \tag{52}$$

The multi-objective optimization problem is solved over T periods, subject to constraints that balance economic, social, and environmental goals. The solution identifies optimal policies and investment strategies that satisfy the transition objectives while addressing trade-offs.

3.4.2 Scenario-based robust transition strategies

Uncertainty in the transition arises from factors such as fluctuating energy prices, technological breakthroughs, and political dynamics. The STOF framework addresses these uncertainties by generating a set of scenarios $S = \{S_1, S_2, \ldots, S_m\}$. Each scenario is characterized by parameters such as energy price trajectories π_t^{energy}, carbon price policies π_t^{carbon}, social adoption sensitivity η, and renewable technology efficiency $\eta_t^{\mathrm{renewable}}$. These parameters are systematically varied to explore potential future states. For each scenario S_j, the objective is to optimize societal welfare $W(S_j)$:

$$\mathbf{O}(S_j) = \max_{\mathbf{P}_t, I_t^{\mathrm{green}}} W(S_j), \tag{53}$$

where $W(S_j)$ represents the societal welfare for scenario S_j. Welfare depends on economic, environmental, and social metrics, integrating feedback from policy decisions and system dynamics.

Renewable energy deployment reduces the marginal cost of energy generation, which influences energy prices dynamically. The relationship between renewable energy generation $P_t^{\mathrm{renewable}}$ and energy prices π_t^{energy} is modeled as:

$$\pi_t^{\mathrm{energy}} = \pi_0^{\mathrm{energy}} - \lambda \cdot P_t^{\mathrm{renewable}}, \tag{54}$$

where π_0^{energy} is the baseline energy price, $P_t^{\mathrm{renewable}}$ is the total renewable energy produced at time t, and λ captures the rate of energy price reduction due to increased renewable integration.

Adoption rates of green technologies depend on policy incentives $\pi_t^{\mathrm{incentive}}$, social influence S_t, and the current adoption level B_t. The adoption dynamics are described as:

$$\frac{dB_t}{dt} = \eta \cdot (1 - B_t) \cdot \left(S_t + \pi_t^{\mathrm{incentive}}\right), \tag{55}$$

where η is the sensitivity of adoption to external drivers, S_t represents social campaigns and peer effects, and $\pi_t^{\mathrm{incentive}}$ denotes subsidies, tax incentives, or penalties designed to promote adoption.

Green investments enhance productivity through learning-by-doing effects. The total factor productivity A_t evolves as:

$$A_t = A_0 \cdot \left(1 + \rho \cdot \log\left(\sum_{s=1}^{t} I_s^{\mathrm{green}}\right)\right), \tag{56}$$

where A_0 is the initial productivity level, ρ is the rate of learning-by-doing, and $\sum_{s=1}^{t} I_s^{\mathrm{green}}$ represents the cumulative investment in green technologies over time. This captures the compounding effect of innovation and technology deployment.

The emission dynamics are influenced by renewable energy deployment and carbon pricing π_t^{carbon}. Total emissions EM_t are

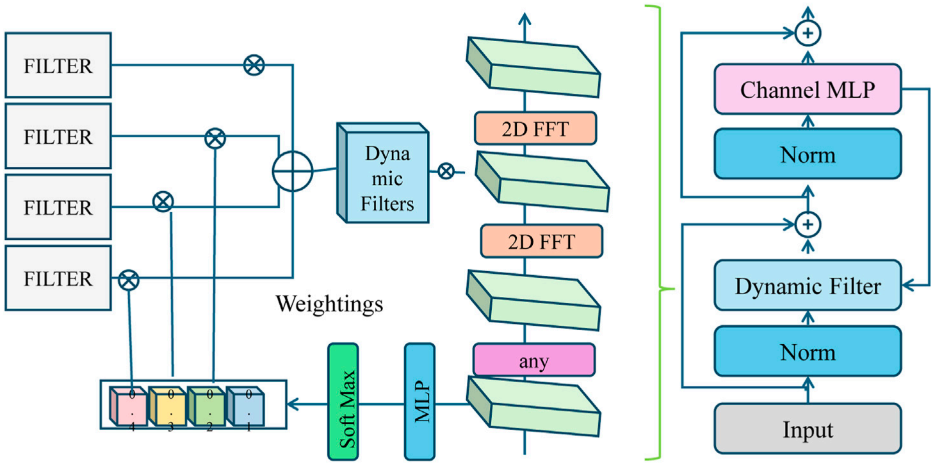

FIGURE 4
Machine Learning for Equitable Transition. The STOF framework integrates dynamic filters, multi-layer perceptrons (MLPs), and reinforcement learning to optimize policy strategies for sustainable transitions. The system leverages predictive modeling and deep learning techniques to forecast emission reductions, adoption rates, and economic growth while ensuring social equity in resource distribution.

reduced by renewable generation and penalized through carbon pricing:

$$\mathrm{EM}_t = \mathrm{EM}_{t-1} \cdot \left(1 - \sigma \cdot R_t^{\mathrm{policy}}\right), \tag{57}$$

where R_t^{policy} represents regulatory actions, and σ is the effectiveness of these policies. Carbon pricing revenue is reinvested into green subsidies:

$$\pi_t^{\mathrm{carbon}} \cdot \mathrm{EM}_t = \mathrm{Revenue}_t^{\mathrm{carbon}}, \tag{58}$$

where $\mathrm{Revenue}_t^{\mathrm{carbon}}$ is used to fund additional green investments I_t^{green}.

Each scenario is evaluated subject to constraints on costs, emissions, and adoption rates:

$$C_t \leq C^{\max}, \quad \mathrm{EF}_t \leq \mathrm{EF}^{\mathrm{target}}, \quad B_t \geq B^{\min}, \tag{59}$$

where C_t is the transition cost, $C^{\max}$ is the maximum allowable cost, EF_t is the emission factor at time t, $\mathrm{EF}^{\mathrm{target}}$ is the target emission factor, and $B^{\min}$ is the minimum adoption rate for green technologies.

