

Article

Benchmarking Türkiye's Sustainable Development Performance: SDG Interactions, Macroeconomic Predictors, and Explainable Machine Learning Evidence from Selected Major Muslim Economies

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Abstract

Sustainable development has become a strategic priority for countries seeking long-term economic prosperity while balancing social, environmental, and institutional objectives. According to the April 2026 International Monetary Fund World Economic Outlook projections, Türkiye is expected to become the largest economy among the selected major Muslim economies in terms of nominal gross domestic product. Motivated by this development, this study benchmarks Türkiye's sustainable development performance against nine comparable economies and examines the relationships between selected Sustainable Development Goal (SDG) indicators and economic performance. The analytical framework integrates benchmarking, correlation, SDG network analysis, regression modeling, and explainable machine learning using SDG and macroeconomic data. The findings reveal both synergies and trade-offs among the selected SDGs. Strong positive relationships emerge between SDG12 and SDG13 and between SDG4 and SDG16, confirming the interconnected structure of sustainable development. Türkiye ranks second in overall SDG performance and performs particularly strongly in clean energy, innovation and infrastructure, and international partnerships. Regression results identify education, clean energy, innovation, and climate action as statistically associated with economic performance. Under a strict year-based chronological holdout and rolling-origin validation framework, the tuned Random Forest model achieved the strongest out-of-sample predictive performance. SHapley Additive exPlanations analysis indicates that one-year lagged economic performance is the dominant predictor, while current macroeconomic conditions and selected SDG indicators provide additional predictive information. The findings demonstrate substantial temporal persistence in economic performance and show that sustainability indicators complement prior economic information in forecasting. The study contributes to sustainability research by integrating comparative assessment, systems-oriented analysis, econometric modeling, and explainable machine learning while clearly distinguishing statistical association from predictive contribution.



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Keywords: sustainable development goals (SDGs); major Muslim economies; economic development; explainable machine learning; SHAP; Türkiye

1. Introduction

Economic size and sustainable development do not necessarily advance together. While countries may achieve substantial economic growth, they often experience uneven progress across environmental, social, and institutional dimensions. This tension lies at the center of sustainability research, which seeks to understand how economic prosperity can be achieved while maintaining environmental integrity, social well-being, and institutional resilience [1–3]. Consequently, an important question emerges: Does economic leadership also correspond to sustainability leadership?

This question has become increasingly relevant in the context of the Sustainable Development Goals (SDGs), which provide a globally recognized framework for evaluating progress across multiple dimensions of sustainable development. Since the adoption of the 2030 Agenda, SDGs have been widely used to assess national sustainability performance and monitor development trajectories [4]. However, substantial disparities persist across countries in terms of education, innovation, institutional quality, environmental sustainability, and economic development [5,6].

Importantly, sustainability outcomes do not emerge from isolated policy domains. The SDGs form an interconnected system characterized by feedback mechanisms, synergies, and trade-offs, where progress in one dimension may reinforce or constrain progress in another [1,7]. Recent systems-oriented research argues that understanding these interactions is essential for identifying sustainability priorities and designing coherent policy interventions [3,8]. Therefore, sustainable development should be evaluated not only through aggregate SDG scores but also through the relationships among sustainability dimensions.

Within this broader context, understanding how sustainability performance relates to economic outcomes remains a central challenge. Previous studies suggest that countries performing well in education, innovation, infrastructure, institutional quality, and international cooperation often achieve more favorable long-term development outcomes [9,10]. Nevertheless, the extent to which sustainability dimensions are associated with economic performance remains contested and may vary across country groups and development contexts.

This issue is particularly relevant for selected major Muslim economies. In the present study, the term “major Muslim economies” refers to the ten largest Muslim-majority economies in terms of nominal Gross Domestic Product (GDP), according to the April 2026 International Monetary Fund (IMF) World Economic Outlook, all of which are members of the Organization of Islamic Cooperation (OIC). The selected countries were included not only on the basis of their economic size but also because they represent considerable diversity in terms of industrial structure, energy dependence, demographic characteristics, and institutional capacity. Accordingly, the sample encompasses resource-rich economies, industrializing economies, and emerging middle-income economies, providing a suitable context for examining sustainability–development relationships across diverse development trajectories. Despite their growing economic significance and diverse development trajectories, comparative sustainability assessments focusing specifically on this country group remain limited [5,11].

Türkiye provides a particularly timely case within this context. According to the April 2026 International Monetary Fund (IMF) World Economic Outlook projections, Türkiye is projected to become the largest economy among the selected Muslim-majority economies in terms of nominal Gross Domestic Product (GDP) [12]. This development raises an

important sustainability question: does projected economic leadership coincide with balanced progress across sustainability dimensions, or does it mask important sustainability trade-offs and imbalances? Addressing this question contributes not only to understanding Türkiye's development trajectory but also to broader debates regarding sustainability transitions in emerging economies.

Against this background, the present study benchmarks Türkiye's sustainable development performance against nine selected Muslim-majority economies and investigates the relationships between selected SDG indicators and economic performance. By integrating benchmarking analysis, SDG interaction analysis, regression modeling, and explainable machine learning techniques, the study examines both sustainability performance and the interconnected structure of sustainability dimensions.

The study therefore combines two complementary levels of analysis. Türkiye constitutes the focal case in the benchmarking stage, where its performance, ranking, and trajectory are evaluated relative to the other selected economies. By contrast, the correlation, network, regression, and machine learning analyses are conducted using the pooled country-year observations from all ten countries. Accordingly, the results of these analyses represent relationships and predictive patterns across the full multi-country sample rather than Türkiye-specific estimates.

Accordingly, the study addresses the following research questions:

RQ1. *How does Türkiye's sustainable development performance compare with other selected Muslim-majority economies?*

RQ2. *Which SDG indicators are most strongly associated with economic performance?*

RQ3. *Which sustainability dimensions emerge as the most influential predictors of economic performance in explainable machine learning models?*

The study contributes to the sustainability literature in three ways. First, it provides a comparative and problem-oriented assessment of sustainable development performance among selected Muslim-majority economies, a country group that remains underexplored despite its increasing economic and geopolitical importance. Second, it adopts a systems perspective by examining synergies and trade-offs among SDG indicators rather than treating sustainability dimensions as independent policy domains. Third, it combines conventional statistical techniques with explainable machine learning approaches to identify sustainability dimensions that contain the greatest explanatory and predictive information regarding economic performance. By integrating SDG benchmarking, network analysis, regression modeling, and explainable machine learning, the study offers evidence-based insights that may support sustainability-oriented policy prioritization and long-term development planning.

2. Literature Review

2.1. Sustainable Development Goals and the Measurement of National Progress

The SDGs have become a central framework for evaluating national development performance across economic, social, environmental, and institutional dimensions. Since the adoption of the 2030 Agenda, numerous studies have developed indicators, composite indices, and benchmarking tools to measure progress toward sustainable development. Ref. [13] proposed a global SDG progress index supporting the "Leaving No One Behind" principle, emphasizing the need for comparable and interpretable measures of SDG achievement. Similarly, refs. [14,15] developed quantitative frameworks for assessing SDG performance across countries and regions, demonstrating the usefulness of composite indicators for identifying development priorities and monitoring progress over time.

Sectoral and country-specific applications further highlight the importance of context-sensitive measurement. Ref. [16] developed an agriculture-related SDG index for Southern Africa, while Ref. [17] evaluated Morocco's national SDG performance and identified key policy strengths and weaknesses. At the regional level, Ref. [6] discussed methodological challenges related to indicator selection, standardization, and aggregation. Together, these studies suggest that SDG assessment is not merely a measurement exercise but also a policy-relevant process that informs development strategies.

Recent global evidence indicates that SDG progress remains uneven across countries. Ref. [4] analyzed 117 indicators for 167 countries and projected SDG achievements toward 2030, showing substantial variation in progress trajectories. Similarly, Ref. [5] identified significant disparities across income groups and geographical regions. These findings underscore the value of comparative studies focusing on specific country groups where sustainability outcomes and development trajectories may differ substantially.

2.2. Cross-Country and Regional SDG Performance Assessment

A major stream of SDG research focuses on cross-country and regional comparisons. Ref. [11] examined SDG performance in Belt and Road Initiative countries and found substantial disparities across social, economic, and environmental dimensions. Their findings suggested that economic SDGs often outperform environmental SDGs, highlighting the risk that aggregate SDG indices may conceal important sustainability imbalances.

Similarly, Ref. [18] investigated SDG achievement in seven developed economies and found that social, ecological, and economic dimensions contribute differently to sustainability outcomes across countries. Using panel data from 83 countries, Ref. [9] identified income, education, prior SDG performance, and women's political representation as important drivers of SDG achievement, while unemployment acted as a constraint. Ref. [19] demonstrated that institutional quality and regulatory environments influence SDG reporting and sustainability commitment, whereas Ref. [10] showed that fintech development and financial inclusion positively contribute to several SDGs, particularly those related to education, innovation, and economic growth.

Collectively, these studies indicate that sustainable development outcomes are shaped by economic, institutional, technological, and governance-related factors. However, most existing research focuses on global samples or broad regional classifications. Comparative sustainability assessments focusing specifically on selected major Muslim economies remain relatively limited despite the growing economic significance and diverse development trajectories of these countries.

2.3. SDG Interactions, Synergies, and Trade-Offs

The SDGs should not be viewed as isolated targets but rather as components of an interconnected system. Progress in one goal may reinforce, complement, or constrain progress in others. Ref. [1] empirically examined SDG synergies and trade-offs and showed that relationships among goals are highly context dependent. Similarly, Ref. [7] employed network analysis to investigate SDG interlinkages and demonstrated that network-based approaches can reveal complex patterns of synergy and conflict among goals.

Ref. [8] further argued that effective SDG prioritization requires consideration of country-specific challenges and interactions among goals. Likewise, Ref. [2] identified underlying dimensions structuring global SDG performance and showed that sustainability outcomes emerge from interconnected economic, social, environmental, and governance systems. Using a systems-thinking perspective, Ref. [3] demonstrated that sustainability outcomes are shaped by feedback mechanisms and interdependencies operating across multiple systems.

Together, these studies emphasize the importance of moving beyond isolated indicator analysis toward systems-oriented approaches capable of capturing interactions, synergies, and trade-offs among sustainability dimensions.

