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ANALYZING THE IMPACT OF MACROECONOMIC FACTORS ON THE IMPLEMENTATION OF SUSTAINABLE DEVELOPMENT GOALS USING MACHINE LEARNING: EVIDENCE FROM MONGOLIA

Otgonsuren Gotov[1*], Tsetsegjargal Uuganbayar[1], Nurjigmaa Ootoi[1], Oyuntsetseg Dorjpalam[1]

[1]National University of Mongolia, Ulaanbaatar, Mongolia

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Corresponding Author: Otgonsuren Gotov (otgonsuren.g@num.edu.mn)

ABSTRACT

The purpose of this study is to analyze the impact of key macroeconomic factors and the time-lag effects of Sustainable Development Goals (SDGs) on their implementation in Mongolia using modern machine learning (ML) techniques. The analysis employs annual data from 2000–2024, including macroeconomic indicators, the SDG Index, and performance metrics for 17 goals. Core variables include GDP growth, inflation, unemployment, exports, fiscal revenue, and government expenditure. In 2025, Mongolia's SDG Index score reached 66.7, ranking 100th globally, which is close to the regional average but still reflects weak performance in environmental goals. To explain SDG Index fluctuations, four ML models - Linear Regression, Gradient Boosting, Support Vector Regression (SVR), and Artificial Neural Network (ANN) - were compared. Gradient Boosting achieved the highest accuracy ($R^2 = 0.844$, RMSE = 0.8735), explaining 84.4% of the variance. SHAP analysis revealed that the most influential factors for SDG performance are health (SDG3), exports, poverty reduction (SDG1), internet usage (SDG9), and food security (SDG2), while inflation and unemployment exert negative effects. Time-lag analysis shows that foundational service goals—SDG3 (health), SDG6 (water and sanitation), SDG11 (urban development), SDG9 (infrastructure), and SDG1 (poverty reduction)—have strong positive one-year lag effects on the SDG Index. In contrast, environmental goals (SDG12–15) exhibit persistent negative lag effects, indicating that ecosystem degradation slows SDG progress in subsequent years. SDG4 (education) and SDG7 (energy) display weak lag impacts, with long-term delayed effects. Additionally, K-Means clustering grouped SDG indicators into three development patterns: (i) economy-driven, (ii) social-service-driven, and (iii) environment-challenged clusters. Findings suggest that improving SDG implementation in Mongolia requires export diversification, investment in health services, inflation control, and strategic reforms in environmental policy.

KEYWORDS: Sustainable Development Goals, Macroeconomic Factors, Machine Learning, GDP Growth, Fiscal Policy, Exports, Mongolia.

1. INTRODUCTION

The United Nations' "2030 Agenda for Sustainable Development" sets a global framework of 17 interrelated goals aimed at eradicating poverty, ensuring equality, and protecting the environment. Mongolia has integrated these goals into its national policy and planning system through the "Sustainable Development Vision–2030" (2016) and the "Vision–2050" strategic document (2020).

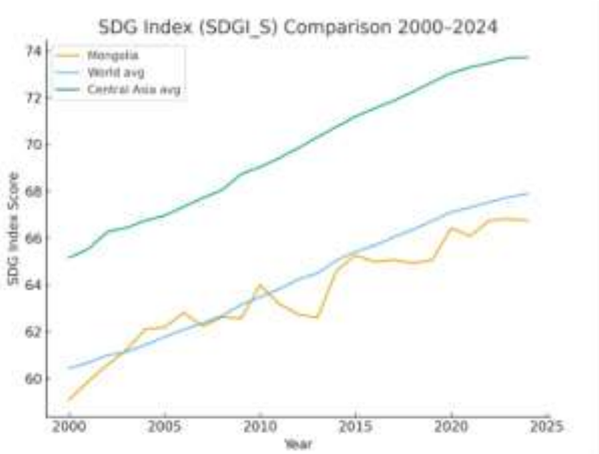

Figure 1: SDG Index (SDGI_S) Comparison 2000–2024.
Source: Sachs, J., Lafortune, G., Fuller, G., Drumm, E., & Schmidt-Traub, G. (2000–2024). Sustainable Development Report. Cambridge University Press. https://www.sdgindex.org

From 2000 to 2024, Mongolia's SDG Index has shown continuous growth - from around 50 points in 2000 to approximately 66–67 points in 2024. While global averages have also increased steadily, Mongolia's growth trajectory has been relatively dynamic compared to some regional peers. The Eastern Europe & Central Asia regional average started higher but grew more slowly. Since 2015, Mongolia's SDG performance has occasionally lagged behind the regional average but has converged since 2020, indicating a positive long-term trend despite structural challenges.

When SDG achievements are classified into three tiers, the highest progress is observed in SDG1 (No Poverty), SDG4 (Quality Education), and SDG10 (Reduced Inequalities). Moderate progress is seen in SDG3 (Good Health), SDG5 (Gender Equality), and SDG6 (Clean Water and Sanitation). However, SDG2 (Zero Hunger), SDG7 (Affordable and Clean Energy), and SDG9 (Industry, Innovation, and Infrastructure) remain below 50–60 points, reflecting persistent difficulties.

Environmental goals such as SDG13 (Climate Action), SDG14 (Life Below Water), and SDG15 (Life on Land) show some improvement but require greater attention to address land degradation and pollution.

