

Article

How Governance Relates to Sustainability Across Economic, Social, and Environmental Domains: Evidence from Interpretable Machine Learning

Wei Huang ¹, Yuqi Zhang ²  and Xiaofang Tu ^{1,*} ¹ School of Public Administration, Beihang University, Beijing 100191, China; huang7@buaa.edu.cn² School of Computer Science and Engineering, Beihang University, Beijing 100191, China; yqzhang@buaa.edu.cn

* Correspondence: tuxiaofang@buaa.edu.cn

Abstract

Sustainable development is multidimensional, yet governance is often examined through aggregate SDG performance, leaving limited understanding of whether different governance dimensions are equally salient across economic, social, and environmental domains. This study investigates domain-specific governance salience using cross-national data from 2015 to 2024. Governance is measured through the Worldwide Governance Indicators, while sustainability performance is modeled through the overall SDG index and three domain-specific indices covering economic, social, and environmental sustainability. Tree-based machine learning and SHAP analysis are used to compare the relative importance of governance indicators and socioeconomic control variables. The findings reveal a domain-sensitive governance pattern that is obscured by aggregate SDG performance. Governance indicators are secondary in the overall SDG model but become more salient in the economic dimension, especially through Government Effectiveness, Rule of Law, and Regulatory Quality. In the social dimension, governance retains moderate relevance alongside health and development-related conditions. By contrast, the environmental domain exhibits limited predictability, highlighting an important boundary condition in the role of governance. Further analysis of high-income countries reveals that specific governance dimensions exhibit greater predictive relevance, although the overall governance pattern remains less consistent. These findings provide support for a metagovernance-informed perspective, showing that the relevance of governance for sustainable development differs across sustainability domains.

Keywords: sustainable development goals; governance quality; metagovernance; interpretable machine learning; SHAP



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1. Introduction

The Sustainable Development Goals (SDGs) have become the central framework for assessing national progress toward sustainable development, but their multidimensional structure complicates how such progress should be interpreted. The 2030 Agenda brings together economic, social, and environmental objectives, while also emphasizing their interdependence and indivisibility [1–3]. Although overall SDG performance provides a useful summary of national progress, it may also conceal variation across specific sustainability domains. Studies on SDG interactions show that progress in one goal area can generate synergies, tensions, or trade-offs in others, suggesting that sustainability outcomes should

not be treated as fully homogeneous [4,5]. Recent cross-national evidence further shows that countries follow uneven development trajectories across SDG targets and domains, reinforcing the need to examine sustainability performance beyond a single aggregate score [6].

Governance has been widely recognized as a key condition for SDG implementation. The achievement of the SDGs depends not only on economic resources or demographic conditions, but also on institutional capacity, policy coherence, accountability, and coordination across sectors and levels of government [7–9]. Research on SDG governance has shown that the 2030 Agenda has generated political attention and institutional responses, but its effects remain uneven across countries, sectors, and governance levels [10,11]. This unevenness points to the need to understand governance not only as a general background condition, but also as a set of differentiated institutional capacities. Glass and Newig make this point directly by arguing that the key question is not simply whether governance matters for SDG achievement, but which aspects of governance matter for which goals [9]. This question is particularly relevant for cross-national sustainability research because different sustainability domains may place emphasis on different combinations of administrative, legal, regulatory, and participatory capacities.

Existing empirical studies have examined how governance quality relates to sustainable development from different perspectives. Some research finds evidence of Granger causality from country-level governance to economic growth, although the relationship between governance and adjusted net savings is less conclusive [12]. Other studies show that political and institutional governance contributes positively to the economic, social, and environmental dimensions of sustainable development, and that institutional quality and sound governance are relevant to national progress toward the SDGs [13,14]. More recent research has moved closer by examining the role of governance and foreign direct investment in relation to overall SDGs and their economic, social, and environmental pillars in Sub-Saharan Africa and the Middle East and North Africa. Their findings suggest that governance contributes more clearly to overall and economic SDG outcomes, while its relationship with environmental sustainability is weaker [15]. Other research similarly examines how the World Governance Indicators relate to SDG achievement, finding that all six governance dimensions are positively and significantly associated with national SDG performance [16].

However, much of the literature continues to focus on aggregate SDG outcomes, composite governance measures, or broad governance-sustainability relationships. It therefore remains unclear whether specific governance dimensions have similar or different relative importance across economic, social, and environmental sustainability domains. A related methodological limitation also concerns the dominant use of linear estimation strategies in governance-sustainability research. Panel regression, GMM, and related econometric approaches are valuable for estimating average associations, but in conventional linear specifications they are less suited to identifying nonlinear patterns, threshold relationships, and complex interactions unless such structures are explicitly modeled [17]. Recent work has begun to use machine learning to model complex sustainability outcomes. For example, some research applies machine learning to examine how governance, human development, macroeconomic conditions, and energy structures jointly shape environmental sustainability outcomes [18]. Yet machine learning models can remain difficult to interpret if they are used only for prediction. As Mullainathan and Spiess [19] note, machine learning offers powerful predictive tools for social science, but its substantive value depends on careful interpretation. Rudin [20] similarly cautions against relying on black-box models when interpretability is central to the research question. This leaves a methodological gap

between the ability to model complex sustainability patterns and the need to explain how different governance dimensions are positioned within those patterns.

Adopting a theory-informed exploratory framework, this study addresses these gaps by investigating domain-specific patterns in the relationship between governance dimensions and sustainability outcomes. Using cross-national data from 2015 to 2024, the analysis models four outcomes: the overall SDG index and three domain-specific indices representing economic, social, and environmental sustainability. Governance is measured through the six WGI dimensions, while structural socioeconomic and demographic variables are included as controls. The study applies tree-based machine learning models and uses SHAP-based interpretation to compare the relative importance and direction of governance predictors across outcomes. In doing so, it moves beyond the general question of whether governance matters for sustainable development and examines how different governance dimensions matter differently across specific sustainability domains. The study therefore contributes to the governance and sustainability literature by combining a domain-specific SDG framework with an interpretable machine learning approach to reveal cross-domain variation in governance salience.

2. Theoretical Framework

Metagovernance provides a useful conceptual basis for understanding why governance may matter differently across sustainability domains. Rather than assuming that there is a single best model of governance, the metagovernance perspective emphasizes the coordination of different governance modes, instruments, and institutional capacities according to policy context [21]. Meuleman and Niestroy [8] develop this argument in relation to the SDGs, suggesting that sustainable development requires context-sensitive combinations of hierarchical, network-based, and market-oriented governance arrangements rather than a uniform governance model. This perspective is particularly relevant to the SDGs because economic, social, and environmental objectives involve different implementation problems and coordination demands.

This conceptual perspective also supports treating governance as multidimensional rather than as a single aggregate attribute. The Worldwide Governance Indicators framework distinguishes six dimensions of governance: Voice and Accountability (VA), Control of Corruption (CC), Political Stability and Absence of Violence/Terrorism (PV), Rule of Law (RL), Government Effectiveness (GE), and Regulatory Quality (RQ) [22]. These dimensions capture different aspects of institutional capacity, including participatory accountability, political stability, administrative and service-delivery capacity, regulatory credibility, rule-based order, and corruption control. Glass and Newig [10] similarly emphasize that the key issue for SDG governance is not only whether governance matters, but which governance aspects are relevant to which goals.

Different sustainability domains may involve distinct governance challenges and implementation requirements. Economic sustainability outcomes are often related to institutional capacities for effective regulation and policy implementation. Research on state capacity highlights that effective states contribute to long-term economic performance through the provision of public goods, regulation of economic activities, and enforcement of institutional rules [23,24]. Social sustainability is more directly related to human development outcomes, including improvements in health, education, and living conditions. Achieving social goals requires not only adequate resources but also the administrative capacity to implement public interventions effectively. Research on policy implementation emphasizes that policy outcomes depend on whether public institutions possess sufficient capacity to translate policy commitments into practice [25]. Environmental governance research emphasizes that addressing such challenges often involves institutional change,

as existing governance arrangements may need to be transformed to respond to evolving environmental conditions [26]. Empirical evidence further indicates that the relationship between institutional quality and environmental performance is context-dependent, with environmental outcomes shaped by both governance conditions and broader socio-economic factors [27,28]. These domain-specific governance demands provide a basis for examining whether different governance dimensions vary in their relative importance across sustainability outcomes.

Building on this logic, this study adopts a theory-informed exploratory approach and expects governance dimensions to exhibit domain-specific patterns of relative importance, as different sustainability outcomes may place different demands on institutional capacities. Accordingly, this study examines how the relative importance of the six WGI dimensions varies across overall, economic, social, and environmental SDG performance.

3. Materials and Methods

3.1. Data and Variables

This study uses cross-national data from 2015 to 2024 to examine the relative salience of governance across different dimensions of sustainability. The dataset contains 1323 country-year observations covering 143 countries, with some countries having incomplete time coverage. The analysis includes four outcome variables: the overall SDG index and three domain-specific sustainability indices constructed for the economic, social, and environmental dimensions. The outcome data are compiled from annual releases of the Sustainable Development Report (SDR) datasets covering 2015–2024. The overall SDG index is used as a baseline measure of aggregate national sustainability performance and is reported on a 0–100 scale, with higher values indicating better overall progress toward the SDGs [29]. The classification and naming of the SDGs follow the official United Nations framework [30]. The data processing and machine learning analyses were conducted using Python 3.13.5.

The predictor variables are organized into two sets: governance indicators and structural development variables. Governance is captured through the six Worldwide Governance Indicators (WGI), obtained from the World Bank database [31]. The WGI provide country-level measures of perceived governance quality across six institutional dimensions: Voice and Accountability, Control of Corruption, Political Stability and Absence of Violence/Terrorism, Rule of Law, Government Effectiveness, and Regulatory Quality. These indicators represent different aspects of the governance environment, including public participation and accountability, corruption control, political stability and absence of violence, rule-based institutional order, administrative and service-delivery capacity, regulatory formulation and implementation [32].

In addition to governance indicators, the models include a set of structural development variables drawn from the World Development Indicators and Our World in Data [31,32]. GDP per capita is used to represent national income levels and is expressed in constant international dollars. Educational attainment captures the share of adults aged 25 and above who have completed at least a bachelor's degree or an equivalent level of education. Unemployment refers to the proportion of the labor force that is unemployed. Life expectancy is measured at birth and reflects population health conditions. Population aging is represented by the proportion of residents aged 65 and above, while urbanization captures the proportion of the population living in urban areas. These variables account for cross-national differences in countries' income levels, educational profiles, employment structures, population health, age composition, and urban settlement patterns. All variables are aligned at the country-year level before model estimation.

3.2. Construction of Sustainability Indices

The overall SDG index is used as a baseline measure of aggregate sustainability performance. Following the widely used three-pillar conception of sustainability, which distinguishes economic, social, and environmental dimensions of sustainable development [33], this study further constructs three domain-specific sustainability indices in addition to the overall SDG index. An unweighted mean is used because this approach keeps the construction of the domain-specific indices transparent and comparable across domains. This choice is consistent with established SDG index construction practices, in which goal scores and aggregate SDG scores are commonly calculated through arithmetic averaging [34,35]. It also avoids imposing additional normative weights among selected goals in the absence of a clear theoretical basis for weighting one goal more heavily than another.

The economic sustainability index is defined as the mean of Goal 8 (Decent Work and Economic Growth), Goal 9 (Industry, Innovation and Infrastructure), and Goal 11 (Sustainable Cities and Communities). The social sustainability index is defined as the mean of Goal 2 (Zero Hunger), Goal 3 (Good Health and Well-Being), and Goal 4 (Quality Education). The environmental sustainability index is defined as the mean of Goal 7 (Affordable and Clean Energy), Goal 13 (Climate Action), and Goal 15 (Life on Land).