2.4. Governance, Monitoring, and Sustainability Assessment

Effective implementation of the SDGs depends not only on development outcomes but also on governance quality, monitoring capacity, and institutional coordination. Ref. [20] identified substantial monitoring and evaluation challenges even among developed economies, highlighting the difficulties of constructing comprehensive SDG monitoring systems. Similarly, Ref. [21] emphasized the role of stakeholder participation, local knowledge, and multi-level governance in supporting sustainability transitions.

The importance of integrated sustainability assessment is also reflected in the work of [22], who proposed a multidimensional sustainability index combining social, ecological, economic, and governance dimensions. Although developed within a sector-specific context, their framework reinforces a broader principle of sustainability assessment: meaningful sustainability evaluation requires transparent, multidimensional, and policy-relevant indicators.

2.5. Data-Driven and Explainable Sustainability Assessment

Recent research has increasingly employed computational and machine learning approaches to analyze sustainability dynamics. Refs. [23,24] demonstrated that external shocks such as the COVID-19 pandemic can disrupt SDG trajectories through complex and interconnected mechanisms. These findings suggest that sustainability outcomes are dynamic, nonlinear, and sensitive to changing socio-economic conditions.

To address such complexity, machine learning methods have become increasingly common in sustainability research. Ref. [25] employed Random Forest and XGBoost models to assess the impacts of COVID-19 on SDG trajectories, while Ref. [26] proposed a data-driven framework for evaluating global SDG progress. These studies highlight the growing role of predictive analytics in sustainability assessment.

Despite their predictive advantages, machine learning models are often criticized for limited interpretability. Consequently, explainable artificial intelligence (XAI) techniques have gained increasing attention. Among these methods, SHapley Additive exPlanations (SHAP) provide a transparent framework for quantifying the contribution of individual predictors to model outcomes. The integration of machine learning and explainability offers an opportunity to complement conventional statistical approaches by identifying nonlinear relationships, interaction effects, and predictor importance within sustainability systems.

2.6. Research Gap and Positioning of the Present Study

The reviewed literature demonstrates substantial progress in SDG benchmarking, cross-country assessment, systems-oriented sustainability analysis, governance studies, and data-driven modeling. Nevertheless, three important gaps remain.

First, comparative sustainability assessments focusing specifically on selected major Muslim economies remain limited despite the increasing economic importance and diversity of these countries. Second, while many studies examine the determinants of SDG performance, fewer investigate how sustainability indicators and macroeconomic conditions jointly relate to economic performance across countries. Third, although machine learning applications are becoming more common in sustainability research, explainable machine learning approaches remain relatively underutilized in studies linking sustainability indicators to economic outcomes.

The present study addresses these gaps by examining sustainability–economy relationships in selected major Muslim economies through an integrated framework combining

benchmarking analysis, SDG interaction analysis, econometric modeling, and explainable machine learning. By linking sustainability assessment, macroeconomic analysis, and interpretable predictive modeling, the study contributes to the growing literature on systems-oriented and policy-relevant sustainability evaluation.

3. Methodology

This section describes the methodological framework used to investigate the relationship between sustainable development and economic performance among selected major Muslim economies. First, the research design, country selection criteria, and data sources are presented. Next, the benchmarking, correlation, network, regression, and machine learning procedures are described. Finally, the explainable artificial intelligence framework used to interpret machine learning results is introduced.

3.1. Research Design

This study adopts a comparative and data-driven research design to benchmark Türkiye's sustainable development performance against nine selected Muslim-majority economies: Algeria, Bangladesh, Egypt, Indonesia, Iran, Malaysia, Pakistan, Saudi Arabia, and the United Arab Emirates.

The country sample was constructed using three predefined inclusion criteria. First, all selected countries are Muslim-majority nations and members of the Organization of Islamic Cooperation (OIC). Second, countries were selected according to the April 2026 International Monetary Fund (IMF) World Economic Outlook and represent the ten largest Muslim-majority economies in terms of nominal Gross Domestic Product (GDP), which constitutes the primary economic inclusion criterion adopted in this study. Third, only countries with comparable Sustainable Development Goal (SDG) and macroeconomic data covering the study period were retained. Applying these criteria resulted in a sample consisting of Türkiye, Indonesia, Saudi Arabia, the United Arab Emirates, Malaysia, Bangladesh, Egypt, Pakistan, Algeria, and Iran.

The objective of this sampling strategy was not to obtain a representative sample of all Muslim-majority countries but rather to benchmark Türkiye against the largest economies in the Islamic world. Accordingly, other Muslim-majority countries were not included because they fell outside the top-ten economic ranking according to the IMF World Economic Outlook or did not satisfy the data availability requirements necessary for consistent longitudinal comparisons.

Sustainable development performance was measured using selected SDG indicators obtained from the SDG Index Data Portal maintained by the Sustainable Development Solutions Network (SDSN), corresponding to the 2025 database release accompanying the Sustainable Development Report 2025 [27]. Macroeconomic variables were obtained from the International Monetary Fund (IMF) World Economic Outlook (WEO) database [12]. Table 1 summarizes the variables included in the analysis.

Table 1. Variables and Data Sources.

Variable	Abbreviation	Description	Source
Overall SDG Index	SDGI	Overall Sustainable Development Goal Index score	SDSN
Quality Education	SDG4	Performance score for Sustainable Development Goal 4	SDSN
Affordable and Clean Energy	SDG7	Performance score for Sustainable Development Goal 7	SDSN

Table 1. *Cont.*

Variable	Abbreviation	Description	Source
Decent Work and Economic Growth	SDG8	Performance score for Sustainable Development Goal 8	SDSN
Industry, Innovation and Infrastructure	SDG9	Performance score for Sustainable Development Goal 9	SDSN
Responsible Consumption and Production	SDG12	Performance score for Sustainable Development Goal 12	SDSN
Climate Action	SDG13	Performance score for Sustainable Development Goal 13	SDSN
Peace, Justice and Strong Institutions	SDG16	Performance score for Sustainable Development Goal 16	SDSN
Partnerships for the Goals	SDG17	Performance score for Sustainable Development Goal 17	SDSN
Nominal Gross Domestic Product	NGDPD	Gross domestic product at current prices (billion USD)	IMF-WEO
Real GDP Growth Rate	NGDP_RPCH	Annual percentage change in real GDP	IMF-WEO
Inflation Rate	PCPIPCH	Annual percentage change in consumer prices	IMF-WEO
Unemployment Rate	LUR	Percentage of the total labor force unemployed	IMF-WEO

Note: SDG indicators were obtained from the SDG Index Data Portal maintained by the Sustainable Development Solutions Network (SDSN). IMF-WEO variable codes are NGDPD (Nominal GDP), NGDP_RPCH (Real GDP Growth Rate), PCPIPCH (Inflation Rate), and LUR (Unemployment Rate). For the machine learning analysis, one-year lagged values were additionally generated for log GDP, all selected SDG indicators, real GDP growth, inflation, and unemployment. Calendar year was also included as a temporal predictor.

Appendix A Table A1 presents the descriptive statistics of all variables used in the empirical analyses. The summary statistics indicate substantial variation across the selected SDG indicators and macroeconomic variables, reflecting the heterogeneous development trajectories of the countries included in the sample.

The primary analysis covers the period 2000–2024, corresponding to the availability of SDG indicators. IMF data extending to 2026 were additionally used for descriptive trend analyses. Because SDG indicators are currently available only through 2024, all statistical and machine learning analyses were conducted using the common observation period.

The benchmarking stage used observations from all ten selected countries to establish comparative rankings, sample averages, and longitudinal trajectories, while Türkiye was treated as the focal country for detailed interpretation. The correlation and network analyses were based on pooled country-year observations for the selected SDG indicators across all ten countries. The regression models were likewise estimated using the pooled country-year dataset obtained by combining the SDG and macroeconomic variables by country and year. The machine learning analyses used the complete-case subset of the same pooled dataset, with chronological training and test periods defined by calendar year. No correlation, network, regression, or machine learning model was estimated exclusively using Türkiye’s observations.

Prior to the statistical analyses, all variables were converted to numeric format and merged by country and calendar year. Nominal GDP was transformed using the natural logarithm to reduce skewness and stabilize variance. Because the subsequent predictive models were based on tree-based algorithms, no additional normalization or standardiza-

tion of the predictor variables was performed. One-year lagged variables were subsequently generated separately within each country after ordering observations chronologically.

The resulting dataset contains approximately 250 country-year observations. While this sample size is sufficient for comparative benchmarking, econometric analysis, and exploratory machine learning applications, it remains relatively small compared with large-scale machine learning datasets. Consequently, the machine learning results should be interpreted primarily as evidence of predictive patterns within the observed sample rather than as highly generalizable forecasting models. Missing values arising from unavailable observations or lag construction were handled using a complete-case strategy. Observations containing missing or non-finite values in either the dependent variable or any contemporaneous or lagged predictor were excluded from the machine learning analyses. No statistical imputation was applied.

The selected SDG indicators were chosen because of their direct relevance to economic development, productive capacity, institutional quality, and long-term sustainability. Specifically, SDG4 represents human capital and education; SDG7 reflects access to affordable and clean energy; SDG8 captures employment and economic growth; SDG9 represents industrialization, innovation, and infrastructure; SDG12 and SDG13 represent environmental sustainability dimensions; SDG16 reflects governance and institutional quality; and SDG17 represents international cooperation and partnerships. Together, these dimensions provide a comprehensive representation of the sustainability factors potentially associated with economic performance.

3.2. Analytical Framework

The analytical framework consists of four sequential stages designed to evaluate sustainable development performance and its relationship with economic outcomes.

Unless otherwise stated, all analytical stages were implemented using observations from the full ten-country sample. Türkiye served as the focal case for comparative benchmarking and substantive interpretation, whereas the statistical relationships reported in the correlation, network, regression, and machine learning stages describe the pooled multi-country dataset.

In the first stage, benchmarking and trend analyses were conducted to compare sustainable development performance across countries. Longitudinal trends in the overall SDG Index and selected SDG indicators were examined to identify relative strengths, weaknesses, and development trajectories.

In the second stage, pairwise Pearson correlation coefficients were calculated to examine the relationships among the selected SDG indicators using the pooled country-year observations from all ten countries. Correlations were computed using complete observations only. Statistical significance was evaluated at the 5% level ($\alpha = 0.05$). Because multiple pairwise correlations were examined simultaneously, *p*-values were adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure to control for multiple testing while maintaining adequate statistical power.

