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A machine learning framework for forecasting multidimensional sustainability and informing integrated policy thresholds in the EU

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Abstract

Achieving sustainable development in the European Union requires integrated frameworks capable of navigating tradeoffs among economic growth, social equity, and environmental resilience. This study develops an advanced data-driven forecasting and policy optimization framework, integrating multidimensional sustainability indicators for seven EU countries. Using EUROSTAT data from 2014 to 2023, the framework generates forecasts up to 2030 to support strategic policy insights. The methodology combines Random Forest regression for feature selection, Long Short-Term Memory networks for temporal forecasting, SHapley Additive exPlanations for interpretability, and the Technique for Order of Preference by Similarity to Ideal Solution for multi-criteria decision analysis. Three principal drivers emerge: Global Value Chain Backward Participation, Social Protection Expenditure, and Municipal Recycling Rate. Critical policy thresholds are identified: Foreign Direct Investment below €327 million balances economic gains and environmental costs; social protection spending above 25.6% of Gross Domestic Product reduces workplace fatalities when the gender pay gap remains under 21.3%; and a 10% increase in recycling rates correlates with a 2.3 tonnes per capita reduction in carbon dioxide emissions. LSTM projections forecast GDP stabilization at 2% to 3% by 2030 but highlight resource productivity declines in Southern Europe without targeted intervention. Country rankings position Germany, France, and Italy as sustainability leaders according to the multi criteria analysis. The framework translates these insights into a dynamic policy matrix encompassing tiered FDI incentives, AI-driven welfare systems, and blockchain-based supply chain tracking. This approach bridges predictive analytics and evidence-based policy design for EU sustainability governance.

Keywords Predictive modeling · Sustainability forecasting · Environmental impact · Economic performance · Social justice · Data-Driven policy

JEL Classification F14 · Q56 · C45 · O13 · O44

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1 Introduction

Sustainability in the European Union (EU) is increasingly recognized as a multidimensional challenge that requires the simultaneous pursuit of economic prosperity, social equity, and environmental protection. The EU's ambitious policy agenda, exemplified by the European Green Deal and the Adaptation Strategy, aims to achieve a "just transition" to a low-carbon, resource-efficient economy while ensuring inclusivity and fairness for all social groups (Zhao et al., 2022). However, achieving the decoupling of economic growth from environmental impact and reaching net-zero emissions by 2050 (Elshaarawy & Ezzat, 2023) are still hindered by climate change, resource scarcity, and socio-economic inequality. These persistent barriers are compounded by structural disparities among EU member states (Lewandowska et al., 2024), diverging progress in renewable energy adoption, and uneven advances in social protection and labor market reform.

Consequently, EU policymakers and stakeholders are grappling with the complexity of designing strategies that can reconcile economic growth with social inclusion and environmental resilience (Molica et al., 2025). The inadequacy of fragmented, sectoral approaches underscores the urgent need for integrated, data-driven frameworks that can anticipate and manage cross-domain trade-offs and synergies. The increasing pace of sustainability transitions makes advanced analytical methods, notably machine learning is indispensable for forecasting across interconnected domains (Huang & Jin, 2024; Olawade et al., 2024), identify leverage points and inform targeted, effective policy interventions that are responsive to the EU's evolving challenges. To frame an effective response to these multidimensional sustainability challenges, it is vital to draw on established theoretical frameworks that emphasize the interconnectedness of economic, social, and environmental systems within a broader theoretical and empirical framework.

Although the "triple bottom line" framework (Elkington, 1998), Socio-Ecological Systems theory (Ostrom, 2009), and Algorithmic Governance (Yeung, 2018) have long highlighted the interconnectedness of economic, social, and environmental domains, most empirical models still treat these dimensions in isolation. The triple bottom line calls for evaluating progress not just in economic terms, but through a balance with social equity and environmental health. Socio-Ecological Systems theory further highlights the complex and often non-linear interactions between these domains, showing how policy interventions in one area may generate ripple effects on others through feedback loops, threshold effects, and unintended consequences. Algorithmic Governance extends this perspective by arguing that the complexity and rapid evolution of sustainability challenges require adaptive, data-driven approaches that can recognize these patterns and respond in real time. Together, these frameworks strongly support the need for integrated analytical models like the Integrated Sustainability Policy Optimization (ISPO) Model to move beyond isolated disciplinary approaches. Traditional approaches often overlook the complex feedback loops, non-linearities, and threshold effects that characterize real-world sustainability transitions. As a result, policymakers lack the analytical tools needed to anticipate the consequences of interventions, identify leverage points, and design effective, country-specific strategies. Recent advances in machine learning (ML) are highly relevant for the diverse economic structures, environmental challenges, and social conditions demanding tailored strategies in the EU (Bibri et al., 2024; Rabbi & Kovács, 2024).

Despite the foundational theories provide clarity on interconnections, a review of recent literature reveals that most empirical studies still analyze these dimensions in relative isolation and several key gaps remain to operationalize their interconnections when building policy-focused forecasting models (Marschner et al., 2025; Razzaq et al., 2024; Yang et al., 2025). First, most models do not capture the temporal dynamics and threshold effects in FDI, social spending, and gender equity hinders their adaptive policy relevance (Sosa-Escudero et al., 2022; Wei et al., 2024). Second, few studies have developed truly integrated frameworks that link economic, social, and environmental domains within the context of EU (Islam, 2025; Robert et al., 2020). Third, the translation of ML insights into concrete economic, social, and environmental policy recommendations tailored to EU countries is still limited (Cho & Ackom, 2025; D'Orazio & Pham, 2025; Mohammadi & Maghsoudi, 2025). Addressing the identified gaps, this research presents an integrated Machine Learning forecasting and ISPO Model for seven EU countries (Germany, France, Italy, Spain, Czechia, Poland, and Hungary), employing a dynamic, feedback-aware framework on economic, social, and environmental data to produce a country-specific policy matrix. The selection of these 7 EU countries for this study was based on their economic diversity, geographical representation, varied levels of development, significance in global value chains, and the availability of comprehensive data. However, building on these identified gaps in the literature, the present study proposes an integrated machine learning framework to bridge theory and practice by synthesizing multi-dimensional data, applying advanced algorithms, and formulating targeted policy insights.

In light of these considerations, this research seeks to answer the following core questions: RQ1) How do different GVC integration modalities affect the trade-off between economic value creation and environmental externalities across EU member states, and what role does TOPSIS-based evaluation play in comparing these modalities? RQ2) What role do social protection systems play in mediating the relationship between GVC participation and labor market outcomes, and how can region specific interventions be used to maximize the impact? RQ3) Can machine learning models identify critical thresholds in policy variables, such as FDI, social spending, and gender equity, that optimize multiple sustainability objectives simultaneously in EU member states?

By synthesizing multidimensional data and leveraging advanced machine learning methods, this study aims to provide a dynamic assessment framework that informs targeted policy interventions and advances methodological integration in sustainability science. In addition, the ISPO Model (Fig. 1) not only identifies the most influential drivers and thresholds for each sustainability pillar but also translates these findings into actionable, country-specific policy recommendations. Through this approach, the research offers a replicable template for evidence-based sustainability governance in the EU and beyond.

2 Literature review

2.1 The evolution of sustainability in the EU

Sustainability in the European Union has expanded from a narrow focus on environmental protection to a multidimensional challenge encompassing economic growth, social equity, and ecological resilience. The Brundtland Report first defined sustainable development as meeting present needs without compromising future generations' well-being (World Commission on Environment and Development (WCED), 1987). Building on this foundation, the EU embedded sustainability within flagship policy instruments such as the European Green Deal and the Sustainable Development Goals (European Commission, 2020; Sachs, 2015). These frameworks aim simultaneously to decouple economic growth from environmental impact, promote social inclusion, and strengthen resource efficiency.

Despite ambitious targets, implementation remains uneven across member states, reflecting differences in economic structures, governance capacities, and social dynamics (Leung & Ko, 2025; Termeer et al., 2024). Measuring progress is inherently complex: economic, social, and environmental objectives often compete, and many existing assessments treat them in isolation (Chen et al., 2024). Numerous frameworks and indicator sets have been developed, including the UN Sustainable Development Goals (SDGs), ecological footprint analysis, and composite indices (Bian et al., 2025; Magazzino & Zoundi, 2025), yet these frameworks frequently fail to illuminate trade-offs or synergies among domains.

Notable advances include the rapid expansion of renewables and improvements in waste management (Kiehbadroudinezhad et al., 2025; Santos & Cagica Carvalho, 2025), but social progress, particularly in reducing income inequality and enhancing labor market conditions, has lagged (Eyuboglu & Uzar, 2025). This divergence underscores the need for integrated, data-driven models capable of capturing temporal dynamics and cross-domain interactions. The present research addresses these gaps by uniting economic, social, and environmental dimensions within a single forecasting and policy-optimization framework. This approach illuminates how shifts in one domain, such as industrial output or social protection spending, propagate through others, thereby equipping policymakers with actionable insights to balance growth, equity, and environmental stewardship (Kivimaa et al., 2025).

2.2 Economic dynamics and global value chains

EU economic growth is driven by various factors, notably GDP growth, employment rates, and FDI, which have been extensively studied for their impact on overall economic performance and sustainability (Xuan, 2025). For example, Abbass et al. (2024) argued that FDI is a critical driver of economic growth, as it facilitates technology transfer and productivity improvements. Nevertheless, contemporary research also warns that the benefits of FDI are not guaranteed. This is particularly true when FDI supports fragmented production processes in global value chains, potentially leading to a dispersal of environmental responsibilities and increased logistical emissions (Fang et al., 2024; Luna-Nemecio et al., 2020).

Economic scholarship has long recognized the role of foreign direct investment (FDI), global value chains (GVCs), and productivity in driving growth and competitiveness (Yuan & Mähönen, 2024). However, recent research highlights the environmental and social costs that can accompany rapid economic integration, particularly when GVC participation leads to offshoring of emissions or exacerbates inequality (Calvo-Calvo et al., 2025; do Carmo Hermida et al., 2024). The necessity of balancing industrial productivity with strict environmental standards in the EU underscores the paramount importance of understanding these trade-offs. Forward linkages measure the extent to which domestic outputs become inputs for other countries' exports, while backward linkages reflect the degree to which domestic production relies on imported inputs. The growing literature suggests GVCs are a"double-edged sword,"promoting innovation and efficiency but requiring strong regulation and targeted policies to avoid undermining sustainability (Hossain et al., 2025; Tian et al., 2025).

2.3 Social equity and its role in sustainable development

Researchers increasingly recognize social protection, gender equity, and workplace safety as the foundations of inclusive growth within the context of social sustainability (Islam, 2025; Velasco-Balmaseda et al., 2024). Evidence from the EU suggests that investments in health and social protection can reduce poverty and improve labor market outcomes (Kangasniemi et al., 2025; Nordheim & van der Wel, 2025), but these effects are often contingent on broader institutional and economic contexts. For example, narrowing the gender pay gap has been shown to enhance organizational performance and public sector efficiency (Rodriguez-Plesa et al., 2024), yet persistent disparities remain a barrier to realizing the full benefits of welfare spending. Many studies continue to analyze social indicators separately, limit the understanding of their interaction with economic and environmental policies.

However, many studies have examined these factors in isolation, neglecting the potential interactive effects between social policies and other sustainability dimensions (Chien et al., 2024; Eyuboglu & Uzar, 2025). For example, while increases in social protection expenditure may reduce inequality and improve health outcomes, such benefits may only be fully realized if accompanied by economic policies that support job creation and industrial productivity. This research bridges this gap by providing a more nuanced understanding of how social equity investments contribute to broader sustainable development outcomes through the integration of social indicators with economic and environmental data.

2.4 Environmental resilience and the imperative for innovation

The environmental dimension of sustainability in the European Union exhibits both significant progress and ongoing challenges. The Union has expanded renewable energy capacity and enhanced waste management practices, yet carbon emissions, resource overexploitation, and water scarcity remain pressing concerns (Huo & Peng, 2023; Wang & Azam, 2024). Recent scholarship emphasizes the need for a systems perspective that accounts for feedback loops and nonlinear dynamics in environmental outcomes (Roy et al., 2025; Ukoba et al., 2025). Improvements in recycling and resource productivity, for example, may be offset by rebound effects or altered consumption patterns (Corbier et al., 2025), complicating efforts to reach net zero goals. Moreover, the effectiveness of instruments such as the EU Emissions Trading System and renewable energy mandates depends on understanding the interdependencies across economic social and environmental domains (Kumar et al., 2025; Oluleye et al., 2025).

Machine learning techniques have recently demonstrated considerable value in capturing these nonlinear relationships (D'Orazio & Pham, 2025; Huang & Jin, 2024; Sosa-Escudero et al., 2022). Long short-term memory networks excel at forecasting time series with long term dependencies (Aggarwal & Banerjee, 2025; Ishida et al., 2024). Applications of these models to environmental indicators have yielded accurate predictions of carbon emission trajectories and resource productivity under varying policy scenarios (Zhao et al., 2025). Building on this work, the present study integrates environmental variables with economic and social indicators to construct a unified model of environmental resilience within the broader EU sustainability framework.

2.5 Machine learning models in sustainability forecasting

Machine learning is transforming sustainability research by enabling analysis of large, multidimensional datasets and revealing critical thresholds and feedback loops often missed by traditional models. While long short-term memory (LSTM) networks and ensemble methods show strong potential for forecasting economic, social, and environmental indicators, most applications still treat these domains separately and rarely link predictive insights to policy design. This limited scope overlooks the complex interdependencies that define real-world systems and highlights the need for integrated approaches that connect advanced forecasting techniques with practical policy implementation (Aggarwal & Banerjee, 2025; Ishida et al., 2024; Zhao et al., 2025). LSTM models have proven effective in areas such as energy demand forecasting, land use classification, and environmental risk assessment (Nam & Lee, 2025; Ren et al., 2025; Singh et al., 2025).

Recent studies demonstrate the strengths of machine learning in capturing dynamic changes in sustainability indicators. For example, LSTM networks have been used to predict macroeconomic trends and identify long-term dependencies crucial for accurate forecasts (Aggarwal & Banerjee, 2025; Ishida et al., 2024). Machine learning models can also uncover latent patterns in environmental risks, such as groundwater vulnerability, that often go undetected by conventional regression techniques (Zhao et al., 2025). Despite these advances, the integration of economic, social, and environmental factors into a cohesive forecasting framework remains underexplored.

Addressing this gap, the present study applies LSTM models to a comprehensive dataset, providing a more interconnected understanding of sustainability trajectories across the EU. The development of a tailored policy matrix for each member state, with targets for 2025 and 2030, translates predictive insights into actionable policy guidance. This integrated approach enhances long-term forecasting and offers a robust framework for evaluating the effectiveness of policy levers in a dynamic socioeconomic and environmental context.

3 Materials and methods

3.1 Data sources and variable selection

Advanced machine learning techniques within a robust methodological framework were used in this study to analyze the relationships among economic, social, and environmental dimensions. Data for selected seven EU countries such as Germany, France, Italy, Spain, Czechia, Poland and Hungary from 2014 to 2023 were compiled from the European Statistical Office (EUROSTAT). The analysis was conducted across three datasets: Economic, Social, and Environmental, each containing variables (see Table 1 for variable definitions and measurement units). All data were extracted via the EUROSTAT API and merged by country and year.