The selection of goals for each domain was guided by three considerations: substantive relevance to the conceptual scope of each sustainability domain, cross-national comparability, and data availability. The selected goals were therefore intended to capture broad domain-specific sustainability patterns while preserving sufficient cross-national and longitudinal coverage. In particular, the economic index reflects a balance between conceptual fit and sample coverage. Goal 11 is included because the official SDG framework links sustainable cities and communities to housing, infrastructure, services, and the role of cities as centers of innovation and economic growth [30]. Although Goal 11 also contains social and environmental elements, its urban and infrastructural content makes it relevant to the economic index when considered alongside Goal 8 and Goal 9 [36].

Several alternative goal combinations were considered during index construction, but some produced missingness levels exceeding 10%, which would have substantially reduced sample coverage and comparability. The final specification was therefore adopted to preserve broader country-year coverage. Because some SDGs conceptually overlap across domains, the classification is intended to capture broad domain-specific patterns rather than mutually exclusive categories. To assess the robustness of the index construction, alternative specifications based on different goal combinations and weighting schemes were further examined. The corresponding robustness analyses are reported in Appendices A.1 and A.2.

3.3. Missing Data Treatment

Given the cross-national scope of the dataset, some socioeconomic variables contained incomplete observations. Missing observations were primarily addressed using Multiple Imputation by Chained Equations (MICE) with Predictive Mean Matching (PMM). This procedure was adopted to preserve country-year coverage and avoid the substantial sample reduction that would result from listwise deletion. Specifically, missing values were primarily concentrated in socioeconomic control variables, including GDP per capita, life expectancy, unemployment rate, and education indicators, whereas the overall SDG index and governance indicators from the Worldwide Governance Indicators (WGI) dataset were complete in the original dataset. Missingness among the selected SDG goal scores used for constructing the domain-specific sustainability indices was limited, with the highest missing proportion being 5.8%. Therefore, observations with unavailable SDG goal

scores were excluded during index construction. Before applying MICE, variables with extensive missing observations were initially imputed using the median value within the corresponding World Bank income group. The income-group classification followed the World Bank categories in 2019, which were selected as a pre-pandemic benchmark for cross-country comparisons. The remaining variables with missing values were imputed using MICE-PMM and the imputed dataset was then used for all subsequent analyses. Robustness checks based on alternative imputation approaches are reported in Appendix A.3.

3.4. Machine Learning Models

The analytical workflow consists of three sequential steps. First, a linear regression model is used as a benchmark to evaluate whether nonlinear algorithms provide additional predictive value beyond conventional linear specifications. Second, multiple nonlinear machine learning algorithms are trained and compared using five-fold GroupKFold cross-validation, with countries treated as grouping units to prevent information leakage across observations from the same country. The best-performing algorithm is selected based on predictive performance metrics, including R^2 , MAE, and MSE. Third, SHAP analysis is applied to the selected model to interpret feature contributions and identify domain-specific variation in the relative predictive salience of governance indicators.

The relationship between governance quality and sustainability outcomes may not follow a simple linear structure, as governance dimensions may exhibit nonlinear associations, threshold patterns, and interactions with socioeconomic conditions. Therefore, this study employs a combination of linear and nonlinear machine learning approaches to examine whether nonlinear algorithms provide additional predictive value beyond conventional linear specifications. The candidate models include a linear benchmark (Linear Regression) and several nonlinear algorithms, including Multilayer Perceptron (MLP), AdaBoost, Random Forest, Gradient Boosting, and Extra Trees. Linear Regression is included as a baseline model to assess the incremental predictive value of nonlinear approaches. Among the nonlinear algorithms, tree-based ensemble models are particularly suitable because they can capture complex nonlinear relationships and interactions without requiring pre-specified functional assumptions. Furthermore, the correlation structure among WGI dimensions highlights the advantages of tree-based ensemble methods in handling related predictors, as governance indicators represent related institutional dimensions and may introduce challenges for coefficient interpretation in conventional linear models.

Model evaluation follows a five-fold GroupKFold cross-validation design, where countries are used as the grouping units. This procedure ensures that all candidate models are compared under the same validation framework while preventing observations from the same country from appearing in both training and validation folds. Specifically, countries are assigned to individual folds, and all corresponding country-year observations are kept within the same fold. In each iteration, four folds are used for model training and the remaining fold is used for validation. For each candidate algorithm, hyperparameter selection was conducted within the training folds using grid search, ensuring that performance comparisons were based on tuned rather than default model specifications.

Model performance is assessed using mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2) based on aggregated out-of-fold predictions. MSE and MAE evaluate prediction error by comparing observed and predicted outcome values. R^2 evaluates the proportion of variation in the observed outcome that is accounted for by the model predictions.

3.5. SHAP-Based Interpretation

SHAP (SHapley Additive exPlanations) analysis is used to interpret the selected Extra Trees models by decomposing each prediction into feature-level attributions [37]. SHAP allows the study to examine which predictors contribute most to each sustainability outcome and whether their contributions are generally upward or downward. Mean absolute SHAP values are used to compare the relative importance of governance and structural development variables across the overall, economic, social, and environmental models. SHAP beeswarm plots further display the distribution of feature attributions across country-year observations, making it possible to assess both the direction and heterogeneity of predictive patterns. Because SHAP describes the behavior of fitted models, these results are interpreted as conditional predictive patterns and relative feature salience rather than causal effects. A larger SHAP contribution indicates that a governance indicator provides greater predictive information for explaining model outputs under the observed conditions. However, it does not imply that changes in a specific governance dimension would directly lead to changes in sustainability outcomes.

4. Results

4.1. Correlational Analysis

Figure 1 presents the Spearman correlation matrix among the overall SDG index, governance indicators, and structural development variables. The overall SDG index is positively correlated with most governance and development indicators. Among the governance variables, Government Effectiveness shows the strongest association with the SDG Index ($\rho = 0.80$), followed by Regulatory Quality ($\rho = 0.78$), Rule of Law ($\rho = 0.77$), Voice and Accountability and Control of Corruption (both $\rho = 0.73$), and Political Stability ($\rho = 0.71$). These results indicate that higher levels of perceived governance quality are generally related to higher aggregate sustainability performance. All correlations between the SDG Index and the predictor variables are statistically significant at $p < 0.05$.

The structural development variables also show strong positive correlations with the SDG Index. Population aging has the largest bivariate association ($\rho = 0.92$), followed by GDP per capita ($\rho = 0.83$) and life expectancy ($\rho = 0.82$), education ($\rho = 0.74$), and urbanization ($\rho = 0.61$). In contrast, unemployment is only weakly correlated with the SDG Index ($\rho = 0.15$). The matrix also shows high correlations among several governance indicators, particularly between Control of Corruption and Rule of Law ($\rho = 0.95$), Government Effectiveness and Regulatory Quality ($\rho = 0.95$), and Rule of Law and Regulatory Quality ($\rho = 0.94$). This pattern is consistent with the multidimensional but closely related nature of the WGI measures [38] and suggests potential multicollinearity among governance indicators, which can make coefficient estimates in conventional linear models less stable [39]. It further supports the use of the Extra Trees model that does not rely on individual regression coefficients and can model complex predictive relationships between related predictors and outcomes [40].

4.2. Predictive Model Performance

As shown in Table 1, the candidate models achieved generally strong predictive performance across sustainability outcomes, and differences were observed across model types and outcomes. For the overall SDG index, Extra Trees achieved the strongest performance among the candidate models, with the lowest MSE and MAE and the highest R^2 . Accordingly, the Extra Trees model was selected for subsequent SHAP-based interpretation to examine the relative importance and contribution of predictors. Similar patterns were also observed for the economic and social sustainability indices. The environmental model performance results are discussed separately in Section 4.6.

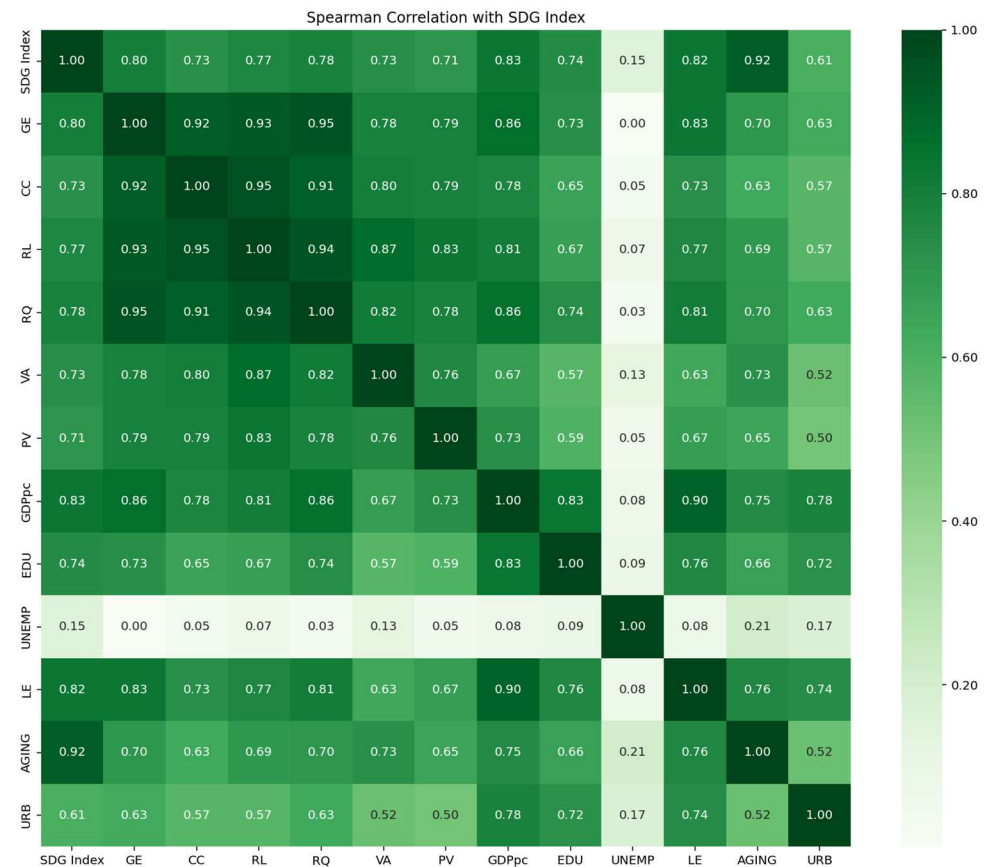


Figure 1. Spearman correlation matrix of the SDG Index, WGI, and socioeconomic control variables. Notes. SDG Index = overall SDG index; GE = government effectiveness; CC = control of corruption; RL = rule of law; RQ = regulatory quality; VA = voice and accountability; PV = political stability and absence of violence/terrorism; GDPpc = GDP per capita; EDU = bachelor's degree attainment, population 25+ (%); UNEMP = unemployment, total (% of labor force); LE = life expectancy at birth; AGING = population aged 65 and above (% of total population); URB = urban population (% of total population).

Table 1. Predictive Performance of Candidate Models across Sustainability Indices.