To further explore SDG interdependencies, a correlation-based network analysis was conducted. In this network, each SDG indicator was represented as a node and pairwise correlations were represented as edges. To focus on substantively meaningful relationships while reducing visual complexity, only pairwise correlations with an absolute Pearson correlation coefficient of at least 0.50 were retained as network edges. This threshold was selected to emphasize moderate-to-strong associations and exclude weaker relationships from the network visualization. The network was visualized using the Fruchterman–Reingold force-directed layout algorithm [28]. The structural role of each SDG within the network was subsequently characterized using degree, strength, betweenness, and closeness cen-

trality measures. Degree represents the number of direct connections of a node, strength represents the sum of the absolute weights of its incident edges, betweenness quantifies the extent to which a node lies on shortest paths between other nodes, and closeness reflects the inverse average distance from a node to all other reachable nodes [29,30].

In the third stage, multiple regression models were estimated using log-transformed GDP as the dependent variable. The objective was to estimate the statistical associations between selected SDG indicators, macroeconomic conditions, and economic performance using pooled country-year observations from all ten countries. The regression analysis provides an interpretable statistical baseline for understanding sustainability–economy relationships before applying more flexible machine learning techniques. Ordinary Least Squares (OLS) regression was selected because the dependent variable (log-transformed GDP) is continuous and the primary objective was to estimate interpretable linear associations between sustainability indicators and economic performance. Two nested model specifications were estimated to evaluate the incremental contribution of macroeconomic control variables beyond the selected SDG indicators. Model 1 included only the selected SDG indicators to assess their direct associations with economic performance, whereas Model 2 additionally incorporated real GDP growth, inflation, and unemployment as macroeconomic control variables. All explanatory variables entered the regression models simultaneously using the enter specification, allowing the partial association of each predictor to be estimated while controlling for the remaining variables. The logarithmic transformation of GDP was applied to reduce skewness, stabilize variance, and facilitate interpretation of the regression coefficients. The regression analysis was intended to identify statistically significant associations rather than causal effects and therefore provides an interpretable statistical benchmark against which the predictive performance of the subsequent machine learning models can be evaluated.

The selected model specification should therefore not be interpreted as implying that sustainable development goals are conceptually subordinate to economic growth or that improvements in SDG performance mechanically cause subsequent economic expansion. Rather, the empirical framework treats economic performance as a measurable macroeconomic outcome against which the explanatory and predictive information contained in sustainability indicators can be evaluated. This approach is consistent with a growing body of sustainability research that investigates how different dimensions of sustainable development are statistically associated with economic outcomes while explicitly avoiding causal interpretation.

Although SDG8 (Decent Work and Economic Growth) is conceptually related to economic performance, the Sustainable Development Goal framework treats SDG8 as a multidimensional sustainability construct that incorporates employment quality, labour market conditions, productive employment, and inclusive economic development rather than GDP alone. Consequently, some conceptual proximity between SDG8 and the dependent variable is unavoidable but does not imply direct duplication of measurement. Because the objective of the present study is to identify statistical associations and predictive relationships rather than causal effects, the results should not be interpreted as evidence of causality. To further assess the potential influence of conceptual overlap, an additional robustness analysis excluding SDG8 was conducted, and the principal conclusions remained substantively unchanged.

In the fourth stage, machine learning models were implemented to capture potential nonlinearities, temporal persistence, and interaction effects that may not be fully represented by conventional regression models. Random Forest and Extreme Gradient Boosting (XGBoost) algorithms were estimated using current-period predictors together with one-year lagged economic, sustainability, and macroeconomic variables. Random Forest was

implemented through the ranger framework and served as the primary predictive model because it achieved the strongest chronological out-of-sample performance, whereas XGBoost was retained as a comparative model. Both algorithms were developed using the same predictor set and identical chronological training-test partitions to ensure a fair comparison.

Figure 1 summarizes the overall analytical workflow adopted in the study.

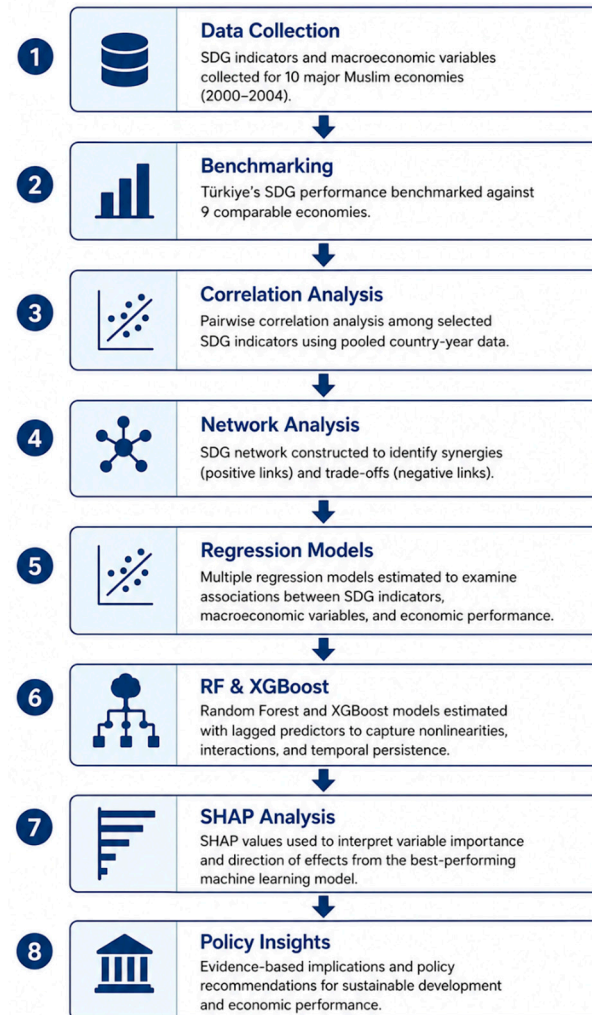


Figure 1. Research framework and analytical workflow of the study. The numbered boxes (1–8) represent the sequential stages of the analytical process, while the arrows indicate the workflow from data collection to policy insights.

3.3. Explainable Machine Learning

To complement the regression analysis and capture nonlinear, interaction-based, and temporally persistent relationships, Random Forest and XGBoost regression models were estimated. The dependent variable was the natural logarithm of nominal GDP. The predictor set included the calendar year; contemporaneous SDG4, SDG7, SDG8, SDG9, SDG12, SDG13, SDG16, and SDG17 scores; real GDP growth, inflation, and unemployment; and one-year lagged values of log GDP, the eight SDG indicators, and the three macroeconomic variables.

Lagged predictors were constructed separately within each country after ordering observations by country and year. A lagged value was retained only when the preceding observation corresponded to the immediately previous calendar year. This procedure avoided assigning artificial lag relationships across nonconsecutive observations or between different countries. Because the inclusion of lagged GDP introduces strong autoregressive

information, the machine learning models were interpreted as predictive rather than causal specifications.

A strict year-based chronological holdout strategy was used to evaluate out-of-sample performance. The earliest 80% of available years constituted the training period, while the most recent 20% of years were reserved as an independent test period. All country observations belonging to a given year were assigned to the same partition, thereby preventing the same calendar year from appearing in both training and test sets.

Hyperparameter tuning was performed exclusively within the training period using expanding-window rolling-origin validation. In each validation iteration, models were trained on all observations available up to a given point and validated on a subsequent year. This procedure preserved temporal ordering throughout model selection and reduced the risk of temporal information leakage.

The Random Forest model was implemented using the ranger algorithm. Candidate values of the number of variables considered at each split (*mtry*), splitting rule, and minimum terminal-node size were evaluated, and 1000 trees were grown in the final model. XGBoost was tuned over combinations of tree depth, learning rate, minimum child weight, gamma, subsampling ratio, column-sampling ratio, and L1 and L2 regularization parameters. Early stopping was applied within the rolling validation procedure to identify an appropriate number of boosting iterations.

Predictive performance was evaluated on the untouched chronological test period using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and out-of-sample R^2 , calculated relative to the mean of the test-period outcome. Lower RMSE and MAE and higher out-of-sample R^2 indicate stronger predictive performance. Accordingly, the reported performance reflects true forward prediction rather than interpolation across randomly mixed observations.

Because the tuned Random Forest model achieved the strongest out-of-sample performance, the primary explainability analysis was conducted for this model. Tree-based SHAP values were calculated for the chronological test period to quantify the contribution of each predictor to individual model predictions. Global feature importance was summarized using mean absolute SHAP values. SHAP values were interpreted as measures of predictive contribution and not as estimates of causal effects. All analyses were conducted in RStudio (Version 2026.04.0+526; Posit Software, PBC, Boston, MA, USA).

4. Results

4.1. Benchmarking Sustainable Development Performance

Unless explicitly identified as Türkiye-specific, the empirical results presented below are based on the pooled observations from all ten selected countries. Türkiye-specific findings refer to its comparative ranking, trajectory, or position relative to the remaining economies.

The analysis begins by examining the economic context that motivated this study. As shown in Figure 2, IMF projections for 2026 indicate that Türkiye is projected to become the largest economy among the selected major Muslim economies, surpassing Indonesia and Saudi Arabia in nominal GDP.

Figure 3 further illustrates the recent GDP trajectories of the selected countries. Türkiye experienced the most rapid nominal GDP growth during the 2020–2026 period, increasing from approximately USD 730 billion in 2020 to an estimated USD 1.64 trillion in 2026. In contrast, although Indonesia and Saudi Arabia remain among the largest economies in the sample, their growth trajectories are comparatively more moderate. This projected economic leadership raises an important question: does stronger economic performance coincide with stronger sustainable development performance?