Table 1. Key Challenges in Achieving Sustainable Development Goals (SDGs) by ESG Category.
Source: Sachs, J., Lafortune, G., Fuller, G., Drumm, E., & Schmidt-Traub, G. (2000–2024). Sustainable Development Report. Cambridge University Press. https://www.sdgindex.org

Challenge Area	Impact Level	Main Issues	Affected SDGs
Environment	Very High	Desertification, air pollution, energy shortage	7, 13, 15
Social	High	Urban–rural gap, inequality	3, 4, 10, 11
Economy	High	Dependence on mining, nutrition issues, job instability	1, 2, 8, 9
Institutions	Medium–High	Governance, data monitoring, corruption risk	16, 17

1.1. Environmental Challenges (SDG 6, 7, 12, 13, 14, 15)

- Desertification and pasture degradation (~70%) remain a major challenge for SDG15.
- Air pollution (PM2.5) in Ulaanbaatar is at a high level, directly affecting SDG3 and SDG11.
- Low share of clean energy keeps SDG7 among the lowest-rated goals.
- Climate change risks (zud, drought) are increasing, posing challenges for SDG13.

1.2. Social Challenges (SDG 3, 4, 5, 10, 11)

- Access to healthcare declines significantly from urban to rural areas (SDG3).
- Child and elderly poverty remains high, affecting SDG10.
- Quality of education (SDG4) is unstable due to teacher shortages and migration.
- Urban–rural disparities in income, health, water supply, and jobs persist (SDG11).

1.3. Economic Challenges (SDG 1, 2, 8, 9)

- Heavy dependence on mining limits long-term sustainable growth (SDG8, SDG9).
- Income volatility increases the risk of returning to poverty (SDG1).
- Innovation and infrastructure (SDG9) remain below regional averages.
- Food security issues (SDG2) persist in rural areas, worsened by frequent zud.

1.4. Institutional Challenges (SDG 16, 17)

- Governance efficiency (SDG16) is below regional average.
- Weak transparency and open data hinder SDG monitoring systems.
- Corruption risks remain a major barrier (SDG16).
- International financing and partnerships (SDG17) are unstable, with low project efficiency.

International studies confirm that macroeconomic factors (GDP growth, inflation, unemployment, fiscal revenue, and exports) have a significant impact on SDG implementation. However, in the case of Mongolia, research using modern data-analytics approaches remains scarce. Existing studies mostly rely on traditional OLS regression, which limits the ability to account for nonlinear and multidimensional relationships among macroeconomic indicators.

Therefore, the objective of this study is to quantitatively analyze how key macroeconomic factors influence SDG implementation in Mongolia using machine learning (ML) methods and explainable artificial intelligence (Explainable AI) techniques. The study compares ML models such as Linear Regression, Gradient Boosting, and Artificial Neural Network (ANN) to identify the most accurate model and applies SHAP analysis to transparently explain the contribution of each variable. Additionally, SDG indicators are grouped using K-Means clustering to identify distinct development patterns.

2. LITERATURE REVIEW

Sustainable Development Goals and the Macroeconomic Context: The most common approach to measuring the implementation of Sustainable Development Goals (SDGs) is through the SDG Index, which is reported annually by the United Nations and the Sustainable Development Solutions Network (SDSN). This composite index aggregates indicators across 17 goals to provide a single score, widely used to compare countries, regional disparities, and long-term trends. For Mongolia, the SDG Index score remains slightly below the regional average. While progress has been observed in social goals such as health, education, and gender equality, performance in energy access, climate resilience, and environmental sustainability remains weak according to UN and UNDP reports.

Macroeconomic Factors and SDG Performance: Global studies demonstrate that macroeconomic indicators - GDP growth, inflation, unemployment, fiscal revenue, and trade openness—play a critical role in SDG achievement. Reports by the OECD and the Global Sustainable Development Report highlight that limited fiscal space, high debt burdens, and rising inflation often constrain investments in SDG-related sectors, slowing progress. Conversely, strong fiscal revenues and diversified exports positively influence SDG performance. Evidence from emerging economies shows that corporate tax revenues and structural reforms can significantly improve SDG outcomes, emphasizing the importance of aligning macroeconomic policy with SDG financing strategies. For instance, Saudi Arabia's Vision 2030 illustrates how economic diversification and targeted public spending accelerate SDG progress.

Application of Artificial Intelligence and Machine Learning in SDG Analysis: Recent years have witnessed a surge in studies applying artificial intelligence (AI) and machine learning (ML) to sustainability research. These methods outperform traditional linear models in predicting SDG trends, clustering countries by performance, and identifying key drivers through feature importance and explainable AI techniques. Systematic reviews confirm that ML approaches - such as Gradient Boosting, Random Forest, and Neural Networks - offer superior accuracy in forecasting SDG Index scores and uncovering complex, nonlinear relationships among indicators. Explainable AI methods, particularly SHAP (Shapley Additive Explanations), have emerged as powerful tools for interpreting model outputs, enabling policymakers to understand variable contributions at both global and local levels.

Cluster Analysis and Development Patterns: Given the heterogeneity of SDG performance across countries, clustering techniques such as K-Means and hierarchical models are widely used to group nations with similar development profiles. Studies reveal three dominant clusters: (i) high-income countries with strong institutional quality and balanced SDG performance; (ii) middle-income countries with moderate progress in social goals but lagging environmental indicators; and (iii) vulnerable states facing persistent poverty, weak governance, and climate risks. Mongolia's profile aligns with the second cluster, showing relatively strong progress in social dimensions but structural weaknesses in environmental sustainability.