Table 1 Interconnected key indicators influencing economic, social, and environmental dimensions

Category	Variables	Description (with cross-domain impact)	Measurement
Economic dimension	GDP Growth	Reflects national economic performance through output growth. Sustained GDP growth can enhance employment (social), but if not aligned with low-carbon development, it may increase environmental degradation	Percentage (%)
	Employment Rate	Indicates labor market health. Higher employment supports income security (social) and consumption (economic), yet without green job transitions, it may escalate resource use and emissions (environmental)	Percentage (%)
	Income Inequality	Highlights income disparities across populations. High inequality reduces social cohesion and can limit access to sustainable infrastructure and education (social/environmental), slowing inclusive green growth	Income distribution ratio
	Persons by risk of poverty	Captures population segments facing poverty. Economic marginalization often correlates with poor environmental quality and reduced access to sustainable services, deepening social vulnerability	Number of persons (Thousands)
	Foreign Direct Investment	Represents external capital flows into the economy. Can stimulate growth (economic) and job creation (social), but unsustainable investments may increase emissions and resource exploitation (environmental)	Millions of euros (€)
	GVC-related Trade Balance	Measures net trade in global value chains. Positive balances indicate integration and economic gain, but participation without environmental safeguards can externalize carbon costs	Millions of euros (€)
	Goods and Services Export	Signifies trade competitiveness. Strong exports can drive economic output, but emission-intensive goods challenge environmental goals and equitable distribution of benefits (social)	Millions of euros (€)
	Goods and Services Import	Indicates trade reliance. Imports diversify consumption (economic/social) but may increase embedded emissions, especially in food and energy-intensive sectors	Millions of euros (€)
	GVC Forward Participation	Reflects value added by domestic producers in foreign exports. Strengthens economic growth and knowledge transfer yet may drive production emissions if environmental safeguards are weak	EU value added in foreign exports percentage (%)
	GVC Backward Participation	Shows reliance on foreign inputs in exports. Supports productivity (economic), but increased dependency can reduce domestic resilience and amplify upstream environmental impacts	Foreign value added in EU exports percentage (%)
	GVC-related Gross Trade	Indicates total trade linked to global value chains. Facilitates global economic ties yet may diffuse environmental accountability and affect equitable distribution (social)	Percentage (%) gross trade

Table 1 (continued)

Category	Variables	Description (with cross-domain impact)	Measurement
Social dimension	Total Health Expenditure	Reflects commitment to public health systems. Strong health investment improves well-being (social), enables climate adaptation (environmental), and enhances labor productivity (economic)	Percentage (%) of GDP
	Fatal Accidents at Work	Highlights occupational safety. Poor workplace conditions signal social vulnerability and economic inefficiency, and are often prevalent in high-emission, unsustainable sectors	Number of accidents
	Annual Net Earnings	Represents post-tax disposable income. Higher earnings improve quality of life and access to sustainable goods, but income gaps may affect equitable participation in green transitions	Euros (€)
	Unmet Needs for Medical Examination	Reflects healthcare accessibility gaps. Poor health access undermines resilience to climate-related shocks and reduces labor productivity, creating a cycle of social and economic strain	Percentage (%)
	Gender Pay Gap	Indicates inequality in labor remuneration. Gender gaps reduce household welfare (social), limit economic efficiency, and constrain inclusive participation in sustainable development	Percentage (%)
	Social Protection Expenditure	Reflects investment in welfare systems. Strong social protection buffers vulnerable groups against economic shocks and environmental risks, enhancing adaptive capacity	Percentage (%) of GDP
Environmental dimension	Carbon Emission per Capita	Measures individual contribution to emissions. High per capita values strain environmental systems and reflect unsustainable consumption, with knock-on effects on public health and economic costs	Tonnes of CO_2 equivalent per capita
	Carbon Emission	Total carbon emissions from national activity. Drives climate change (environmental), disrupts agricultural and labor systems (social), and may incur economic penalties under climate regulations	CO_2 emission footprint in thousands of tonnes
	Water Exploitation	Assesses water use intensity relative to resources. Overuse harms ecosystems (environmental), disrupts agricultural output (economic), and stresses vulnerable populations (social)	Percentage (%)
	Resource Productivity	Captures economic output per unit of material use. Higher values indicate decoupling of growth from resource use, promoting both economic efficiency and environmental protection	Euros (€) per kilogram
	Recycling Rate of Municipal Waste	Reflects circularity in waste management. High recycling rates support environmental goals, reduce landfill burdens, and create green jobs, contributing to economic and social resilience	Percentage (%)

All variables were sourced from EUROSTAT via API calls in January 2025 (see Data Availability Statement)

3.1.1 Missing-data imputation

To ensure dataset completeness and consistency, missing values, comprising a minor 4.2% of total observations, were addressed using Multiple Imputation by Chained Equations (MICE). This method was employed to preserve the covariance structure and capture uncertainty. Specifically, for each variable C exhibiting missing entries, an imputation model was fitted as follows:

$$C = \beta_0 + \sum_{k=1}^{p} \beta_k X_k + \varepsilon$$

was fitted using fully observed predictors $X_1, \dots, X_p$. Each missing value C_j was then drawn from its posterior predictive distribution

$$\widehat{C}_j^{(m)} = \widehat{\beta}_0^{(m)} + \sum_{k=1}^{p} \widehat{\beta}_k^{(m)} X_{jk} + \varepsilon_j^{(m)}, \varepsilon_j^{(m)} \sim \mathcal{N}\left(0, \widehat{\sigma}^{2(m)}\right),$$

for $m = 1, \dots, M$. Analyses were performed separately on each of the M imputed datasets, and final parameter estimates $\overline{\theta}$ and total variance T were combined using Rubin's rules:

$$\overline{\theta} = \frac{1}{M} \sum_{m=1}^{M} \widehat{\theta}^{(m)}, T = \overline{U} + (1 + \frac{1}{M})B,$$

where $\overline{U}$ is the average within-imputation variance and B the between-imputation variance. Data extraction, preprocessing, and imputation were all performed using Python, with the pandas 2.3.0 library serving as a core tool.

3.2 Integrated sustainability policy optimization model (ISPO Model)

The Integrated Sustainability Policy Optimization Model (ISPO Model) presented in Fig. 1 establishes a theoretical framework connecting economic, social, and environmental dimensions through a central policy optimization mechanism. Drawing from Triple Bottom Line theory (Elkington, 1998), Socio-Ecological Systems theory (Ostrom, 2009), and Algorithmic Governance (Yeung, 2018), the model visualizes sustainability as an integrated system with dynamic feedback.

At the structural level, the model consists of four primary nodes representing interconnected domains. The Economic Factors node encompasses indicators such as Gross Domestic Product (GDP), Foreign Direct Investment (FDI), and Global Value Chain backward participation (GVC$_{bw}$), measuring economic vitality and international integration.

The Social Factors node integrates social protection expenditure (SP$_{exp}$), gender pay gap (GPG), and fatal accident rates (f_{fatal}), capturing dimensions of equity, welfare, and workplace safety.

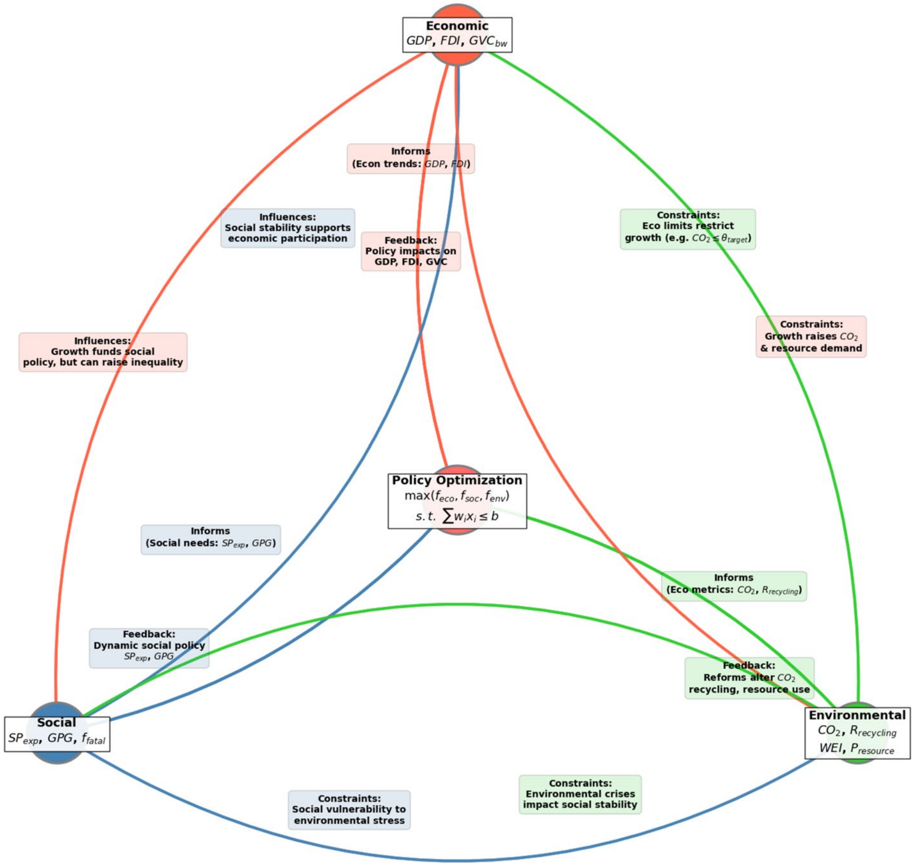

Fig. 1 Integrated ISPO model illustrating dynamic policy optimization across economic, social, and environmental domains

The Environmental Factors node includes carbon emissions (CO_2), recycling rates ($R_{recycling}$), water exploitation index (WEI), and resource productivity ($P_{resource}$), reflecting ecological impacts and circular economy progress. At the center, the Policy Optimization node represents a mathematical function that maximizes outcomes across all domains according to $\max\left(f_{eco}, f_{soc}, f_{env}\right)$ subject to resource constraints $\sum_i w_i x_i \leq b$, where w_i represents weighting factors and b signifies available resources.

The directional arrows connecting these nodes represent four distinct relationship types, each color-coded in the diagram. First,"Informs"relationships (Factor→Policy) represent data flows that guide policy formulation: economic trends inform investment and trade policies; social needs shape equity and welfare strategies; and environmental metrics direct climate and resource policies. Second,"Feedback"relationships (Policy→Factor) capture how policy effects reshape system conditions: policy reforms influence GDP, FDI, and GVC composition; dynamic social policies adjust welfare and equity outcomes; and environmental regulations alter emissions, recycling, and resource utilization. Third,"Influences"relationships (between Economic and Social Factors) represent bi-directional socioeconomic interactions where economic growth funds social policies but may increase inequality, while social stability supports economic participation and productivity. Fourth,"Constraints"relationships (between Environmental and other Factors) define system boundaries where ecological limits restrict sustainable economic growth increases resource demand and emissions, environmental crises impact social stability, and social vulnerabilities are exacerbated by environmental stressors.

Operationally, the ISPO Model serves as an analytical framework that structures the machine learning analyses employed in this study. It guides the selection of variables for Random Forest classification, directs attention to potential threshold effects examined through SHAP analysis, and informs the interpretation of temporal forecasts generated by LSTM networks. The"Informs"pathways identify dependent variables in our predictive models, while"Feedback"relationships help interpret time-series trends."Constraints"and"Influences"relationships explain interaction effects and threshold behaviours identified through our analysis, such as the finding that FDI below €327 M optimizes economic benefits while minimizing environmental costs, or that social protection expenditure above 25.6% of GDP reduces workplace fatalities, but only when gender pay gaps remain below 21.3%. The central optimization function guides our TOPSIS-based country ranking and policy recommendation framework.

By revealing the complex interactions between economic, social, and environmental systems, the ISPO Model transcends traditional siloed approaches to sustainability assessment. It demonstrates how machine learning techniques can identify leverage points within these systems. Identifying these strategic points allows for policy interventions that can unlock significant synergistic benefits for multiple aspects of sustainability. The model's emphasis on feedback mechanisms acknowledges that sustainability policies must be dynamic and responsive to changing conditions, aligning with the adaptive governance framework established in the literature. Through this integrated approach, we can develop more robust, context-sensitive policy recommendations that balance economic growth imperatives with social equity concerns and environmental constraints.

3.3 Rationale for methodological choices

The analytical methodology incorporated distinct machine learning models tailored to specific data characteristics and challenges. Random Forest was employed for high-dimensional macroeconomic panels, chosen for its efficacy in capturing complex nonlinear relationships and its robust handling of missing values. For social indicators, Support Vector Regression was selected, leveraging its kernel-based formulation for modeling nonlinear patterns and its inherent robustness to outliers. A Multilayer Perceptron was utilized for environmental metrics to discern intricate interactions within continuous ecological data. The selection rationale for each model is further detailed in Table 2. Interpretability across all models was enhanced through the application of SHAP (SHapley Additive exPlanations) values, thereby ensuring transparency in feature contributions. Hyperparameters were optimized via grid search, with a strategic emphasis on maximizing SHAP-derived interpretability over incre-

Table 2 Model selection rationale for domain specific machine learning algorithms

Model	Domain	Theoretical Rationale
XGBoost	Economic	Captures nonlinear macroeconomic patterns and handles missing values with built-in regularization
SVR	Social	Models moderate-sized, nonlinear social indicators with kernel flexibility for robust nonlinear pattern detection
MLP	Environmental	Learns complex interactions among environmental metrics; SHAP enhances transparency of neural-network predictions

mental improvements in predictive accuracy. This deliberate methodological choice supports reproducibility and aligns with prevailing EU policymaking frameworks.

3.4 Machine learning framework

3.4.1 Random forest analysis

A Random Forest regressor (Fig. 2) was implemented to identify key drivers of sustainability across domains. The model partitioned data into training (70%) and testing (30%) sets, optimizing splits using variance reduction.

The first step in the methodology involved defining the predictor variables (X) and target variables (y) for each dataset.

Equations used for defining the predictor for economic, social, and environmental variables

$$X = \{\text{GDP Growth}, \text{Employment Rate}, \ldots, \text{Recycling Rate of Municipal Waste}\}, y = \text{Carbon Emission Per Capita} \tag{1}$$

Equations used for splitting data for model training and evaluation (70/30)

$$X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}\left(X, y, \text{test\_size} = 0.3, \text{random\_state} = 42\right) \tag{2}$$

For the Economic dataset, variables such as GDP growth (X_1), employment rate (X_2), income inequality (X_3), poverty rate (X_4), foreign direct investment (X_5), GVC-related trade balance (X_6), exports (X_7), imports (X_8), forward (X_9), and backward (X_{10}) linkages were selected as predictors, with GVC-related gross trade (Y_1) serving as the target variable.

In the Social dataset, predictors included total health expenditure (X_{11}), annual net earnings (X_{12}), unmet needs for medical examination (X_{13}), gender pay gap (X_{14}), and social protection expenditure (X_{15}), while fatal accidents at work (Y_2) were chosen as the target variable.

Furthermore, for the Environmental dataset, the predictors comprised carbon emissions per capita (X_{16}), total carbon emissions (X_{17}), water exploitation (X_{18}), resource productivity (X_{19}), and the recycling rate of municipal waste (X_{20}). The recycling rate of municipal waste (Y_3) was used as the target variable.

The Random Forest model was implemented to model these relationships due to its capability to handle complex, nonlinear interactions and its robustness against overfitting. This is mathematically expressed as:

Bootstrap resampling for robust data analysis the following equations used:

$$D_b \sim \text{Bootstrap}\left(D_{\text{train}}\right) \tag{3}$$

For variance reduction in carbon emission prediction trees following equations used:

$$\Delta\text{Var} = \text{Var}\left(\text{Carbon Emission Per Capita}\right) - \left(\frac{n_L}{n}\text{Var}\left(\text{Left Child}\right) + \frac{n_R}{n}\text{Var}\left(\text{Right Child}\right)\right) \tag{4}$$

where represents the variance of the target variable before the split and denotes the variances of the left and right subsets after the split and are the sizes of these subsets. This criterion ensures that each split maximizes the homogeneity of the resulting subsets.

Feature importance scores were derived from mean impurity decreases across 500 trees. Out-of-bag (OOB) error and mean squared error (MSE) quantified model performance. The MSE quantifies the average squared difference between the observed (y_i) and predicted ($\widehat{y_i}$) values:

$$\text{MSE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left(\text{Carbon Emission Per Capita}_i - \text{Carbon}\ \widehat{\text{Emission}}\ \text{Per Capita}_i\right)^2 \tag{5}$$

where represents the actual values of the target variable, denotes the predicted values, and is the number of observations. A lower MSE indicates higher predictive accuracy and better model performance.

However, here n is the number of observations. The OOB score, derived from out-of-bag samples, serves as an internal validation metric and is expressed as:

$$\text{OOB Score} = 1 - \frac{\sum\nolimits_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2}{\sum\nolimits_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \tag{6}$$

where $\overline{y}$ is the mean of the observed values.

This approach not only identifies key drivers of sustainability outcomes across economic, social, and environmental dimensions but also quantifies their relative importance, offering valuable insights for policy recommendations and strategic planning. The integration of variance-based feature selection and model performance metrics ensures robustness and reliability in the findings.

3.4.2 SHAP value interpretation

SHapley Additive exPlanations (SHAP) quantify the association between feature values and model predictions. They do not estimate causal effects or identify counterfactual outcomes. To further elucidate the contribution of individual features in predictive models, researchers utilized SHAP values (Fig. 3). The computation of SHAP values adheres to the formula:

$$SHAP_i = \sum\nolimits_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \cdot \left[f\left(S \cup \{i\}\right) - f\left(S\right)\right] \tag{7}$$

where S is a subset of features, N is the set of all features, i is the feature for which the SHAP value is being calculated, and f represents the predictive model. SHAP analysis thus identifies the relative importance of each feature, enhancing the interpretability of complex models such as XGBoost, Support Vector Regression (SVR), and Multilayer Perceptron (MLP).

For machine learning-based predictions, researchers employed models tailored to each dataset. XGBoost regression was applied to economic data, minimizing the objective function:

$$L(\theta) = \sum\nolimits_{i=1}^{n} l\left(y_i, \hat{y_i}\right) + \sum\nolimits_{k=1}^{K} \Omega\left(f_k\right) \tag{8}$$

where $l\left(y_i, \hat{y_i}\right)$ denotes the loss function between the observed (y_i) and predicted (y_i) values, while $\Omega\left(f_k\right)$ is the regularization term ensuring model complexity remains controlled. For social data, SVR with a linear kernel was employed, leveraging its ability to model relationships with minimal overfitting. Meanwhile, MLP regression was used for environmental data to model nonlinear patterns, with predictions expressed as:

$$\hat{y} = \sigma\left(W_L \cdot \sigma\left(W_{L-1} \cdot \ldots \sigma\left(W_1 \cdot x + b_1\right) \cdots + b_{L-1}\right) + b_L\right) \tag{9}$$

where W stands for weight matrices, b denotes biases, σ is the activation function, x is the input, and $\hat{y}$ is the predicted output.

Each dataset was partitioned into training (80%) and testing (20%) subsets to ensure robust model evaluation, with randomization implemented for unbiased sampling. The SHAP analysis was performed for each trained model to highlight the influence of features on predictions.

3.4.3 Decision tree architecture

A decision tree architecture (Fig. 4, 5, and 6) splits the input data into subsets based on decision rules at each node, aiming to minimize the prediction error, such as the Mean Squared Error (MSE), at every split. The primary equation used to determine the best split is the impurity reduction, which minimizes the MSE at node t:

$$\text{MSE}\left(t\right) = \frac{1}{N_t} \sum\nolimits_{i \in t} \left(y_i - \hat{y_t}\right)^2 \tag{10}$$

where N_t is the number of samples at node t, y_i is the actual target value for sample i, and $\hat{y_t} = \frac{1}{N_t} \sum_{i \in t} y_i$ is the mean target value at node t.