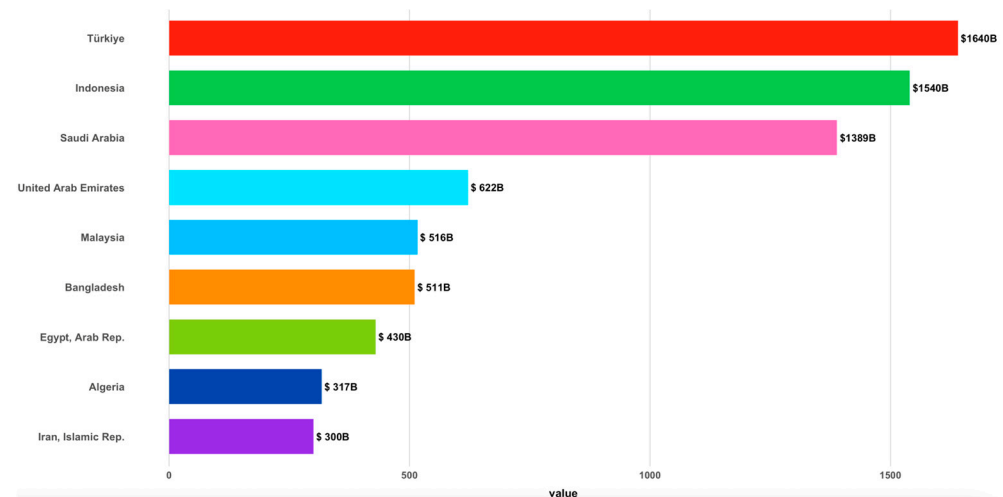


Figure 2. Largest Muslim Economies by Nominal GDP (2026). Note: Pakistan is not displayed because the IMF World Economic Outlook database reports no projected value for the NGDPD indicator in 2026. Consequently, only countries with available IMF 2026 projections are included in the figure.

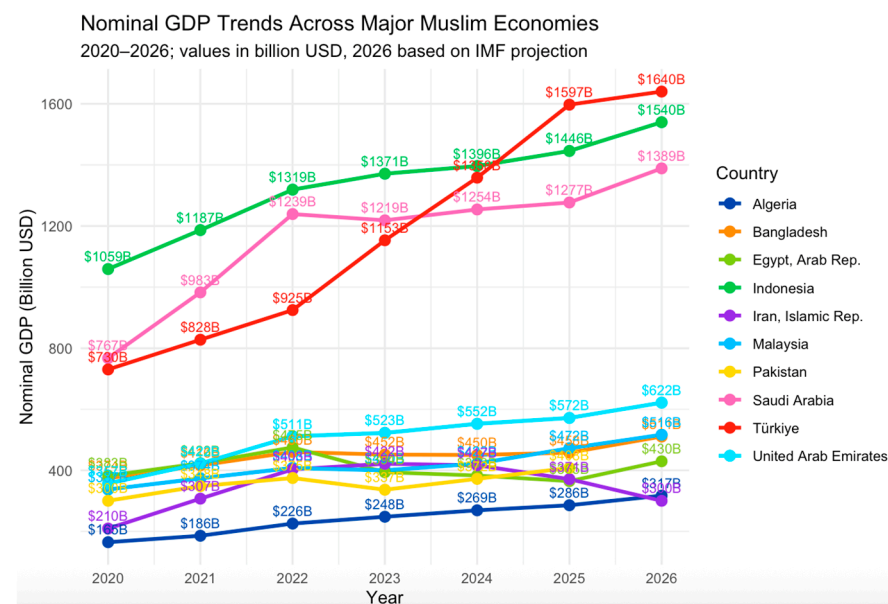


Figure 3. Nominal GDP Trends Across Selected Major Muslim Economies (2020–2026).

To address this question, the sustainable development performance of the selected countries was benchmarked using the SDG Index and eight SDG dimensions associated with education, energy, economic development, innovation, environmental sustainability, governance, and international partnerships. Table 2 summarizes Türkiye's average SDG performance and relative ranking across the selected economies.

The benchmarking results indicate that Türkiye ranks second overall among the examined countries, achieving an average SDG Index score of 70.2. As shown in Table 2, Türkiye performs particularly well in SDG7 (Affordable and Clean Energy), where it ranks first among the selected countries. Strong performances are also observed in SDG17 (Partnerships for the Goals), where Türkiye ranks second, and SDG9 (Industry, Innovation and Infrastructure), where it ranks third. In contrast, Türkiye occupies comparatively lower positions in SDG8 (Decent Work and Economic Growth), SDG12 (Responsible Consumption and Production), and SDG13 (Climate Action) relative to its performance in the remaining

SDGs. Nevertheless, SDG13 remains above the sample average, indicating that its lower ranking reflects the relatively compressed distribution of SDG13 scores across countries rather than weak absolute performance.

Table 2. Türkiye’s Ranking Across Sustainable Development Goals.

SDG	Description	Score	Rank
SDG-4	Quality Education	80.0	4
SDG-7	Affordable and Clean Energy	71.5	1
SDG-8	Decent Work and Economic Growth	61.2	7
SDG-9	Industry, Innovation and Infrastructure	51.9	3
SDG-12	Responsible Consumption and Production	74.0	7
SDG-13	Climate Action	87.6	6
SDG-16	Peace, Justice and Strong Institutions	65.0	5
SDG-17	Partnerships for the Goals	70.4	2
Overall SDG	Overall SDG Performance	70.2	2

These findings suggest that Türkiye’s sustainability profile is not driven uniformly across all dimensions. Instead, its strongest performance appears in areas associated with long-term transformation capacity, particularly clean energy, innovation, and international partnerships. From a sustainability perspective, these dimensions are commonly associated in the sustainability literature with technological upgrading, energy transition, knowledge exchange, and adaptive capacity. Accordingly, the ranking differences should be interpreted as relative positions within the selected country group rather than as indications of weak sustainability performance in absolute terms.

Figure 4 presents the evolution of overall SDG Index scores across the selected countries between 2000 and 2024. Although all countries exhibit some degree of improvement, the pace and magnitude of progress differ substantially. Türkiye consistently remains among the higher-performing countries throughout the observation period and demonstrates a steady upward trajectory.

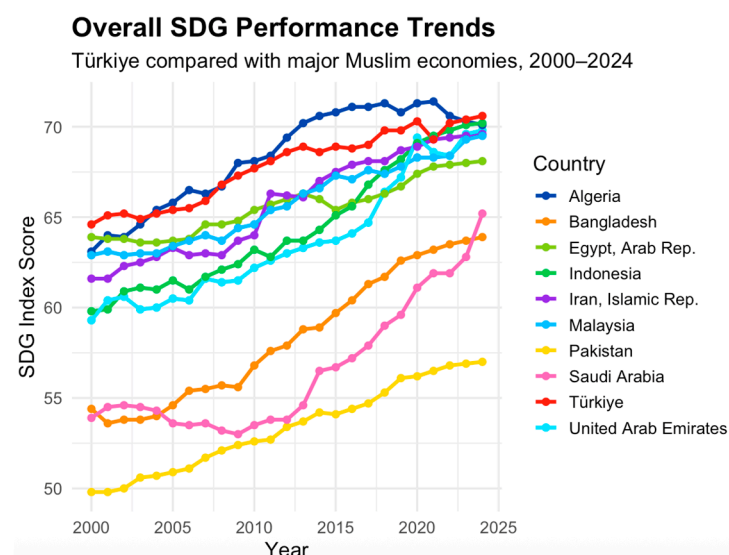


Figure 4. Overall SDG Performance Trends.

Figure 5 focuses specifically on Türkiye’s SDG performance trajectory relative to the other countries in the sample. The figure shows that Türkiye has maintained a position above most countries over time and has experienced sustained improvements in overall

sustainability performance. This pattern suggests that Türkiye's recent economic expansion has been accompanied by broader progress in several sustainability dimensions.

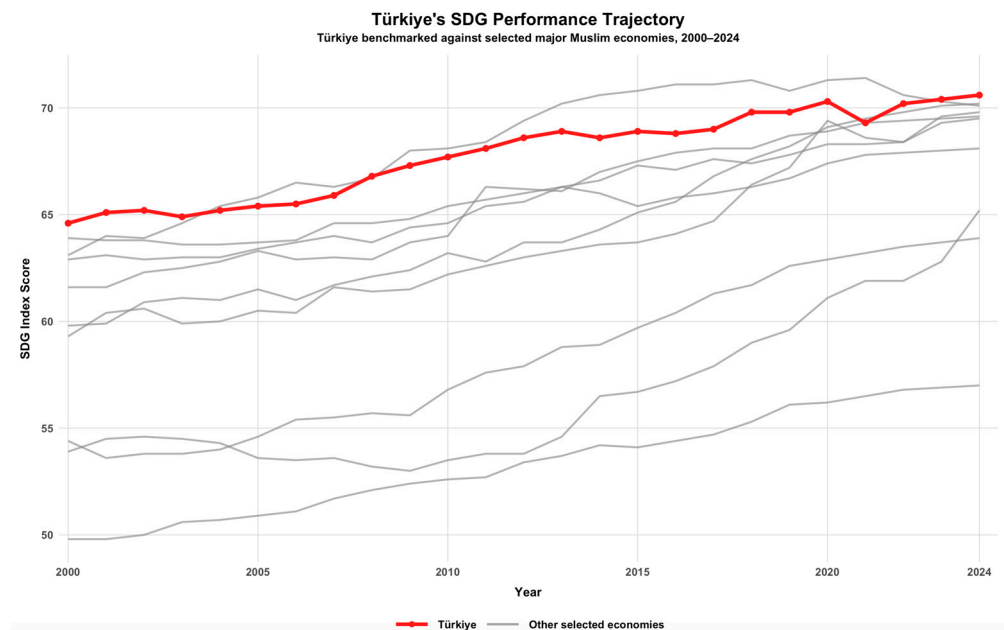


Figure 5. Türkiye's SDG Performance Trajectory.

To provide a more detailed comparison, Figure 6 contrasts Türkiye's average SDG scores with the sample average across the selected economies. The results show that Türkiye performs above the sample average in SDG4 (Quality Education), SDG7 (Affordable and Clean Energy), SDG9 (Industry, Innovation and Infrastructure), SDG13 (Climate Action), SDG16 (Peace, Justice and Strong Institutions), and SDG17 (Partnerships for the Goals). Particularly large advantages are observed in SDG4, SDG7, SDG9, and SDG13. By contrast, Türkiye performs below the sample average in SDG8 (Decent Work and Economic Growth) and, to a lesser extent, SDG12 (Responsible Consumption and Production). Although Türkiye ranks sixth among the selected countries in SDG13 performance, its score remains above the sample average. This apparent discrepancy reflects the relatively compressed distribution of SDG13 scores across the sample, where small score differences result in noticeable changes in ranking. Overall, the comparison suggests that Türkiye's sustainability profile is characterized by relatively strong performance in education, innovation, clean energy, climate action, institutional quality, and international partnerships, while challenges remain in employment-related outcomes and sustainable consumption patterns.