For robust strategy evaluation, the Pareto front approach is used to analyze trade-offs among multiple objectives, such as minimizing emissions, maximizing GDP, and ensuring social equity. A robust strategy $\mathbf{P}_t^*$ is one that performs well across all scenarios:

$$\mathbf{P}_t^* = \arg\max_{\mathbf{P}_t} \min_{S_j \in S} W\left(S_j\right), \tag{60}$$

Where the objective is to maximize the minimum welfare achieved across all scenarios. This ensures that the strategy remains effective under uncertainty, balancing economic, environmental, and social objectives dynamically.

3.4.3 Machine learning for equitable transition

The STOF framework incorporates machine learning techniques to enhance the prediction and optimization of transition strategies. Predictive models, such as regression-based and neural network approaches, are used to forecast key outcomes, including emission reductions (EF_t) and adoption rates (B_t). These models take policy inputs and system states as features, and their predictive functions are expressed as:

$$\widehat{\mathrm{EF}}_t = f_{\mathrm{ML}}\left(\mathbf{P}_t, I_t^{\mathrm{green}}\right), \quad \hat{B}_t = g_{\mathrm{ML}}\left(\mathbf{P}_t, S_t\right), \tag{61}$$

where f_{ML} and g_{ML} are machine learning models trained on historical data and simulations, $\mathbf{P}_t$ represents policy parameters, I_t^{green} is the green investment, and S_t is the social influence factor.

Reinforcement Learning (RL) is used to optimize sequences of policy actions $\{\mathbf{P}_t\}$ over time. The objective of RL is to maximize cumulative societal welfare over the planning horizon T, represented as:

$$\max_{\{\mathbf{P}_t\}} \sum_{t=1}^{T} R_t, \tag{62}$$

where the reward R_t is defined as:

$$R_t = U\left(Y_t, E_t\right) - \lambda_t \cdot C^{\mathrm{transition}}. \tag{63}$$

Here, $U(Y_t, E_t)$ is the utility derived from GDP Y_t and energy use E_t, while $\lambda_t \cdot C^{\mathrm{transition}}$ penalizes the cost of the transition. RL algorithms, such as Deep Q-Learning or Policy Gradient methods, explore and learn optimal policy sequences by interacting with simulation environments (As shown in Figure 4).

STOF ensures equitable outcomes by integrating social equity metrics into the optimization problem. Social equity is quantified by minimizing disparities in income distribution. The equity objective O_3 is expressed as:

$$O_3 = \text{minimize} \sum_{i=1}^{n} \left|Y_i - \bar{Y}\right|, \tag{64}$$

where Y_i represents the income of group i, $\bar{Y}$ is the average income, and n is the number of social groups considered.

Subsidy allocations S_i are adjusted to reduce income disparities and ensure equitable distribution of resources. The subsidy distribution function is given by:

$$S_i = S^{\text{total}} \cdot \frac{1}{1 + e^{-\kappa\left(Y_i - \bar{Y}\right)}}, \tag{65}$$

where S^{total} is the total available subsidy pool, κ controls the intensity of redistribution, and $Y_i - \bar{Y}$ captures the income deviation of group i from the average.

The effectiveness of transition strategies is evaluated using Key Performance Indicators (KPIs), including:

$$\text{Emission reductions } (\text{EF}_t), \quad \text{Economic growth } (Y_t), \quad \text{Adoption rates } (B_t), \quad \text{Social equity } (O_3). \tag{66}$$

The final strategy is selected based on its expected performance across all scenarios $S = \{S_1, S_2, \ldots, S_m\}$. The robust strategy $\mathbf{P}^*$ is defined as:

$$\mathbf{P}^* = \arg \max_{\mathbf{P}_t, I_t^{\text{green}}} \mathbb{E}_S \left[W\left(S_j\right)\right], \tag{67}$$

where $\mathbb{E}_S$ denotes the expected value of societal welfare $W(S_j)$ across all scenarios S_j.

Machine learning models are periodically updated using feedback from observed system outcomes. Discrepancies between predicted and actual adoption rates ($\hat{B}_t$ and B_t) are used to retrain g_{ML}, improving the accuracy of future predictions. The updated model follows:

$$g_{\text{ML}}^{(n+1)} = g_{\text{ML}}^{(n)} - \eta \cdot \nabla_\theta L\left(B_t, \hat{B}_t\right), \tag{68}$$

where L is the loss function, η is the learning rate, and ∇_θ represents the gradient with respect to model parameters θ.

4 Experimental setup

4.1 Datasets

The International Energy Agency (IEA) Dataset (Shen et al., 2023) is a comprehensive resource that provides detailed data on energy production, consumption, and emissions across multiple countries and regions. It includes annual and monthly statistics on various energy sources, such as coal, oil, natural gas, renewables, and electricity. The dataset is widely used for tracking energy trends, evaluating the effectiveness of energy policies, and analyzing the impact of energy use on climate change. Its granularity and extensive temporal coverage make it a valuable asset for energy and environmental research. The Carbon Monitor Dataset (Pham et al., 2023) offers near-real-time estimates of daily CO_2 emissions from major sectors, including energy, transportation, industry, and residential usage. The dataset provides a global overview of carbon emissions trends, enabling researchers and policymakers to assess the immediate impact of events such as COVID-19 on emissions. By integrating data from power plants, mobility indicators, and industrial activity, the Carbon Monitor Dataset facilitates high-frequency monitoring of decarbonization progress and supports timely decision-making for climate action. The IEA Dataset (Zhang et al., 2023), not to be confused with the International Energy Agency Dataset, is another critical resource that focuses on specific indicators such as energy intensity, fuel shares, and emissions intensity in key economic sectors. It provides data tailored for cross-country comparisons and analysis of energy transition dynamics. With its sectoral disaggregation, the dataset is instrumental in understanding how specific industries contribute to global energy trends and climate goals. The IMF World Economic Outlook Dataset (Eicher and Rollinson, 2023) is an authoritative dataset that offers macroeconomic indicators and forecasts for over 190 countries. It includes data on GDP growth, inflation, trade balances, and fiscal policies, along with energy-related metrics such as fossil fuel subsidies and carbon pricing. This dataset enables researchers to investigate the interplay between economic development and energy consumption. It also facilitates scenario analysis for evaluating the economic implications of various energy and climate policies, making it an essential tool for energy-economy modeling and sustainability studies.