Mongolia's SDG Research and Data Characteristics: In Mongolia, SDG monitoring systems are gradually being established through collaboration between the National Statistics Office, relevant ministries, and UN agencies. While official portals provide disaggregated data on poverty, health, education, and infrastructure, most existing studies rely on traditional econometric approaches such as OLS regression. These methods fail to capture nonlinear and multidimensional interactions between macroeconomic factors and SDG indicators. Therefore, this study introduces machine learning models and explainable AI techniques to fill this gap, offering a more robust analytical framework for understanding SDG dynamics in Mongolia.

Export and SDG Performance: International and Regional Evidence: International studies confirm that export growth and economic openness have a significant impact on the achievement of Sustainable Development Goals (SDGs). The Sustainable Development Report (2023) by the Sustainable Development Solutions Network (SDSN) notes that export expansion positively influences progress in core goals such as SDG1 (No Poverty), SDG3 (Good Health and Well-being), SDG4 (Quality Education), and SDG9 (Industry, Innovation, and Infrastructure). The report emphasizes that "export-driven economies show faster convergence in SDG performance," indicating a strong link between export performance and SDG advancement.

Studies based on data from developing and middle-income countries confirm that exports serve as a primary source of SDG financing. Halim et al. (2022), analyzing BRICS and other emerging economies, conclude that export revenues support social service financing and improve indicators for SDG1, SDG3, and SDG4. At the regional level, Çelik (2025) applied machine learning methods (Gradient Boosting, Random Forest, SVM) to evaluate factors influencing SDG performance and found that trade openness consistently ranked among the top three variables. Export-related features dominated feature importance in ML models, demonstrating higher explanatory power compared to traditional regression approaches.

The United Nations SDG Report (2023) warns that economies overly dependent on exports face a risk of "systemic slowdown" in SDG progress. For Mongolia, the UNDP Mongolia (2023) report highlights that the boom–bust cycle of mineral exports increases economic volatility, affecting poverty, unemployment, and fiscal spending, thereby hindering SDG advancement. Malik et al. (2024), writing in Nature Sustainability, argue that global trade inequalities directly influence SDG implementation, and countries with weak export infrastructure experience slower progress in environmental goals such as SDG12–15.

These findings demonstrate that export cycles, economic openness, and commodity structure strongly affect the speed and sustainability of SDG achievement. This aligns with the results of this study, where Mongolia's data show exports as the most influential positive determinant of the SDG Index (GBR feature importance: exp = 0.0313; OLS $p < 0.001$), while inflation and unemployment exert negative effects - consistent with the evidence presented in international literature.

3. METHODOLOGY

This study employs a mixed-method approach that integrates quantitative econometric modeling, machine learning techniques, and exploratory data analysis to explain fluctuations in Mongolia's Sustainable Development Goals Index (SDGI) over the period 2000–2024. The methodological framework consists of the following key components.

3.1. Data Sources and Variable Specification

The analysis utilizes 25 annual observations obtained from multiple national and international databases, including the National Statistics Office of Mongolia, the Bank of Mongolia, the Ministry of Finance, the World Bank Open Data platform, and the SDSN Sustainable Development Report.

The dependent variable is the composite Sustainable Development Goals Index (SDGI), denoted as:

$$Y_t = SDGIndex_t \quad (1)$$

The core macroeconomic explanatory variables are grouped as follows:

$$X\_t = [\, GDPG_t,\ INF_t,\ UNEMP_t,\ EXP\_t,\ REV\_t,\ GEXP\_t \,] \quad (2)$$

Where:

- GDPGt - GDP growth rate
- INFt- inflation rate
- UNEMPt- unemployment rate
- EXP_t- exports
- REV_t— government revenue
- GEXP_t— government expenditure

The selection of these six macroeconomic variables is grounded in established theoretical and empirical literature on the determinants of sustainable development, as well as in the structural characteristics of the Mongolian economy. GDP growth (GDPG) captures the overall pace of economic expansion that finances public investment in SDG-related sectors; it is identified by Alamsyahbana (2025) and the OECD (2025) as a primary precondition for SDG financing. Inflation (INF) and unemployment (UNEMP) represent macroeconomic stability and labour-market conditions, both of which directly affect household welfare (SDG1), food security (SDG2), and access to services (SDG3, SDG4); their inclusion follows the framework of the Global Sustainable Development Report (UN, 2023). Exports (EXP) are particularly critical for Mongolia, whose economy is highly trade-dependent and subject to mineral-commodity cycles; Halim et al. (2022) and Çelik (2025) both show exports to be among the dominant predictors of SDG performance in resource-rich and middle-income economies. Government revenue (REV) and government expenditure (GEXP) jointly capture the fiscal capacity through which SDG policies are implemented, reflecting the OECD (2025) emphasis on aligning fiscal policy with SDG financing strategies. Together, these six variables span the demand-side, supply-side, stability, external-balance, and fiscal-policy dimensions of the macroeconomic environment, ensuring a comprehensive yet parsimonious specification consistent with the limited annual sample (n = 25). Additionally, SDG goal-level indicators (goal1–goal17) and the internet-usage variable (sdg9_intuse) were incorporated to capture the within-system dynamics of sustainable development progress.