The comparison between Figures 2–6 also reveals that economic leadership and sustainability leadership do not necessarily coincide. Although Türkiye is projected to become the largest economy in the sample and ranks among the leading countries in overall SDG performance, substantial variation exists across individual sustainability dimensions. This finding highlights the importance of evaluating development through a multidimensional sustainability lens rather than relying solely on aggregate economic indicators.

While the benchmarking results presented above focus on Türkiye's relative sustainability performance, benchmarking alone cannot explain how sustainability dimensions interact or how they are associated with economic performance across countries. To address these broader questions, the subsequent analyses shift from country-specific comparison to the pooled country-year observations from all ten selected economies. This transition enables the identification of general sustainability interactions, statistical associations, and predictive patterns that extend beyond the experience of any individual country.

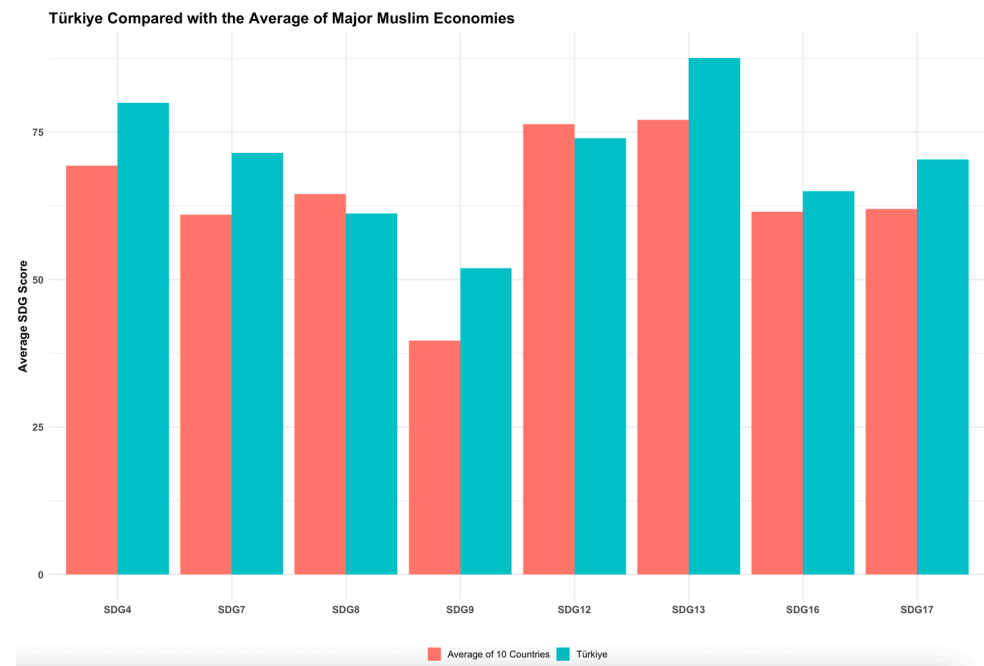


Figure 6. Türkiye Compared with the Average of Selected Major Muslim Economies.

4.2. SDG Interactions and Network Structure

While the benchmarking results reveal differences in sustainability performance across countries, they do not explain how individual sustainability dimensions interact. Sustainable development is inherently multidimensional, and progress in one goal may either reinforce or constrain progress in others. To better understand the systemic nature of sustainable development, correlation and network analyses were conducted.

Table 3 presents the Pearson correlation matrix of the selected SDG indicators based on the pooled country-year observations from all ten countries. Statistical significance was evaluated at the 5% level ($\alpha = 0.05$), and p -values were adjusted using the Benjamini–Hochberg FDR procedure to account for multiple testing. Only relationships remaining statistically significant after FDR adjustment were interpreted as statistically supported associations. The results indicate that sustainability dimensions are highly interconnected and exhibit both synergistic and trade-off relationships.

Table 3. Correlation Matrix of SDG Indicators.

	SDG-4	SDG-7	SDG-8	SDG-9	SDG-12	SDG-13	SDG-16	SDG-17	SDGI
SDG-4	1.0000	0.4803	0.1781	0.5422	−0.4795	−0.4499	0.7967	0.3362	0.6495
SDG-7	0.4803	1.0000	−0.2346	0.5923	−0.5025	−0.3766	0.5888	0.4719	0.5908
SDG-8	0.1781	−0.2346	1.0000	−0.0208	0.4960	0.5441	−0.0661	0.3483	0.3170
SDG-9	0.5422	0.5923	−0.0208	1.0000	−0.5158	−0.4573	0.3956	0.1877	0.5365
SDG-12	−0.4795	−0.5025	0.4960	−0.5158	1.0000	0.9511	−0.5426	0.0770	0.0533
SDG-13	−0.4499	−0.3766	0.5441	−0.4573	0.9511	1.0000	−0.5260	0.2399	0.0652
SDG-16	0.7967	0.5888	−0.0661	0.3956	−0.5426	−0.5260	1.0000	0.4905	0.5762
SDG-17	0.3362	0.4719	0.3483	0.1877	0.0770	0.2399	0.4905	1.0000	0.5669
SDGI	0.6495	0.5908	0.3170	0.5365	0.0533	0.0652	0.5762	0.5669	1.0000

Several strong positive associations emerge from the analysis. The strongest relationship is observed between SDG12 (Responsible Consumption and Production) and SDG13 (Climate Action) ($r = 0.951$), suggesting that improvements in sustainable production and consumption practices are closely associated with stronger climate-related performance. This finding is consistent with the notion that environmental sustainability objectives often

reinforce one another through shared policy mechanisms, technological adoption, resource efficiency improvements, and behavioral change.

Another notable finding is the strong positive relationship between SDG4 (Quality Education) and SDG16 (Peace, Justice and Strong Institutions) ($r = 0.797$). This result suggests that educational development and institutional quality tend to progress together. From a sustainability perspective, investments in human capital may contribute not only to economic and social development but also to stronger governance capacity, institutional effectiveness, and social cohesion.

The results also reveal several moderate positive relationships involving SDG8 (Decent Work and Economic Growth). In particular, SDG8 is positively associated with SDG12 ($r = 0.496$) and SDG13 ($r = 0.544$), suggesting that economic activity and environmental sustainability may advance simultaneously under certain development conditions. However, the relatively weaker relationships observed between SDG8, and several other goals indicate that economic growth alone does not guarantee balanced progress across the broader sustainability system.

At the same time, the results reveal notable negative associations involving SDG16 (Peace, Justice and Strong Institutions). The negative relationships observed between SDG12 and SDG16 ($r = -0.543$), as well as between SDG13 and SDG16 ($r = -0.526$), suggest that environmental and institutional dimensions do not always progress at the same pace. These patterns may reflect differences in national policy priorities, resource allocation decisions, and development trajectories. In some countries, policy efforts may be concentrated on environmental improvements, whereas institutional reforms require longer implementation periods and often generate benefits that materialize gradually over time. Consequently, short-term trade-offs may emerge among sustainability dimensions even when long-term objectives remain complementary.

To further examine the structure of these interrelationships, a correlation-based SDG interaction network was constructed.

Figure 7 further highlights the systemic nature of sustainable development. The network analysis indicates that SDG12 and SDG16 occupy highly connected positions within the sustainability system, while SDG13 serves as an important bridging node linking multiple sustainability dimensions. The central position of SDG12 and SDG16 suggests that these goals function as key coordination nodes within the broader sustainability network. Consequently, improvements or setbacks in these dimensions may influence multiple sustainability outcomes simultaneously.

The network structure also confirms that sustainability outcomes emerge not from isolated progress in individual goals but from interactions among environmental, economic, social, and institutional systems. This finding is consistent with systems-oriented sustainability perspectives that view development as a complex adaptive system characterized by feedback mechanisms, interdependencies, and nonlinear relationships.

From a sustainability perspective, these results emphasize the importance of integrated policy approaches. Improvements in one sustainability domain may generate spillover effects across multiple SDGs, while interventions targeting a single objective without considering broader system interactions may produce unintended consequences elsewhere in the sustainability system. The findings therefore support the view that sustainability transitions should be approached as system-wide processes rather than as independent sectoral objectives. Policies targeting education, environmental sustainability, institutional quality, and international cooperation are likely to generate broader benefits when designed in an integrated manner.

Having established the interdependencies among sustainability dimensions, the next stage investigates whether these sustainability characteristics are statistically associated

with economic performance. Whereas the preceding analyses focused on relationships among SDG indicators themselves, the following regression models evaluate how selected sustainability dimensions jointly relate to national economic performance across the pooled multi-country sample.

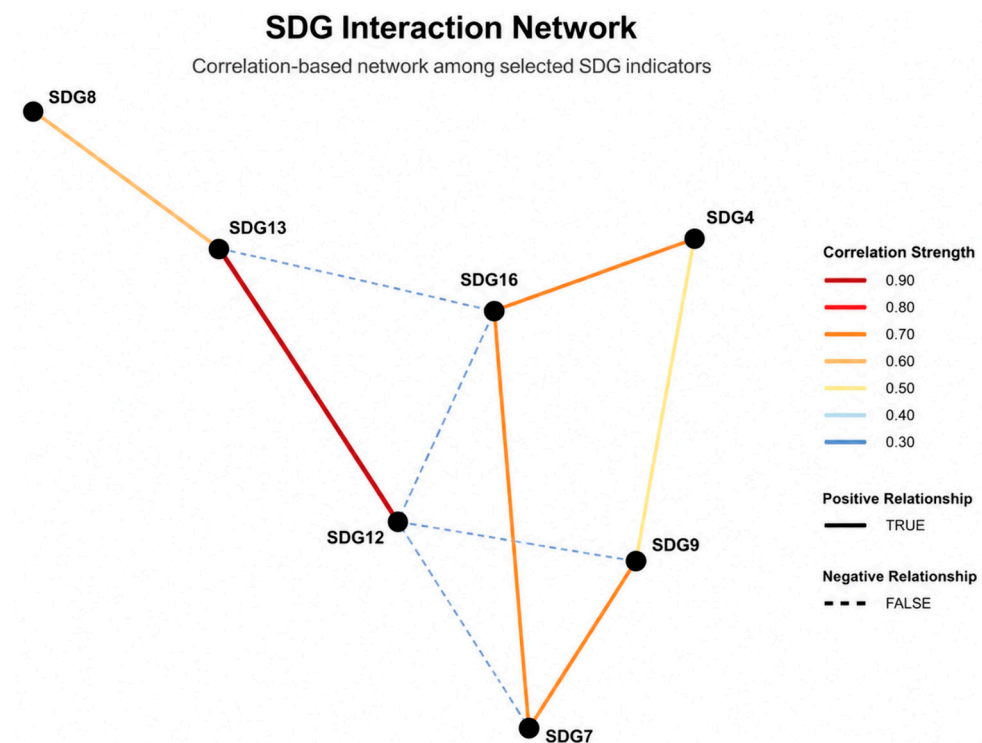


Figure 7. SDG Interaction Network. Edge colors represent the absolute correlation strength ($|r|$), while solid and dashed lines indicate positive and negative correlations, respectively.