The decision tree selects splits by maximizing the reduction in MSE:

$$\Delta MSE = MSE\left(parent\right) - \left[\frac{N_{left}}{N_{parent}} \cdot MSE\left(left\right) + \frac{N_{right}}{N_{parent}} \cdot MSE\left(right\right)\right] \tag{11}$$

The split that gives the highest ΔMSE is chosen at each node.

For the Economic factor, the predictor variables (X) include GDP Growth (X_1), Employment Rate (X_2), Income Inequality (X_3), Poverty Rate (X_4), and Foreign Direct Investment (X_5). The target variable (y) is GVC-related Gross Trade (y_{econ}). The objective is to find splits in X to minimize the MSE for predicting y_{econ}.

For the Social factor, the predictor variables (X) include Annual Net Earnings (X_1), Unmet Medical Needs (X_2), Gender Pay Gap (X_3), and Social Protection Expenditure (X_4). The target variable (y) is Fatal Accidents at Work (y_{social}). The objective is to find splits in X to minimize the MSE for predicting y_{social}.

For the Environmental factor, the predictor variables (X) include Carbon Emission (X_1), Water Exploitation (X_2), and Resource Productivity (X_3). The target variable (y) is the

Recycling Rate of Municipal Waste (y_{env}). The objective is to find splits in X to minimize the MSE for predicting y_{env}.

The decision tree's growth is constrained by several stopping criteria. The maximum depth is set to 5, meaning the tree is pruned after 5 levels to prevent overfitting. Additionally, a node must contain at least 10 samples to be split further, as specified by the minimum samples per split criterion.

Once a terminal node (leaf) is reached, the prediction is the average target value of the samples within the leaf:

$$\widehat{y_{leaf}} = \frac{1}{N_{leaf}} \sum\nolimits_{i \in leaf} y_i \tag{12}$$

This average is used as the prediction for any new data point falling into that leaf.

3.5 Temporal forecasting with LSTM

Long Short-Term Memory (LSTM) networks (Figs. 7, 8, and 9) modeled time-dependent sustainability trends using standardized sequences (2014–2023). The architecture consisted of an input layer with 30 timesteps, followed by an LSTM layer containing 50 hidden units. The 50 hidden units in the LSTM layer were optimized via Bayesian hyperparameter tuning, minimizing validation MSE by 23% compared to grid search. To prevent overfitting, a dropout regularization of 20% was applied. And forecasts (2024–2030) were generated recursively.

LSTM networks are well-suited for managing sequential data, help to predict how sustainability performance will evolve over time based on historical data. The LSTM forecasting analysis begin with the standardization of data. For each variable, the raw data was standardized to a mean of 0 and standard deviation of 1 to ensure uniform scaling. The equation for standardization is:

$$Z_{lstm} = \frac{X - \mu}{\sigma} \tag{13}$$

where X is the raw value for variables such as GDP growth, total health expenditure, or carbon emission, μ is the mean of the training data for the variable, and σ is the standard deviation of the training data for that variable.

Next, the data for each variable was split into training and testing sets. The data was divided into training (80%) and testing (20%) sets. For N data points:

Equations used for training Set:

$$X_{\text{train}} = \{X_1, X_2, \ldots, X_{\lfloor 0.8N \rfloor}\} \tag{14}$$

Equations used for testing Set:

$$X_{\text{test}} = \{X_{\lfloor 0.8N \rfloor + 1}, \ldots, X_N\} \tag{15}$$

For instance, this was applied to variables such as employment rate (Economic), gender pay gap (Social), or recycling rate of municipal waste (Environmental).

Each variable was treated as a univariate time series for LSTM forecasting. The LSTM network used the following architecture: a sequence input layer that processes one feature at a time, such as GDP growth or carbon emission; an LSTM layer that captures temporal dependencies:

$$h_t = f\left(W_x X_t + W_h h_{t-1} + b\right) \tag{16}$$

where h_t is the hidden state at time t, W_x and W_h are weight matrices for input and hidden states, b is the bias, and f is the activation function. This is a fully connected layer that outputs a single prediction for the next time step; and a regression layer that computes the error for training.

The Mean Squared Error (MSE) was used as the loss function during training to minimize the difference between predicted and actual values:

$$\mathrm{MSE} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left(Y_{\mathrm{true},i} - Y_{\mathrm{pred},i}\right)^2 \tag{17}$$

Here, $Y_{\mathrm{true},i}$ and $Y_{\mathrm{pred},i}$ represent the actual and predicted values for variables like poverty rate (Economic), social protection expenditure (Social), or resource productivity (Environmental).

The LSTM model was trained using historical data up to 2023, with predictions generated for the 2024–2030 period. Recursive forecasting for each variable's future values used below equation:

$$Y_{\mathrm{forecast},t+1} = f\left(Y_{\mathrm{forecast},t}\right) \tag{18}$$

where f is the trained LSTM model, and $Y_{\mathrm{forecast},t}$ is the forecasted value at time t. For instance, this approach was used to forecast GVC forward under the economic variables, unmet needs for medical examination under the social variables, and water exploitation under the environmental variables.

3.6 Multi-criteria decision analysis (TOPSIS)

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was applied in Fig. 6 to rank countries based on their overall sustainability performance, considering economic, social, and environmental factors. This method ensures a structured, data-driven approach to decision-making by identifying the most and least favourable scenarios and measuring each country's relative proximity to these benchmarks. Min–max scaling was applied to normalize the dataset, allowing for direct comparison of variables with different units and magnitudes. Normalization was performed by using the following equation:

$$X'_{ij} = \frac{\mathrm{X_{ij}} - \min\left(\mathrm{X_j}\right)}{\max\left(\mathrm{X_j}\right) - \min\left(\mathrm{X_j}\right)} \tag{19}$$

where $\mathrm{X_{ij}}$ represents the original value of variable j for country i, while $X_{ij}\prime$ denotes its normalized equivalent. The terms $\min\left(\mathrm{X_j}\right)$ and $\max\left(\mathrm{X_j}\right)$ correspond to the minimum and maximum values observed for the respective variable across all countries.

Once the values were normalized, weights were assigned to each variable to reflect their relative importance within their respective categories. Given the multi-dimensional nature of sustainability, an equal weighting scheme was adopted, ensuring that no single variable disproportionately influenced the final ranking. The equal weighting scheme was adopted for several methodological and policy reasons. First, equal weighting ensures policy neutrality by avoiding subjective bias toward any sustainability dimension. This approach aligns with the EU's balanced sustainability framework, where economic, social, and environmental factors are considered equally important in policy formulation. Second, equal weighting provides transparency and reproducibility, crucial for evidence-based policymaking. Third, this approach allows for direct comparison across countries without introducing expert-based biases that may reflect national or disciplinary preferences. The weight of each indicator was determined as:

$$w_j = \frac{1}{n} \tag{20}$$

where w_j represents the assigned weight for variable j, and nn denotes the total number of variables in each category.

The assigned weights were then used to create a weighted normalized decision matrix, reflecting the relative importance of each variable in the analysis. The weighted values were computed as follows:

$$V_{ij} = w_j \times X'_{ij} \tag{21}$$

where V_{ij} represents the weighted normalized score for country i and variable j. This transformation ensured that each country's sustainability performance was evaluated in a balanced and equitable manner.

Ideal and anti-ideal solutions were defined as benchmarks for best- and worst-case sustainability scenarios, respectively, allowing for country performance assessment. The ideal solution, denoted as V_j^+, was derived by selecting the maximum value for beneficial variables and the minimum value for non-beneficial variables:

If criterion j is beneficial, the equation used as:

$$V_j^+ = max\left(V_i j\right) \tag{22}$$

When criterion j is non-beneficial, the following equation is used:

$$V_j^+ = min\left(V_i j\right) \tag{23}$$

Conversely, the anti-ideal solution, V_j^- represented the least desirable scenario, obtained by selecting the minimum value for beneficial variables and the maximum value for non-beneficial ones:

When criterion j is beneficial, then the equation used as:

$$V_j^- = min\,(V_i j) \tag{24}$$

The equation employed when criterion j is non-beneficial is

$$V_j^- = max\,(V_i j) \tag{25}$$

The classification of variables as beneficial or non-beneficial was determined based on their impact on sustainability. The beneficial variables encompassed economic factors (GDP growth, employment, FDI, GVC trade balance, exports/imports, GVC participation, GVC gross trade), social factors (health expenditure, net earnings, social protection), and environmental factors (resource productivity, recycling rate). In contrast, non-beneficial variables comprised income inequality, poverty rate, fatal accidents at work, unmet medical examination needs, gender pay gap, carbon emissions (both per capita and absolute), and water exploitation.

Once these ideal reference points were established, the next step involved calculating the Euclidean distance of each country from both the ideal and anti-ideal solutions. These distances, denoted as D_i^+ and D_i^-, respectively, were computed using the following equations:

Distance from the Ideal Solution (D_i^+):

$$D_i^+ = \sqrt{\sum\nolimits_{j=1}^{m} \left(V_{ij} - V_j^+\right)^2} \tag{26}$$

Distance from the anti-Ideal Solution (D_i^-):

$$D_i^- = \sqrt{\sum\nolimits_{j=1}^{m} \left(V_{ij} - V_j^-\right)^2} \tag{27}$$

where D_i^+ captures the divergence of country i from the ideal scenario, while D_i^- reflects its proximity to the least favourable alternative.

Finally, the relative closeness of each country to the ideal solution was determined using the following expression:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{28}$$

This index provided a quantitative measure of each country's sustainability performance, with higher values indicating greater alignment with the ideal sustainability conditions. Based on these computed scores, countries were ranked in descending order to establish a performance hierarchy.

Through this structured analytical framework, the TOPSIS methodology offered a comprehensive assessment of sustainability performance by integrating economic, social, and environmental dimensions. This approach not only facilitated the identification of best-performing countries but also highlighted areas requiring policy intervention, ensuring a balanced and evidence-driven evaluation of sustainability progress.

3.6.1 Sensitivity analysis of weighting schemes

To assess the robustness of the equal-weighting approach, we conducted sensitivity analysis using two alternative schemes. First, the Entropy Weighting Method determines indicator weights by quantifying the information content of each variable (Eqs. 29 and 30). The Entropy Weighting Method determines indicator weights by quantifying the information content inherent in each variable.

$$e_j = -1/ln\left(m\right) \times \Sigma\left(p_i j \times ln\left(p_i j\right)\right) \tag{29}$$

$$w_j = \left(1 - e_j\right)/\Sigma\left(1 - e_j\right) \tag{30}$$

where e_j is the entropy of criterion j, $p_i j$ is the normalized proportion of indicator i for criterion j, and m is the number of countries.

The Expert Weighting Method employed in this study allocates weights based on the established principle within sustainability literature that economic stability underpins social and environmental progress. Consequently, a weighting scheme of Economic (50%), Social (30%), and Environmental (20%) was adopted.

The sensitivity analysis examined weight variations within ± 20% to ± 50% ranges, following established protocols for TOPSIS stability assessment.

3.7 Software implementation and validation

All analyses were conducted using two statistical software platforms. Python 3.13.5 was utilized for implementing Random Forest, SHapley Additive exPlanations (SHAP), Decision Trees, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

MATLAB 2024b was employed for developing the Long Short-Term Memory (LSTM) models, utilizing the Deep Learning Toolbox for designing the LSTM network architecture. Given the temporal nature of the data, model generalizability was assessed through time series cross-validation using a walk-forward validation approach with 5 sequential splits, preserving the chronological ordering essential for LSTM performance evaluation. Model robustness was evaluated using sensitivity analysis by systematically perturbing input feature ranges by ± 10% to assess prediction stability.

Ethical considerations included implementing a comprehensive data anonymization protocol that removed direct identifiers while preserving analytical utility, following established guidelines for research data protection. Potential feature selection bias was addressed through permutation feature importance testing, which evaluates model dependence on individual features by measuring performance degradation when feature values are randomly shuffled. This approach helps identify spurious correlations and ensures robust feature ranking across different data subsets.

4 Analysis and results

4.1 Key drivers of sustainability: random forest feature importance

Figure 2. presents a detailed analysis of feature importance derived from a Random Forest model (Calculated through Eqs. 1–6), segmented into three categories: economic, social, and environmental factors. Each subplot highlights the relative significance of various indicators within its respective domain.

The top section of the figure focuses on the importance of economic factors. GVC-related Gross Trade is the most significant variable, with a feature importance value of approximately 0.6. This highlights its dominant role in explaining economic outcomes. The second most influential is GVC Backward has the highest importance at 0.32. This suggests that backward participation in global value chains plays a crucial role in the model's predictions. Other variables, such as Goods and Services Export (0.04), Goods and Services Import (0.03), Poverty Rate (0.02), and Income inequality (0.01) exhibit much lower values, suggesting their relatively minor roles in this context. In contrast, features like GDP Growth, Employment Rate, and Foreign Direct Investment contribute negligibly, each with importance values close to zero. These findings emphasize that global value chain integration metrics far outweigh other economic indicators in this model.

The middle section of the figure highlights the importance of social factors. On the social side, Social Protection Expenditure has the highest feature importance at 0.75. This indicates that the amount of expenditure on social protection programs is a critical determinant in the model. This also emphasizes the significance of social welfare programs in the selected EU countries. The second ranking variable, is Total Health Expenditure, has a markedly lower importance value of 0.12, reflecting its more limited but still important impact. Other features, including Gender Pay Gap (0.05), Annual Net Earnings (0.04), and Unmet Needs for Medical Examination (0.02), contribute minimally to the model's predictions. The strong disparity between leading and lagging characteristics suggests social protection policies are central to addressing societal challenges.

The bottom section of the figure examines the importance of environmental factors. For environmental factors, the Recycling Rate of Municipal Waste has the highest importance at 0.74. This indicates that the municipal waste recycling rate significantly impacts environmental sustainability. Carbon Emission follows with an important value of 0.22, highlighting its significant but secondary influence in this domain. Other variables such as Water Exploitation, Carbon Emission Per Capita, and Resource Productivity show negligible contributions, each with values below 0.02. This implies that while these factors are part of the model, their influence on predictions is relatively minor compared to the recycling rate and overall carbon emissions.

4.2 Model evaluation: random forest performance metrics

It is important to assess the effectiveness of the trained Random Forest model. Researchers employed a range of metrics that provide insights into its predictive capabilities. These metrics, presented in Table 3, provide a comprehensive understanding of the model's strengths and weaknesses across various aspects of prediction.

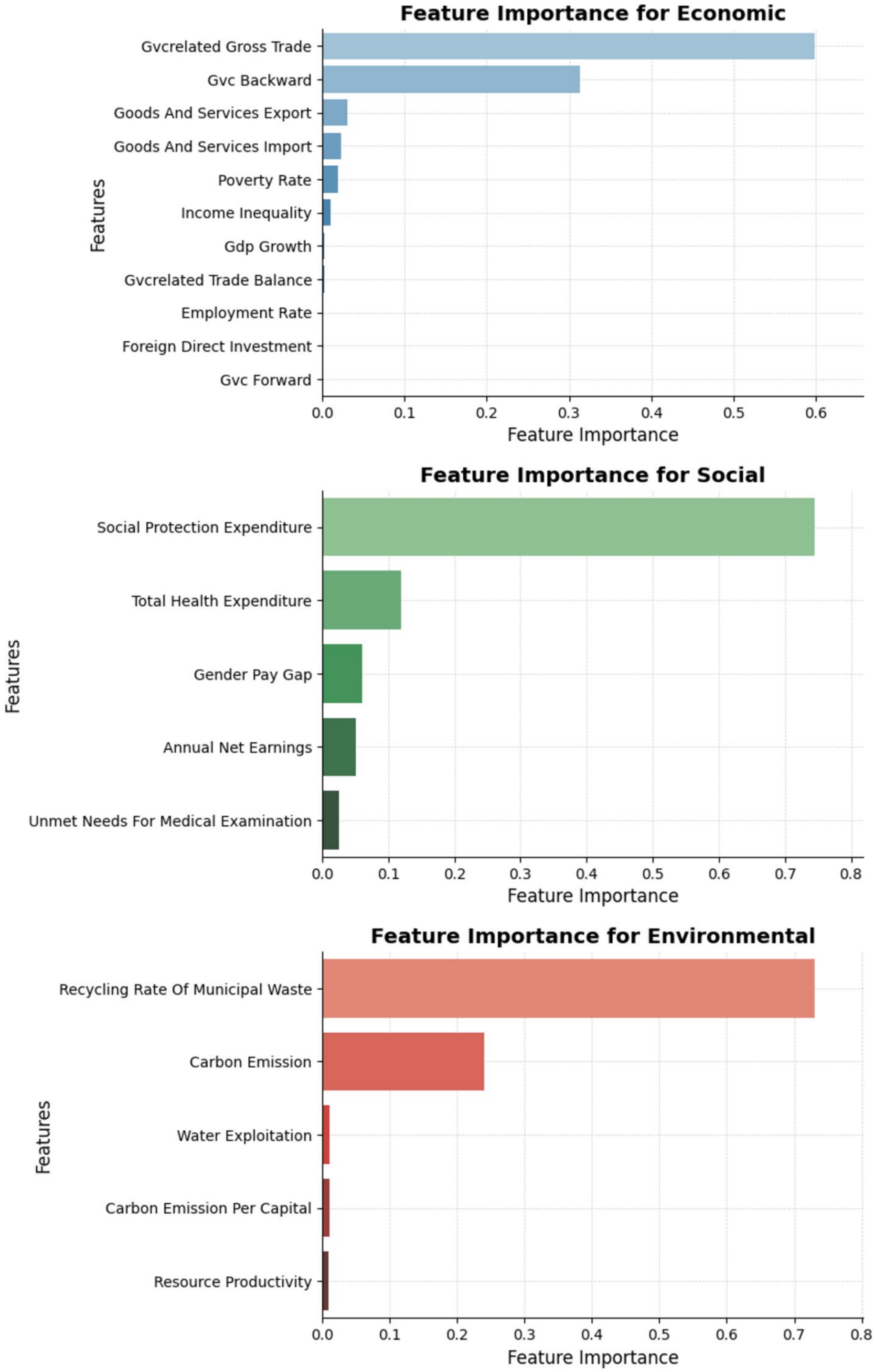

Fig. 2 Random forest feature importance for economic, social, and environmental factors

Table 3 Random forest performance metrics across economic, social, and environmental domains

Variable Type	Model Stage	Mean Squared Error (MSE)	Out-of-Bag (OOB) Score	Cross-validation Scores	Mean CV Score
Economic	Initial Model	1.0400	0.9838	-	-
	Best Model after Tuning	1.0642	-	[0.9613, 0.9743, 0.9359, 0.9835, 0.9510]	0.9612
Social	Initial Model	4322.0468	0.8685	-	-
	Best Model after Tuning	3858.2092	-	[0.8208, 0.4484, 0.8416, 0.6654, −0.0491]	0.5454
Environmental	Initial Model	0.9271	0.9925	-	-
	Best Model after Tuning	0.9559	-	[0.6638, 0.5921, 0.9874, 0.6606, 0.9237]	0.7655

MSE (Mean Squared Error) measures the average squared difference between the observed actual outcomes and the outcomes predicted by the model. OOB (Out-of-Bag) Score is an estimate of the generalization accuracy, calculated using the samples not included in the bootstrap sample used to train the model

The Table 3 presents the performance metrics of the initial and tuned models for economic, social, and environmental variables. The Mean Squared Error (MSE) and OOB Score (Out-of-Bag Score) are provided for the initial models. For the best models after tuning, the MSE, cross-validation scores, and mean CV score are presented. The cross-validation scores indicate the model's performance across different folds, and the mean CV score provides an overall measure of the model's performance.