3.2. Machine Learning Modeling Strategy

To model and predict the SDGI, four machine learning algorithms with different structural properties were employed:

1. Linear Regression
2. Gradient Boosting Regressor (GBR)
3. Support Vector Regression (SVR)
4. Artificial Neural Network (ANN)

These models were chosen to capture linear, nonlinear, ensemble-based, and deep-learning representations of the SDGI's relationship with macroeconomic and SDG-related indicators. The diversity of model architectures allows for a robust comparison and a more comprehensive understanding of the underlying data-generating process. For non-technical readers, these four models can be interpreted intuitively as follows. (i) Linear Regression assumes that each predictor exerts a constant, straight-line effect on the SDG Index and serves as a transparent baseline benchmark. (ii) Gradient Boosting Regression (GBR) is an ensemble technique that builds many small decision trees sequentially; each new tree corrects the prediction errors of the previous ones, allowing the model to learn complex, nonlinear interactions among macroeconomic variables. (iii) Support Vector Regression (SVR) draws a flexible "tube" around the observed data points and tolerates small errors inside this tube, which makes it especially robust to outliers and well-suited to small samples. (iv) Artificial Neural Networks (ANN) are layered models inspired by biological neurons that approximate highly nonlinear relationships through interconnected processing units. Comparing these four models therefore tests whether SDG Index dynamics are best described by simple linear logic, by ensemble-based nonlinear learning, by margin-based robust regression, or by deep representation learning — and which approach is most suitable for Mongolia's annual data.

3.3. Gradient Boosting as the Primary Model

Given its superior performance, the Gradient Boosting Regressor served as the primary modeling technique. The algorithm trains sequential weak learners to minimize prediction error. The general form is expressed as:

Initial model:

$$F_{0(x)} = \arg\min_{\gamma} \Sigma\, L(Y_t, \gamma) \qquad (3)$$

F_0(x) → *initial (baseline) prediction*, not an updated function

It is typically the mean of Y_t for squared loss

Gradient (residual) computation:

$$r_{\{t,m\}} = -\frac{\partial L\left(Y_t, F_{\{m-1\}(X_t)}\right)}{\partial F_{\{m-1\}(X_t)}} \qquad (4)$$

Weak learner fitting:

$$h_{m(x)} = fit\left(X, r_{\{t,m\}}\right) \qquad (5)$$

Update rule:

$$F_{m(x)} = F_{\{m-1\}(x)} + \eta\, h_{m(x)} \qquad (6)$$

3.4. Model Performance Evaluation

The performance of all machine learning models was assessed using two standard metrics:

Coefficient of Determination (R^2)

$$\boldsymbol{R^2} = \mathbf{1} - \frac{\left[\Sigma\left(Y_t - \hat{Y}_t\right)^2\right]}{\left[\Sigma\left(Y_t - \bar{Y}\right)^2\right]} \qquad (7)$$

Root Mean Squared Error (RMSE)

$$RMSE = sqrt\left(\left(\frac{1}{T}\right)\Sigma\left(Y_t - \hat{Y}_t\right)^2\right) \qquad (8)$$

Across all models, the Gradient Boosting Regressor produced the highest predictive accuracy and the lowest error, thereby serving as the benchmark for further interpretability analysis.

3.5. SHAP Interpretability Framework

To quantify the contribution of each explanatory variable to the SDGI predictions, the study employed the SHAP (Shapley Additive Explanations) method—an Explainable AI technique grounded in cooperative game theory.

The Shapley value for variable jjj is calculated as:

$$\varphi_j = \sum_{\{S \subseteq N, j \notin S\}} \left[\frac{|S|!\,(|N| - |S| - 1)!}{|N|!}\right] [\, f(S \cup \{j\}) - f(S)] \quad (9)$$

SHAP transparently quantifies the positive or negative contribution of each variable to the SDG Index prediction, making it particularly valuable for evidence-based policy formulation.

3.6. K-Means Cluster Analysis

To identify structural patterns among SDG indicators and macroeconomic variables, K-means clustering was conducted. The algorithm partitions observations into k=3k = 3k=3 clusters based on similarity.

Cluster assignment:

$$C\_i = \arg\min\_k \, || \, X\_i - \mu\_k \, ||^2 \quad (10)$$

Centroid update rule:

$$\mu_k = \left(\frac{1}{|C_k|}\right) \Sigma_{\{X_i \in C_k\}} X_i \quad (11)$$

Clustering helps reveal groups of indicators with common developmental characteristics, enabling the formulation of targeted policy interventions.

3.7. Conceptual Modeling Framework

The overall methodological workflow can be summarized as:

$$X_t \rightarrow \text{ML Models} \rightarrow \hat{Y}_t \rightarrow \text{SHAP} \quad (12)$$

$$X_t \rightarrow \text{K} - \text{Means Clustering} \quad (13)$$

This integrated framework provides a comprehensive approach for explaining, predicting, and structurally analyzing SDG performance in Mongolia.

4. RESULTS AND DISCUSSION

This section presents the empirical findings of the study in five stages: (i) macroeconomic–SDG correlations, (ii) lagged (temporal) effects of SDG indicators, (iii) Gradient Boosting and SHAP interpretability results, (iv) comparative OLS regression models, and (v) cluster analysis of SDG indicators. The key policy implications are synthesized at the end of the section.