4.3. Sustainability Dimensions Associated with Economic Performance

To examine the relationships between sustainability indicators and economic performance, two regression models were estimated. Model 1 includes only SDG indicators, while Model 2 incorporates additional macroeconomic control variables. The results are reported in Table 4.

Table 4. Regression results.

Variable	Model-1	Model-2
Intercept	8.545 ***	9.961 ***
SDG-4	0.030 ***	0.036 ***
SDG-7	0.008	0.017 ***
SDG-8	−0.046 ***	−0.096 ***
SDG-9	0.019 ***	0.023 ***
SDG-12	−0.032 ***	0.004
SDG-13	0.032 ***	0.016 **
SDG-16	−0.019 *	0.015 +
SDG-17	−0.032 ***	−0.069 ***
NGDP_RPCH	−	0.006
PCPIPCH	−	−0.013 ***
LUR	−	−0.059 ***
N	250	195
Adj R ²	0.572	0.791
F-statistic	42.66 ***	67.84 ***

Note: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4 shows that the sustainability indicators explain a substantial proportion of the variation in economic performance. Model 1 achieves an adjusted R^2 of 0.572, while the explanatory power increases to 0.791 in Model 2 after incorporating macroeconomic variables. Model 2 was estimated using complete-case observations. Accordingly, the sample size decreased from 250 to 195 country-year observations due exclusively to missing values in the unemployment rate (LUR) variable. These missing observations were limited to Bangladesh (2000–2024), the United Arab Emirates (2000–2024), and Algeria (2020–2024). These findings suggest that sustainability dimensions and macroeconomic conditions jointly contribute to differences in economic performance across the selected countries.

Because SDG8 (Decent Work and Economic Growth) is conceptually related to economic performance, its inclusion as an explanatory variable may raise concerns regarding conceptual overlap with the dependent variable (log GDP). To address this issue, two additional robustness analyses were conducted and are reported in Appendix A Tables A2 and A3. Appendix A Table A2 re-estimates the baseline SDG model using the reduced sample employed in Model 2, while Appendix A Table A3 excludes SDG8 from the specification entirely. The results remain broadly consistent across both robustness checks, indicating that the main findings are not driven solely by sample composition or by the inclusion of SDG8. These robustness checks were conducted in response to the potential conceptual overlap between SDG8 and the GDP-based dependent variable. As an additional robustness analysis, the pooled OLS models were re-estimated using country fixed effects, year fixed effects, and two-way fixed effects. The results presented in Tables A4 and A5 show that several associations identified by pooled OLS become statistically insignificant after controlling for unobserved country-specific heterogeneity and common year-specific shocks. In the SDG-only model, SDG7 retains a positive and significant coefficient under the two-way fixed-effects specification, whereas none of the SDG indicators remains significant after macroeconomic controls are included. These results support a more cautious interpretation of the pooled regression findings.

Model 1 identifies several significant sustainability dimensions associated with economic performance, particularly SDG4 (Quality Education), SDG9 (Industry, Innovation and Infrastructure), and SDG13 (Climate Action). After introducing macroeconomic controls in Model 2, SDG4, SDG7, SDG9, and SDG13 remain positive and statistically significant, indicating that these dimensions retain explanatory relevance even after accounting for broader economic conditions.

The positive contribution of SDG4 highlights the importance of human capital and educational development. Beyond its direct contribution to labor productivity, education strengthens a country's capacity to absorb new technologies, support innovation, and adapt to economic and sustainability-related transformations. From this perspective, education functions as a foundational capability that facilitates long-term development, resilience, and sustainability transitions.

Similarly, the strong and consistent role of SDG9 emphasizes the importance of innovation systems, infrastructure quality, and industrial capabilities. Rather than reflecting economic activity alone, SDG9 can be interpreted as a proxy for transformation capacity—the ability of economies to convert knowledge, investment, and technological development into sustainable long-term outcomes. This finding is particularly relevant for countries seeking to balance economic growth with sustainability objectives.

The significance of SDG7 further suggests that access to affordable and clean energy contributes positively to economic performance. As countries increasingly face the dual challenge of maintaining economic competitiveness while reducing environmental pressures, energy systems become a critical component of sustainable development strategies.

The positive coefficient of SDG7 indicates that progress toward cleaner and more reliable energy systems may support both economic and sustainability goals.

Interestingly, SDG8 exhibits a negative and statistically significant association with economic performance in both specifications. This result should be interpreted cautiously and does not imply that economic growth reduces national income. Rather, it may reflect the multidimensional structure of SDG8, which combines employment conditions, labor market outcomes, productivity, and inclusive growth indicators. Within the selected country group, countries with larger economic size do not necessarily achieve stronger performance across all SDG8 dimensions. This finding further supports the argument that economic scale and broader sustainability outcomes do not always evolve simultaneously.

SDG17 also exhibits negative coefficients across the regression models. However, this finding should not be interpreted as evidence that international partnerships hinder economic performance. Instead, the coefficient likely reflects the complex interactions among sustainability dimensions and the broad scope of SDG17, which encompasses technology transfer, financing, capacity building, and international cooperation mechanisms. As demonstrated later through the explainable machine learning analysis, SDG17 remains an important component of the broader sustainability-development nexus.

By contrast, SDG16 appears relatively weak and statistically inconsistent across the estimated models. One possible explanation is that improvements in governance and institutional quality often generate benefits gradually over longer time horizons. Consequently, their effects may be less visible in contemporaneous measures of economic performance than those associated with education, innovation, infrastructure, or energy systems.

Taken together, the regression results suggest that economic performance is associated less with isolated sustainability achievements and more with capabilities that support long-term transformation. Education, innovation, clean energy, and international cooperation emerge as the sustainability dimensions most consistently associated with economic performance across the selected major Muslim economies.

Although the regression models provide an interpretable assessment of average linear associations, they cannot fully capture nonlinear effects, temporal dependence, or complex interactions among sustainability and macroeconomic variables. The subsequent machine learning analysis therefore extends the regression framework by incorporating one-year lagged predictors and evaluating predictive performance under a strict chronological holdout and rolling-origin validation strategy. This complementary analysis enables the identification of the variables that contribute most strongly to forward prediction while avoiding temporal information leakage.

4.4. Machine Learning Results

To complement the regression analysis and capture nonlinear relationships and temporal persistence, Random Forest and XGBoost models were estimated using current and one-year lagged predictors under the year-based chronological holdout and rolling-origin validation framework described in Section 3.3.

Table 5 summarizes predictive performance during the independent chronological test period. The tuned Random Forest model achieved the strongest performance, with an RMSE of 0.2082, an MAE of 0.1785, and an out-of-sample R^2 of 0.8665. The expanded XGBoost model also demonstrated substantial predictive ability, yielding an RMSE of 0.2797, an MAE of 0.2331, and an out-of-sample R^2 of 0.7592.

These results were obtained under a strict temporal evaluation design in which the most recent years were excluded from model development and used only for final testing. Hyperparameters were selected through rolling-origin validation conducted entirely within

the earlier training period. The resulting performance estimates therefore reflect genuine forward-looking prediction more closely than conventional random train–test partitions.

Table 5. Predictive Performance of Machine Learning Models.

Model	RMSE	MAE	Out of Sample R ²
Random Forest	0.2082	0.1785	0.8665
XGBoost	0.2797	0.2331	0.7592

Note: Higher R² and lower RMSE/MAE indicate better predictive performance. Random Forest was implemented using the ranger algorithm.

Random Forest outperformed XGBoost across all three evaluation measures. Its superior performance suggests that the predictive structure of the dataset may be captured effectively through an ensemble of decorrelated decision trees, particularly when economic persistence, sustainability indicators, macroeconomic conditions, and their one-year lags are considered jointly. Nevertheless, these results should be interpreted within the observed country group and study period rather than as evidence of unrestricted generalizability.

4.5. Explainable Machine Learning Results

Because Random Forest achieved the strongest chronological out-of-sample performance, SHAP analysis was applied to the optimized Random Forest model. Figure 8 reports global feature importance based on mean absolute SHAP values calculated for the independent test period.