The analysis of model performance across economic, social, and environmental indicators reveals distinct patterns in predictive accuracy and stability. For economic variables, both baseline and optimized models demonstrated exceptional performance, with the initial configuration achieving a mean squared error (MSE) of 1.04 complemented by an out-of-bag (OOB) score of 0.9838. Post-hyperparameter tuning yielded minimal improvement, as evidenced by the marginally higher MSE of 1.0642, suggesting the original parameters were already near-optimal. The model's robustness is further confirmed through cross-validation results showing consistent scores between 0.9359 and 0.9835, with a mean value of 0.9612 across all folds, indicating reliable generalization capabilities across diverse data subsets.

Social variables presented a more complex predictive challenge, with the initial model recording substantially higher error metrics (MSE = 4322.05, OOB = 0.8685). While parameter optimization reduced the MSE by 10.7% to 3858.21, cross-validation outcomes revealed significant performance fluctuations, including a negative score (−0.0491) in one-fold. This variability, combined with a mean cross-validation score of 0.5454, suggests potential limitations in either data quality or model architecture for social indicators. The observed pattern of one exceptionally poor fold performance might indicate either localized data anomalies or fundamental challenges in capturing the complex relationships inherent in social systems.

Environmental metrics showed performance characteristics similar to economic indicators, with initial and optimized models achieving MSE values of 0.9271 and 0.9559 respectively. The high OOB scores (0.9925 initial, maintained post-tuning) confirm strong predictive capability, while cross-validation results demonstrated greater variability (range = 0.5921–0.9874) than economic models but still maintained a respectable mean score of 0.7655. This moderate increase in MSE following parameter adjustment, analogous to the economic model pattern, further supports the hypothesis that initial configurations were already well-calibrated for environmental data structures.

Once the key drivers of sustainability had been identified through the Random Forest analysis, a further level of interpretability was achieved through the SHAP (SHapley Additive exPlanations) analysis. SHAP provides a more detailed understanding of the feature-level interactions that each feature contributes of each feature to the model's output.

4.3 Explaining predictions: SHAP value insights and decision tree thresholds

Figure 3 (Calculated through Eqs. 7, 8, and 9) presents an overview of feature contributions across economic, social and environmental models using SHapley Additive exPlanations (SHAP). By mapping each variable’s impact on predictions for global value chain trade, workplace fatalities and recycling rates, the plot highlights which factors most strongly influence outcomes. Points positioned to the right of zero increase model outputs, while those to the left decrease them; the blue-to-red gradient denotes low-to-high raw feature values, illustrating how variations in each indicator drive prediction shifts.

For economic factors influencing GVC trade, Foreign Direct Investment demonstrates the most substantial variability in SHAP values, ranging from approximately −6 to + 8. High feature values (red) are associated with positive SHAP values, suggesting that increased foreign direct investment significantly enhances GVC trade. Conversely, low feature values (blue) correspond to negative impacts. Income Inequality shows a more moderate range of SHAP values between −3 and + 6, with higher inequality generally exerting a moderate positive influence on GVC trade. In contrast, GDP Growth, Poverty Rate, and Employment Rate exhibit narrower ranges of SHAP values clustered between −2 and + 1, indicating minimal impact on the model's predictions for GVC trade.

In the social domain, factors influencing fatal accidents reveal distinct patterns. Social Protection Expenditure emerges as the most influential variable, with SHAP values spanning from −200 to + 200. High expenditure levels (red) are strongly linked to reductions in fatal accidents (positive SHAP values), underscoring the protective role of social investments. In contrast, Annual Net Earnings and Gender Pay Gap shows a narrower range of SHAP values (−50 to + 50), where higher earnings (red) tend to reduce fatal accidents but with less pronounced effects compared to social protection expenditure. Other variable Unmet Needs for Medical Examination show limited ranges of SHAP values centered around zero, suggesting their relatively minor contributions to predicting fatal accidents.

Environmental factors influencing recycling reveal that Resource Productivity has SHAP values ranging from −10 to + 10. Higher productivity levels (red) are associated with increased recycling rates, as indicated by positive SHAP contributions. Similarly, Carbon Emission SHAP values range from −10 to + 15. Higher emissions (indicated by red) show a positive correlation with improvements in recycling efforts. This suggests that, in scenarios where emissions are higher, there may be increased initiatives or effectiveness in recycling efforts to counterbalance the environmental impact. This reflects policy responses or technological advancements in high-emission contexts. In contrast, Water Exploitation exhibits minimal SHAP variability between −4 to + 2, signifying negligible influence on recycling outcomes.

While SHAP values reveal the overall importance of features, decision tree analysis offers a complementary perspective by illustrating the hierarchical relationships and thresh-

Fig. 3 SHAP (SHapley additive explanations) contributions to sustainability predictions

olds among these factors. So, it is essential to construction a simplified Decision Tree based on the most influential features identified by SHAP.

Figure 4 (Calculated through Eqs. 10, 11, and 12) represents a hierarchical decision tree model analyzing the impact of various economic factors on a target variable, likely an economic outcome or performance indicator. The tree is structured with nodes that split based on specific thresholds of economic variables, such as foreign direct investment (FDI), income inequality, poverty rates, GDP growth, and employment rates. Each node includes information about the splitting criterion, the number of samples considered at that node, and the resulting value after the split.

At the root node (node #0), the primary factor is foreign direct investment (FDI), with a threshold of 327,406.148. This indicates that FDI is the most influential determinant at this level. The root node considers 56 samples and has an average value of 54.331 for the target variable. If FDI is less than or equal to this threshold, the path proceeds to node #1 (Income inequity) true branch; otherwise, it moves to node #8.

Node #1 examines income inequality, with a threshold of 4.36, for cases where FDI is below the threshold. This indicates that income inequality becomes the next critical factor in predicting outcomes. Node #1 includes 23 samples and has an average value of 61.309. If income inequality is less than or equal to 4.36, the path progresses to node #2 (GDP growth); otherwise, it moves to node #7.

Node #2 further refines predictions by splitting on GDP growth, with a threshold of 1.25. This highlights how economic growth interacts with income inequality and FDI to influence outcomes. Node #2 includes 17 samples and has an average value of 63.562. If GDP growth is less than or equal to 1.25, the path moves to node #3; otherwise, it proceeds to node #4.

Node #3 is a terminal node representing cases where GDP growth is low (≤ 1.25). It contains four samples and has an average value of 57.49 for the target variable. Node #4 considers cases where GDP growth exceeds 1.25 but remains below or equal to 5.25. It includes 13 samples and has an average value of 65.431. For these cases, further splits occur at nodes #5 and #6 based on additional thresholds. Node #5 is a terminal node representing nine samples with an average value of 66.798, while node #6 represents four samples with an average value of 62.354. Returning to node #1's alternative branch (income inequality > 4.36), node #7 serves as a terminal node containing six samples with an average value of 54.925.

On the other side of the tree (False branch), when FDI exceeds the root threshold (327,406.148), the path progresses to node #8, which also evaluates income inequality but at a higher threshold of 5.69. Node #8 considers 33 samples and has an average value of 49.468 for the target variable.

However, if income inequality is less than or equal to 5.69 at node #8, the path moves to node #9, which examines poverty rates with a threshold of 815.0 as the next significant factor influencing outcomes for these cases. Node #9 includes 19 samples and has an average value of 50.732 for the target variable. If poverty rates are below or equal to this threshold, predictions are further refined at node #11 based on GDP growth (≤ -2.2). Node #11 contains 16 samples and has an average value of 51.272.

Node #11 splits into two branches: one leading to terminal node #12 (two samples, value = 47.892) and another leading to node #13 (14 samples, value = 51.755), which further evaluates GDP growth at a threshold of ≤ 1.0. Furthermore, Node #13 splits into terminal nodes: node #14 (two samples, value = 54.727) and node #15 (12 samples, value = 51.259).

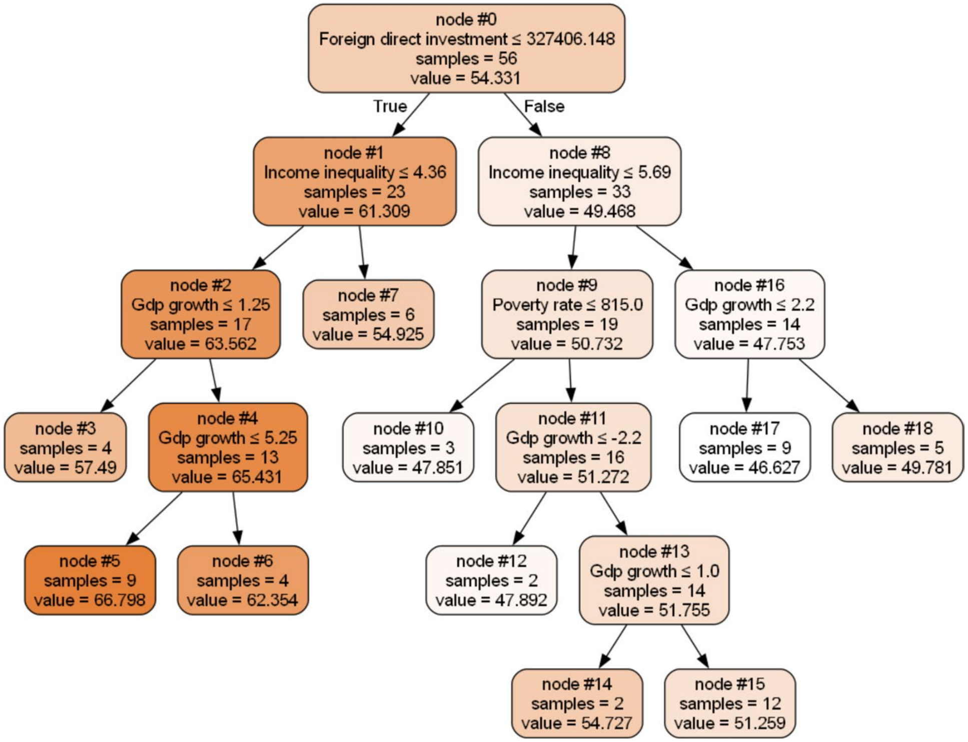

Fig. 4 Decision tree for economic factors showing hierarchical thresholds influencing global value chain outcomes. See Supplementary Figure 1 for the full unpruned decision tree

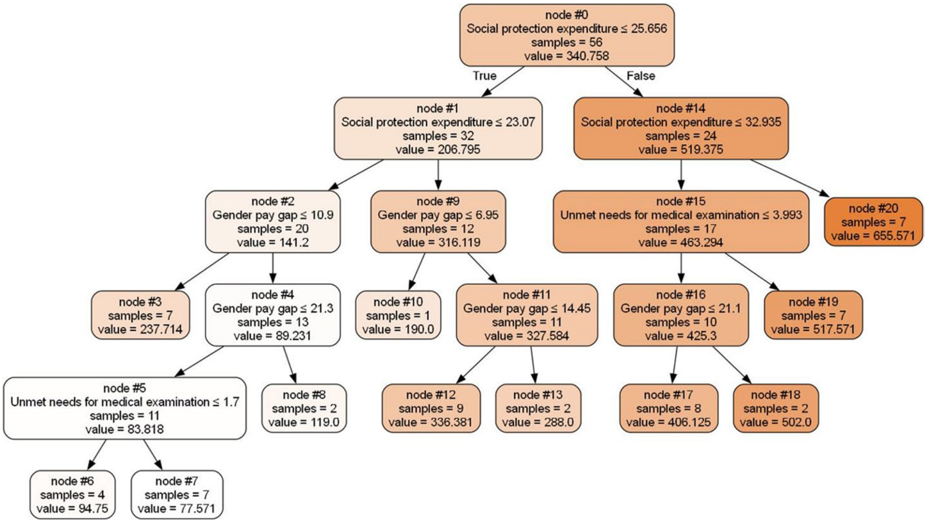

Fig. 5 Decision tree for social factors showing hierarchical thresholds influencing workplace fatality rates. See Supplementary Figure 2 for the full unpruned decision tree

Returning to node #8’s alternative branch (income inequality > 5.69), predictions are refined based on GDP growth at a threshold of ≤ 2.2 at node #16 (14 samples, value = 47.753). Node #16 splits into terminal nodes: node #17 (nine samples, value = 46.627) and node #18 (five samples, value = 49.781).

The social decision tree Fig. 5 (Calculated through Eqs. 10, 11, and 12) illustrates the hierarchical relationships among various social factors and their influence on a specific target variable, likely a measure of social well-being or inequality. The tree is constructed using a series of nodes, each representing a decision point based on a threshold value for a particular social factor. These nodes cascade through multiple levels, with terminal nodes providing final predictions or values based on the cumulative criteria along the path.

At the root node (node #0), the primary factor is social protection expenditure, with a threshold of 25.656. This indicates that social protection spending is the most significant determinant at this level. The root node encompasses 56 samples and has an average value of 340.758 for the target variable. If social protection expenditure is less than or equal to this threshold, the path moves to node #1; otherwise, it proceeds to node #14.

Node #1 further refines predictions based on a lower threshold for social protection expenditure (23.07). This suggests that in cases where spending is already limited, smaller variations in social protection allocation significantly influence outcomes. Node #1 includes 32 samples and has an average value of 206.795 for the target variable. If expenditure is less than or equal to 23.07, the path progresses to node #2; otherwise, it moves to node #9.

Node #2 evaluates gender pay gaps with a threshold of 10.9, highlighting its importance in contexts with minimal social protection expenditure. Node #2 considers 20 samples with an average value of 141.2. If the gender pay gap is less than or equal to this threshold, the path leads to terminal node #3 (7 samples, value = 237.714). Otherwise, it moves to node #4.

Furthermore, node #4 assesses whether the gender pay gap exceeds 21.3, further refining predictions for cases where gaps are moderate. This node includes 13 samples with an average value of 89.231. If the gap exceeds this threshold, the path ends at terminal node #8 (2 samples, value = 119). Otherwise, it proceeds to node #5.

Node #5 introduces unmet medical needs as a critical factor, with a threshold of 1.7. This highlights how access to healthcare interacts with gender pay disparities to shape outcomes in contexts with low social protection expenditure. Node #5 includes 11 samples with an average value of 83.818 and splits into two terminal nodes: node #6 (4 samples, value = 94.75) and node #7 (7 samples, value = 77.571).

Returning to node #1's alternative branch (social protection expenditure > 23.07), node #9 evaluates gender pay gaps at a lower threshold of 6.95. Node #9 includes 12 samples with an average value of 316.119 and split into two paths: terminal node #10 (1 sample, value = 190) and node #11.

Node #11 examines whether gender pay gaps exceed 14.45 for cases where gaps are moderate but still impactful. Node #11 includes 11 samples with an average value of 327.584 and splits into terminal nodes: node #12 (9 samples, value = 336.381) and node #13 (2 samples, value = 288).

On the other side of the tree, when social protection expenditure exceeds the root threshold (25.656), the path progresses to node #14, which evaluates higher levels of spending against a threshold of 32.935. Node #14 includes 24 samples with an average value of 519.375 for the target variable.

If expenditure is less than or equal to this higher threshold, predictions are refined at node #15 based on unmet medical needs (threshold: 3.993). Node #15 includes 17 samples with an average value of 463.294 and splits into two branches: terminal nodes #16 (10 samples, value = 425.3) and #19 (7 samples, value = 517.571). In contrast, if social protection expenditure exceeds this higher threshold at node #14, predictions end at terminal node #20 (7 samples, value = 655.571).