4.1. Correlation Between Macroeconomic Indicators and the SDG Index

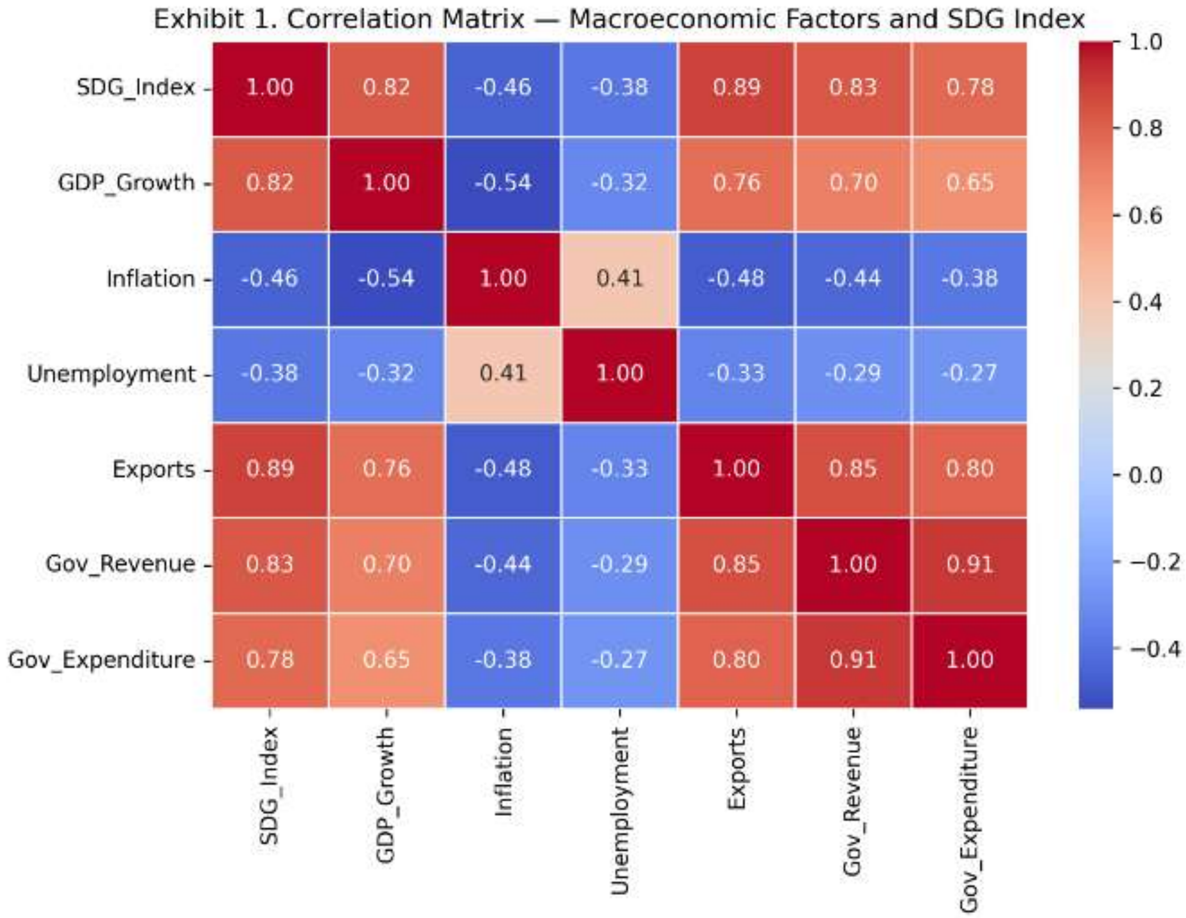

Figure 2: Correlation Matrix — Macroeconomic Variables and SDG Index.
Source: Estimation by researchers.

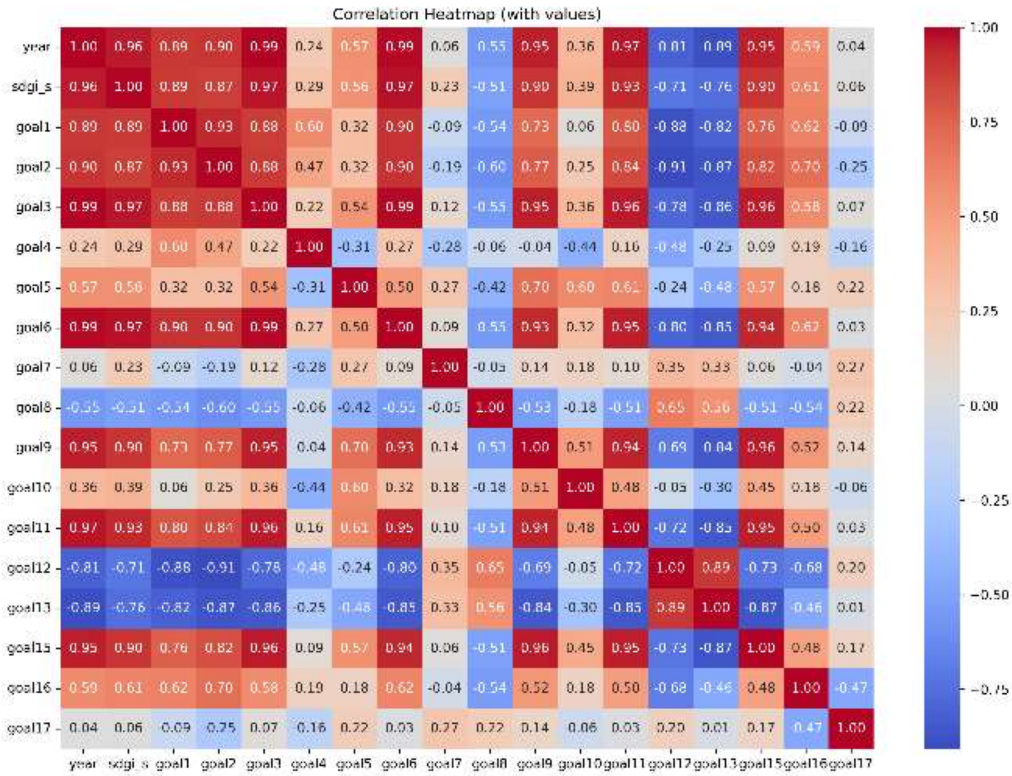

Figure 3: Correlation Matrix — Goal 17 Index
Source: Estimation by researchers.