(a) Overall SDG Index			
Model	MSE	MAE	R ²
AdaBoost	14.358 (13.220–15.544)	3.010 (2.890–3.131)	0.868 (0.857–0.879)
Random Forest	14.526 (13.355–15.718)	3.052 (2.934–3.182)	0.867 (0.854–0.879)
Gradient Boost	13.398 (12.360–14.522)	2.893 (2.779–3.011)	0.877 (0.865–0.888)
Linear Regression	15.648 (14.373–17.041)	3.231 (3.113–3.361)	0.856 (0.841–0.869)
MLP	15.011 (13.721–16.321)	2.991 (2.865–3.129)	0.862 (0.847–0.876)
Extra Trees	11.889 (10.909–12.907)	2.751 (2.640–2.864)	0.891 (0.880–0.901)
(b) Economic Sustainability Index			
Model	MSE	MAE	R ²
AdaBoost	23.479 (21.778–25.359)	3.918 (3.763–4.072)	0.908 (0.900–0.916)
Random Forest	23.188 (21.331–25.217)	3.686 (3.525–3.857)	0.910 (0.901–0.918)
Gradient Boost	22.298 (20.536–24.192)	3.626 (3.459–3.788)	0.913 (0.904–0.921)
Linear Regression	21.029 (19.305–22.763)	3.579 (3.427–3.734)	0.918 (0.910–0.925)
MLP	23.763 (21.547–26.009)	3.914 (3.740–4.082)	0.907 (0.897–0.917)
Extra Trees	19.701 (18.127–21.386)	3.429 (3.283–3.584)	0.923 (0.916–0.930)

Table 1. Cont.

(c) Social Sustainability Index			
Model	MSE	MAE	R ²
AdaBoost	43.752 (40.107–47.603)	4.957 (4.726–5.188)	0.856 (0.841–0.868)
Random Forest	43.574 (39.689–47.576)	4.938 (4.704–5.172)	0.856 (0.842–0.869)
Gradient Boost	41.104 (37.560–44.672)	4.804 (4.571–5.036)	0.864 (0.852–0.878)
Linear Regression	39.459 (36.546–42.425)	4.695 (4.480–4.914)	0.870 (0.858–0.882)
MLP	44.466 (40.676–48.444)	5.010 (4.775–5.239)	0.853 (0.839–0.866)
Extra Trees	38.814 (35.272–42.323)	4.657 (4.439–4.877)	0.872 (0.859–0.884)

Notes: (a) Overall SDG index model; (b) economic SDG model; (c) social SDG model. MAE = Mean absolute error; MSE = mean squared error; R² = coefficient of determination. Values in parentheses represent 95% confidence intervals.

4.3. Overall SDG Performance as a Baseline

The overall SDG model is first examined as a baseline for assessing the general pattern of predictor salience across sustainability performance. Figure 2 presents the SHAP-based feature importance for the overall SDG score. Population aging emerged as the dominant predictor in the overall SDG model, with a mean absolute SHAP value (4.59) higher than that of any other feature. It was followed by life expectancy (1.26), GDP per capita (1.10), and Government Effectiveness (0.64). Among the governance indicators, Voice and Accountability (0.46), Rule of Law (0.46), Regulatory Quality (0.36), Control of Corruption (0.30), and Political Stability (0.26) showed comparatively smaller but still measurable contributions, whereas unemployment had the lowest overall importance (0.14).

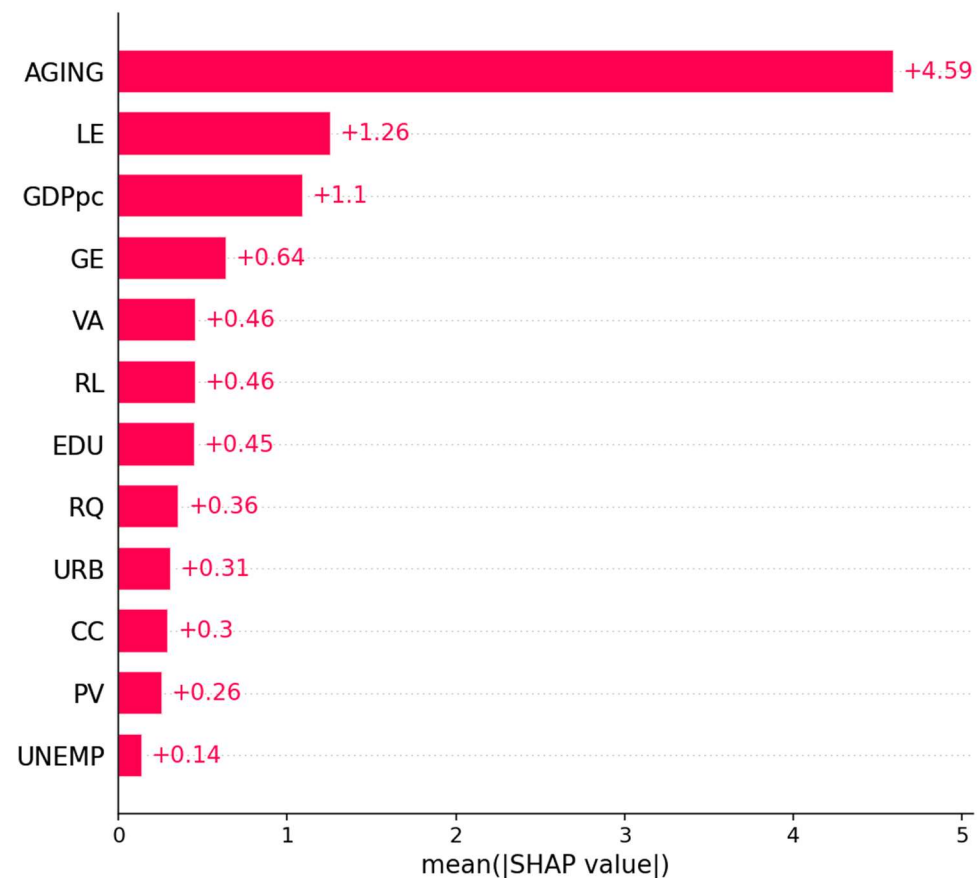


Figure 2. SHAP feature importance plot for the overall SDG performance model.

The beeswarm plot provides further detail on the direction and distribution of these effects (Figure 3). Higher levels of population aging were generally related to positive SHAP values, indicating a positive contribution to the predicted overall SDG score, while lower levels tended to reduce model predictions. Life expectancy shows a positive but more compressed pattern, with SHAP values plateauing at higher levels. This suggests a diminishing marginal contribution to predicted overall SDG performance once basic health and longevity conditions are well established. By contrast, GDP per capita shows greater overlap between high- and low-value observations around zero, indicating more heterogeneous contributions rather than a strictly monotonic pattern. Within the governance group, Government Effectiveness shows a clear positive pattern: higher values are generally related to positive SHAP values, while lower values tend to reduce the predicted overall SDG score. Its dependence pattern also suggests a diminishing marginal contribution, as the positive predictive gain becomes more limited once Government Effectiveness reaches relatively high levels. Other governance indicators, including Voice and Accountability, Rule of Law, Control of Corruption, and Political Stability, show weaker but broadly similar distributions. Within the governance group, Government Effectiveness shows a clear positive pattern: higher values are generally related to positive SHAP values, while lower values tend to reduce the predicted overall SDG score. Its dependence pattern also suggests a diminishing marginal contribution, as the positive predictive gain becomes more limited once Government Effectiveness reaches relatively high levels. Other governance indicators, including Voice and Accountability, Rule of Law, Control of Corruption, and Political Stability, show weaker but broadly similar distributions.

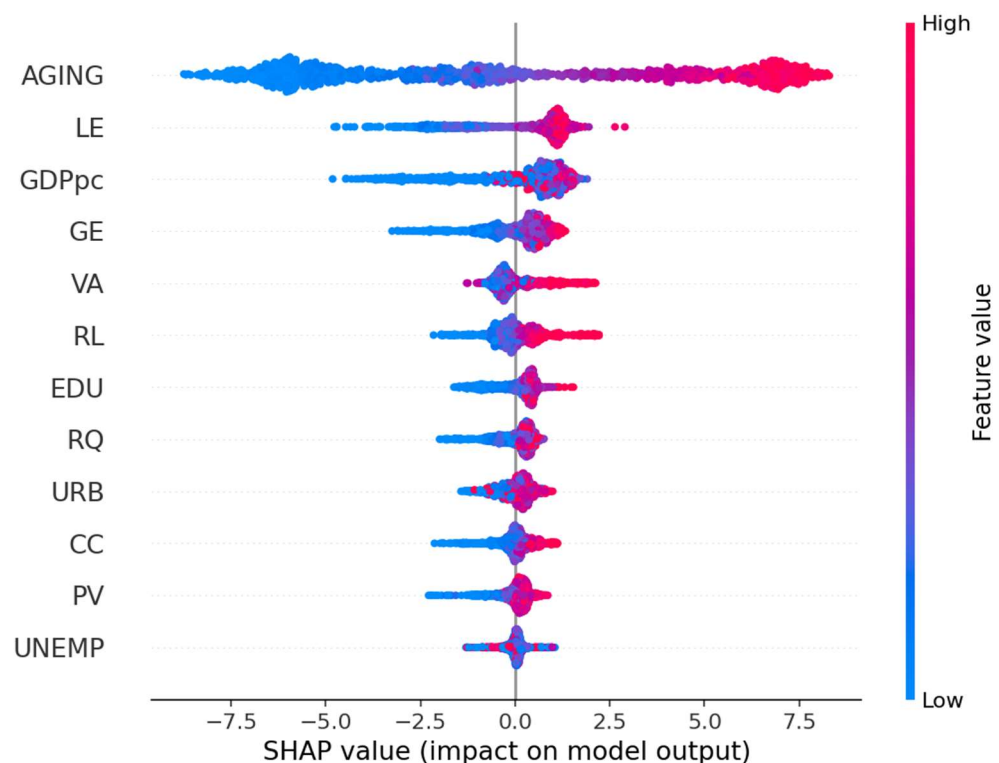


Figure 3. SHAP beeswarm plot for predictors in the overall SDG performance model.

Overall, the SDG model suggests that structural socioeconomic characteristics dominate the prediction of overall SDG performance, while governance variables make smaller but still visible contributions. Among the governance variables, Government Effectiveness stands out as the most influential institutional predictor, with a positive but diminishing marginal contribution to model predictions. Additional sensitivity analyses, including analyses excluding population aging and life expectancy, income-group comparisons, and pre-/post-COVID analyses, are reported in Appendices A.4–A.6.

To further examine the nonlinear patterns behind these feature rankings, dependence plots are presented for two representative predictors: population aging, the most influential variable overall, and Government Effectiveness, the highest-ranked governance indicator. The dependence plot for population aging shows a strong positive pattern (Figure 4). SHAP

values increase rapidly at low-to-moderate levels of population aging, indicating that higher shares of older population tend to raise the predicted overall SDG score within this range. At higher levels, the curve becomes flatter, suggesting a diminishing marginal contribution to model predictions. This nonlinear pattern suggests that population aging contributes most strongly to the prediction when countries move from low to moderate levels of aging, while its additional predictive contribution becomes weaker at already high levels. In this sense, the dependence plot indicates that population aging has a nonlinear association with the predicted overall SDG score, with its predictive contribution being relatively stronger at low-to-moderate levels of aging and gradually attenuating at higher levels.