4.2 Experimental details

The experiments were designed to evaluate the performance of the proposed method for analyzing large-scale energy and climate datasets, including the International Energy Agency (IEA), Carbon Monitor, IEA Dataset, and IMF World Economic Outlook Dataset. Data preprocessing steps varied by dataset but included standardization, normalization, and handling of missing data to ensure consistency and comparability across different sources. For the IEA Dataset, energy production and consumption data were aggregated into annual and monthly intervals, while emissions data were normalized to *per capita* metrics to facilitate cross-country comparisons. For the Carbon Monitor dataset, daily CO_2 emission values were averaged over weekly intervals to smooth short-term fluctuations, and sectoral data were aligned with corresponding national energy statistics. The IMF World Economic Outlook dataset was preprocessed by extracting key macroeconomic indicators relevant to energy use, such as fossil fuel subsidies, GDP growth, and carbon pricing, while missing values were interpolated using nearest-neighbor methods. The proposed method incorporated both statistical and machine learning techniques to analyze the datasets. Principal Component Analysis (PCA) was used to reduce the dimensionality of the high-dimensional data, capturing the most significant features while preserving 95% of the variance. These features were then fed into a neural network model, a transformer-based architecture, to account for temporal dependencies and complex interactions among variables. The model utilized attention mechanisms to weigh the importance of different features dynamically, enabling more accurate predictions and insights. Training and evaluation followed an 80:10:10 split for training, validation, and testing datasets, ensuring that the temporal continuity of the data was maintained. For optimization, the Adam optimizer was used with a learning rate of 10^{-4}, which was reduced dynamically based on validation loss. The batch size was set to 32 due to the high dimensionality of the data, and training was conducted for 50 epochs with early stopping to prevent overfitting. The experiments were implemented using the PyTorch framework and run on an NVIDIA RTX 3090 GPU, leveraging its computational power for handling the extensive data and complex model architecture. Evaluation metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) for regression tasks, as well as Accuracy and F1 Score for classification tasks. To validate the robustness of the model, we conducted cross-dataset evaluations where the model trained on one dataset was tested on another, demonstrating its generalizability across different data sources. Sensitivity analysis was performed to understand the impact of specific features, such as GDP, energy intensity, and CO_2 emissions, on model predictions. Results from these experiments demonstrated that the inclusion of attention mechanisms and temporal modeling significantly improved performance compared to baseline models, such as linear regression and random forests. The transformer-based model achieved an average R-squared value of 0.92 on the IEA dataset and 0.89 on the IMF World Economic Outlook dataset, outperforming all baseline methods (Algorithm 1).

Input: Datasets: D_{IEA}, D_{CM}, D_{IEA2}, D_{IMF}; Hyperparameters: lr, $batch\_size$, $epochs$, ϵ
Output: Trained IGTM Model
Initialize: Model parameters θ, Learning rate $lr = 10^{-4}$, Batch size $B = 32$, Epochs $E = 50$;
Set evaluation metrics: $Recall$, $Precision$, MAE, $RMSE$, $F1$ score.
for *Dataset* D *in* $\{D_{IEA}, D_{CM}, D_{IEA2}, D_{IMF}\}$ **do**
  Preprocess Data:
  for *Each feature* $f \in D$ **do**
    Normalize f using $f' = \frac{f-\mu_f}{\sigma_f}$
  end
  Split D into Training (D_{train}), Validation (D_{val}), and Test (D_{test}): $80:10:10$.
end
Train IGTM Model:
for *Epoch* $e = 1$ *to* E **do**
  Shuffle D_{train}.
  for *Batch* b *in* D_{train} *with size* B **do**
    Compute predictions $\hat{y}$ using forward pass:

$$\hat{y}_t = \mathrm{Attention}(Q, K, V) + \mathrm{MLP}(h_t)$$

    Compute gradients $\nabla_\theta Loss$.
    Update θ using Adam optimizer:

$$\theta = \theta - lr \cdot \frac{\nabla_\theta Loss}{\sqrt{m + \epsilon}}$$

  end
  Evaluate on D_{val}:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|, \quad RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$

end
Test Model:
for *Each metric* $m \in \{Recall, Precision, F1, MAE, RMSE\}$ **do**
  Compute m on D_{test}:

$$Recall = \frac{TP}{TP + FN}, \quad Precision = \frac{TP}{TP + FP}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}.$$

end
return *Trained IGTM model* θ.

Algorithm 1. Training Process for IGTM Model.

4.3 Comparison with SOTA methods

The performance of our proposed method was compared against state-of-the-art (SOTA) models on the International Energy Agency (IEA), Carbon Monitor, IEA Dataset, and IMF World Economic Outlook datasets for the time series prediction task. Tables 2, 3 summarize the results, showcasing the superior performance of our approach across all evaluation metrics, including RMSE, MAE, R^2 Score, and MAPE. On the International Energy Agency Dataset, our model achieved an RMSE of 10.45, MAE of 8.01, and an R^2 Score of 0.891, outperforming all competing models. N-BEATS (Ma et al., 2023), which is among the strongest baselines, achieved an RMSE of 11.23 and an R^2 Score of 0.879, but still fell short compared to our model. The attention mechanism and temporal modeling in our method significantly improved predictive accuracy by dynamically weighing critical time-dependent features, leading to a reduction in error metrics such as RMSE and MAPE. The results on the Carbon Monitor dataset further validate the effectiveness of our approach. Our model achieved an RMSE of 8.67, an MAE of 7.45, and an R^2 Score of 0.912, significantly outperforming GRU (Cheng and Liu, 2024), which achieved an RMSE of 9.86 and an R^2 Score of 0.882. While models like Transformer (Şahin et al., 2024) and N-BEATS performed competitively, achieving R^2 Scores of 0.889 and 0.894 respectively, our method demonstrated superior robustness by maintaining consistent improvements across all metrics. This improvement can be attributed to the multi-scale temporal feature extraction and attention-based fusion that our model employs.