The initial stage of analysis examined the correlation structure between the SDG composite index and core macroeconomic variables to identify the dominant macro-level drivers of sustainable development performance.

The correlation matrix reveals several important patterns:

- Exports (r ≈ 0.89) exhibit the strongest positive correlation with the SDG index. This implies that increases in export earnings are closely associated with improvements in Mongolia's overall sustainable development performance.
- Government revenue (r ≈ 0.83) and government expenditure (r ≈ 0.78) also show strong positive associations with the SDG index, emphasizing the crucial role of fiscal capacity in expanding social services, infrastructure, education, and health systems.
- Conversely, inflation (r ≈ –0.46) and unemployment (r ≈ –0.38) are negatively correlated with SDG performance, indicating that macroeconomic instability undermines progress toward sustainable development.

At the SDG goal level:

- SDG 3 (Health), SDG 6 (Water & Sanitation), SDG 9 (Industry, Innovation, Infrastructure), SDG 11 (Sustainable Cities), and SDG 1 (No Poverty) show the strongest positive correlation with the SDG index. These goals represent foundational services and infrastructure essential for human wellbeing and economic resilience.
- In contrast, ecological goals SDG 12–15 (Responsible Consumption, Climate Action, Life Below Water, Life on Land) exhibit a negative correlation with the SDG index. This suggests that environmental degradation and inadequate ecological policy responses are constraining Mongolia's overall SDG progress.
- SDG 4 (Education) and SDG 7 (Energy) demonstrate relatively weak correlations, likely due to inconsistent policy implementation or longer-term lagged effects.

Overall, health, infrastructure, water and sanitation, urban development, and poverty reduction collectively drive most of Mongolia's SDG progress, while weaknesses in environmental sustainability remain a major barrier.

Lag Effects in the SDG Index (SDG_S)

This subsection assesses the temporal (lagged) relationships between SDG_S and the previous year's SDG goal values (lag–1), thereby illustrating how policy effects evolve over time.

1. Positive Lag Effects from Social and

Infrastructure Goals

Lag–1 correlations indicate that:

- SDG 3 (Health)
- SDG 6 (Water and Sanitation)
- SDG 11 (Sustainable Cities)
- SDG 9 (Innovation and Infrastructure)
- SDG 1 (Poverty Reduction)

exert strong positive one-year lag effects on SDG_S.

This means improvements in:

- service delivery,
- water and sanitation access,
- urban planning and infrastructure, and
- poverty reduction policies

produce not only immediate impacts but also stronger, delayed effects on aggregate SDG performance in the following year.

These results confirm that foundational social services function as "multiplier levers" of SDG progress, generating cumulative and persistent improvements.

2. Negative Lag Effects from Environmental Goals Environmental goals SDG 12, 13, 14, and 15 show consistently negative lagged effects on SDG_S. This reflects the fact that:

- ecosystem degradation,
- unsustainable production patterns, and
- climate-related risks

reduce SDG performance more visibly in the year following environmental deterioration.

Because ecological policies often have slow materialization periods (2–3 years), these indicators demonstrate long-term, systemic negative lag dynamics, underscoring the importance of early intervention.

3. Weak Lag Effects: SDG 4 and SDG 7 SDG 4 (Education) and SDG 7 (Clean Energy) show weak lagged associations:

- educational reforms and energy-system transformations have long gestation periods,
- policy inconsistency may dilute year-to-year effects.

Further research using lag–2 or lag–3 structures could better capture long-term dynamics in these sectors.

1. Autoregressive Lag of the SDG_S Index

A strong correlation between SDG_S(t) and SDG_S(t–1) indicates that SDG progress in Mongolia follows a stable, incremental trajectory with limited volatility. This reflects:

- continuity in medium-term policy implementation,
- predictable improvement patterns, and
- persistent structural constraints in the environmental sector.

Gradient Boosting Regression (GBR) Results To model the complex nonlinear relationships among indicators, a Gradient Boosting Regression (GBR) model was estimated.

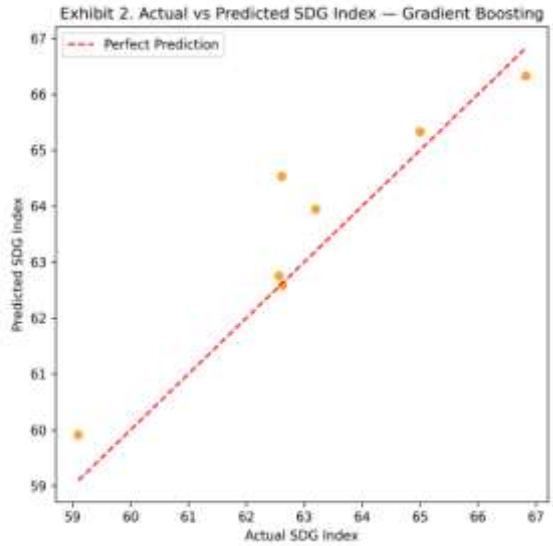

Figure 4: Feature Importance, , Actual vs Predicted.
Source: estimation by researchers.