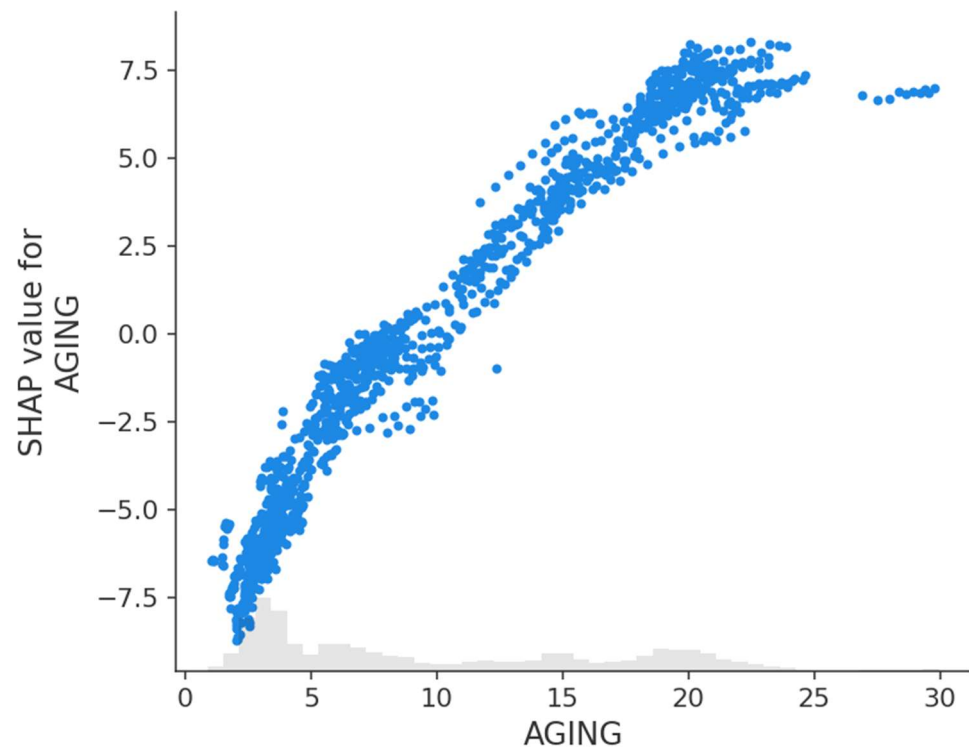


Figure 4. SHAP dependence plot for population aging in the overall SDG performance model. Blue dots represent individual observations, with their positions indicating the corresponding SHAP values, while grey bars indicate the distribution of feature values.

Government Effectiveness shows a clear but asymmetric nonlinear pattern (Figure 5). Very low levels of Government Effectiveness are related to strongly negative SHAP values, indicating that weak administrative capacity substantially pulls down the model's predicted overall SDG score. As Government Effectiveness moves from low to moderate levels, SHAP values increase sharply and cross into positive territory. However, once Government Effectiveness reaches relatively high levels, the curve becomes flatter, suggesting a diminishing marginal contribution to model predictions. This pattern indicates a positive nonlinear association between Government Effectiveness and the predicted overall SDG score. At lower levels of Government Effectiveness, SHAP values increase rapidly as GE rises, indicating a greater positive SHAP contribution within this range. However, the curve becomes substantially flatter around the central range of GE values, suggesting that the marginal predictive contribution of further improvements in Government Effectiveness decreases at higher levels.

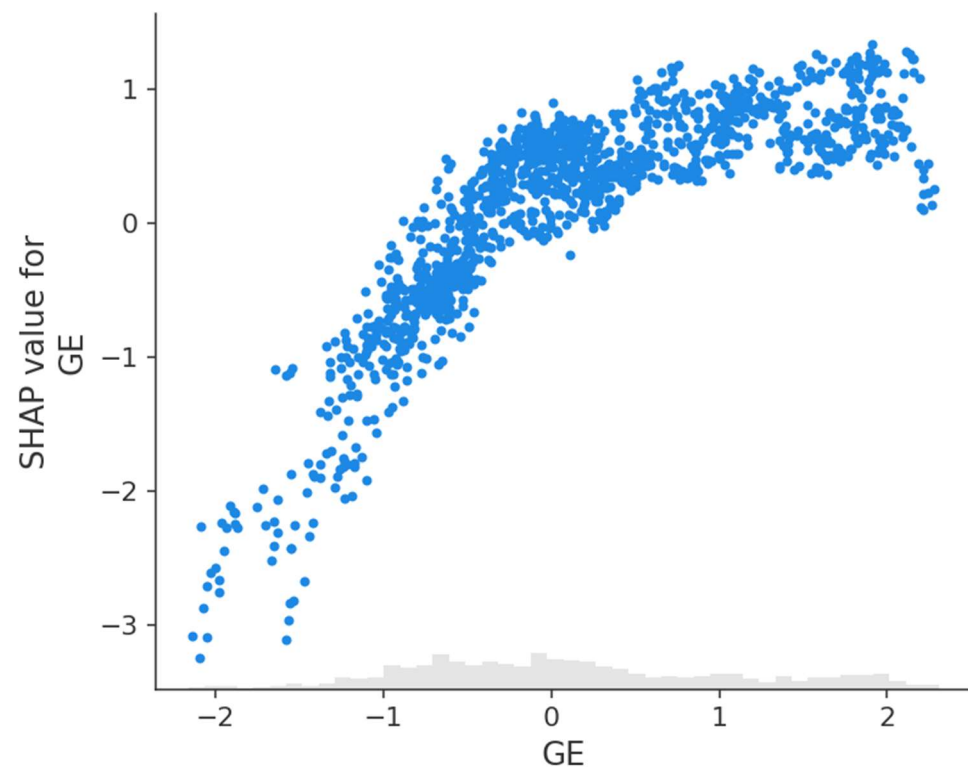


Figure 5. SHAP dependence plot for Government Effectiveness in the overall SDG performance model. Blue dots represent individual observations, with their positions indicating the corresponding SHAP values, while grey bars indicate the distribution of feature values.

4.4. Economic Sustainability

The economic sustainability model is then examined to assess whether governance and structural development variables show a distinct predictive profile for economically oriented SDG outcomes. Figures 6 and 7 present the SHAP feature importance ranking and beeswarm distribution for the economic sustainability model. Population aging remains the most influential predictor (mean $|\text{SHAP}| = 4.33$), followed by GDP per capita (3.35). However, in contrast to the overall SDG model, governance indicators occupy a more prominent position in the economic dimension, with governance-related predictors generally showing higher relative rankings and greater predictive contributions across the feature hierarchy. Government Effectiveness (1.60), Rule of Law (1.39), and Regulatory Quality (1.13) are the most prominent governance-related features, showing relatively large mean absolute SHAP values. This pattern suggests that administrative capacity, legal-institutional quality, and regulatory conditions have greater predictive salience in the economic sustainability model than in the overall SDG model. The beeswarm distribution further shows that this contribution is largely positive in direction: higher values of Government Effectiveness, Rule of Law, and Regulatory Quality are generally concentrated on the positive side of the SHAP axis, whereas lower values tend to shift model predictions downward. Overall, the economic sustainability model differs from the overall SDG model by showing a stronger and more positive governance profile, in which governance indicators move closer to the top of the feature hierarchy.

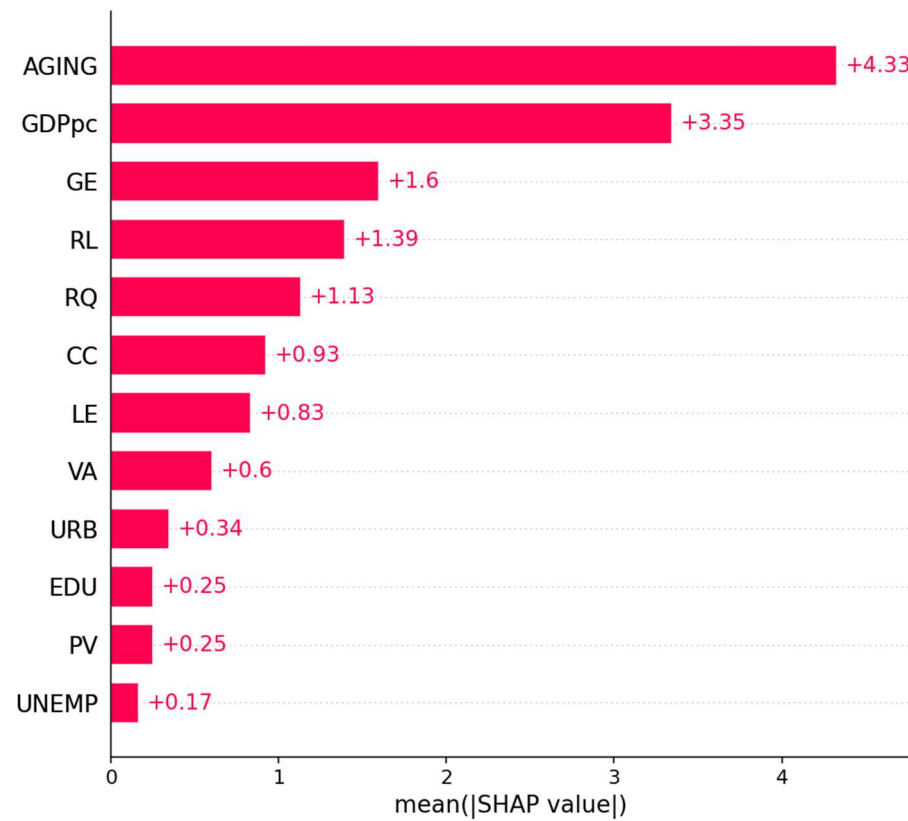


Figure 6. SHAP feature importance plot for predictors in the economic sustainability model.

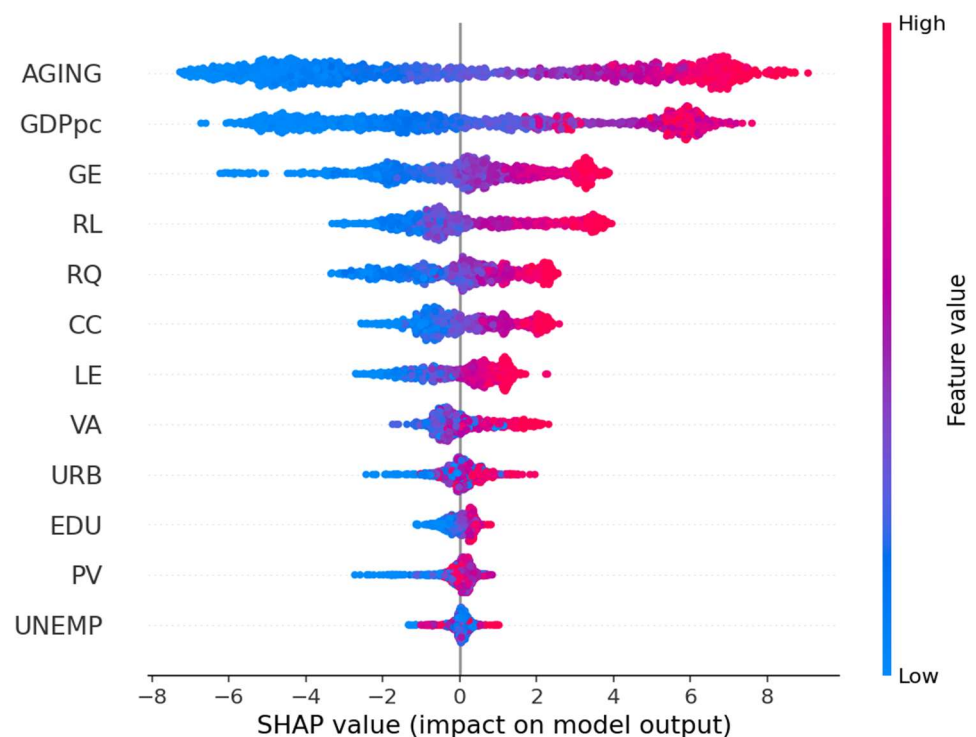


Figure 7. SHAP beeswarm plot for predictors in the economic sustainability model.