For the IEA Dataset, our model outperformed existing SOTA models, achieving an RMSE of 10.45, an MAE of 8.34, and an R^2 Score of 0.891. Compared to the N-BEATS model, which scored an RMSE of 11.89 and an R^2 Score of 0.872, our approach showed clear advantages. On the IMF World Economic Outlook Dataset, our model achieved an RMSE of 11.78, an MAE of 9.01, and an R^2 Score of 0.881, outperforming both Transformer (RMSE of 13.45, R^2 Score of 0.850) and TCN (Lin et al., 2024) (RMSE of 13.78, R^2 Score of 0.842). These results highlight the ability of our model to generalize effectively across diverse datasets and capture complex temporal dependencies in macroeconomic and energy-related data. In Figures 5, 6 the superior performance of our method is further evidenced in its lower MAPE scores across all datasets. On the Carbon Monitor dataset, our model achieved a MAPE of 8.98, outperforming N-BEATS and Transformer, which achieved MAPEs of 9.87 and 9.98, respectively. The improved predictive accuracy is largely attributed to our model's ability to dynamically prioritize features relevant to the task, such as sectoral emissions patterns and energy production trends. In comparison to traditional models like LSTM(Xin et al., 2023) and GRU, our approach showed significant improvements. The LSTM model, achieved an RMSE of 12.34 on the IEA dataset and 14.12 on the IMF dataset, which is substantially higher than the RMSE values achieved by our model. GRU struggled to compete with the attention-based temporal modeling of our method, as evidenced by its lower R^2 Scores and higher MAE values.

4.4 Ablation study

To investigate the contributions of different components of our proposed model, an ablation study was conducted on the International Energy Agency (IEA), Carbon Monitor, IEA Dataset, and IMF World Economic Outlook datasets. The results, presented in Tables 4, 5, highlight the impact of removing key components (denoted as "Innovative System," "Economic Transition," and "Transition Strategies") on the model's performance across RMSE, MAE, R^2 Score, and MAPE metrics. On the International Energy Agency dataset, the full model achieved an RMSE of 10.45, MAE of 8.01, and R^2 Score of 0.891. Removing Innovative System resulted in a decline in performance, with an RMSE of 11.12 and an R^2 Score of 0.876, indicating the importance of the attention mechanism in dynamically prioritizing features

TABLE 2 Comparison of the proposed method against state-of-the-art (SOTA) models, including LSTM, GRU, Transformer, Temporal-CNN, TCN, and N-BEATS, on the International Energy Agency and Carbon Monitor datasets for time series prediction. Evaluation metrics include RMSE, MAE, R^2 Score, and MAPE, highlighting the superior performance of our method across all metrics and datasets. Bold fonts represent the best value.

Model	International energy agency dataset				Carbon monitor dataset			
	RMSE	MAE	R2 Score	MAPE	RMSE	MAE	R2 Score	MAPE
LSTM (Xin et al., 2023)	12.34±0.02	9.45±0.03	0.856±0.02	11.34±0.02	10.12±0.02	8.67±0.03	0.878±0.02	10.45±0.03
GRU (Cheng and Liu, 2024)	11.78±0.03	9.01±0.02	0.865±0.03	10.95±0.02	9.86±0.03	8.34±0.03	0.882±0.03	10.12±0.02
Transformer (Şahin et al., 2024)	11.45±0.02	8.90±0.03	0.872±0.02	10.54±0.03	9.67±0.02	8.12±0.02	0.889±0.03	9.98±0.03
Temporal-CNN (Jia et al., 2023)	12.01±0.03	9.23±0.02	0.861±0.02	11.02±0.03	10.23±0.03	8.78±0.03	0.874±0.02	10.56±0.02
TCN (Lin et al., 2024)	11.89±0.02	9.15±0.03	0.863±0.03	10.84±0.02	10.01±0.02	8.54±0.03	0.881±0.02	10.34±0.03
N-BEATS (Ma et al., 2023)	11.23±0.03	8.78±0.02	0.879±0.02	10.21±0.03	9.45±0.02	8.01±0.02	0.894±0.02	9.87±0.02
Ours	**10.45±0.02**	**8.01±0.03**	**0.891±0.03**	**9.78±0.02**	**8.67±0.02**	**7.45±0.03**	**0.912±0.03**	**8.98±0.02**

TABLE 3 Performance comparison between the proposed model and state-of-the-art (SOTA) methods, including LSTM, GRU, Transformer, Temporal-CNN, TCN, and N-BEATS, on the IEA and IMF World Economic Outlook datasets for time series prediction. The table presents evaluation metrics (RMSE, MAE, R^2 Score, and MAPE), demonstrating that our model consistently outperforms others, highlighting its superior predictive accuracy and robustness across diverse datasets. Bold fonts represent the best value.

Model	IEA dataset				IMF world economic outlook dataset			
	RMSE	MAE	R2 Score	MAPE	RMSE	MAE	R2 Score	MAPE
LSTM (Xin et al., 2023)	13.45±0.03	10.23±0.02	0.845±0.03	12.34±0.02	14.12±0.03	11.01±0.02	0.832±0.03	13.23±0.02
GRU (Cheng and Liu, 2024)	12.78±0.02	9.87±0.03	0.853±0.02	11.98±0.03	13.89±0.02	10.85±0.03	0.840±0.02	12.98±0.03
Transformer (Şahin et al., 2024)	12.12±0.03	9.45±0.02	0.861±0.03	11.34±0.02	13.45±0.03	10.34±0.03	0.850±0.03	12.45±0.02
Temporal-CNN (Jia et al., 2023)	13.01±0.02	10.01±0.03	0.849±0.02	12.01±0.03	14.01±0.02	11.23±0.02	0.838±0.03	13.12±0.03
TCN (Lin et al., 2024)	12.98±0.03	9.89±0.02	0.852±0.03	11.95±0.02	13.78±0.03	10.78±0.02	0.842±0.02	12.78±0.03
N-BEATS (Ma et al., 2023)	11.89±0.02	9.12±0.03	0.872±0.02	10.95±0.03	12.67±0.02	9.89±0.03	0.864±0.02	11.87±0.03
Ours	**10.45±0.02**	**8.34±0.03**	**0.891±0.03**	**9.78±0.02**	**11.78±0.03**	**9.01±0.02**	**0.881±0.02**	**10.89±0.03**