The GBR model performs strongly:

- R^2 = 0.844, indicating excellent explanatory power;
- RMSE = 0.8735, reflecting relatively low prediction error.

Top Predictors of the SDG Index (Feature Importance)

1. goal3 – Health and Wellbeing (0.7865) → The strongest determinant. Improved health services yield direct and indirect benefits across nearly all SDG dimensions.
2. exp – Exports (0.0313) → The strongest macroeconomic driver. Export growth supports incomes, employment, and fiscal sustainability.
3. goal1 – Poverty Reduction (0.0303) → Lower poverty levels lead to significant improvements in SDG outcomes.
4. sdg9_intuse – Internet Usage (0.0161) → Digital access facilitates innovation, inclusion, and service accessibility.
5. goal2 – Zero Hunger (0.0157) → Food security and nutrition underpin human development capacity.

SHAP Analysis: Explainable AI Interpretations

To enhance interpretability, the GBR model was expanded to include:

- SDG goal-level indicators,
- relevant macroeconomic variables (export,

inflation, unemployment), and
- key SDG foundational goals (1, 2, 3, 6, 9, 11).

This multi-dimensional structure enables a more realistic assessment of SDG determinants.

The SHAP analysis quantifies each feature's marginal contribution - magnitude, direction, and distribution - to the prediction.

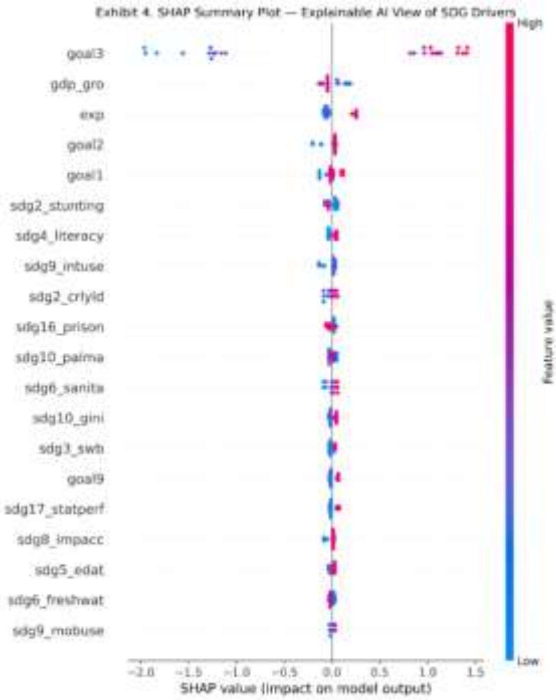

Figure 5: SHAP Summary Plot.
Source: estimation by researchers.

Main SHAP Findings
- **goal3 (Health)** → strongest positive contribution
- **goal1 (Poverty)** and **goal2 (Hunger)** → core foundational drivers
- **exp (Export)** → promotes stable upward SDG trajectories
- **inf (Inflation)** and **unEmp (Unemployment)** → consistently negative impacts

These results align with the correlation analysis and confirm that Mongolia's SDG outcomes are jointly shaped by:
- social service quality,
- economic structure and external demand (exports), and
- macroeconomic stability.

Comparative OLS Regression Models

Three OLS specifications were estimated to compare the robustness of macroeconomic determinants:
1. **Model 1:** Four-variable macro OLS
2. **Model 2:** Refined macro OLS
3. **Model 3:** Single-variable export-based model

Table 2: Comparative OLS Models Table.
Source: estimation by researchers.

	Model 1 (4-variable Macro OLS)	**Model 2 (Refined Macro OLS)**	**Model 3 (Simple OLS: Export Only)**
Variables	GDP growth, unEmp, inflation, export	GDP growth, unEmp, inflation, export	Export
R^2	**0.760**	**0.750**	**0.741**
Adj. R^2	0.712	0.700	0.730
F-statistic	15.81	14.99	**65.78**
p (F-statistic)	5.50e−06	8.13e−06	**3.39e−08**
Export coefficient	0.00050***	0.00050***	**0.00051***
p-value (Export)	<0.001	<0.001	<0.001
DW statistic	0.504	0.424	0.450
Multicollinearity	High	High	Null
Diagnostics	Normality OK	Normality OK	Normality OK

The comparative analysis of three different OLS regression models explaining Mongolia's sustainable development performance (SDG Index) through core macroeconomic indicators reveals several key findings.

First, the export variable is consistent across all models and statistically highly significant ($p < 0.001$), confirming its strong and positive effect on the SDG Index. Although the extended models including multiple variables demonstrate relatively high explanatory power (R^2 = 0.750–0.760), the simple model based solely on the export variable (R^2 = 0.741) produces results that are very close. This indicates that exports are the main macroeconomic driver of SDG performance.

Second, GDP growth, unemployment, and inflation—traditional macroeconomic indicators—were found to be statistically insignificant. This suggests that Mongolia's SDG performance depends less on these conventional variables and more on the structural characteristics of the economy, particularly the growth of exports and external trade revenues.