4.5. Social Sustainability

The social sustainability model focuses on whether predictor salience differs for socially oriented SDG outcomes. Figures 8 and 9 present the SHAP feature importance ranking and beeswarm distribution for the social sustainability model. The social dimen-

sion presents a mixed but meaningful governance pattern. Population aging is the leading predictor (mean $|SHAP| = 4.31$), followed by life expectancy (3.85) and GDP per capita (2.75), indicating that demographic, health, and material development conditions make a large contribution to model prediction. Compared with the overall SDG model, however, governance-related predictors show higher relative rankings in the feature hierarchy, and this pattern is less pronounced than that observed in the economic sustainability model. Government Effectiveness shows the highest predictive contribution among governance indicators (1.26), followed by Regulatory Quality (0.82), with Political Stability (0.73) also exhibiting a higher relative position compared with the overall SDG model. Control of Corruption (0.37) and Voice and Accountability (0.40) show relatively lower contributions. The beeswarm distribution further clarifies the direction of these contributions. Higher values of population aging, life expectancy, and GDP per capita are generally concentrated on the positive side of the SHAP axis, whereas lower values tend to shift model predictions downward. A similar, though less dominant, pattern is observed for Government Effectiveness, Regulatory Quality, and Political Stability, whose higher values also tend to contribute positively to predicted social sustainability. This suggests that the social model is not predicted by structural variables alone, even though its overall hierarchy continues to be led by development-related and health-related factors. Overall, the social sustainability model displays a pattern in which demographic and socioeconomic conditions provide the strongest predictive contributions, while multiple governance dimensions, particularly Government Effectiveness, Regulatory Quality, and Political Stability, show increased predictive salience compared with the overall SDG model.

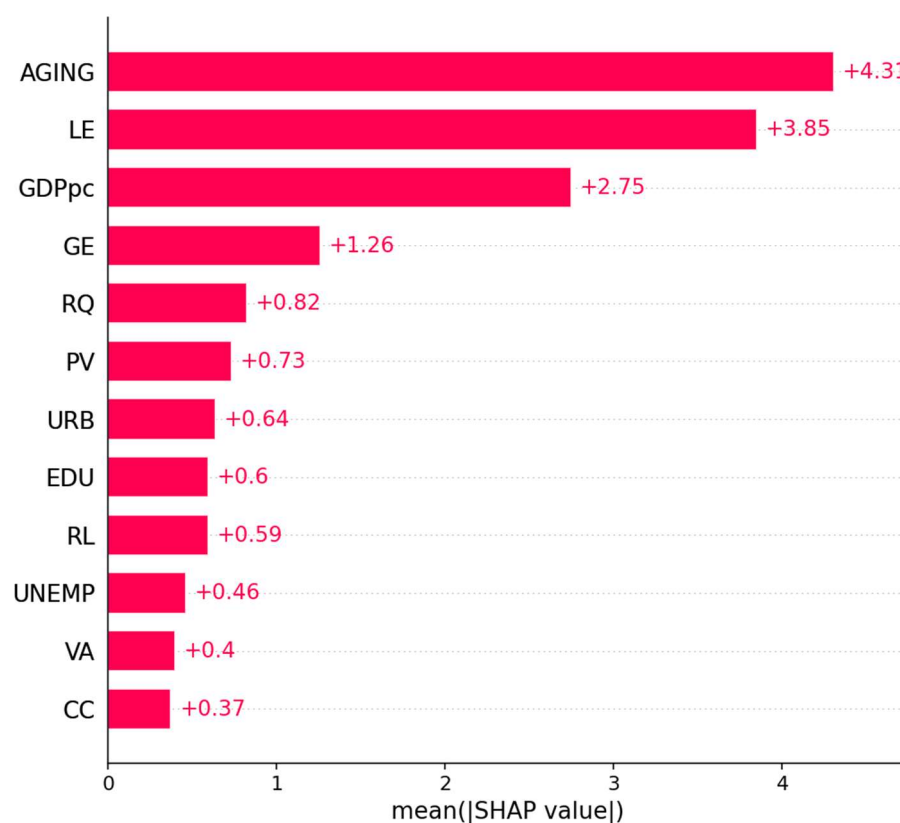


Figure 8. SHAP feature importance plot for predictors in the social sustainability model.

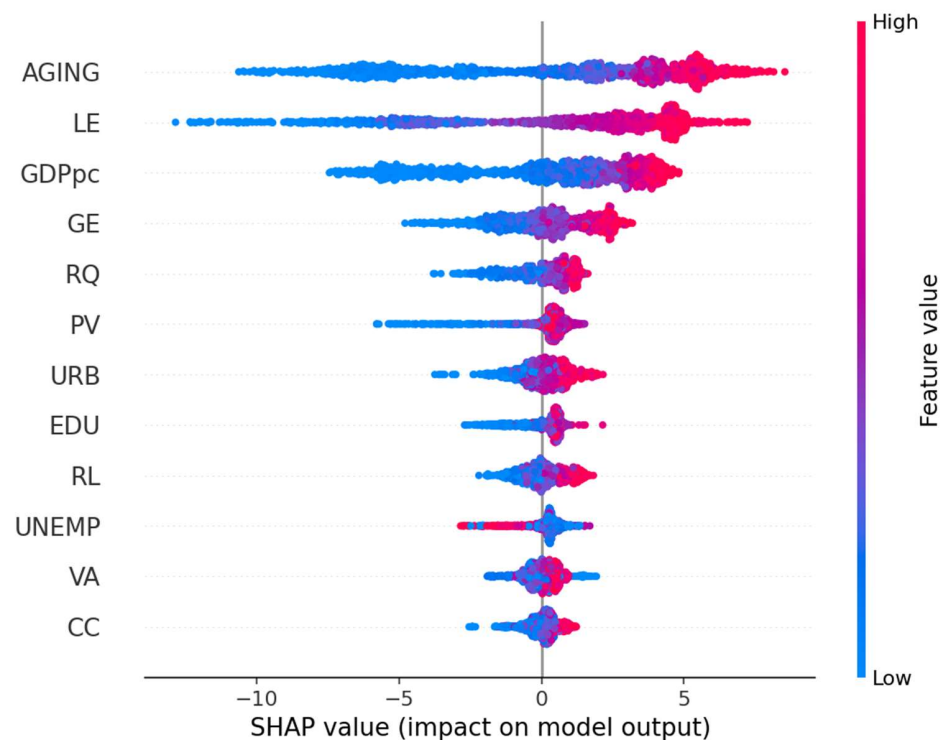


Figure 9. SHAP beeswarm plot for predictors in the social sustainability model.

4.6. Environmental Sustainability in High-Income Countries

The Environmental Sustainability Index showed comparatively weaker predictive performance under the country-level GroupKFold validation strategy. Given the potential heterogeneity in environmental sustainability patterns across different levels of economic development, income-group-specific analyses were further conducted to examine whether the limited predictive performance reflected differences across development contexts. The high-income subgroup included 450 country-year observations, whereas the combined middle- and low-income subgroup included 864 country-year observations. The difference in sample size relative to the baseline model results from the construction of domain-specific indices. While the overall SDG index was directly obtained from the original dataset without missing observations, the environmental sustainability index was calculated from selected goal-level indicators and excluded country-year observations with incomplete component data. The results showed that predictive performance improved substantially among high-income countries, as shown in Table 2, but remained more limited among middle- and low-income countries. Given the stronger predictive performance observed among high-income countries, this subgroup was further examined using SHAP analysis to explore the underlying predictor patterns.

Table 2. Predictive Performance of Candidate Models for the Environmental Sustainability Index across Different Samples.

(a) Environmental Sustainability Index (Full Sample)			
Model	MSE	MAE	R ²
AdaBoost	40.651 (37.249–44.054)	4.815 (4.450–5.170)	0.522 (0.472–0.565)
Random Forest	39.434 (35.928–42.941)	4.756 (4.392–5.122)	0.536 (0.483–0.586)
Gradient Boost	39.821 (36.247–43.394)	4.764 (4.400–5.137)	0.532 (0.478–0.580)
Linear Regression	40.983 (37.515–44.451)	4.827 (4.463–5.181)	0.518 (0.468–0.565)
MLP	45.125 (41.474–48.775)	5.033 (4.667–5.403)	0.469 (0.408–0.523)
Extra Trees	34.755 (31.636–37.874)	4.472 (4.118–4.811)	0.591 (0.543–0.635)

Table 2. Cont.

(b) Environmental Sustainability Index (Middle- and Low-Income Countries)			
Model	MSE	MAE	R ²
AdaBoost	40.510 (36.144–44.877)	4.861 (4.472–5.230)	0.210 (0.143–0.273)
Random Forest	43.426 (38.541–48.311)	5.003 (4.600–5.397)	0.153 (0.073–0.234)
Gradient Boost	43.417 (38.532–48.302)	4.991 (4.599–5.387)	0.154 (0.075–0.229)
Linear Regression	41.971 (37.744–46.197)	4.918 (4.550–5.285)	0.182 (0.114–0.244)
MLP	60.652 (54.542–66.763)	5.961 (5.484–6.429)	−0.182 (−0.321–−0.072)
Extra Trees	36.084 (31.903–40.263)	4.593 (4.196–4.978)	0.297 (0.232–0.355)
(c) Environmental Sustainability Index (High-Income Countries)			
Model	MSE	MAE	R ²
AdaBoost	37.978 (32.275–44.048)	4.601 (4.236–4.953)	0.747 (0.697–0.790)
Random Forest	56.387 (46.861–67.464)	5.672 (5.115–6.228)	0.624 (0.537–0.696)
Gradient Boost	52.907 (44.772–62.394)	5.470 (4.975–5.982)	0.647 (0.570–0.711)
Linear Regression	52.033 (44.081–60.799)	5.390 (4.932–5.843)	0.653 (0.578–0.712)
MLP	156.202 (134.782–178.424)	8.554 (7.978–9.135)	−0.042 (−0.239–0.122)
Extra Trees	35.661 (30.355–41.246)	4.472 (4.129–4.811)	0.762 (0.715–0.802)

Notes: (a) full sample; (b) middle- and low-income countries; (c) high-income countries. MAE = mean absolute error; MSE = mean squared error; R² = coefficient of determination. Values in parentheses represent 95% confidence intervals.

This model presents a distinct predictive pattern compared with the other sustainability domains. Figures 10 and 11 present the SHAP feature importance ranking and beeswarm distribution for the environmental sustainability model among high-income countries. Population aging remains the dominant predictor (mean $|SHAP| = 5.22$), substantially exceeding the contributions of other features. This is followed by Voice and Accountability (1.61), urbanization (1.29), Government Effectiveness (1.15), and GDP per capita (1.03), indicating that demographic structure, governance conditions, urban development, and economic capacity jointly contribute to the prediction of environmental sustainability outcomes. Compared with the overall SDG, economic, and social sustainability model, the environmental model for high-income countries shows a distinct governance profile. Among governance-related predictors, Voice and Accountability exhibits the highest predictive contribution, followed by Government Effectiveness and Regulatory Quality, whereas other governance dimensions show relatively smaller contributions. This suggests that governance-related predictors are not uniformly salient within the environmental domain, with certain governance dimensions demonstrating greater predictive relevance in the high-income context.

The beeswarm distribution further shows that the environmental model for high-income countries exhibits different predictor direction patterns compared with the economic and social models. Higher values of population aging are clearly concentrated on the positive side of the SHAP axis, whereas lower values tend to shift model predictions downward. In contrast, several development-related indicators display an inverse pattern. Higher values of GDP per capita are predominantly concentrated on the negative side of the SHAP axis, while lower values are more frequently related to positive SHAP contributions. Urbanization shows a similar tendency, although with a less pronounced distribution pattern. This suggests that the environmental dimension captures a different sustainability logic, in which material development and urbanization do not exhibit the same positive associations with predicted performance as observed in the economic and social dimensions.