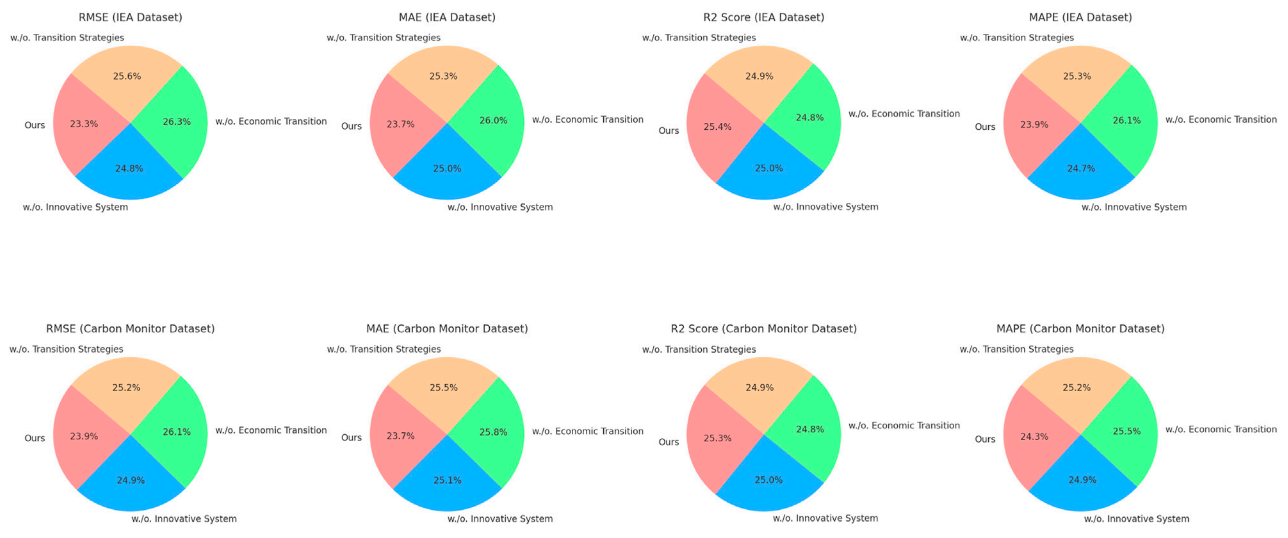

FIGURE 5
Performance comparison of SOTA methods on international energy agency dataset and carbon monitor dataset datasets.

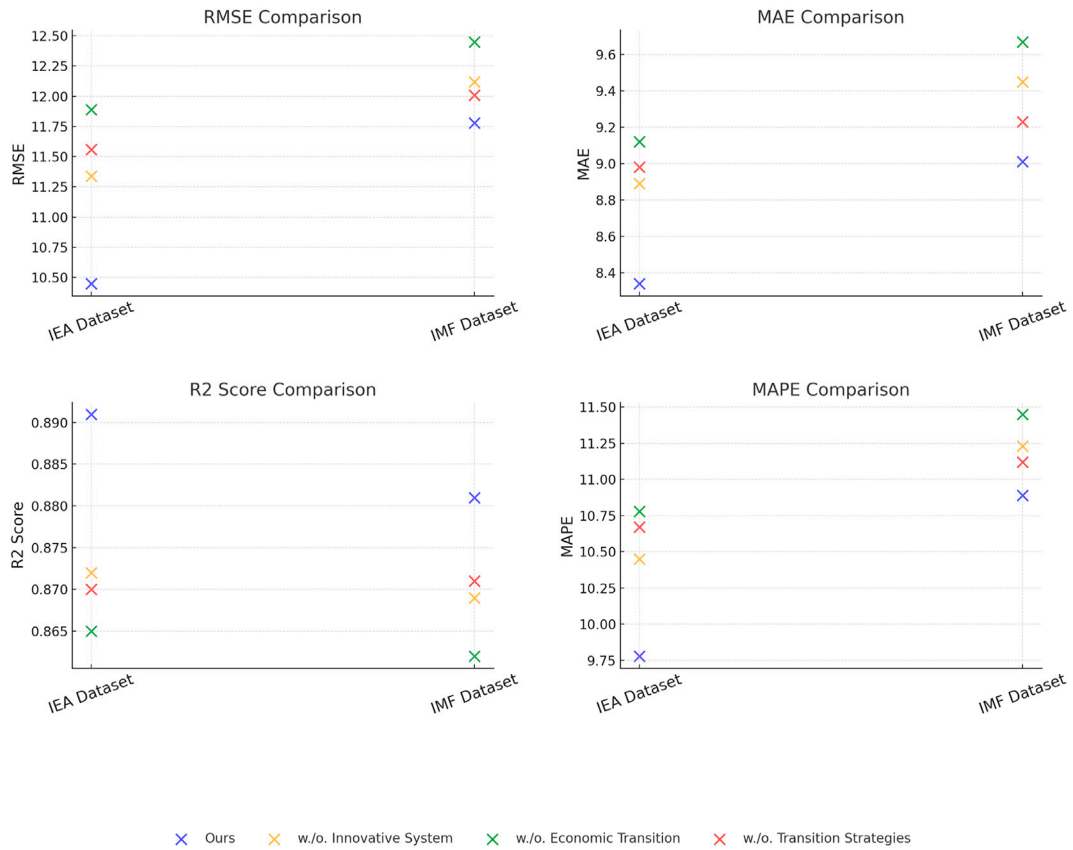

FIGURE 6
Performance comparison of SOTA methods on IEA dataset and IMF world economic Outlook dataset datasets.