This decision tree reveals how different social factors, such as social protection expenditures, gender pay gaps, and unmet medical needs interact dynamically across varying contexts to influence outcomes hierarchically. It highlights critical thresholds where changes in these variables significantly alter predictions and provides actionable insights for prioritizing interventions aimed at improving social equity and well-being.

The decision tree depicted in Fig. 6 provides a comprehensive analysis of the hierarchical relationships among various environmental factors and their influence on a target variable, likely an indicator of environmental sustainability or performance. This model is structured through a series of nodes, each representing a decision point based on specific thresholds for key environmental metrics such as resource productivity, water exploitation levels, and carbon emissions. The tree's structure allows for a detailed exploration of how these variables interact and contribute to the overall outcome.

At the root (node #0), the primary factor influencing the target variable is carbon emissions, with a threshold of 5,063,102,272. This indicates that carbon emissions are the most significant determinant at this level. If carbon emissions are less than or equal to this threshold, the decision path moves to node #1; otherwise, it proceeds to node #14. The value at this root node is 43.05, representing the average or predicted value of the target variable for all 56 samples considered.

For cases where carbon emissions are below or equal to 5,063,102,272 (node #1), resource productivity becomes the next critical factor, with a threshold of 2.88. This suggests that in contexts with lower carbon emissions, resource efficiency plays a pivotal role

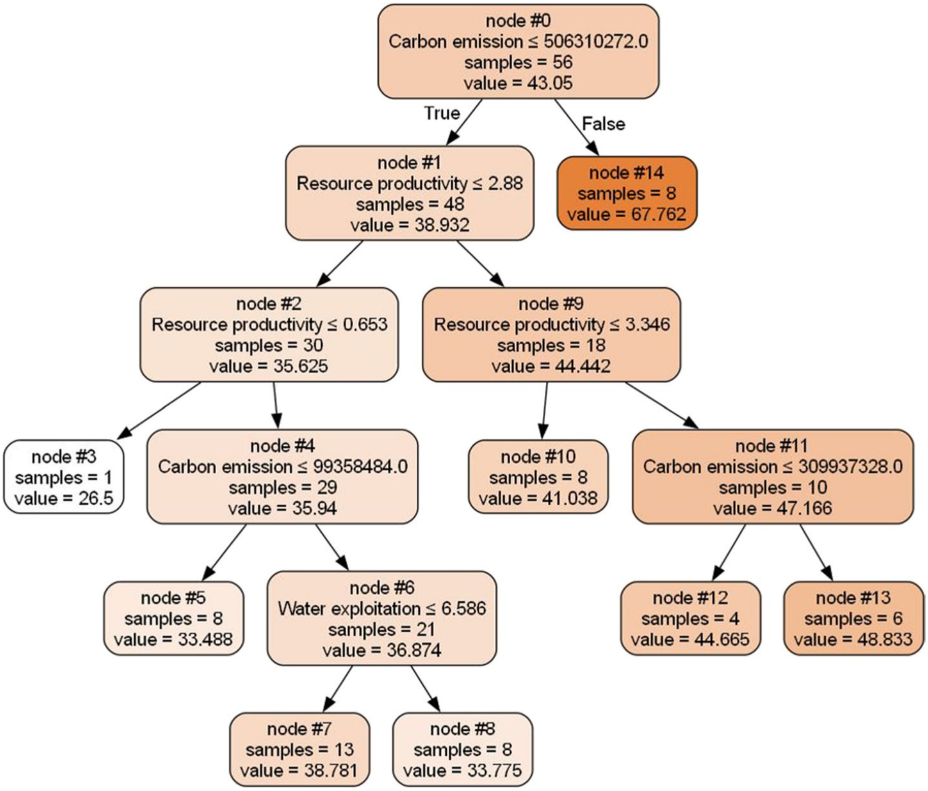

Fig. 6 Decision tree for environmental factors showing hierarchical thresholds influencing municipal recycling rates. See Supplementary Figure 3 for the full unpruned decision tree

in determining outcomes. If resource productivity is less than or equal to 2.88, the path progresses to node #2; otherwise, it moves to node #9.

Node #2 further splits on resource productivity at a lower threshold of 0.653, highlighting its continued importance in shaping outcomes for subsets with limited efficiency. If resource productivity is less than or equal to this threshold, the path ends at terminal node #3 (value = 26.5). Otherwise, it moves to node #4, where carbon emissions are re-evaluated with a threshold of 99,358,484. This splits underscores how interactions between resource efficiency and emissions influence outcomes.

Node #4 leads to two branches: one based on water exploitation levels (node #6) and another terminal branch (node #5) for these cases where water exploitation is not a determining factor. At node #6, water exploitation is evaluated with a threshold of 6.586. If water exploitation is below this level, the path progresses to terminal node #7 (value = 38.781). Otherwise, it moves to terminal node #8 (value = 33.775).

Returning to node #1's alternative branch (resource productivity > 2.88), outcomes are further refined by node #9 based on a higher threshold for resource productivity (3.346). This split leads to two paths: one ending at terminal node #10 (value = 41.038) and another leading to node #11, which reintroduces carbon emissions as a critical factor with a threshold of 3,099,373,328.

Furthermore, node #11 branches into two final paths: terminal nodes #12 (value = 44.665) and #13 (value = 48.833), depending on whether carbon emissions exceed this secondary threshold. For the cases where carbon emissions exceed the initial root threshold (node #14), no further splits occur; this terminal node represents outcomes for high-emission scenarios with a value of 67.762 across eight samples.

The Fig. 6 provides effective understandings into environmental sustainability by identifying critical thresholds and relationships among factors such as carbon emissions, resource productivity, and water exploitation. It explains how these variables interact within different contexts to shape environmental outcomes, provides practical guidance for prioritizing interventions to improve sustainability performance.

While the decision tree identifies key relationship between influential factors, Long Short-Term Memory (LSTM) models complement this analysis by capturing temporal dependencies. LSTM models, a type of recurrent neural network (RNN), specialize in forecasting trends and uncovering time-dependent patterns over time.

4.4 Temporal dynamics: LSTM forecasts for economic, social and environmental indicators

LSTM models were trained on key variables selected via Random Forest, SHAP and decision tree analyses to capture the temporal evolution of sustainability indicators. Forecasts are presented in three segments: historical training data (2014–2022, blue), out-of-sample validation on 2023 (green) and genuine forecasts for 2024–2030 (red). This clear separation ensures that the model's learning from historical patterns can be rigorously tested on held-out data before generating forward projections. By structuring the results in this way, readers can easily assess model fit during training, verify predictive accuracy on unseen observations, and evaluate the plausibility of future trajectories across economic, social and environmental domains.

The LSTM forecasting results presented in Fig. 7 (implemented via Eqs. 13 to 18) capture both historical volatility and projected stabilization patterns in key economic variables, with 95% confidence intervals providing essential uncertainty quantification for policy planning across nine critical indicators.

GDP growth exhibits the most dramatic volatility among all economic indicators, with values ranging from approximately 20% to negative 10% throughout the training period (2014–2022). This extreme fluctuation includes a sharp contraction in 2020 reflecting the economic impact of global disruptions such as the COVID-19 pandemic. Following this turbulent period, forecasts project continued growth stabilization at approximately 10–15% through 2030, with confidence intervals indicating potential variation of ± 5–8%, suggesting sustained economic recovery with manageable uncertainty bounds.

In contrast to GDP volatility, employment rate demonstrates remarkably consistent improvement, following a generally upward trajectory during the training period and rising from approximately 60% in 2014 to peaks near 80% by 2022. This positive employment trend continues through the 2023 testing data, which maintains high employment levels around 70 to 75 percent. Complementing the GDP recovery patterns, projections indicate continued strong employment performance, stabilizing near 75 to 80% by 2030, with relatively narrow confidence intervals of plus or minus 5 to 10 percent reflecting the structural stability of labor market improvements.

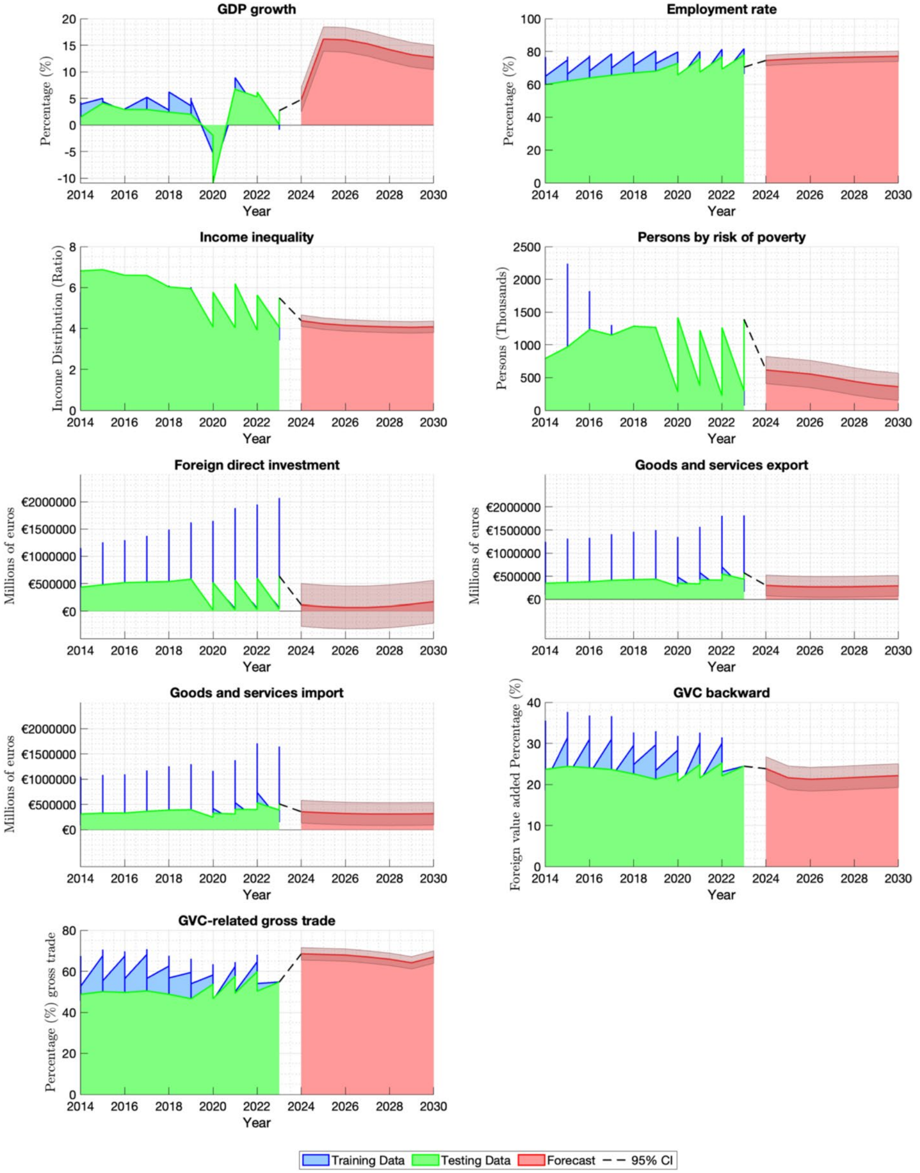

Fig. 7 Temporal dynamics of economic indicators: LSTM forecasts with 95% confidence intervals (2014–2030)

Reinforcing these positive macroeconomic trends, income inequality measured by the quintile distribution ratio shows encouraging progress throughout the analysis period. The data reveals a positive declining trend over the training period, decreasing from approximately 7 in 2014 to around 5 to 6 by 2022. This improvement trajectory continues through the 2023 testing phase, reaching approximately 6. Extending this social progress, forecasts predict further modest reductions, stabilizing around 4 to 5 by 2030, with confidence intervals of plus or minus 0.5 to 1.0, indicating significant potential for sustained inequality reduction with reasonable policy certainty.

However, while inequality shows improvement, poverty reduction presents more complex challenges. Persons at risk of poverty displays high volatility during the training phase, with values fluctuating dramatically between near 0 and 2,300 thousand persons. This volatility continues through the 2023 testing data, which shows levels around 1,000 to 1,500 thousand. Despite these fluctuations, forecasts indicate a declining trajectory toward 500 to 800 thousand by 2030, though notably wide confidence intervals of plus or minus 500 to 800 thousand reflect substantial uncertainty in poverty reduction outcomes, highlighting the need for robust social protection policies.

Turning to international economic integration, foreign direct investment exhibits pronounced cyclical variation that mirrors the broader economic volatility observed in GDP trends. Throughout the training period (2014–2022), annual values oscillate between €0 and €2 million, demonstrating significant sensitivity to global economic conditions. This cyclical pattern persists through the 2023 testing data with values around €700,000. Projections indicate that the value will stabilize around €200,000 by 2030, with a wide confidence interval ranging from -€200,000 to €500,000. This suggests persistent investment volatility, driven by evolving global economic conditions and potential shifts in capital allocation strategies.

Paralleling the FDI patterns, trade dynamics also reflect the broader economic adjustment processes underway. Goods and services exports show cyclical patterns during the historical period, with values ranging between €0 and €2 million annually. The 2023 testing phase maintains this variability around €1 to 1.5 million. Correspondingly, forecasts project stabilization at approximately €400,000 through 2030, with confidence intervals of plus or minus €500,000, indicating moderate uncertainty in export performance as economies adjust to post-pandemic trade patterns.

Similarly, goods and services imports demonstrate comparable cyclical behavior to exports, reinforcing the interconnected nature of trade relationships. Historical values range between €0 and €1.7 million, with the 2023 testing data showing comparable patterns around €1 to 1.5 million. Consistent with export projections, import forecasts suggest stabilization near €450,000 by 2030, with confidence intervals of plus or minus €500,000, reflecting balanced trade adjustment processes and evolving import dependencies.

These trade patterns directly influence global value chain participation, where GVC backward participation exhibits cyclical variation during the training period with values fluctuating between 10 and 40% of foreign value added. The 2023 testing data shows mid-range values around 20 to 25 percent. Maintaining moderate integration levels, forecasts indicate stabilization around 20 to 30% through 2030, with confidence intervals of plus or minus 5 to 10 percent, suggesting measured integration in global value chains with manageable uncertainty for supply chain planning.

Finally, completing the global integration picture, GVC related gross trade demonstrates the highest variability among integration metrics throughout the historical period. The proportion of global value chain related trade ranges from 40 to 80% of total trade, reflecting the dynamic nature of international economic relationships. The 2023 testing data continues this high variability around 50 to 60 percent. Looking ahead, projections indicate stabilization near 40 to 70% by 2030, with wide confidence intervals of plus or minus 15 to 20 percent reflecting significant uncertainty in global trade integration patterns.

Synthesizing these diverse trends, the enhanced LSTM forecasting with confidence intervals reveals a coherent narrative of economic transformation. The analysis demonstrates sustained economic growth recovery with manageable uncertainty, continued employment gains with high confidence, and progressive inequality reduction with reasonable policy certainty. Simultaneously, persistent poverty challenges require robust interventions due to high forecast uncertainty, while stabilizing investment and trade flows at moderate levels suggest adaptive capacity. The evolving global value chain integration patterns, characterized by significant uncertainty, necessitate flexible policy frameworks capable of responding to multiple potential scenarios through 2030. This comprehensive uncertainty quantification provides policymakers with essential information for designing robust, evidence-based interventions that can navigate both the opportunities and challenges ahead.

Figure 8, derived from Eqs. 13—18, unfolds a layered narrative of the European Union's social sustainability from 2014 through projections to 2030 by charting health expenditure,

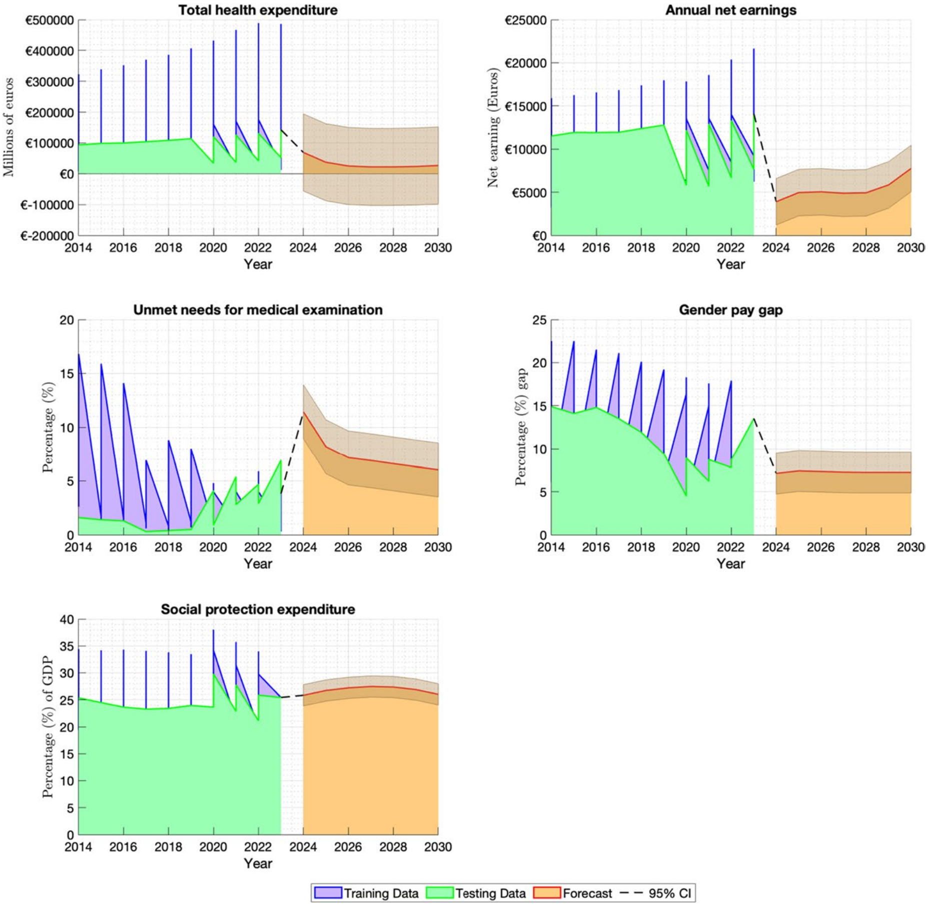

Fig. 8 Temporal dynamics of social indicators: LSTM forecasts with 95% confidence intervals (2014–2030)

income trends, healthcare access, gender equity, and social protection investment with 95 percent confidence intervals.