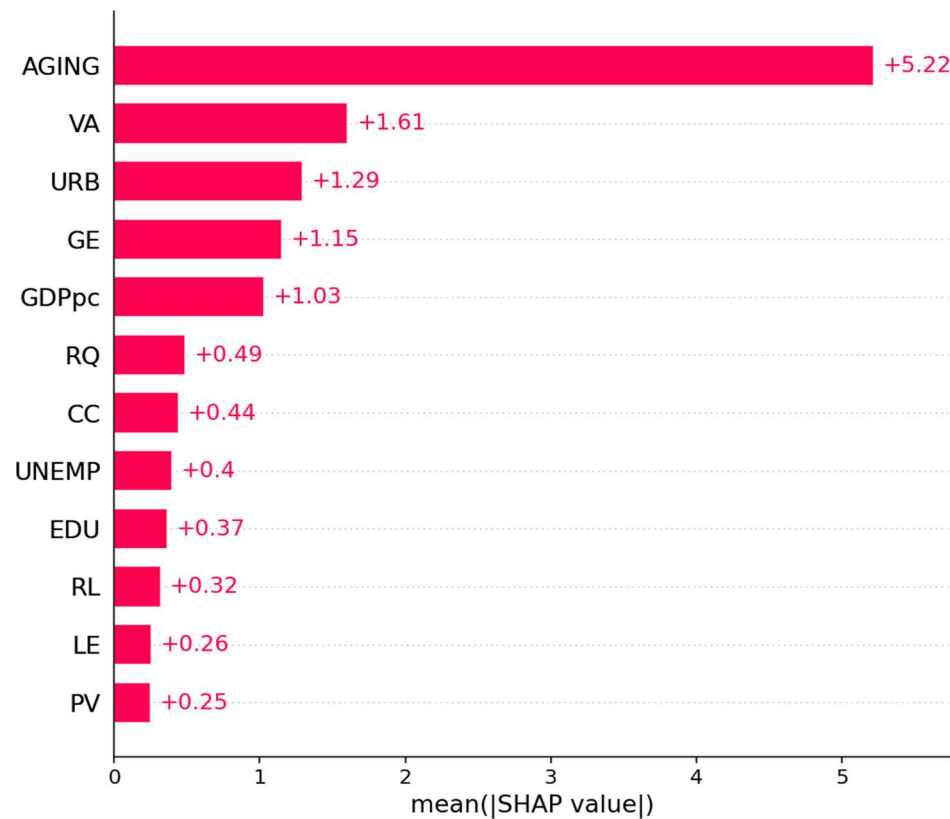


Figure 10. SHAP feature importance plot for predictors in the environmental sustainability model among high-income countries.

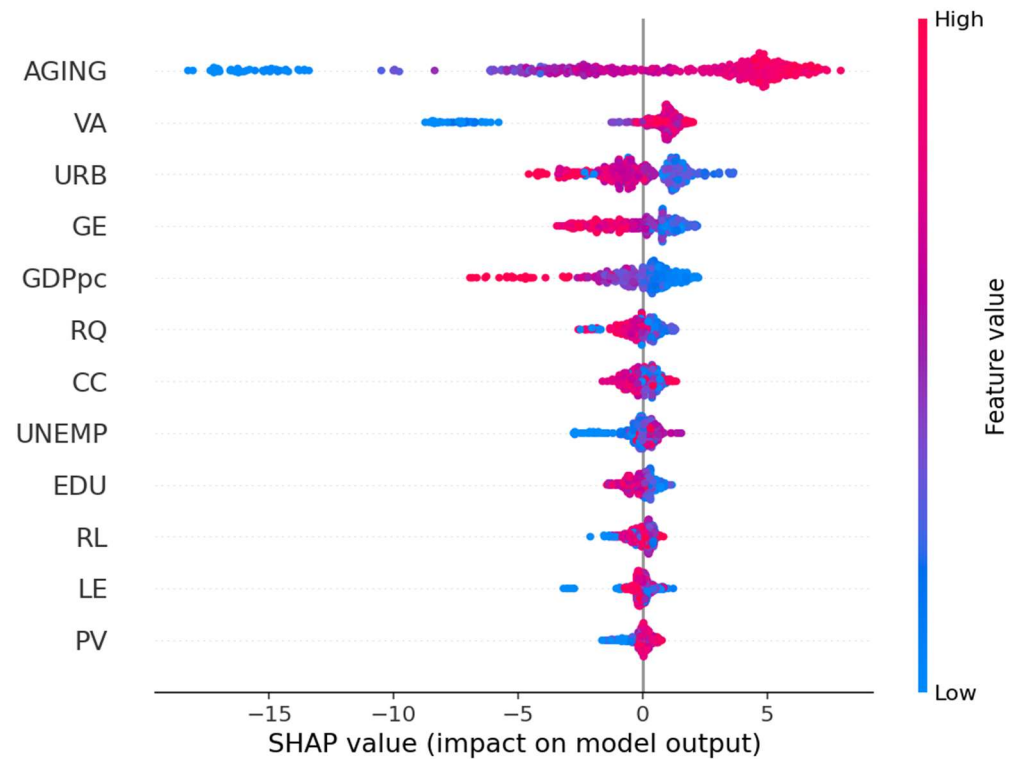


Figure 11. SHAP beeswarm plot for predictors in the environmental sustainability model among high-income countries.

Governance-related predictors show a more heterogeneous directional pattern in the environmental sustainability model for high-income countries. Although Government

Effectiveness remains one of the more prominent governance predictors in the feature ranking, its SHAP distribution does not display a consistently positive pattern, with observations distributed across both positive and negative SHAP values and a tendency toward the negative side. Other governance dimensions, including Regulatory Quality and Control of Corruption, show relatively weaker and more dispersed SHAP distributions. Overall, the environmental sustainability model for high-income countries is characterized by strong demographic predictors, an inverse pattern for material development indicators, and a selective governance profile, with Voice and Accountability and Government Effectiveness showing relatively higher predictive contributions among governance dimensions. This governance profile should be interpreted as context-specific and may not extend to developing economies, where structural differences and data heterogeneity may lead to different governance-sustainability patterns.

4.7. Cross-Domain Comparison

The four models reveal that governance shows varying predictive relevance across sustainability outcomes. The overall SDG model provides a baseline in which structural development variables occupy the leading positions in the feature hierarchy, but governance variables, especially Government Effectiveness, also retain a visible and non-trivial predictive role. Once overall SDG performance is disaggregated into economic, social, and environmental dimensions, the relative importance, internal ordering, and directional pattern of governance variables change substantially across domains.

The clearest shift appears in the economic sustainability model. Compared with the overall SDG model, governance indicators move much closer to the top of the feature hierarchy, with Government Effectiveness, Rule of Law, and Regulatory Quality ranking immediately after population aging and GDP per capita. Their beeswarm distributions also show a largely positive pattern, indicating that higher values of these governance indicators tend to shift model predictions upward. This suggests that economic sustainability is the domain in which governance is most broadly and positively reflected, particularly through administrative capacity, legal-institutional quality, and regulatory conditions.

The social sustainability model presents an intermediate pattern between the overall and economic sustainability models. Demographic, health, and socioeconomic conditions remain the dominant predictors, with population aging, life expectancy, and GDP per capita occupying the leading positions in the feature hierarchy. However, compared with the overall SDG model, governance-related predictors become more prominent, with Government Effectiveness, Regulatory Quality, and Political Stability retaining visible positions among the higher-ranked features. The social model therefore does not simply reproduce the structural dominance of the overall SDG model, nor does it display the strong governance profile observed in the economic model. Instead, it represents an intermediate pattern: social sustainability is primarily predicted by human-development conditions, such as life expectancy, but governance, especially Government Effectiveness, continues to make a positive and meaningful predictive contribution.

The environmental sustainability model among high-income countries shows the most distinct predictive profile among the three domain-specific models. Unlike the economic and social models, where GDP per capita generally shows a positive predictive pattern, the environmental model exhibits an inverse pattern for material development indicators, with higher values of GDP per capita and urbanization more frequently related to negative SHAP contributions. Governance-related predictors remain relevant but show a more heterogeneous pattern. While Government Effectiveness and Voice and Accountability emerge as relatively prominent governance predictors, other governance dimensions display weaker and less consistent predictive contributions. Therefore, the environmental model differs

from the other sustainability domains by showing a more selective governance profile, in which the predictive relevance of governance varies considerably across dimensions rather than exhibiting the broader positive pattern observed in the economic model.

Government Effectiveness appears as the highest-ranked governance indicator in the overall and social models and remains among the leading governance indicators in the economic model. However, the governance dimensions accompanying Government Effectiveness vary by domain. Rule of Law and Regulatory Quality are especially prominent in the economic model; Regulatory Quality and Political Stability retain visibility in the social model; and the environmental model for high-income countries shows a more differentiated governance profile, in which Voice and Accountability and Government Effectiveness demonstrate relatively higher predictive salience while other governance dimensions exhibit weaker and more heterogeneous patterns. This internal variation suggests that governance should not be treated as a single undifferentiated institutional factor. Rather, different dimensions of governance acquire different levels of predictive salience depending on the sustainability domain under consideration.

In summary, the cross-domain comparison shows that aggregate SDG performance masks important variation in the governance–sustainability relationship. Governance is strongest and most broadly positive in the economic dimension. In the social dimension, governance remains meaningful but secondary to structural development conditions. In the environmental dimension among high-income countries, governance relevance is more selective and heterogeneous. These findings reinforce the central argument of the study: governance matters for sustainability, but its relevance is domain-specific, multidimensional, and conditional on the type of sustainability outcome being predicted.

5. Discussion

These findings build on prior studies on governance and SDG achievement [13–16], but extend them by showing that governance salience is not uniform across sustainability domains or across specific WGI dimensions. The results therefore provide empirical support for metagovernance perspectives that emphasize context-sensitive and domain-sensitive governance arrangements for SDG implementation [8,21]. Methodologically, the study also shows how interpretable machine learning can help reveal cross-domain differences in predictor salience that may be less visible in aggregate or purely linear analyses. At the same time, these findings suggest that governance should be understood within a broader development context. The contribution of governance indicators lies in their relative predictive salience after accounting for broader socioeconomic and demographic conditions, rather than suggesting that governance alone is the primary predictor of sustainability performance.

This domain-sensitive pattern can be understood through a metagovernance perspective on sustainable development. From this perspective, governance relevance is shaped by the specific demands of different sustainability domains, consistent with Meuleman's argument that SDG implementation requires differentiated governance arrangements [8,21]. The present results support this logic by showing that governance relevance differs in composition across domains: implementation, regulatory, and legal dimensions are more visible where sustainability tasks depend directly on policy execution and coordination, whereas governance variables are less prominent where outcomes are more strongly mediated by long-term structural or developmental conditions.

The population-aging pattern in the baseline model has broader theoretical implications for interpreting aggregate SDG performance. This indicator can be understood as reflecting a development-stage signal. Importantly, this interpretation does not imply that population aging represents a governance-specific mechanism. Rather, its strong predictive

contribution likely captures broader socioeconomic and development-related conditions that tend to accompany different stages of national development. In cross-national terms, higher levels of population aging typically reflect mortality decline, longer life expectancy, and broader socioeconomic development [41,42]. This interpretation helps explain why the contribution of population aging rises most clearly at lower-to-moderate levels. Within this range, increases in aging are likely to reflect substantial movement along a broader development gradient, where improvements in health, education, public services, and material well-being are closely related to higher overall SDG performance. Recent cross-national evidence similarly suggests that countries at lower development levels often experience faster gains in sustainability performance, which may reflect greater scope for coordinated improvement, whereas countries already located in more advanced developmental contexts face more limited opportunities for additional aggregate gains [43]. Likewise, research on SDG trajectories suggests that sustainable development pathways evolve as countries move through different stages of development, rather than following a single uniform pattern [6]. The flattening of the curve at higher aging levels can therefore be interpreted as a diminishing marginal contribution of the broader development-stage signal to predicted overall SDG performance. In this sense, the baseline model appears to reflect a broad developmental gradient underlying cross-national difference in sustainability performance.