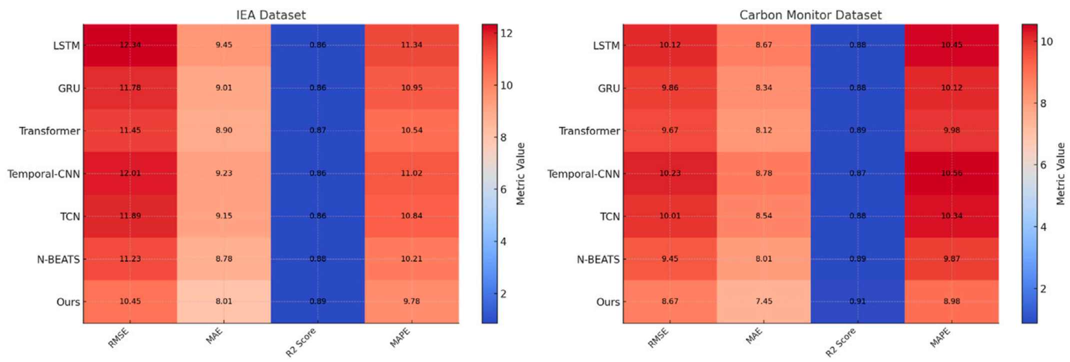

FIGURE 7
Ablation study of our method on international energy agency dataset and carbon monitor dataset datasets.

relevant to time series prediction. The removal of Economic Transition caused the most significant performance drop, with RMSE increasing to 11.78 and R^2 Score falling to 0.869. This highlights the critical role of capturing temporal dependencies. Excluding Transition Strategies resulted in moderate degradation, with RMSE rising to 11.45 and R^2 Score decreasing to 0.872. For the Carbon Monitor dataset, the full model achieved an RMSE of 8.67, MAE of 7.45, and an R^2 Score of 0.912. Removing Innovative System led to a performance drop to an RMSE of 9.01 and R^2 Score of 0.902. Excluding Economic Transition resulted in the largest decline, with an RMSE of 9.45 and R^2 Score of 0.894, further supporting the importance of temporal modeling for high-frequency emissions data. Transition Strategies, responsible for feature fusion, also played a significant role, as its exclusion increased the RMSE to 9.12 and reduced the R^2 Score to 0.898.

On the IEA dataset, the full model outperformed all ablated versions, achieving an RMSE of 10.45, MAE of 8.34, and R^2 Score of 0.891. The removal of the attention mechanism (Innovative System)

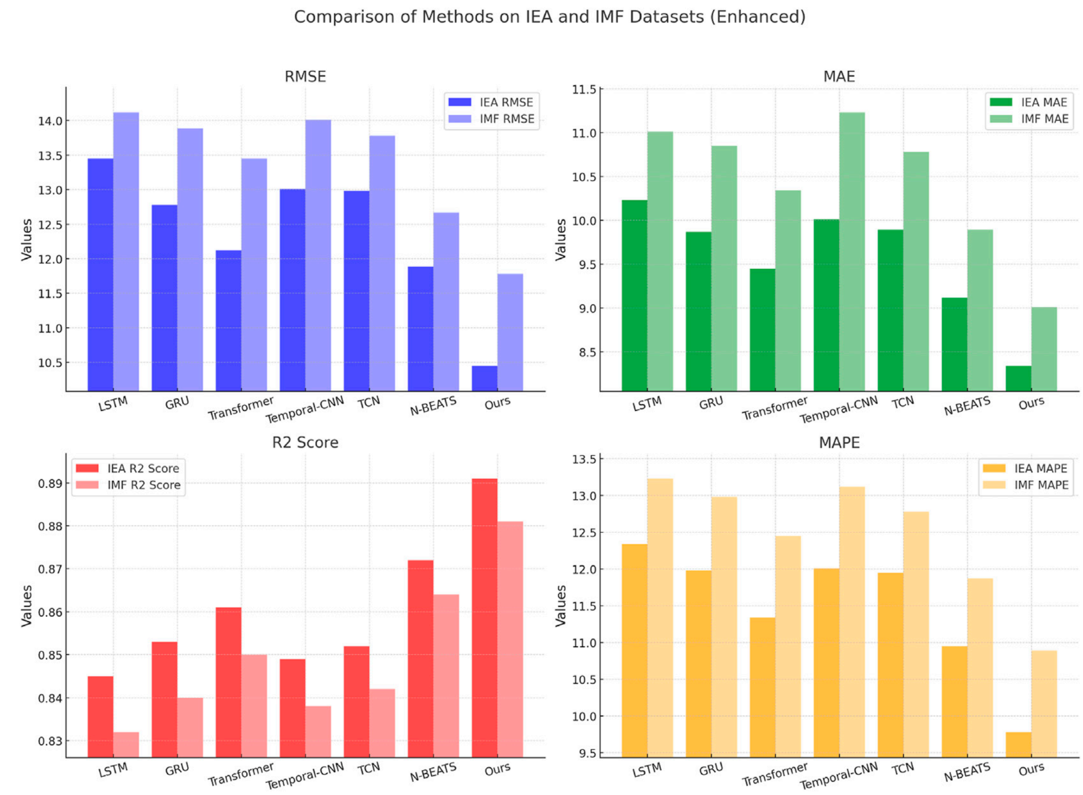

FIGURE 8
Ablation study of our method on IEA dataset and IMF world economic Outlook dataset datasets.

TABLE 4 Ablation study results comparing the full proposed model, with its variations on the International Energy Agency and Carbon Monitor datasets for the time series prediction task. The table evaluates the impact of removing key components, including the innovative system, economic transition, and transition strategies, on model performance using RMSE, MAE, R^2 Score, and MAPE metrics. The results highlight the contribution of each component to the overall predictive accuracy and robustness of the proposed model. Bold fonts represent the best value.