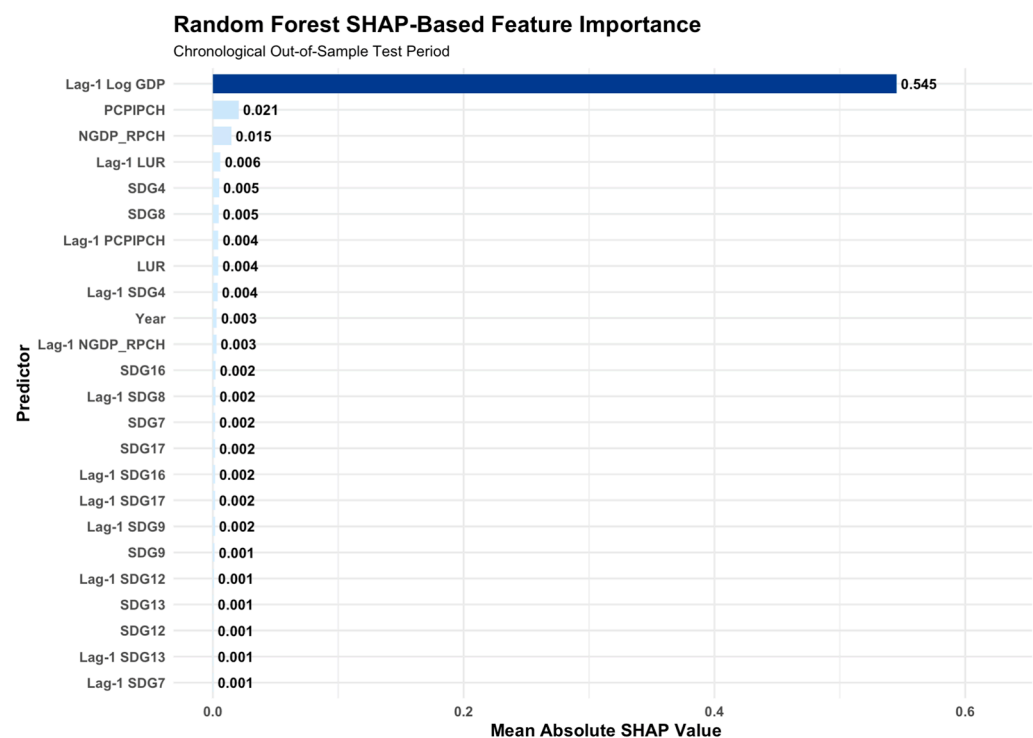


Figure 8. Random Forest SHAP-Based Feature Importance During the Chronological Out-of-Sample Test Period.

The results indicate that one-year lagged log GDP was by far the most influential predictor, with a mean absolute SHAP value of 0.545 (Figure 8). This finding points to substantial temporal persistence in national economic performance, indicating that the economic scale observed in the preceding year contains considerably more predictive information about current log GDP than any individual contemporaneous sustainability or

macroeconomic indicator. Because SHAP values preserve the direction of individual feature contributions, the predominance of lagged GDP indicates that higher previous economic performance generally contributes positively to predicted current GDP, whereas lower lagged values contribute negatively. By comparison, current macroeconomic conditions and selected SDG indicators exhibit considerably smaller but non-negligible predictive contributions. Collectively, these findings suggest that sustainability indicators complement rather than replace prior economic information when explaining future economic performance.

Among the contemporaneous macroeconomic variables, inflation and real GDP growth exhibited the next-highest SHAP importance values, at 0.021 and 0.015, respectively. One-year lagged unemployment also contributed to prediction, although its importance was markedly lower than that of lagged GDP. These results indicate that both prior economic scale and current macroeconomic conditions contribute to short-horizon prediction.

The SDG indicators provided additional but comparatively modest predictive information. Among the sustainability dimensions, SDG4 and SDG8 displayed the highest mean absolute SHAP values, followed by SDG16, SDG7, and SDG17. Their lagged counterparts also contributed to the model, but none approached the predictive dominance of lagged GDP. Accordingly, the machine learning results do not imply that sustainability indicators are unimportant; rather, they show that their incremental predictive contribution is smaller once strong autoregressive economic information is included.

These findings should be distinguished from the regression results. The regression models were designed to estimate contemporaneous statistical associations between SDG indicators and economic performance, whereas the enhanced machine learning models were designed for forward-looking prediction and included lagged GDP and lagged predictors. Consequently, differences between regression coefficients and SHAP rankings are methodologically expected. SHAP values describe the contribution of predictors to model predictions and should not be interpreted as causal effects or as direct measures of policy impact.

5. Discussion

According to the IMF's April 2026 projections, Türkiye is projected to become the largest economy among the selected Muslim-majority economies. This development motivated the central question of whether economic leadership is accompanied by stronger sustainability performance. By integrating benchmarking analysis, SDG interaction analysis, regression modeling, and explainable machine learning techniques, the study provides evidence that sustainability indicators and economic performance are closely associated within the selected country group.

The findings provide direct answers to the research questions. Regarding RQ1, Türkiye demonstrates one of the strongest sustainability performances among the selected economies. Although it is projected to become the largest economy in the sample, it also ranks second in overall SDG performance and performs particularly well in clean energy (SDG7), innovation and infrastructure (SDG9), and partnerships (SDG17). These findings suggest that economic growth and sustainability progress may coexist within the analysed sample, although the observed relationships should not be interpreted as evidence of causal or universally generalizable mechanisms.

Regarding RQ2, the regression analysis identifies several sustainability dimensions—particularly education, clean energy, innovation, and climate action—as statistically associated with economic performance. Regarding RQ3, the enhanced machine learning analysis shows that one-year lagged economic performance is the dominant predictor of future log GDP, while current macroeconomic conditions and selected SDG indicators provide additional predictive information. These findings demonstrate that explanatory

association and predictive contribution represent distinct analytical concepts and should not be interpreted as interchangeable.

An additional consideration concerns the inclusion of SDG8 (Decent Work and Economic Growth) among the explanatory variables. Because SDG8 explicitly incorporates an economic dimension, some degree of conceptual proximity to the dependent variable (log GDP) is unavoidable. However, SDG8 represents a broader sustainability construct encompassing productive employment, labour market conditions, inclusive economic development, and decent work rather than national income alone. Consequently, the observed relationships should be interpreted as statistical associations rather than evidence of causal effects, thereby reducing concerns regarding conceptual overlap and possible simultaneity. Furthermore, the robustness analysis excluding SDG8 produced substantively similar results, indicating that the principal findings are not driven solely by the inclusion of SDG8.

The correlation and network analyses further demonstrate that sustainable development operates as a highly interconnected system. Strong positive relationships between SDG12 and SDG13, as well as between SDG4 and SDG16, indicate that progress in one sustainability dimension may generate positive spillover effects in others. At the same time, the presence of several negative relationships highlights the existence of sustainability trade-offs. These findings are consistent with previous studies emphasizing that SDGs should be viewed as an integrated system characterized by synergies, feedback mechanisms, and competing priorities rather than as independent policy objectives [1,7].

The network structure reinforces this systems perspective. In particular, SDG12, SDG13, and SDG16 occupy relatively central positions within the sustainability network, suggesting that environmental sustainability and institutional quality are embedded within broader patterns of interdependence. Consequently, policy interventions targeting these dimensions may generate wider system-level effects through their connections with other SDGs. This finding supports recent sustainability research emphasizing the importance of integrated and coordinated policy approaches for managing complex sustainability transitions [3,8].

An important contribution of the study concerns the distinction between explanatory association and predictive performance. The regression results suggest that education, clean energy, innovation, and climate-related performance are statistically associated with economic outcomes. By contrast, the enhanced Random Forest model indicates that short-horizon prediction is dominated by temporal economic persistence, particularly one-year lagged log GDP. The SHAP analysis further demonstrates that lagged economic performance provides by far the largest contribution to individual predictions, reflecting the strong persistence commonly observed in national economic trajectories. Higher lagged GDP values generally contribute positively to predicted economic performance, whereas lower lagged values contribute negatively, highlighting the directional influence captured by the explainable machine learning model. Current macroeconomic conditions and selected SDG indicators make considerably smaller but still meaningful predictive contributions beyond prior economic performance. These predictive contributions should not be interpreted as evidence of causal influence but rather as measures of variable importance within the fitted prediction model.

Taken together, the benchmarking, network analysis, regression models, and explainable machine learning results suggest that sustainable development is best understood as an interconnected system characterized by both synergies and trade-offs among social, economic, environmental, and institutional dimensions. The results highlight the importance of policy prioritization, particularly in education, innovation, clean energy, and international partnerships, while emphasizing the need to manage trade-offs across

sustainability objectives. Consequently, sustainability transitions require integrated policy frameworks capable of strengthening transformation capacity, supporting resilience, and promoting balanced long-term development outcomes.

6. Conclusions

This study examined the relationship between sustainable development and economic performance across ten selected Muslim-majority economies by integrating benchmarking analysis, SDG interaction analysis, regression modeling, and explainable machine learning techniques. The research was motivated by IMF projections indicating that Türkiye is projected to become the largest economy in the sample by 2026.

The findings show that Türkiye ranks among the leading countries in terms of sustainable development performance while also exhibiting strong outcomes in areas such as clean energy, innovation, and international partnerships. However, the findings also indicate that economic leadership does not necessarily correspond to uniformly strong sustainability performance, as substantial variation remains across individual sustainability dimensions. More broadly, the results demonstrate that sustainable development operates as an interconnected system characterized by both synergies and trade-offs among economic, social, environmental, and institutional dimensions.

The analyses reveal complementary but distinct findings. The regression models identify education, clean energy, innovation, and climate-related performance as statistically associated with economic outcomes. The enhanced machine learning models, by contrast, show that one-year lagged economic performance is the strongest predictor of future log GDP, while macroeconomic conditions and selected SDG indicators provide additional predictive information. The tuned Random Forest model retained robust out-of-sample predictive performance under a strict chronological holdout and rolling-origin validation framework, indicating that meaningful forward-looking patterns remain detectable without allowing future observations to influence model development.

Nevertheless, these findings should be interpreted with appropriate caution. The regression models identify statistical associations rather than causal relationships, while the SHAP analysis quantifies predictor importance within the fitted machine learning model rather than causal influence. Accordingly, the reported results should be interpreted as evidence of explanatory associations and predictive contributions within the analysed sample, not as proof of generalizable causal mechanisms.

From a policy perspective, the findings suggest that economic development strategies should be designed around sustainability priorities that simultaneously strengthen human capital, technological capability, energy transition, and international cooperation. In particular, investments in education and innovation may generate broad spillover effects by enhancing productivity, adaptive capacity, and long-term resilience. Similarly, expanding clean energy systems and strengthening international partnerships may facilitate knowledge transfer, technological diffusion, and access to financial and institutional resources. Because sustainability dimensions are highly interconnected, policymakers should move beyond sector-specific interventions and adopt integrated policy frameworks that explicitly account for synergies and trade-offs among SDGs. Such an approach may improve policy coherence and contribute to more balanced and resilient long-term development pathways.

Consequently, the study contributes to sustainability literature by combining benchmarking, network analysis, conventional statistical methods, and explainable machine learning to examine sustainability–economy relationships from a systems perspective. The benchmarking approach additionally demonstrates that countries sharing a common Muslim-majority context, while exhibiting substantial economic and institutional diversity, may display markedly different sustainability profiles across individual SDGs. The

use of explainable machine learning further distinguishes the dominant role of temporal economic persistence from the incremental predictive contributions of macroeconomic and sustainability indicators. This evidence may support more cautious policy interpretation by separating variables that improve prediction from variables that exhibit contemporaneous statistical associations.