While the population-aging pattern points to the importance of broader developmental trajectories, the dependence plot for Government Effectiveness highlights the role of institutional capacity as an important contextual condition related to sustainability outcomes. In the WGI framework, Government Effectiveness captures public-service quality, bureaucratic capability, policy formulation and implementation, and the credibility of government commitments [22]. Weak performance on this dimension therefore implies not only lower effectiveness in a single policy area, but broader constraints in the state's ability to organize, coordinate, and sustain public action across multiple development objectives. This interpretation is consistent with administrative-capacity research, which views implementation capability, resource alignment, service delivery, and policy execution as foundational conditions for development performance rather than sector-specific attributes [44,45]. It also aligns with broader governance research suggesting that effective governance is related to development outcomes and reflects conditions that support stability and coordination across economic, social, and environmental objectives [46,47]. The strongly negative SHAP values at the lower end of the distribution suggest that deficiencies in these foundational administrative functions correspond to substantial reductions in predicted sustainability performance. By contrast, the flatter pattern observed at higher levels of Government Effectiveness indicates that, once basic implementation and coordination capacities are broadly established, additional improvements appear to contribute less markedly to differences in predicted sustainability outcomes. From a practical perspective, this threshold-like pattern suggests that, in countries where basic administrative systems remain limited, strengthening core functions such as public service delivery, policy implementation, and bureaucratic coordination may represent a particularly relevant governance priority. Countries with more established administrative systems may experience smaller incremental gains from further improvements in basic administrative capacity and may instead require more targeted institutional refinements.

These findings suggest that aggregate sustainability performance reflects a combination of long-term developmental trajectories and institutional conditions, both of which are related to the opportunities and constraints under which sustainability goals are pursued. Viewed in this way, aggregate indicators may obscure important differences in the governance requirements of particular sustainability domains, highlighting the need for a more

differentiated understanding of how governance dimensions vary in predictive salience across different sustainability outcomes.

The economic dimension provides the clearest example of domain-sensitive governance salience. Compared with the overall SDG model, governance variables move upward more visibly in the economic feature hierarchy, especially Government Effectiveness, Rule of Law, and Regulatory Quality. This pattern is theoretically plausible because the economic index captures goals that are institutionally proximate to conditions governments can shape more directly. Specifically, the economic sustainability index incorporates goals related to economic growth and employment (Goal 8), industry, innovation, and infrastructure (Goal 9), and sustainable urban development (Goal 11). These outcomes relate not only to material resources, but also to institutional conditions reflecting policy implementation capacity, legal stability, regulatory coordination, and long-term planning.

This interpretation is consistent with institutional perspectives that emphasize the role of predictable rules and public authority in structuring economic activity. In North's account, institutions reduce uncertainty and stabilize the conditions under which exchange and coordination take place [48]. Some research suggests that rule-based institutional environments support investment by reducing uncertainty through legal predictability, contract enforcement, and protection against arbitrary intervention [49]. At the same time, higher regulatory quality reflects more predictable and stable market conditions, which are in turn linked to improved economic performance and private-sector development, particularly where institutional credibility remains a constraint [50].

Government Effectiveness appears particularly salient in this dimension because it reflects the state's capacity to translate policies into tangible developmental outcomes. Consistent with Fukuyama's conception of governance as implementation capacity, effective public institutions facilitate policy coordination and execution across complex development domains [47]. This role may be particularly relevant for goals related to infrastructure, innovation, and urban development, which typically require sustained public investment and long-term policy commitment. Empirical evidence further suggests that institutional quality has been linked to the creation of conditions that support investment, productive activity, and sustained economic growth, particularly when combined with effective fiscal and policy capacity [51]. Economic sustainability is more closely aligned with governance capacities related to implementation, coordination, and regulatory credibility, helping to explain the comparatively stronger governance profile observed in the economic model.

The social dimension points to a different institutional logic. Population aging, life expectancy, and GDP per capita remain the leading predictors, indicating that social sustainability is strongly anchored in long-run human-development conditions. Yet these variables should not be treated as entirely separate from governance and institutions. Rather, they reflect the cumulative outcomes of investments in health systems, education, social protection, and broader human-development capacity that have accumulated over time [15,42]. In this sense, the continued salience of Government Effectiveness, Regulatory Quality, and Political Stability suggests that governance remains relevant, but more as a foundational support condition than as the most immediate predictor. Existing research suggests that institutional quality is viewed as an important condition related to the accumulation of human capital and broader human-development capacity [52]. Other research has shown that governance quality reflects differences in public-sector capacity and implementation quality that shape the effectiveness of public spending in health and education outcomes [53], while evidence from sustainable development studies indicates that educational development and governance are closely interconnected foundations of broader development performance [54]. These findings suggest that the relevance of governance for social sustainability extends beyond immediate policy outputs and closely

relates to the institutional capacities upon which human development is accumulated and sustained over time.

The environmental dimension among high-income countries appears to follow a different sustainability logic from the economic and social domains. The inverse contribution pattern of GDP per capita suggests that higher levels of material development do not necessarily correspond to stronger environmental sustainability performance, reflecting potential development–environment trade-offs in balancing economic development objectives with environmental sustainability goals [5]. Environmental sustainability also exhibits a less consistent and more conditional governance pattern. This may reflect the distinctive characteristics of environmental governance, where environmental outcomes often involve complex interactions among multiple stakeholders, policy domains, and cross-sector coordination processes [55].

The stronger predictive performance observed in the high-income subgroup suggests that environmental sustainability patterns may differ across development contexts. In lower- and middle-income countries, environmental trajectories may be more heterogeneous due to differences in industrialization pathways, economic structures, and resource constraints, making cross-national variation more difficult to capture using a common set of predictors. This interpretation is consistent with recent cross-country evidence showing that the relationship between institutional quality and environmental sustainability varies across income groups, as institutional factors and environmental outcomes exhibit different patterns between lower- and higher-income country contexts [56]. Previous research also suggests that governance improvements are related to better environmental outcomes in high-income countries, but this relationship may be weaker or even reversed in lower-income contexts where economic growth priorities remain dominant [57]. Evidence from a global analysis further suggests that the environmental implications of governance differ substantially across regions, reflecting differences in institutional arrangements, development priorities, and environmental challenges across national contexts [28].

However, this pattern does not suggest that governance lacks relevance in the environmental domain among high-income countries. Existing research suggests that Government Effectiveness and Regulatory Quality are closely linked to the institutional capacity needed to implement environmental regulations and support climate-related policy objectives [58,59]. At the same time, recent studies suggest that the environmental role of Government Effectiveness is conditional rather than uniformly positive, as administrative capacity alone may not always positively predict improved environmental outcomes without sufficient environmental policy stringency or regulatory constraints. In some contexts, insufficiently complemented administrative capacity may even be related to adverse environmental outcomes [60,61]. Beyond administrative and regulatory capacities, participatory governance may also represent an important dimension of environmental governance. Recent cross-country evidence suggests that Voice and Accountability is positively connected with environmental quality, emphasizing the relevance of citizen participation and government-society interaction in environmental governance processes, particularly through their role in shaping policy formulation and implementation contexts [62].

Environmental sustainability encompasses multiple policy domains shaped by distinct regulatory, technological, and ecological processes, including energy transitions, climate mitigation, and ecosystem protection, which involve interactions beyond governance capacities alone [63]. In this sense, governance may function more as a coordinating institutional framework for aligning environmental SDG progress with broader sustainability objectives [64].

In summary, the findings suggest that governance should be understood not as a consistent institutional predictor of sustainable development, but as a domain-sensitive

governance architecture whose relevance depends on the specific institutional requirements of different sustainability outcomes. This interpretation supports the metagovernance perspective by showing that sustainable development coordination involves not just combining conventional governance arrangements, but also recognizing that governance capacities fulfill different functions across sustainability domains [8,21]. Economic sustainability is more closely aligned with implementation capacity, legal predictability, and regulatory credibility; social sustainability reflects the longer-term institutional conditions under which human-development outcomes are accumulated; and environmental sustainability among high-income countries appears more conditional on broader institutional and development contexts, where governance capacities interact with environmental policy commitments, participatory arrangements, and development–environment trade-offs. In this sense, the study moves beyond the question of whether governance matters for SDG performance and shows that examining sustainability across separate economic, social, and environmental dimensions makes it possible to identify domain-specific patterns in the role of governance that are less visible in the overall SDG model. This provides a more differentiated theoretical account of governance for sustainable development and highlights the value of interpretable machine learning for identifying domain-specific patterns of governance salience.

5.1. Policy Implications

From a policy perspective, the findings suggest that sustainability strategies should be tailored not only to specific domains but also to the institutional and developmental contexts in which they are implemented. In the economic domain, where governance-related indicators demonstrated stronger predictive salience, policy priorities may focus on strengthening administrative capacity, regulatory quality, and rule-based institutional arrangements to support effective policy implementation, economic transformation, and legal certainty. In the social domain, governance strategies should be integrated with broader investments in healthcare and social protection, as socioeconomic and demographic conditions remain central predictors while effective governance helps enhance the delivery and coordination of public services. Environmental sustainability requires a more context-sensitive approach, as governance indicators showed weaker and more conditional predictive patterns; therefore, improving general administrative capacity alone may be insufficient without complementary sector-specific environmental policies and resource management strategies. Furthermore, the income-group analysis indicates that governance priorities should vary across development contexts, with high-income countries placing greater emphasis on institutional refinement, stronger regulatory coordination, and participatory governance. These differentiated strategies highlight the importance of aligning governance arrangements with specific sustainability objectives and country-level institutional conditions rather than pursuing a uniform governance policy.

5.2. Limitations

There are several limitations related to indicator construction, data availability, and methodology in the study. First, the findings should be interpreted as evidence of predictive salience and conditional associations rather than causal effects. The cross-national panel structure of the dataset, combined with the predictive focus of the Extra Trees model, means that this study identifies robust structural patterns rather than isolating causal mechanisms. Moreover, because the WGI are constructed from expert assessments and survey-based perceptions, some degree of conceptual overlap may exist between governance measures and socioeconomic developments captured by SDG indicators, particularly in the social sustainability domain. Therefore, the predictive contribution of governance variables should

be interpreted as reflecting their relative relevance within the observed governance and development context rather than independent causal effects. Further research could combine interpretable machine learning with causal inference strategies, such as instrumental variable designs or difference-in-differences models, to examine whether and how specific governance reforms affect subsequent sustainability outcomes.

Second, the construction of the domain-specific sustainability indices involves conceptual and methodological choices. The economic, social, and environmental indices are based on selected SDGs and calculated using unweighted averages. This approach keeps the analysis transparent and comparable across domains, but alternative goal classifications or weighting schemes may produce somewhat different patterns. Robustness checks using alternative SDG groupings or weighting strategies would help assess the stability of the cross-domain patterns reported here.

Third, the analysis relies on cross-national indicators that capture broad country-level patterns. The WGI and SDG indicators are useful for comparing governance and sustainability across countries, but they cannot fully capture subnational variation, sector-specific policy processes, or the institutional mechanisms through which governance capacities are translated into sustainability outcomes. This limitation points to the value of complementary subnational and industry-specific studies that examine how governance arrangements operate within specific policy domains, sectoral settings, and institutional contexts.

Fourth, although Extra Trees is generally less affected by multicollinearity for predictive modeling purposes, highly correlated predictors among both structural variables (e.g., population aging and life expectancy) and governance indicators (e.g., Government Effectiveness, Rule of Law, and Regulatory Quality) may complicate SHAP interpretation. In particular, SHAP values may distribute predictive contributions among correlated features, meaning that fine-grained rankings among closely related WGI dimensions should be interpreted with caution. The findings emphasize the collective domain-specific salience of governance-related predictors without claiming that any single highly correlated governance indicator has an independent dominant effect.