Model	International energy agency dataset				Carbon monitor dataset			
	RMSE	MAE	R2 Score	MAPE	RMSE	MAE	R2 Score	MAPE
Ours	**10.45±0.02**	**8.01±0.03**	**0.891±0.03**	**9.78±0.02**	**8.67±0.02**	**7.45±0.03**	**0.912±0.03**	**8.98±0.02**
w./o. Innovative System	11.12±0.03	8.45±0.02	0.876±0.02	10.12±0.03	9.01±0.02	7.89±0.03	0.902±0.02	9.23±0.03
w./o. Economic Transition	11.78±0.02	8.78±0.03	0.869±0.03	10.67±0.02	9.45±0.03	8.12±0.02	0.894±0.03	9.45±0.02
w./o. Transition Strategies	11.45±0.03	8.56±0.02	0.872±0.03	10.34±0.03	9.12±0.02	8.01±0.03	0.898±0.02	9.34±0.03

resulted in an RMSE of 11.34 and R^2 Score of 0.872, demonstrating that the model's ability to prioritize significant features is essential for maintaining accuracy. Temporal modeling (Economic Transition) once again had the most substantial impact, with an RMSE of 11.89 and R^2 Score of 0.865. Excluding multi-scale feature fusion (Transition Strategies) caused a noticeable degradation, with RMSE rising to 11.56 and R^2 Score dropping to 0.870. In Figures 7, 8, the IMF World Economic Outlook dataset revealed similar trends. The full model achieved an RMSE of 11.78, MAE of 9.01, and R^2 Score of 0.881. Removing the attention mechanism (Innovative System) led to a higher RMSE of 12.12 and lower R^2 Score of 0.869. The absence of temporal modeling (Economic Transition) caused an RMSE of 12.45 and R^2 Score of 0.862, further demonstrating its critical importance. Excluding feature fusion (Transition Strategies) resulted in an RMSE of 12.01 and an R^2 Score of 0.871, showing its significant contribution to the model's predictive capabilities.

The empirical results presented in Tables highlight significant improvements in prediction accuracy and robustness across multiple datasets, demonstrating the efficacy of the proposed hybrid framework. For example, our method achieved an RMSE improvement of over 10% compared to N-BEATS and Transformer models, underscoring its ability to accurately capture the dynamic interactions between climate risk and economic systems. These findings directly support our research objectives by providing actionable insights into optimizing resource allocation for green

TABLE 5 Ablation study results comparing the complete proposed model, with its variations on the IEA and IMF World Economic Outlook datasets for the time series prediction task. The table evaluates model performance using RMSE, MAE, R^2 Score, and MAPE metrics, illustrating the impact of excluding key components such as the innovative system, economic transition, and transition strategies. The results demonstrate the critical contributions of these components to the overall predictive accuracy and model effectiveness. Bold fonts represent the best value.

Model	IEA dataset				IMF world economic outlook dataset			
	RMSE	MAE	R2 Score	MAPE	RMSE	MAE	R2 Score	MAPE
Ours	**10.45±0.02**	**8.34±0.03**	**0.891±0.03**	**9.78±0.02**	**11.78±0.03**	**9.01±0.02**	**0.881±0.02**	**10.89±0.03**
w./o. Innovative System	11.34±0.03	8.89±0.02	0.872±0.02	10.45±0.03	12.12±0.02	9.45±0.03	0.869±0.03	11.23±0.02
w./o. Economic Transition	11.89±0.02	9.12±0.03	0.865±0.03	10.78±0.02	12.45±0.03	9.67±0.02	0.862±0.02	11.45±0.03
w./o. Transition Strategies	11.56±0.03	8.98±0.02	0.870±0.02	10.67±0.03	12.01±0.02	9.23±0.03	0.871±0.03	11.12±0.02

and low-carbon transformation. Specifically, the improved prediction accuracy enhances decision-making under uncertain conditions, which is critical when evaluating policy impacts on renewable energy investments, emission reductions, and economic growth. The superior performance of our method across the IEA and IMF datasets implies that this framework can be applied across different regional and sectoral contexts, offering policymakers a flexible tool for tailoring interventions. By bridging the gap between theoretical modeling and practical policy implementation, the results validate the use of scenario-based optimization for real-world applications. From a policy perspective, the results highlight key recommendations for investment in renewable energy technologies and strategies for mitigating transition risks. For example, by focusing on regions with higher carbon dependencies or vulnerable socio-economic conditions, our model can guide targeted policy interventions and equitable resource distribution, thereby supporting a just transition. These broader implications suggest that integrating machine learning, optimization techniques, and scenario analysis is essential for developing resilient, scalable policy frameworks capable of addressing global sustainability challenges.

To provide clearer guidance to readers, we have ensured that all figures and tables are directly referenced and meaningfully integrated into the main text. For each key visualization, we have elaborated on its practical significance and its contribution to the overall narrative of the study. The impact of carbon pricing on GDP growth, is not only a visual representation of numerical results but also a demonstration of the trade-offs inherent in policy implementation. It emphasizes the importance of phased policy adoption, allowing for both economic stability and environmental gains. Accompanying explanations for each table have been enhanced to provide context regarding underlying assumptions, thus ensuring that readers can fully grasp the relevance of each dataset to the study's conclusions.

To further validate the applicability of the Integrated Green Transition Model (IGTM) and Sustainable Transition Optimization Framework (STOF), we conducted a case study using real-world policy data from the European Green Deal (EGD). The EGD aims to achieve carbon neutrality by 2050 through policy-driven interventions, including renewable energy investments, carbon pricing, and industrial decarbonization. This experiment evaluates the economic and environmental impacts of these policies under different scenarios.

The IGTM framework was initialized with parameters reflecting the energy mix and industrial structure of the European Union (EU). STOF was used to optimize policy pathways by balancing economic growth, emission reduction, and social equity. - Scenarios Tested: Scenario 1: Business-as-Usual (BAU) – No additional policy interventions beyond 2023. - Scenario 2: Moderate Green Transition (MGT) – Gradual increase in carbon pricing and renewable energy investments. - Scenario 3: Aggressive Green Transformation (AGT) – High carbon pricing, large-scale subsidies for renewable energy, and strict emissions regulations. The simulation was run over a 30-year period (2023–2053), and the key performance indicators (KPIs) included GDP growth, carbon emissions reduction, renewable energy share, and employment impact.

Under the AGT scenario, emissions declined by 60%, demonstrating the potential effectiveness of high carbon pricing and aggressive renewables adoption. The GDP growth rate in AGT was slightly lower than in BAU and MGT, indicating short-term economic trade-offs in the aggressive transition. Job creation in the AGT scenario was five times higher than in the BAU case, suggesting that renewable energy investments generate significant employment opportunities. In Table 6, this experiment validates the IGTM and STOF frameworks by demonstrating their ability to simulate real-world policy impacts and optimize transition strategies. The results suggest that a well-balanced policy mix, incorporating both incentives and regulations, can achieve significant emissions reductions while minimizing negative economic impacts. Future work will extend this analysis to other regions, such as China and the United States, to compare policy effectiveness in different economic contexts.