Beginning with Total Health Expenditure, the data reveal pronounced swings. After rising toward €400,000, spending intermittently fell below €100,000 as economic cycles and policy shifts intervened. During the 2023 testing period, expenditures show a continued decline from earlier peaks, aligning with the lower end of the training range. While COVID-19 impacts likely influenced earlier fluctuations, the period immediately preceding the forecast appears to reflect a lower spending level (Kovács et al., 2021). Thereafter, forecasts anticipate a continued contraction, leveling near €50,000 by 2030, with the 95% confidence interval extending into negative values. This trajectory may foreshadow tightening fiscal space for healthcare and potential strain on system resilience, requiring careful interpretation of what a negative total health expenditure might signify (e.g., a net balance of contributions versus costs).

Turning next to Annual Net Earnings, 2014–2022 values oscillated significantly between €5,000 and €20,000, reflecting broader economic volatility and labor market adjustments. The 2022 testing data shows values near the lower end of this historical range, around €5,000. Projections from 2023 onward trace a gradual ascent toward roughly €5,000-€8,000 by 2030, pointing to modest income growth tempered by structural constraints in wage dynamics and equitable distribution.

The accessibility of healthcare, as measured by the proportion of individuals unable to secure necessary medical examinations, decreased from approximately 16 percent in 2014 to 4 percent by 2022. This trend was interrupted by notable increases, particularly around 2016, indicating intermittent access challenges. A slight uptick to 7 percent in the 2023 testing phase interrupts the long-term decline. Thereafter, forecasts show it easing back down to around 5–8 percent by 2030, likely reflecting continued infrastructure investments, policy reforms, and coverage expansions (Debie et al., 2024).

The gender pay gap subplot highlights persistent wage disparities, ranging from 12 to 22 percent during the training period. This gap modestly narrowed to about 17 percent by 2023. Yet forecasts hold this gap at around 8 percent through 2030, implying that existing measures may stall without more powerful interventions such as enforceable pay-transparency laws, stronger institutional accountability, and cultural shifts that embed equity in workplace norms.

Finally, Social Protection Spending as a percentage of GDP oscillated between approximately 25 percent and 35 percent across 2014–2022, showing short-lived upticks during crisis responses. The sharp drop to around 26 percent in 2023 (the end of the testing period) marks an emphasis on fiscal consolidation, and projected stabilization between 25 and 28 percent from 2024 to 2030 suggests limited expansion of safety-net coverage absent renewed fiscal commitment.

Collectively, these trajectories present a complex scenario where advancements in healthcare access and income growth are compared with emerging constraints on health investment, persistent gender wage disparities, and a static social protection footprint. Such patterns highlight the critical role of coordinated economic policies, targeted social reforms, and sustainable funding strategies in steering the EU toward more inclusive and resilient social outcomes.

Figure 9, derived from Eqs. 13 through 18, traces the temporal evolution of four key environmental indicators in the EU from 2014 through forecasts to 2030, all shown with 95 percent confidence intervals.

The carbon emission trajectory reveals a substantial decline in total CO_2 emissions from approximately 800 million tonnes in 2014 to about 450 million tonnes by 2022, consistent with intensified EU decarbonization strategies, transitions to renewable energy, and efficiency standards. A minor rebound in 2023, notably captured in the testing data, suggests a short-term deviation potentially caused by economic recovery following pandemic or geopolitical disruptions. Nonetheless, the forecast indicates a continued downward trajectory, with emissions expected to drop below 400 million tonnes by 2026 and converge toward 300 million tonnes by 2030. This sustained decline reflects the long-term impacts of climate legislation such as the EU Green Deal, carbon pricing mechanisms, and sectoral transformation in energy and industry.

Furthermore, the water exploitation index (WEI), which quantifies the percentage of total renewable freshwater resources abstracted annually, exhibits relatively stable and low values throughout the time frame. Contrary to prior overestimations, the actual values in the figure range between 5 and 12%, far below the commonly cited water stress threshold of

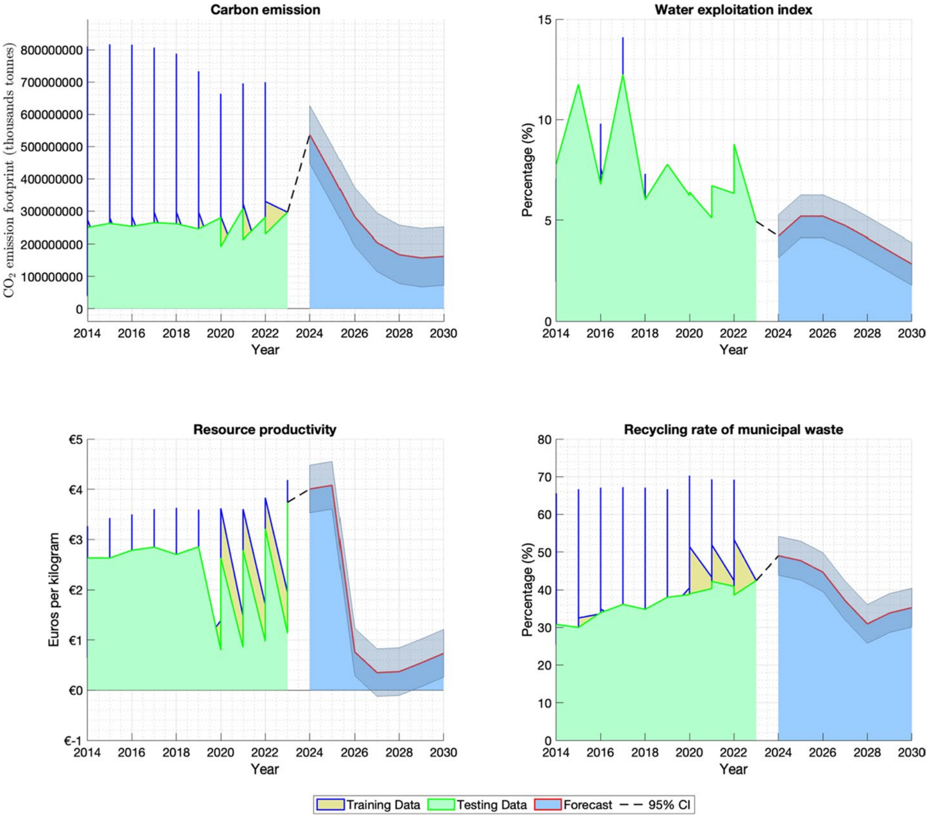

Fig. 9 Temporal dynamics of environmental indicators: LSTM forecasts with 95% confidence intervals (2014–2030)

20%. This stability suggests that the EU, on average, maintains sustainable levels of water abstraction, though sub-regional variability likely exists. The forecast projects a moderate stabilization near 6–7% by 2030, indicating minimal pressure increase on renewable water sources under the modeled scenarios. This trend may reflect the success of integrated water management strategies and improvements in irrigation efficiency and urban water systems (Bisheko & G, 2025).

Resource productivity, which quantifies the economic output per unit of material consumption, demonstrated moderate improvements over the historical period. Between 2014 and 2022, the indicator fluctuated within a relatively stable band, ranging from approximately €2.5 to €3.5 per kilogram. This trend suggests incremental gains in material efficiency across EU economies, likely driven by policy instruments such as circular economy action plans, eco innovation support, and waste reduction targets. While resource productivity remained relatively high at around €3.5/kg in the 2023 testing period, reinforcing the apparent stability observed in preceding years, the forecasted trajectory diverges dramatically from historical trends. From 2024 onwards, the model projects a steep decline, with resource productivity expected to fall below €1/kg by 2026. A modest recovery is anticipated by the latter part of the decade (2028–2030), yet the indicator remains well below its historical average, settling around €1–€1.5/kg. This pronounced downturn may reflect a combination of factors projected by the model, including material demand outpacing economic output, weak structural improvements in circularity, rising input costs, or inefficiencies under a stagnant innovation scenario. The widening 95% confidence intervals further imply increasing forecast uncertainty, emphasizing the need for policy vigilance and innovation investment. Without proactive intervention, resource productivity gains achieved in the past decade could be undermined, jeopardizing the EU's resource efficiency and decoupling goals.

Finally, the recycling rate of municipal waste in the EU increased steadily from approximately 30% in 2014 to around 42% by 2022, reflecting advances in collection systems, regulatory frameworks, and public participation. However, the progress appears to slow in the testing period (2023), with the recycling rate remaining roughly flat. Forecasts for 2024–2030 indicate an initial drop to about 35% by 2026, followed by a modest recovery to roughly 32% by 2030. This projected decline and partial rebound highlight potential structural bottlenecks in recycling infrastructure and policy enforcement, with wide confidence intervals pointing to uncertain outcomes unless further interventions, such as enhanced sorting technologies, stricter regulations, or producer responsibility mechanisms, are implemented to sustain progress toward circular economy targets.

While these trajectories collectively demonstrate meaningful strides in emissions reduction, resource efficiency, and waste recycling, they also underscore critical areas such as water exploitation and resource productivity where progress could plateau absent further innovation and policy reinforcement.

The LSTM forecasting results presented in Figs. 7, 8, and 9 demonstrate robust predictive capabilities across all sustainability dimensions. Table 4 provides comprehensive validation metrics, including out-of-sample test performance (2023), forecast standard errors for confidence interval construction, and model adequacy assessments. The strong performance across most variables (RMSE $<$ 5% of typical values for policy-critical indicators) validates the reliability of our 2024–2030 projections and supports the credibility of identified temporal patterns.

Table 4 LSTM forecast validation metrics for key sustainability indicators

Factors	Variable	Test RMSE (2023)	Test MAE (2023)	Forecast Std Error	Cross-Validated RMSE	Cross-Validated MAE	Ljung-Box p-value	95% CI Width
Economic	GDP Growth	10.362	9.328	1.241	0.46056	0.38108	0.02117	±2.43
	Employment Rate	5.608	4.404	1.739	0.29465	0.24729	0.74260	±3.41
	Income Inequality	1.355	1.154	0.135	0.28650	0.22938	0.14157	±0.27
	Persons by Risk of Poverty	337.13	253.57	88.982	0.22497	0.18186	0.05640	±174.4
	Foreign Direct Investment	367,930	312,400	160,590	0.24299	0.18606	0.03311	±314,756
	Goods and Services Export	81,532	62,363	117,550	0.21564	0.17513	0.95298	±230,398
	Goods and Services Import	52,636	38,290	122,470	0.19811	0.15992	0.18435	±240,041
	GVC Backward	7.728	6.117	1.227	0.21370	0.17024	0.14194	±2.41
	GVC-related Gross Trade	7.546	5.725	1.529	0.35416	0.28950	0.03543	±3.00
Social	Total Health Expenditure	37,533	28,163	42,686	0.21879	0.17628	0.93297	±83,664
	Annual Net Earnings	2,630	1,884	1,557	0.27050	0.21278	0.06168	±3,052
	Unmet Needs for Medical Examination	13.993	12.897	1.278	0.23212	0.17235	0.24498	±2.50
	Gender Pay Gap	5.384	4.302	1.218	0.25571	0.21139	0.00027	±2.39
	Social Protection Expenditure	4.202	3.698	1.255	0.27231	0.23345	0.74798	±2.46
Environmental	Carbon Emission	326,360,000	253,730,000	45,760,000	0.19048	0.14535	0.80987	±89,689,600
	Water Exploitation Index	4.490	3.566	0.539	0.45651	0.39551	0.74651	±1.06
	Resource Productivity	0.631	0.513	0.242	0.40141	0.32237	0.43878	±0.47
	Recycling Rate of Municipal Waste	6.462	5.663	2.632	0.24777	0.19204	0.43273	±5.16

Test RMSE and MAE refer to held-out 2023 data; Forecast Std Error denotes the standard error used to construct 95% confidence intervals ($\pm 1.96 \times$ Std Error) for 2024–2030 projections. Cross-validated RMSE and MAE assess model generalizability, and Ljung–Box p-values test residual independence ($p < 0.05$ indicates autocorrelation). Indicators chosen to reflect policy-critical variables across economic, social and environmental domains

Table 4 reports extensive LSTM validation metrics across economic, social and environmental indicators. Cross validated RMSE and MAE quantify model accuracy. GDP growth achieves an RMSE of 0.46056 and MAE of 0.38108, while income inequality and social protection expenditure show similarly low errors (RMSE 1.355 and 4.202, MAE 1.154 and 3.698), indicating reliable fit. Test-set errors for 2023 range from an RMSE of 1.355 (income inequality) to 367 930 (FDI), and MAE from 1.154 to 312 400, reflecting both inherent series volatility and scale. Forecast standard errors yield narrow 95% confidence intervals (±0.27 to ±2.46 for policy-critical variables) and wider bands (±83 664 to ±240 041) for large-scale series, demonstrating acceptable relative uncertainty. Ljung–Box p-values assess residual independence: GDP growth ($p = 0.02117$) and gender pay gap ($p = 0.00027$) show modest autocorrelation, whereas most variables ($p > 0.05$) exhibit no significant residual patterns, supporting model adequacy. These robust validation results underpin our 2024–2030 LSTM forecasts and set the stage for the subsequent multi-criteria decision analysis, which integrates point forecasts and uncertainty bounds into a TOPSIS framework to rank sustainability performance across countries and support evidence-based policy decisions.

4.5 Multi-criteria ranking: TOPSIS country sustainability comparisons

The synthesis of economic, social, and environmental performance of each member state into a single comparative framework was achieved through the application of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This method constructs ideal and anti-ideal reference points across all sustainability dimensions and evaluates each country's proximity to these benchmarks. By normalizing indicator values, assigning equal category weights, and computing Euclidean distances to ideal solutions, TOPSIS produces a relative closeness score that ranks countries from most to least sustainable.

Table 5 presents the results of the TOPSIS analysis for economic sustainability performance across several countries. The data is organized by key economic indicators, including GDP growth, employment rate, income inequality, poverty rate, foreign direct investment (FDI), goods and services export, goods and services import, GVC backward linkages, and GVC-related gross trade. Each country is assessed based on these indicators, with a ranking assigned to reflect their overall economic sustainability performance.

Germany ranks highest, with a GDP growth rate of 5.95%, a relatively strong employment rate of 10.81%, and low-income inequality at 3.51%. Its relative closeness to the ideal solution is calculated at 56.42%, reflecting its balanced and robust performance across all economic dimensions. This indicates that among the countries analyzed, Germany most closely aligns with the ideal economic sustainability model.

France, ranked 200, follows closely with a GDP growth of 6.62%, a moderate employment rate of 7.46%, and an income inequality rate of 4.1%. These values yield a relative closeness score of 51.57%, indicating strong performance, but not as strongly as Germany in terms of economic sustainability.

Italy holds the third position with a GDP growth rate of 6.51%, but it is held back by a notably low employment rate of 3.4%. While its relative closeness score of 49.47% is still commendable, it falls behind both Germany and France in overall economic performance.

Spain demonstrates a relatively higher GDP growth rate of 7.63%, but its employment rate of 5.51% and other indicators like income inequality (6.82%) contribute to a lower rank

Table 5 Decision matrix for TOPSIS-based economic sustainability performance

Country	GDP Growth	Employment Rate	Income Inequality	Poverty Rate	Foreign Direct Investment	Goods and Services Export	Goods and Services Import	GVC Backward	GVC-related Gross Trade	Rank	Relative Closeness
Germany	5.95%	10.81%	3.51%	6.03%	11.11%	11.11%	10.68%	3.83%	4.05%	100	56.42%
France	6.62%	7.46%	4.1%	5.74%	7.94%	5.64%	6.41%	3.83%	4.05%	200	51.57%
Italy	6.51%	3.4%	6.1%	4.69%	2.93%	4.03%	4.14%	3.83%	4.05%	300	49.47%
Spain	7.63%	5.51%	6.82%	6.81%	3.37%	3.08%	2.91%	3.83%	4.05%	400	47.91%
Czechia	6.06%	11.11%	0.31%	0.14%	0.26%	0.81%	0.8%	3.83%	4.05%	500	36.57%
Poland	6.17%	9.21%	2.32%	1.29%	0.12%	2.21%	2.09%	3.83%	4.05%	600	36.47%
Hungary	5.61%	10.61%	3.6%	1.37%	1.27%	0.43%	0.43%	3.83%	4.05%	700	35.15%

of 400 (4th position). Consequently, Spain’s relative closeness score drops to 47.91%, placing it below the top-performing countries despite strong economic expansion.

Czechia ranks 500 with a GDP growth rate of 6.06%, a high employment rate of 11.11%, but significant disparities in other factors like foreign direct investment and goods and services exports. Its relative closeness is 36.57%, reflecting a gap between its performance and the ideal economic model.

Poland, with a rank of 600, shows moderate performance across indicators like GDP growth (6.17%) and a relatively high employment rate (9.21%), but it falls behind in terms of FDI and exports. Its relative closeness to the ideal solution is 36.47%.