7. Limitations and Future Research

Several limitations should be acknowledged. First, the analysis focuses on a selected group of major Muslim economies and therefore may not be fully generalizable to other country groups. Second, data availability restricted the analysis to specific SDG indicators and macroeconomic variables. Third, although the regression and explainable machine learning models provide valuable analytical and predictive insights, they do not establish causal relationships.

Another limitation concerns the panel structure of the dataset. Although the data consist of repeated country-year observations, the regression analysis employed pooled OLS models rather than fixed-effects or random-effects panel estimators. Consequently, country-specific and time-specific unobserved heterogeneity was not explicitly controlled for, and the estimated coefficients should therefore be interpreted as pooled statistical associations rather than causal panel effects.

The machine learning analysis is also subject to several limitations. Although a strict chronological validation strategy was adopted to reduce temporal information leakage and evaluate predictive performance for future observations within the same country panel, the relatively small number of countries limits the generalizability of the reported prediction results. Accordingly, the reported performance metrics should be interpreted as evidence of within-panel predictive ability rather than universal forecasting performance across previously unseen countries. In addition, the inclusion of one-year lagged log GDP substantially improves predictive accuracy because macroeconomic performance exhibits strong temporal persistence. Consequently, the resulting SHAP importance rankings primarily reflect predictive importance within the fitted models rather than policy importance or causal influence. Likewise, the comparatively smaller SHAP values of the SDG indicators represent their incremental predictive contribution after prior economic performance and contemporaneous macroeconomic conditions have been taken into account.

Future research may extend the analysis by incorporating larger country samples, additional sustainability indicators, and more advanced panel-data techniques, including fixed-effects, random-effects, and dynamic panel-data models. Future studies may also compare the present chronological validation framework with alternative validation strategies, such as leave-one-country-out cross-validation and naïve benchmark models, to further evaluate predictive robustness and cross-country generalizability. Finally, causal machine learning approaches may help distinguish predictive relationships from causal mechanisms and provide a deeper understanding of how sustainability–economy relationships evolve across different stages of economic development.

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Abbreviations

The following abbreviations are used in this manuscript:

SDG	Sustainable Development Goals
OIC	Organization of Islamic Cooperation
IMF	International Monetary Fund
GDP	Gross Domestic Product
RQ	Research Question
SHAP	SHapley Additive exPlanations
XGBoost	Extreme Gradient Boosting
XAI	Explainable Artificial Intelligence
WEO	World Economic Outlook
SDSN	Sustainable Development Solutions Network
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
OLS	Ordinary Least Squares

Appendix A

The appendix provides supplementary robustness and network analyses supporting the findings reported in the main text.

Table A1. Descriptive Statistics of Variables Used in the Analyses.

Variable	N	Mean	SD	Min	Max
SDG-4	250	69.31	20.26	21.00	100.00
SDG-7	250	61.04	10.85	26.00	73.00
SDG-8	250	64.52	6.84	51.00	79.00
SDG-9	250	39.64	16.72	16.00	83.00
SDG-12	250	76.33	15.66	37.00	94.00
SDG-13	250	77.06	28.75	1.00	99.00
SDG-16	250	61.50	8.86	39.00	75.00
SDG-17	250	61.95	7.64	47.00	78.00
LUR	195	8.46	4.11	2.88	29.50
NGDP_RPCH	250	4.34	3.07	−8.69	12.32
PCIPCH	250	8.76	10.92	−4.72	72.30
Log GDP	250	5.73	0.74	4.08	7.24
Overall SDG	250	62.96	5.60	49.80	71.40

Table A2. Robustness Check: Baseline Regression Re-estimated Using the Reduced Sample (N = 195).

Variable	Reduced Sample Model
Intercept	10.161 ***
SDG-4	0.033 ***
SDG-7	0.007
SDG-8	−0.062 ***

Table A2. *Cont.*

Variable	Reduced Sample Model
SDG-9	0.021
SDG-12	−0.017 +
SDG-13	0.016 **
SDG-16	0.001
SDG-17	−0.061 ***
N	195
Adj R ²	0.708
F-statistic	59.89 ***

Note: + $p < 0.10$, ** $p < 0.01$, *** $p < 0.001$.

Table A2 re-estimates the baseline SDG model using the reduced sample employed in Model 2. The consistency of coefficient signs, significance levels, and overall model fit indicates that the exclusion of observations with missing macroeconomic data does not materially alter the substantive conclusions of the study.

Table A3. Robustness Check: Regression Results Excluding SDG8 (Decent Work and Economic Growth).

Variable	Reduced Sample Model
Intercept	6.263 ***
SDG-4	0.021 ***
SDG-7	0.021 ***
SDG-9	0.015 ***
SDG-12	−0.030 ***
SDG-13	0.025 ***
SDG-16	−0.012
SDG-17	−0.043 ***
N	250
Adj R ²	0.506
F-statistic	37.87 ***

Note: *** $p < 0.001$.

Table A3 excludes SDG8 (Decent Work and Economic Growth) from the regression specification. This robustness check addresses potential conceptual overlap between SDG8 and the dependent variable (economic performance). The results remain broadly consistent with the baseline model, suggesting that the main findings are not driven solely by the inclusion of SDG8.

Table A4. Comparison of Pooled OLS and Fixed-Effects Results: SDG-Only Model.

Variable	Pooled OLS	Country FE	Year FE	Two-Way FE
SDG-4	0.030 *** (0.003)	0.014 (0.007)	0.015 * (0.006)	0.003 (0.005)
SDG-7	0.008 (0.005)	0.045 *** (0.006)	−0.012 (0.009)	0.021 * (0.008)
SDG-8	−0.046 *** (0.007)	−0.035 (0.027)	−0.040 * (0.014)	−0.013 (0.014)
SDG-9	0.019 *** (0.003)	0.019 ** (0.005)	−0.010 (0.010)	−0.000 (0.007)
SDG-12	−0.032 *** (0.007)	−0.003 (0.025)	−0.103 ** (0.023)	−0.021 (0.027)
SDG-13	0.032 *** (0.005)	−0.034 (0.031)	0.067 *** (0.011)	0.022 (0.035)
SDG-16	−0.019 * (0.008)	0.010 (0.018)	0.040 * (0.018)	0.019 (0.018)
SDG-17	−0.032 ** (0.011)	−0.023 (0.015)	−0.058 * (0.022)	−0.017 (0.014)
N	250	250	250	250
R ²	0.586	0.855	0.803	0.937

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported outside parentheses, while standard errors are presented in parentheses. Heteroskedasticity-robust standard errors are reported for the pooled OLS model, and country-clustered standard errors are reported for the fixed-effects models.

Table A4 compares the pooled OLS estimates with country fixed-effects, year fixed-effects, and two-way fixed-effects estimates for the SDG-only specification. The results show that several statistically significant relationships observed in the pooled OLS model weaken after controlling for unobserved country-specific heterogeneity and common year-specific shocks. In the most restrictive two-way fixed-effects specification, SDG7 retains a positive and statistically significant coefficient, whereas the coefficients of the remaining SDG indicators are not statistically significant. This indicates that SDG7 represents the most robust SDG-related association in the baseline specification. By contrast, the other pooled OLS relationships appear to be partly attributable to persistent structural differences across countries or common temporal patterns rather than within-country changes over time.

Table A5. Comparison of Pooled OLS and Fixed-Effects Results: Extended Model.

Variable	Pooled OLS	Country FE	Year FE	Two-Way FE
SDG-4	0.036 *** (0.003)	0.016 ** (0.004)	0.023 ** (0.004)	−0.008 (0.005)
SDG-7	0.017 ** (0.005)	0.038 *** (0.003)	0.006 (0.007)	−0.002 (0.008)
SDG-8	−0.096 *** (0.006)	−0.059 * (0.019)	−0.075 *** (0.009)	0.031 (0.022)
SDG-9	0.023 *** (0.003)	0.020 ** (0.005)	0.001 (0.009)	−0.010 (0.005)
SDG-12	0.004 (0.010)	−0.041 (0.047)	−0.066 (0.030)	−0.049 (0.037)
SDG-13	0.016 * (0.007)	−0.026 (0.031)	0.050 * (0.017)	0.047 (0.043)
SDG-16	0.015 (0.008)	0.001 (0.020)	0.057 * (0.019)	0.016 (0.018)
SDG-17	−0.069 *** (0.009)	−0.024 (0.024)	−0.083 ** (0.018)	−0.019 (0.018)
NGDP_RPCH	0.006 (0.009)	0.005 (0.005)	0.006 (0.008)	0.006 + (0.003)
PCPIPCH	−0.013 *** (0.003)	−0.009 (0.004)	−0.010 (0.004)	−0.011 * (0.004)
LUR	−0.059 *** (0.008)	−0.038 (0.020)	−0.033 (0.018)	0.012 (0.021)
N	195	195	195	195
R ²	0.803	0.877	0.892	0.953

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported outside parentheses, while standard errors are presented in parentheses. Heteroskedasticity-robust standard errors are reported for the pooled OLS model, and country-clustered standard errors are reported for the fixed-effects models.

Table A5 presents the corresponding comparison for the extended model, which additionally controls for real GDP growth, inflation, and unemployment. After both country and year fixed effects are introduced, none of the SDG indicators remains statistically significant at the 5% level. Inflation retains a negative and statistically significant coefficient, while real GDP growth exhibits a positive coefficient that is significant only at the 10% level. Unemployment is not statistically significant in the two-way fixed-effects specification. These results suggest that the associations between the SDG indicators and economic performance become weaker after macroeconomic conditions, persistent country-specific characteristics, and common temporal shocks are considered simultaneously. The extended model is based on 195 complete observations from eight countries because of missing macroeconomic data; therefore, comparisons with the SDG-only model should also consider the difference in sample composition.

Taken together, Tables A4 and A5 demonstrate that the pooled OLS findings are sensitive to the treatment of unobserved heterogeneity. The fixed-effects results do not imply that sustainability dimensions are unrelated to economic performance; rather, they show that several pooled associations primarily reflect differences across countries or common changes over time and are not consistently reproduced through within-country variation. The findings therefore support a more cautious interpretation of the regression results as conditional statistical associations rather than causal effects.

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