6. Conclusions

Governance is often treated as a general institutional condition for sustainable development, but this study suggests that its relevance is more domain-specific. Governance is most prominent in the economic dimension, remains visible but secondary in the social dimension, and appears weaker and more conditional in the environmental dimension. These patterns suggest that governance should be understood as a domain-sensitive institutional architecture rather than a uniform predictor of SDG performance. The findings also highlight that governance should be evaluated within a broader development context, with the relative predictive salience of governance indicators assessed after considering socioeconomic and demographic conditions.

Existing studies have shown that governance quality is relevant to SDG achievement and sustainable development, but they have often examined governance in relation to overall sustainability performance. This study extends that literature by showing that governance is not only multidimensional in measurement, but also functionally differentiated across sustainability domains. The central contribution is therefore to extend beyond whether governance matters for sustainable development and to show how different governance capacities matter differently across specific sustainability outcomes.

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X.T.; project administration, X.T. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1

The economic sustainability index was reconstructed by incorporating SDG1 (No Poverty) into the original economic domain, resulting in an alternative index based on SDG1, SDG8, SDG9, and SDG11 with equal weighting. This alternative specification was used as a robustness check to examine whether the main findings were sensitive to the composition of the economic sustainability index. Although SDG1 is conventionally categorized as a social sustainability goal, poverty reduction is closely linked to inclusive economic development and provides a theoretically plausible alternative specification for assessing economic sustainability. The alternative economic index was evaluated using the Extra Trees model, which achieved the highest predictive performance among candidate models under this specification, together with a country-level GroupKFold cross-validation strategy. The alternative economic index model showed slightly stronger predictive performance than the baseline specification, with R^2 values of 0.948 and 0.923, respectively. The results are reported in Table A1. The main predictive patterns remained broadly consistent with the baseline specification. Structural development indicators, particularly GDPpc and AGING, continued to dominate the prediction of economic sustainability, while governance-related predictors, especially Government Effectiveness, Regulatory Quality, and Rule of Law, remained among the highest-ranked predictors. The inclusion of SDG Goal 1 increased the relative importance of socioeconomic indicators, particularly LE, which is consistent with the human development implications of SDG1. However, the overall governance-related patterns remained largely unchanged. These results suggest that the main findings regarding the domain-specific predictive relevance of governance are not driven solely by the original SDG goal composition.

Table A1. Robustness analysis of economic sustainability index construction using an alternative SDG goal composition.

Model	SDG Goal Composition	Top 6 Predictors Ranked by SHAP Values	R^2
Baseline Model	SDG8 + SDG9 + SDG11	AGING (4.33) GDPpc (3.35) GE (1.6) RL (1.39) RQ (1.13) CC (0.93)	0.923 (0.916–0.930)

Table A1. Cont.

Model	SDG Goal Composition	Top 6 Predictors Ranked by SHAP Values	R ²
Alternative Model	SDG1 + SDG8 + SDG9 + SDG11	GDP _{pc} (4.78) AGING (4.38) LE (2.10) GE (1.22) RQ (1.20) RL (0.94)	0.948 (0.942–0.952)

Appendix A.2

A robustness analysis was further conducted to examine whether the findings were sensitive to alternative weighting schemes. The economic sustainability index was reconstructed using principal component analysis (PCA)-based weighting rather than equal weighting. Both indices were evaluated using the Extra Trees model, which achieved the strongest predictive performance among candidate models, with a country-level Group-KFold cross-validation strategy. The PCA-based economic sustainability index showed comparable predictive performance to the baseline equal-weighted index. Because the PCA-based index is constructed on a standardized scale, its SHAP values are not directly comparable in magnitude with those from the equal-weighted index. The robustness assessment therefore focuses on the consistency of predictor rankings rather than absolute SHAP values. The results are reported in Table A2. The SHAP results based on the PCA-derived outcome were highly consistent with those from the equal-weighted index. AGING and GDP_{pc} remained the two most influential predictors, while Government Effectiveness, Rule of Law, and Regulatory Quality continued to represent the most prominent governance dimensions. These findings suggest that the main conclusions regarding the predictive relevance of governance remain consistent across alternative weighting schemes.

Table A2. Robustness analysis of the economic sustainability index using an alternative PCA-based construction.

Model	Index Construction	Top 6 Predictors Ranked by SHAP Values	R ²
Baseline Model	Equal weighting	AGING (4.33) GDP _{pc} (3.35) GE (1.60) RL (1.39) RQ (1.13) CC (0.93)	0.923 (0.916–0.930)
Alternative Model	PCA	AGING (0.45) GDP _{pc} (0.27) GE (0.16) RL (0.15) RQ (0.13) VA (0.09)	0.899 (0.890–0.908)

Appendix A.3

To further assess whether the findings were sensitive to the choice of missing-data treatment, we conducted additional robustness analyses using alternative imputation strategies, including global median imputation and rolling mean imputation. The predictive performance of these specifications was compared using the same evaluation metrics (MSE, MAE, and R²) to evaluate the effectiveness of alternative imputation strategies, with results summarized in Table A3. The MICE-PMM approach used in the main analysis achieved the

best predictive performance, with the lowest MSE and MAE and the highest R^2 among the tested strategies. Meanwhile, the alternative imputation approaches produced comparable predictive performance, suggesting that the overall predictive performance of the model remained stable across different imputation strategies.

Table A3. Predictive performance comparison under alternative imputation strategies.

Imputation Strategy	MSE	MAE	R^2
MICE-PMM	11.889 (10.909–12.907)	2.751 (2.640–2.864)	0.891 (0.880–0.901)
Global Median	12.178 (11.153–13.220)	2.769 (2.652–2.884)	0.888 (0.877–0.898)
Rolling Mean	12.103 (11.108–13.183)	2.766 (2.655–2.879)	0.889 (0.878–0.899)

Appendix A.4

To examine whether the dominant predictive importance of population aging (AGING) over life expectancy (LE) was sensitive to their correlation, we conducted an additional leave-one-feature-out sensitivity analysis. Specifically, we re-estimated the overall sustainability index models after separately excluding AGING and LE from the predictor set. The sensitivity analyses followed the same validation strategy as the main analysis, including GroupKFold cross-validation by country to avoid potential information leakage across country-year observations. The candidate models were evaluated using the same performance metrics (MSE, MAE, and R^2), and the Extra Trees model remained the best-performing model, achieving the highest R^2 and the lowest MSE and MAE among all candidate algorithms. Therefore, SHAP interpretation was again based on the Extra Trees model to ensure consistency with the main analysis. The results are summarized in Table A4. The sensitivity models maintained comparable predictive performance, with R^2 values ranging from 0.857 to 0.880. When AGING was removed, LE became the most important predictor, with a mean absolute SHAP value of 2.12. However, this value remained substantially lower than the SHAP contribution of AGING in the baseline model (4.59) and the model excluding LE (4.89), suggesting that LE did not fully account for the predictive information related to AGING. When LE was excluded, AGING remained the dominant predictor with the highest mean absolute SHAP value of 4.89. This pattern indicates that the prominence of AGING in the baseline model is not solely attributable to feature attribution instability caused by multicollinearity. Instead, AGING appears to contain predictive information that overlaps with, but is not fully represented by, life expectancy.

Table A4. Sensitivity analysis of the most important predictor after excluding correlated predictors (AGING and LE).

Model	Most Important Predictor	Mean SHAP	R^2
Baseline Model (Overall SDG Index)	AGING	4.59	0.891 (0.880–0.901)
Without AGING	LE	2.12	0.857 (0.843–0.870)
Without LE	AGING	4.89	0.880 (0.868–0.891)

As shown in Table A5, the overall pattern remained broadly consistent across the sensitivity specifications. After removing AGING, life expectancy and GDP per capita became the most influential predictors, while governance-related indicators, including Voice and Accountability, Rule of Law, and Government Effectiveness, remained among

the top-ranked predictors. Similarly, after excluding LE, population aging continued to dominate model predictions, and governance dimensions maintained their predictive relevance, with Government Effectiveness, Rule of Law, and Voice and Accountability remaining among the leading governance-related predictors. These findings suggest that the observed governance-related patterns remained robust after accounting for potential overlap among highly correlated predictors.

Table A5. Sensitivity analysis of SHAP feature importance after excluding correlated predictors (AGING and LE).

Model	Top 6 Predictors Ranked by SHAP Values	R ²
Without AGING	LE (2.12) GDPpc (2.02) VA (1.60) RL (1.12) EDU (0.99) GE (0.79)	0.857 (0.843–0.870)
Without LE	AGING (4.89) GDPpc (1.42) GE (0.81) EDU (0.66) RL (0.54) VA (0.47)	0.880 (0.868–0.891)

Appendix A.5

Given the dominant predictive importance of population aging (AGING) in the overall model, we further examined whether its contribution remained stable across different income contexts and conducted additional subsample analyses based on income groups using the World Bank income classification. Specifically, the sample was divided into high-income countries and middle- and low-income countries, and Extra Trees models with the country-based GroupKFold cross-validation strategy were applied. The results are reported in Table A6. The high-income model showed predictive performance comparable to that of the middle- and low-income model. AGING remained the most prominent predictor in both income groups, showing the highest mean absolute SHAP values among all predictors. Although the relative importance of other socioeconomic predictors varied across income groups, the consistent prominence of AGING suggests that its predictive contribution is not solely attributable to differences in income levels. These findings provide additional evidence that the predictive importance of AGING is robust across development contexts.

Table A6. Comparative Analysis of Model Performance and Predictor Importance across Income Groups.

Model	Top 6 Predictors Ranked by SHAP Values	R ²
High-Income Model	AGING (3.15) VA (0.81) RL (0.63) CC (0.39) URB (0.28) GDPpc (0.19)	0.810 (0.775–0.837)

Table A6. *Cont.*

Model	Top 6 Predictors Ranked by SHAP Values	R ²
Middle- and Low-Income Model	AGING (2.41) GDP _{pc} (2.10) LE (1.44) GE (0.71) EDU (0.46) CC (0.36)	0.829 (0.809–0.847)

Appendix A.6

To examine whether temporal shocks, particularly the COVID-19 pandemic, affected the stability of the identified predictive patterns, we estimated the models separately for the pre-pandemic period (2015–2019) and the COVID-19 and post-COVID period (2020–2024). The results showed that the overall predictor structure remained broadly consistent across temporal contexts, with population aging (AGING) remaining the most influential predictor in both periods (Table A7). Before COVID-19, life expectancy showed a relatively stronger contribution, whereas GDP per capita became slightly more prominent in the later period. Among governance indicators, Rule of Law showed relatively higher contribution before COVID-19, while Government Effectiveness and Voice and Accountability exhibited slightly greater predictive prominence in the later period. Overall, these findings suggest that the main predictive patterns were stable over time, while the relative contributions of specific socioeconomic and governance indicators varied modestly across temporal contexts.

Table A7. Temporal Heterogeneity Analysis of Predictive Performance and Predictor Importance across Pre- and Post-COVID-19 Periods.

Period	Top 6 Predictors Ranked by SHAP Values	R ²
Pre-COVID Period (2015–2019)	AGING (4.55) LE (1.75) GDP _{pc} (0.94) RL (0.57) GE (0.53) VA (0.44)	0.905 (0.892–0.916)
Post-COVID Period (2020–2024)	AGING (4.33) GDP _{pc} (1.10) LE (0.95) GE (0.64) VA (0.51) RL (0.39)	0.886 (0.869–0.900)

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