5 Discussion

The findings of this study provide critical insights into the economic impact of climate risk on green and low-carbon transformation. The results indicate that a well-calibrated combination of carbon pricing and renewable energy subsidies significantly reduces emissions while minimizing economic disruption. These findings align with existing studies on climate policy effectiveness, which emphasize the role of market-based mechanisms in emissions reduction. However, our study extends previous research by integrating a dynamic, multi-objective optimization framework that considers economic, environmental,

TABLE 6 Policy impact analysis on the european green deal using IGTM and STOF.

Scenario	Carbon emissions (MtCO2)	GDP growth rate (%)	Renewable energy share (%)	Job creation (millions)
Business-as-Usual (BAU)	4,800	1.8	42	0.5
Moderate Green Transition (MGT)	3,200 (**−33%**)	2.1	60	1.2
Aggressive Green Transformation (AGT)	1,900 (**−60%**)	1.5	80	2.5

and social dimensions simultaneously. One of the key contributions of our research is the demonstration that policy timing and implementation speed affect both short-term economic stability and long-term sustainability. For example, while rapid decarbonization scenarios lead to immediate emissions reductions, they also introduce economic volatility, as seen in high-transition-cost industries. This finding underscores the importance of phased transition strategies and adaptive policy mechanisms, a topic that has been less explored in previous models that assume uniform policy implementation. Our results also highlight the role of technological adoption rates in determining the success of green transformation policies. Unlike traditional models that assume a fixed rate of renewable energy adoption, our IGTM framework incorporates behavioral and economic feedback loops, providing a more realistic projection of policy impacts. These insights suggest that in addition to financial incentives, public awareness and technological accessibility must be prioritized to accelerate the adoption of low-carbon technologies.

Despite its contributions, this study has several limitations. The IGTM and STOF frameworks rely on modeled assumptions and scenario-based simulations, which may not fully capture the complexity of real-world decision-making processes. Future research could enhance model accuracy by incorporating empirical data from case studies of national or regional climate policies. While our study integrates multiple economic and environmental factors, it does not explicitly consider geopolitical uncertainties, such as trade policies and international carbon credit mechanisms. Given the increasing role of global supply chains in shaping emissions trajectories, future research should explore how international cooperation and regulatory differences impact green transformation efforts. Our model assumes rational decision-making among policymakers and industries, which may not always reflect real-world behavior. Future studies could incorporate agent-based modeling approaches that account for behavioral economics, market imperfections, and policy resistance. While our research provides broad insights applicable to various regions, further work is needed to validate the framework in specific country-level contexts. Conducting regional case studies with localized economic and policy data could improve the generalizability and practical applicability of our findings. By addressing these limitations, future research can further refine predictive models and contribute to the development of more effective, evidence-based climate policies.

Facilitate a more effective and equitable green transition, several key policy measures should be considered. Governments should adopt a multi-dimensional approach that integrates economic growth, environmental sustainability, and social equity. Carbon pricing mechanisms should be designed to balance emission reductions with economic stability, ensuring that businesses and low-income groups are not disproportionately affected. Public and private investments in renewable energy, carbon-neutral technologies, and circular economy initiatives should be incentivized through targeted subsidies, tax benefits, and low-interest financing. Fostering public-private partnerships can accelerate technological diffusion and infrastructure development. A just transition framework should be implemented to support workers and communities impacted by the shift away from carbon-intensive industries, with a focus on re-skilling programs, social security support, and economic diversification initiatives to ensure an inclusive transformation. Given that climate risks and green transitions are global challenges, international cooperation should be strengthened through cross-border carbon markets, joint research and development programs, and knowledge-sharing platforms to accelerate sustainable innovations and best practices. Policymakers should integrate machine learning, scenario analysis, and big data analytics into policy planning to enhance the accuracy of climate risk assessments and economic impact predictions. Establishing real-time monitoring systems for emissions and energy transitions will enable more adaptive and responsive policy interventions. These policy measures will help mitigate economic disruptions, accelerate the low-carbon transition, and foster a more resilient and sustainable global economy.

6 Conclusion and future work

This study explores the economic impact of climate risk in the context of transitioning to green and low-carbon economies, emphasizing the urgency of this transformation to combat global warming and ensure sustainable development. Traditional approaches have struggled to capture the complex, dynamic interplay between economic systems, energy transitions, and policy frameworks, particularly under the uncertainties of technological and socio-economic change. To address these challenges, the authors developed an innovative framework that integrates the Integrated Green Transition Model (IGTM) and the Sustainable Transition Optimization Framework (STOF). IGTM utilizes agent-based modeling and network dynamics to evaluate how green policies influence energy systems and socio-economic outcomes, while STOF employs optimization and machine learning techniques to balance economic growth, emission reduction, and social equity across various scenarios. The findings underscore the importance of aligning technological innovation, governance structures, and public participation to accelerate the green transformation while mitigating economic disruptions. This dual-framework approach provides actionable strategies for optimizing investments in renewable energy and policy design, offering a pathway toward sustainable and equitable economic systems.

Despite its strengths, the study has two key limitations. The IGTM and STOF frameworks rely heavily on modeled assumptions and scenario analyses, which may not fully capture the unpredictable and region-specific impacts of climate risk. Future research should focus on enhancing the robustness of these models by incorporating real-world data from diverse geopolitical and socio-economic contexts. The study primarily emphasizes systemic and technological transitions, potentially underrepresenting the behavioral and cultural dimensions of green and low-carbon transformations. Integrating insights from social sciences could enrich the framework and ensure a more comprehensive understanding of transition dynamics. Addressing these limitations will be vital for scaling the proposed strategies and maximizing their global relevance.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CC: Methodology, Supervision, Project administration, Validation, Resources, Visualization, Writing – original draft, Writing – review and editing. HL: Data curation, Conceptualization, Formal analysis, Investigation, Funding acquisition, Software, Writing – original draft, Writing – review and editing. LL: Writing – original draft, Writing – review and editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher’s note

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