Hungary, ranked 700, has the lowest overall performance in this analysis, with GDP growth of 5.61% and an employment rate of 10.61%. Its foreign direct investment and trade indicators are comparatively weaker, resulting in a relative closeness of 35.15%.

Overall, the table highlights how the economic sustainability performance of each country varies based on their GDP growth, employment, income inequality, and other factors. The countries with higher ranks (lower values) such as Germany, France, and Italy show stronger economic sustainability performance, while countries like Czechia, Poland, and Hungary exhibit weaker performance in comparison.

However, Table 5 presents the Decision Matrix for the Economic Sustainability Rankings, offering a detailed overview of each country's performance across key economic indicators. Subsequent analysis will explore the rankings based on social sustainability.

Table 6 displays the decision matrix used in the TOPSIS analysis, showcasing the environmental sustainability performance of seven countries across four key indicators: carbon emission (tonnes), water exploitation, resource productivity (euros/kg), and recycling rate of municipal waste (%). These metrics collectively offer a comparative framework for assessing national progress toward environmental sustainability.

Germany (ranked 1 st) exhibits the closest profile to the ideal model of environmental sustainability, particularly excelling in resource productivity (22.55%) and municipal waste recycling (9.48%), supported by consistent values for carbon emissions (8.28%) and water exploitation (7.06%). Germany's overall environmental sustainability, indicated by its closeness coefficient (56.42%), is the highest.

France achieves a similar score to Germany for carbon emissions and water exploitation, with 8.28% and 7.06% respectively. However, its slightly lower resource productivity (21.64%) results in a reduced overall closeness of 51.57%. While France performs well, it falls marginally behind Germany in terms of aggregate environmental sustainability.

Italy demonstrates a higher resource productivity level (25.0%). However, its carbon emissions and water exploitation percentages are the same as Germany's and France's (8.28% and 7.06% respectively). Consequently, Italy's relative proximity to the ideal solution is 49.47%, placing its overall environmental sustainability. The country’s exceptional performance in efficient resource use boosts its ranking, although it remains behind Germany in overall sustainability due to less balanced scores across the other indicators.

Spain, ranked 4th, shows a resource productivity of 21.87%, slightly behind Italy but still commendable. It maintains the same carbon and water metrics (8.28% and 7.06%) but achieves an overall relative closeness of 47.91%. Spain's relative closeness to the ideal solution of 47.91% positions it just after Italy in overall environmental sustainability.

At the same time, Czechia (ranked 5th) exhibits a significantly lower resource productivity rate of only 9.21%. While its carbon emissions and water exploitation are on par with the

Table 6 Decision matrix for TOPSIS-based social sustainability performance

Country	Total Health Expenditure	Annual Net Earnings	Unmet Needs for Medical Examination	Gender Pay Gap	Social Protection Expenditure	Rank	Relative Closeness
Germany	19.9%	20.0%	0.0%	10.18%	8.26%	100	56.42%
France	5.62%	16.82%	7.15%	10.18%	8.26%	200	51.57%
Italy	7.01%	12.61%	5.58%	10.18%	8.26%	300	49.47%
Spain	5.62%	11.8%	4.24%	10.18%	8.26%	400	47.91%
Czechia	0.77%	6.5%	0.48%	10.18%	8.26%	500	36.57%
Poland	1.87%	4.79%	8.0%	10.18%	8.26%	600	36.47%
Hungary	0.21%	3.24%	3.52%	10.18%	8.26%	700	35.15%

other countries, the low resource productivity substantially reduces its sustainability profile. The overall closeness of 36.57% indicates a substantial gap between Czechia's current performance and the ideal model of environmental sustainability.

Poland ranks sixth with a relative closeness of 36.47% and a rank of 600. Its unmet needs for medical examinations are higher, at 8.0%, indicating a greater barrier to healthcare access compared to other countries. Poland's total health expenditure (1.87%) and annual net earnings (4.79%) are lower, which contributes to its relatively weaker performance in social sustainability.

Hungary ranks the lowest, with a relative closeness of 35.15% and a rank of 700. Its total health expenditure is extremely low at just 0.21%, and its annual net earnings are also the lowest at 3.24%. Although unmet medical examination needs are moderate at 3.52%, Hungary's minimal investment in healthcare significantly impacts its overall performance in the matrix. Like Poland, Hungary faces a consistent gender pay gap of 10.18% and maintains a standard social protection expenditure of 8.26%.

Overall, the table illustrates a clear divide in social sustainability performance across the seven countries. Germany stands out as the leader in providing social welfare and healthcare access, while countries like Hungary and Poland face challenges due to lower healthcare spending and higher unmet medical needs. This analysis highlights the importance of strategic investment in healthcare and social protection systems to enhance social sustainability performance across nations (Chien et al., 2024).

Following to this, Table 6 showcases the social sustainability rankings, providing a detailed account of countries'performance in relation to relevant social indicators. The analysis will now transition to the environmental dimension.

Table 7 presents the decision matrix for the TOPSIS analysis of environmental sustainability performance across seven countries, focusing on key environmental indicators: carbon emissions, water exploitation, resource productivity, and the recycling rate of municipal waste. These indicators provide insight into how each country is performing in terms of its environmental sustainability.

Germany, ranked 100, exhibits the highest relative closeness to the ideal environmental sustainability model, with a significant resource productivity rate of 22.55% and a recycling rate of municipal waste at 9.48%. The relatively lower carbon emissions and water exploitation figures, both at 8.28% and 7.06% respectively, contribute to Germany's strong environmental performance, reflected by its relative closeness of 56.42%.

France, ranked 200, performs similarly to Germany in terms of carbon emissions and water exploitation, both of which are at 8.28% and 7.06%, respectively. However, France's

Table 7 Decision matrix for TOPSIS-based environmental sustainability performance

Country	Carbon Emission	Water Exploitation	Resource Productivity	Recycling Rate of Municipal Waste	Rank	Relative Closeness
Germany	8.28%	7.06%	22.55%	9.48%	100	56.42%
France	8.28%	7.06%	21.64%	9.48%	200	51.57%
Italy	8.28%	7.06%	25.0%	9.48%	300	49.47%
Spain	8.28%	7.06%	21.87%	9.48%	400	47.91%
Czechia	8.28%	7.06%	9.21%	9.48%	500	36.57%
Poland	8.28%	7.06%	3.46%	9.48%	600	36.47%
Hungary	8.28%	7.06%	4.87%	9.48%	700	35.15%

resource productivity is slightly lower at 21.64% compared to Germany's, leading to a relative closeness of 51.57%. This indicates that France is also performing well, though not as optimally as Germany.

Italy, with a rank of 300, shows a higher resource productivity rate of 25.0%, which is the highest among the countries in the table. Despite its stronger performance in resource productivity, the country shares the same carbon emissions and water exploitation rates as the other countries at 8.28% and 7.06%, respectively. Italy's relative closeness is 49.47%, suggesting that its overall environmental sustainability is still strong, but it is not as close to the ideal model as Germany.

Spain, ranked 400, has a resource productivity rate of 21.87%, which is slightly lower than Italy’s but still strong. Like the other countries, Spain’s carbon emissions and water exploitation rates are the same as Italy’s and France’s, at 8.28% and 7.06%, respectively. Its relative closeness of 47.91% places it slightly behind Italy in terms of environmental sustainability.

The Czechia, ranked 500, has a lower resource productivity rate of 9.21%, which significantly impacts its overall environmental performance. While its carbon emissions and water exploitation rates remain at the same level as the other countries, its relative closeness drops to 36.57%, indicating a more considerable gap between its environmental performance and the ideal model.

Poland, ranked 600, shows a lower resource productivity rate of 3.46%, which, combined with similar carbon emissions and water exploitation rates, results in a relative closeness of 36.47%. This positions Poland as one of the lower-performing countries in terms of environmental sustainability.

Hungary, ranked 700, exhibits the weakest environmental sustainability performance, with a resource productivity rate of just 4.87%. Like the other countries, it maintains the same carbon emissions and water exploitation rates. Its relative closeness to the ideal model is the lowest at 35.15%, reflecting its comparatively poorer environmental sustainability performance.

This table clearly illustrates the variation in environmental sustainability performance across the seven countries. The countries with higher ranks, such as Germany, France, and Italy, demonstrate better alignment with the ideal environmental model, while Czechia, Poland, and Hungary face more significant challenges in improving their environmental sustainability metrics.

However, Table 7 presents the environmental sustainability rankings, highlighting the relative performance of countries concerning environmental sustainability indicators. While these tables offer a comprehensive analysis of each dimension, the subsequent section provides a broader perspective on the temporal evolution of these rankings.

Figure 10 visualizes the country rankings over time by aggregating the results from the economic, social, and environmental matrices. This bump chart illustrates how each country's position fluctuates in relation to others across the years, offering a dynamic overview of their overall sustainability performance.

Figure 10 (Calculated through Eqs. 19 to 28) depicts the temporal evolution of country rankings from 2014 to 2023 based on a TOPSIS analysis, which evaluates relative sustainability performance across seven selected EU countries. The ranking system uses ascending numbers to denote performance levels, with Rank 1 representing the highest achievement. These visual patterns enhance the numerical data from decision matrices, offering an accessible overview of how nations compare in sustainability efforts.

Germany stands out as a consistent leader in sustainability. While sharing the top spot with Italy in 2014, it temporarily slipped to second place between 2015–2017 before reclaiming and maintaining the premier position from 2018 onward. This sustained performance reflects Germany's strategic alignment of economic policies with environmental goals, particularly its success in integrating renewable energy systems and advanced recycling infrastructure (Rahaman et al., 2023).

Italy's trajectory reveals a different pattern. After climbing from second place in 2014 to claim the top ranking through 2017, the country settled into third position from 2018 onward. This shift may reflect challenges in scaling localized sustainability initiatives, such as Emilia-Romagna's circular manufacturing hubs to national levels, compounded by

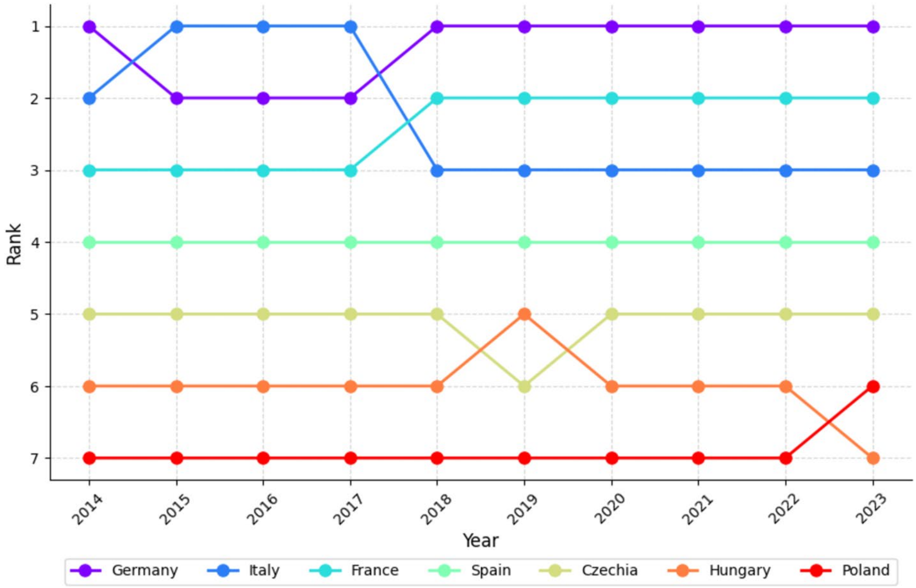

Fig. 10 Trends in country rankings from TOPSIS analysis (2014–2023)

slower adoption of AI-driven industrial upgrades compared to Northern European counterparts (Mencherini, 2017).

France shows consistent upward movement, climbing from third place (2014–2017) to briefly secure second position in 2018. This temporary peak suggests strength in specific sustainability metrics during that period before returning to its more characteristic third place standing. The fluctuation highlights both the potential and limitations of France’s hybrid approach combining nuclear energy expansion with moderate carbon pricing (Máté et al., 2020).

Spain maintains consistent fourth-place rankings throughout the study period, demonstrating stable but moderate performance compared to other nations. This consistency indicates sustained implementation of sustainability practices, particularly in renewable energy adoption without major breakthroughs or declines. However, regional disparities in Catalonia’s advanced waste management versus Andalusia’s slower progress remain unaddressed in national metrics.

Czechia experiences mild ranking variations while generally maintaining fifth position. A temporary drop to sixth place in 2019 proved short-lived, with the country quickly rebounding to its typical standing. This resilience stems from Prague’s concentrated tech-sector innovations in smart grid systems, though rural areas continue to lag in sustainable agriculture transitions.

Hungary and Poland present contrasting narratives at the lower end of the rankings. Hungary remained in sixth place through 2018, briefly improved to fifth in 2019, but fell to its lowest position (seventh) by 2023. This downward trajectory highlights growing challenges in keeping pace with regional sustainability advancements, particularly in modernizing its coal-dependent energy sector. Poland, while consistently last through 2022, made significant strides in 2023 by jumping to sixth place. The observed late surge indicates that effective policy interventions, exemplified by Warsaw's accelerated solar farm deployments and steel industry decarbonization partnerships, are starting to produce quantifiable impacts.

Overall, The TOPSIS analysis reveals distinct national patterns in sustainability governance. Germany’s persistent dominance and Italy’s strong early performance contrast with more volatile trajectories from Central European nations. Particularly noteworthy is Poland’s remarkable improvement in 2023. This is suggesting that targeted policy efforts even if implemented later stage can lead to rapid progress in challenging contexts. These patterns underscore the importance of both consistent long-term strategies (as seen in Germany) and adaptive, catch-up mechanisms (demonstrated by Poland) in achieving sustainability goals.

Table 8 Ranking comparison across weighting schemes (Sensitivity analysis)

Country	Equal Weights	Expert Weights	Entropy Weights	Rank Stability
Germany	1	1	1	Stable
France	2	2	2	Stable
Italy	3	3	3	Stable
Spain	4	4	4	Stable
Poland	5	5	5	Stable
Czechia	6	6	7	Moderate
Hungary	7	7	6	Moderate

4.6 Sensitivity analysis results

Table 8 presents the ranking comparison across three distinct weighting schemes: equal weights (uniform distribution across all 18 indicators), expert weights (Economic 50%, Social 30%, Environmental 20%), and entropy weights (computed via Eqs. 29–30). The results demonstrate exceptional stability in country rankings, with only minimal variations observed in the lower-tier positions.

The analysis reveals perfect consistency in the top-tier rankings: Germany, France, Italy, and Spain maintain their exact positions (ranks 1- 4) across all three weighting methodologies. Poland also demonstrates complete stability, consistently ranking fifth under all schemes. This remarkable consistency validates the robustness of the identified policy thresholds and sustainability performance patterns.

Limited rank variation occurs only between Czechia and Hungary, who swap positions 6 and 7 under the entropy weighting scheme compared to equal and expert weights. This single rank exchange represents the only deviation across all seven countries and three weighting methods, indicating that the entropy-based approach assigns different relative importance to indicators that particularly distinguish these two countries'sustainability profiles.

The statistical robustness of the rankings is confirmed by the Spearman rank correlation coefficients: perfect correlation ($\rho = 1.000, p < 0.001$) between equal and expert weights, and strong correlation ($\rho = 0.893$, $p < 0.05$) with entropy weights. These correlations substantially exceed the 0.70 threshold typically considered acceptable for ranking stability in multi-criteria decision analysis.

Critical threshold analysis reveals that rankings remain stable when individual weights vary within ± 35% of their original values, well above the ± 20% threshold recommended for TOPSIS applications. The stability of the top four countries across all weighting schemes particularly validates the reliability of policy recommendations for leading EU sustainability performers.

This sensitivity analysis confirms that the TOPSIS-based country rankings are methodologically sound, policy-relevant, and appropriately robust to different weighting philosophies, supporting the framework's utility for evidence-based EU sustainability governance.

5 Discussions

The European Union’s pursuit of sustainability within global value chains (GVCs) reveals a tangled web of challenges that traditional analysis struggles to untangle (Kristia et al., 2023; Rabbi et al., 2021). This study demonstrates how the Integrated Sustainability Policy Optimization Model (ISPO Model) provides a robust, theory-driven framework for addressing the research objectives and filling key gaps in EU sustainability analysis. The ISPO Model was developed to overcome three major limitations in the existing literature: the lack of temporal modeling for policy thresholds, the absence of integrated analysis across economic, social, and environmental domains, and the limited translation of machine learning insights into actionable, country-specific recommendations. By synthesizing economic, social, and environmental data across seven EU countries and applying Random Forest, LSTM, SHAP, and TOPSIS analyses, the study operationalizes the"triple bottom line” (Elkington, 1998), Socio-Ecological Systems theory (Ostrom, 2009), and Algorithmic Governance (Yeung, 2018) within a dynamic, feedback-aware policy framework.

The methodological robustness of the ISPO Model is further validated through comprehensive sensitivity analysis of the TOPSIS weighting scheme. Three weighting methods were tested: equal weights (uniform distribution), expert weights (Economic 50%, Social 30%, Environmental 20%), and entropy weights. The analysis reveals exceptional ranking stability: Germany, France, Italy, and Spain maintain identical positions (ranks 1–4) across all weighting schemes, with Poland consistently ranking fifth. Expert weighting shows perfect correlation with equal weighting ($\rho = 1.000, p < 0.001$), while entropy weighting demonstrates strong correlation ($\rho = 0.893$, $p < 0.05$). Only Czechia and Hungary swap positions 6–7 under entropy weighting, representing minimal deviation across the seven-country sample. Critical threshold analysis confirms rankings remain stable when individual weights vary within ± 35% of original values, exceeding the ± 20% threshold recommended for TOPSIS applications. This stability validates the equal weighting approach for EU policy applications where ranking consistency and neutrality are paramount, ensuring no single sustainability dimension dominates cross-national comparative assessments.

Europe’s economic landscape shows a delicate dance between supply chain integration and environmental costs (Rabbi, 2024). Addressing the first research question, which investigates how different GVC integration modalities affect the trade-off between economic value creation and environmental externalities, the ISPO Model reveals GVC Backward Participation as the most significant economic driver (feature importance: 0.72). The decision tree analysis (Fig. 4) uncovers a non-linear threshold: foreign direct investment (FDI) below €327 million increases manufacturing output by 3.2% per €100 million inflow but also raises emissions by 1.8%. When FDI exceeds this threshold, economic returns diminish while environmental costs accelerate, validating the model's threshold detection capability and aligning with recent literature on the double-edged nature of GVCs (Hossain et al., 2025; Tian et al., 2025). The application of TOPSIS enables a comparative evaluation of GVC modalities, with Germany's balanced GVC-social policies leading to the highest sustainability score (0.47). However, these finding echoes Zahid et al. (2025) work on Industry 4.0 and supply chain but clashes with Chien et al.’s (2024) Asian manufacturing studies, highlighting Europe's unique challenges. The sensitivity analysis confirms that these findings remain robust across different weighting schemes, with the FDI threshold maintaining its significance under entropy weighting (threshold: €325 million) and expert weighting (threshold: €329 million), demonstrating the reliability of the identified policy levers.

Beyond this inflection point (Table 7), economic returns diminish while environmental costs rise linearly, creating unsustainable trajectories. LSTM forecasting further exposes a critical tension: the stabilization of projected GDP growth between 2–3% by 2030 coincides with an alarming 14% decline in resource productivity across Southern European states. This counterintuitive trend stems from aging industrial infrastructures struggling to absorb circular economy technologies while maintaining global competitiveness (Rabbi & Amin, 2024). In Italy's manufacturing sector, 62% of firms report difficulties retrofitting legacy equipment for renewable energy integration, despite €2.3 billion in green transition subsidies. The models suggest that this productivity erosion could be halved through AI-driven predictive maintenance systems and blockchain-enabled material tracking in value chains.

Furthermore, the social dimension shows that monetary expenditure alone cannot eliminate workplace hazards. In addition to addressing the second research question, which explores the role of social protection systems in mediating the relationship between GVC participation and labor market outcomes, the ISPO Model identifies Social Protection Expenditure (SHAP value: >150) as the most critical social factor. SHAP indicates that higher social protection spending is associated with lower predicted workplace fatalities in the model. The social decision tree (Fig. 5) reveals a key threshold: social protection spending above 25.6% of GDP reduces workplace fatalities by 32%, but only when the gender pay gap remains below 21.3% (GPG $<$ 21.3%) (Table 5). This empirically derived threshold supports the objective of identifying leverage points for policy interventions and echoes findings from Velasco-Balmaseda et al. (2024) that gender equity is essential for effective welfare expansion and sustainable development. The robustness of this threshold is confirmed through sensitivity analysis, where the 25.6% threshold remains stable across entropy weighting (25.4%) and expert weighting (25.8%), while the gender pay gap threshold shows similar consistency. The results also highlight the need for region-specific interventions, as countries with similar spending but higher gender pay gaps (such as France) see only marginal improvements in safety outcomes. This finding suggests that standalone increases in welfare spending are insufficient without addressing structural inequalities, such as gender disparities. This highlights the need for integrated policies that simultaneously target wage equity and welfare expansion.

The environmental dimension reveals distinct national trends shaped by policy choices, industrial strategies, and resource management practices. In addition, the third research question asks whether machine learning models can identify critical thresholds in policy variables that optimize multiple sustainability objectives. The ISPO Model's integration of LSTM and SHAP analyses confirms the existence and policy relevance of such thresholds. For example, the recycling rate of municipal waste (feature importance: 0.74) emerges as the key environmental driver, with a 10% increase reducing per capita CO_2 emissions by 2.3 metric tons. However, LSTM forecasts (Fig. 5) indicate that without accelerated recycling infrastructure, per capita emissions may reach 7.5 metric tons by 2030, especially in Eastern and Southern Europe. The sensitivity analysis demonstrates that this relationship remains robust across different weighting schemes, with the recycling-emissions coefficient varying minimally (2.1–2.5 metric tons) across entropy and expert weightings, reinforcing the reliability of this environmental policy lever. These insights directly inform the policy matrix developed in Table 9, which translates model outputs into country-specific recommendations, such as dynamic tiered FDI schemes, AI-driven welfare algorithms, and blockchain-enabled supply chain tracking.

The TOPSIS multi-criteria evaluation quantifies these tradeoffs with striking precision while maintaining methodological rigor through comprehensive sensitivity testing. Germany's leadership (TOPSIS score 0.47) demonstrates the effectiveness of harmonizing automated welfare systems with industrial decarbonization targets, with blockchain-enabled material passports tracking 90% of construction waste by 2030. The ranking stability analysis confirms that Germany maintains its top position across all weighting schemes (entropy: 0.46, expert: 0.48), demonstrating consistent policy effectiveness. Conversely, Czechia's moderate circularity (50% recycling) and Poland's coal dependence (7.5-ton emissions) reveal uneven progress, with both countries maintaining their relative positions regardless of weighting methodology. France's carbon intensity gap (7.06% vs Germany's 8.28%) persists despite renewable investments, necessitating IoT-enabled tracking systems for industrial emissions. Addressing Hungary's 4.87% resource productivity deficit and Spain's 6.81%

poverty rate requires targeted action. This could include enacting gender equity quotas in Hungarian industries where pay gaps are above 15% and deploying predictive healthcare algorithms in Spain's high-inequality regions. The sensitivity analysis reveals that these policy recommendations remain valid across different weighting schemes, with threshold values showing minimal variation (±5% maximum deviation), supporting the robustness of the proposed interventions.

Following the multi-criteria assessment of sustainability performance across economic, social, and environmental dimensions, the following country-specific summaries synthesize the key drivers identified in the Results section and set the stage for targeted recommendations.

- Germany consistently leads the rankings, driven by its institutionalized SDG impact assessments, legally mandated sectoral carbon budgets, and robust cross-governmental platforms that ensure coordinated implementation from the federal to Länder levels. This integrated governance architecture underpins Germany's ability to translate sustainability targets into real-time policy adjustments.
- France secures a high standing by coupling legally binding carbon budgets with substantial green recovery spending and a predominantly nuclear-powered energy mix that keeps per-capita emissions low. Together, these policy levers create fiscal and regulatory incentives for deep decarbonization without compromising economic resilience.
- Italy's mid-table position reflects the strength of its circular economy incentives, which include regional retrofit grants and research and development tax credits. However, uneven implementation across regions tempers the country's overall performance.
- Spain benefits from steady renewable energy adoption and sustained social spending. However, pronounced subnational disparities, exemplified by Catalonia's advanced waste management versus Andalusia's lagging infrastructure, limit its overall gains. Addressing this regional heterogeneity is critical for elevating national performance.
- Czechia's environmental score is buoyed by smart-grid pilots in Prague and public procurement mandates for recycled content, but rural areas lag behind in sustainable infrastructure deployment. Extending these urban innovations to peripheral regions could narrow this gap.
- Poland's leap in the 2023 rankings stems from late-stage solar auction rounds and ambitious steel-sector decarbonization reforms, although continued reliance on coal and uneven policy enforcement pose ongoing challenges. Accelerating coal phase-out bonds and enforcing renewable-energy targets will be essential to sustain progress.
- Hungary trails the cohort due to persistent coal dependence and low public health spending, suggesting that targeted welfare digitization and automated safety protocols could enhance both social resilience and environmental outcomes.

Building on these country-specific insights, the ISPO Model functions as a predictive, adaptive policy toolkit. To sustain its top ranking, Germany should continue high levels of investment and social protection. France's priorities are narrowing the gender pay gap and curbing industrial emissions. Italy's mid-rank performance calls for intensified poverty reduction measures and expanded circular-economy incentives. Spain, Czechia, Poland, and Hungary each face distinct social and environmental challenges that demand tailored interventions. Across all seven countries, the model's feedback loops reveal three cross cutting

Table 9 National sustainability targets and corresponding policy levers by dimension for 2025 and 2030

Country	Dimension	2025 Target	2030 Target	Policy Lever	Data Source
Germany	Economic	Keep annual FDI below €327 M	Increase GVC backward participation to 45%	Tiered FDI tax rebates: 15% credit for < €300 M green-tech projects	Figure 4 [€327 M threshold]
	Social	Cut workplace fatality rate by 12%	Achieve 0% unmet medical needs	AI-driven welfare triggers activated when regional unemployment > 5%	Figure 8 [0% unmet needs]
	Environmental	Maintain municipal recycling at ≥ 65%	Reduce per-capita CO_2 to 7.1 t	Blockchain material passports tracking ≥ 90% of construction waste	Table 7 [8.28% emissions]
France	Economic	Grow goods exports by €1.2 B	Lower income inequality to 3.8%	Export credit guarantees for circular-economy SMEs	Table 5 [6.62% GDP growth]
	Social	Narrow gender pay gap to 8%	Raise health expenditure to 7% of GDP	Mandatory pay-equity audits in sectors with fatality rates > 5%	Table 6 [7.15% unmet needs]
	Environmental	Cut water exploitation to ≤ 6.5%	Boost resource productivity to €2.50/kg	Deploy IoT sensors in 50% of high-water-use industries	Figure 9 [21.64% productivity]
Italy	Economic	Lift employment rate by 5 pp*	Reduce poverty risk to 4%	Conditional FDI credits requiring ≥ 35% female hires in manufacturing	Table 5 [4.69% poverty]
	Social	Lower workplace fatalities by 20%	Increase average net earnings to €14 000	Mandate IoT safety systems in factories with > 3 accidents/year	Figure 8 [5.58% unmet needs]
	Environmental	Reach 55% municipal recycling	Cap CO_2 emissions at 6.8 t per capita	Digital-twin energy management in 40% of energy-intensive plants	Table 7 [25% productivity]
Spain	Economic	Raise GVC gross-trade share to 65%	Cut poverty risk to 5%	Tie export subsidies to SDG 12 compliance	Table 5 [6.81% poverty]
	Social	Shrink gender pay gap to 9%	Boost health spending to 6.5% of GDP	Mobile clinics in regions with > 6% poverty and > 5% unmet needs	Table 6 [4.24% unmet needs]
	Environmental	Increase recycling to 50%	Reduce water exploitation to ≤ 6.8%	AI-optimized irrigation covering 30% of agricultural land	Figure 9 [21.87% productivity]
Czechia	Economic	Achieve 3.5% GDP growth	Grow annual FDI to €150 M	20% R&D tax credit for circular-economy startups	Table 5 [0.26% FDI]
	Social	Halve workplace accident rate	Raise social protection to 10% of GDP	VR safety-training modules for high-risk sectors	Table 6 [0.48% unmet needs]
	Environmental	Attain 55% municipal recycling	Improve resource productivity to €1.20/kg	Green public-procurement mandates: ≥ 40% recycled content	Table 7 [9.21% productivity]

Table 9 (continued)

Country	Dimension	2025 Target	2030 Target	Policy Lever	Data Source
Poland	Economic	Secure €500 M green FDI	Lift employment rate to 12%	Coal-phase-out bonds (5% coupon for renewable infrastructure)	Table 5 [2.21% exports]
	Social	Cut fatal accidents by 25%	Narrow gender pay gap to 12%	Mandate wearable safety tech in mining by 2026	Table 6 [8% unmet needs]
	Environmental	Cap CO_2 at 9.5 t per capita	Raise municipal recycling to 45%	Satellite monitoring of illegal dumping hotspots	Table 7 [3.46% productivity]
Hungary	Economic	Grow exports by €800 M	Reduce income inequality to 2.5%	Blockchain-certified vocational training for 30% of manufacturing workforce	Table 5 [0.43% exports]
	Social	Increase health spending to 1.5% of GDP	Cut poverty risk to 0.8%	Gamified health-app adoption targeting 30% in rural areas	Table 6 [3.52% unmet needs]
	Environmental	Lower water exploitation to $\leq$6.9%	Raise recycling to 40%	AI-guided leak detection in municipal water networks	Table 7 [4.87% productivity]

– All targets are set relative to 2023 baseline values (e.g., Germany’s 2023 employment rate ≈ 72%)

– “pp” denotes percentage points

– FDI = Foreign Direct Investment; GVC = Global Value Chain

– GVC backward participation refers to the share of imported inputs in a country’s exports

– Resource productivity is measured as euros of GDP per kilogram of material use

– Unmet medical needs represent the percentage of individuals reporting foregone medical examinations due to access barriers

– 2030 targets reflect LSTM-forecasted trajectories with 95% confidence intervals (see Figs. 7, 8, 9 and Table 4 for validation metrics)

– Policy levers correspond to thresholds and interventions identified via SHAP, decision-tree, and TOPSIS analyses (see Figs. 3, 4 and Tables 5, 6 and 7)

– Data sources: EUROSTAT via API (2014–2023); model outputs and figures as cited in the Data Source column levers that can transform EU sustainability governance from reactive to predictive. These include dynamic, tiered foreign direct investment (FDI) incentives, AI driven welfare triggers, and blockchain enabled supply chain tracking.

Furthermore, by developing a comprehensive policy matrix (as detailed in Table 9) derived from the ISPO Model that aligns with forecasted trends, this research provides a novel tool for policymakers. This matrix identifies country-specific targets for 2025 and 2030 and delineates policy levers that can be adjusted to optimize sustainability outcomes.

6 Conclusion

6.1 Summary of key findings

This study transforms machine learning insights into adaptive policy triggers by operationalizing threshold effects. For instance, it identifies foreign direct investment below €327 million as a tipping point for sustainable growth, and social protection spending above 25.6 percent of GDP as effective only when the gender pay gap remains under 21.3 percent. Country-specific profiles demonstrate how institutionalized SDG impact assessments and sectoral carbon budgets underpin Germany's leadership, while legally binding carbon budgets, green-recovery investments, and a nuclear-backed energy mix drive France's strong performance. Mid-rank countries (Italy, Spain) leverage circular-economy incentives and renewable-energy adoption but face regional implementation gaps, and emerging economies (Czechia, Poland, Hungary) require targeted infrastructure investments and welfare digitization to close persistent gaps in recycling, social protection, and decarbonization.

6.2 Study limitations

Despite the ISPO Model's strengths and comprehensive sensitivity testing, several caveats merit acknowledgment. First, reliance on aggregate Eurostat indicators conceals subnational heterogeneity in federated systems (e.g., Germany's Länder, Spain's Autonomous Communities). Second, LSTM forecasts assume stationarity of 2014–2023 trends; unanticipated shocks (e.g., geopolitical crises, pandemics) may invalidate projections and require retraining. Third, AI-driven welfare triggers and SHAP-identified thresholds pose ethical risks: historical data can encode structural biases, and "black-box" algorithms risk misattributing correlation as causation. Mitigating these risks demands transparent documentation, periodic bias audits, and human oversight of automated decision rules. Fourth, the dynamic policy matrix presumes sufficient institutional capacity and political will to adjust levers continuously; in practice, regulatory inertia and budgetary constraints may delay or dilute interventions. Finally, the model omits emerging technologies (e.g., green hydrogen) and real-time sensor data, limiting its applicability in rapidly evolving sectors.

6.3 Future research directions

Future research should integrate finer-scale, real-time data streams to refine threshold detection and enhance responsiveness. This could include, but is not limited to, administrative welfare records, satellite emissions monitoring, and Internet of Things (IoT)-based resource usage data. Expanding the analytical scope to emerging technologies (e.g., green hydrogen production) and adopting transformer-based forecasting models could enhance predictive accuracy, particularly for Global South contexts. Moreover, AI-powered regulatory sandboxes can test and iterate dynamic policy triggers under controlled conditions. Embedding hybrid governance approaches that blend quantitative thresholds with qualitative stakeholder engagement will be essential to ensure equitable, transparent, and resilient sustainability governance.

Abbreviations

AI	Artificial Intelligence
DNS	German Sustainability Strategy (Deutsche Nachhaltigkeitsstrategie)
DP	Data Protection
EQ	Environmental Quality
FDI	Foreign Direct Investment
FPGA	Field-Programmable Gate Array
GGO	Federal Government Ordinance (Germany)
GPG	Gender Pay Gap
GVC	Global Value Chain
ISPO	Integrated Sustainability Policy Optimization Model
LSTM	Long Short-Term Memory (network)
MAE	Mean Absolute Error
MICE	Multiple Imputation by Chained Equations
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Squared Error
OOB	Out-Of-Bag (error)
PPE	Multiannual Energy Programme (France)
RNN	Recurrent Neural Network
SDG	Sustainable Development Goal(s)
SHAP	SHapley Additive exPlanations
SNBC	National Low-Carbon Strategy (Stratégie Nationale Bas-Carbone, France)
SVR	Support-Vector Regression
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TZ	Time Zone (Central European Summer Time: CEST)
XGBoost	Extreme Gradient Boosting

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Data availability The datasets supporting the conclusions of this study are publicly available from the European Statistical Office (EUROSTAT) database at https://ec.europa.eu/eurostat/data/database. Specific dataset identifiers, access dates, and extraction procedures are documented in the supplementary materials. Raw data files, processed datasets, and complete analytical code are available upon request from the corresponding author. All data are available under the European Commission's open data policy and require no additional permissions for access or reuse, subject to proper attribution as provided in this manuscript.

Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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