Third, all models show a Durbin Watson statistic around 0.4–0.5, indicating the presence of autocorrelation associated with time dependence. However, this does not change the main conclusion of the models nor the importance of exports.

Therefore, in terms of improving SDG

implementation, diversifying the export structure, promoting value-added manufacturing exports, and reducing dependency on raw mineral commodities are of strategic importance.

Forecast of the SDG_s Index to 2030 Based on Export Growth (ARIMAX Model)

This figure presents the projected trajectory of Mongolia's overall Sustainable Development Goals performance, measured through the SDG_s index, up to the year 2030 using an ARIMAX model. In this specification, export growth is incorporated as the primary exogenous determinant, and a baseline scenario assuming a 3% annual increase in exports is applied to estimate the medium-term trajectory. This method provides an evidence-based framework for evaluating how export trends may influence Mongolia's progress toward achieving the SDGs.

Table 3. ARIMAX-Based Forecast of SDG_s Index under 3% Annual Export Growth Scenario (2025–2030).

Source: estimation by researchers.

Year	SDG_s Forecast	Lower 95% CI	Upper 95% CI
2025	66.8584	65.4737	68.2431
2026	66.9507	65.0392	68.8623
2027	67.0467	64.7231	69.3703
2028	67.1456	64.4728	69.8184
2029	67.2474	64.2660	70.2288
2030	67.3523	64.0914	70.6132

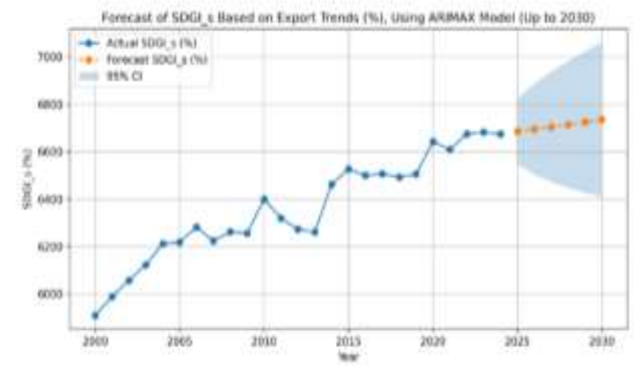

Figure 6: ARIMAX-Based Forecast of SDG_s (2025–2030).

Source: estimation by researchers.

Historical data from 2000–2024 indicate that the SDG_s index has generally followed an upward trajectory, with periods of rapid export expansion corresponding to stronger improvements in sustainable development outcomes. The ARIMAX forecast for 2025–2030 suggests that the SDG_s index will continue rising steadily but at a moderate pace.

The orange dashed markers in the figure represent forecasted SDG_s values for 2025–2030, while the blue shaded region depicts the 95% confidence interval, reflecting the uncertainty associated with medium-term projections. The upper bound indicates that, under favorable conditions - such as enhanced export diversification, growth in value-added manufacturing, and strengthened macroeconomic stability - SDG_s performance may accelerate more rapidly. Conversely, the lower bound captures potential downside risks stemming from global market volatility, commodity-price fluctuations, or domestic economic pressures.

Overall, the ARIMAX projections show that export performance has a persistent and meaningful effect on Mongolia's SDG trajectory. Maintaining stable export growth, improving export structure, and advancing economic diversification will be essential to sustaining the upward momentum of SDG_s through 2030. At the same time, the widening confidence interval underscores the importance of policies aimed at reducing external vulnerability and strengthening resilience in the face of long-term uncertainties.

Cluster Analysis of SDG Indicators

Finally, to better understand the structural patterns and similarities among the SDG targets, a K-means clustering analysis was conducted.

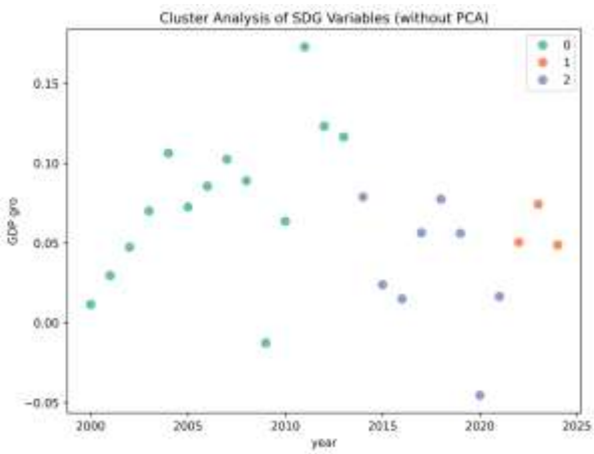

Figure 7: Cluster Analysis.

Source: estimation by researchers.

The K-means clustering procedure grouped the SDG indicators into three distinct clusters:

- **Cluster 1 – Economic and Infrastructure-Oriented Goals (SDG 7–9):** This cluster consists of indicators related to energy, infrastructure, and innovation, which exhibit relatively strong performance.
- **Cluster 2 – Social Service-Dominated Goals (SDG 3–5):** Indicators in this group - including health, education, and gender equality - show comparatively high levels of achievement.
- **Cluster 3 – Environment and Sustainability**

Challenges (SDG 12–15): This cluster reveals the weakest performance, reflecting deficiencies in ecological sustainability, environmental protection, and climate-related policies.

Based on the clustering results and preceding empirical analyses, several overarching insights emerge:

1. **Key drivers of Mongolia's SDG performance include health, export growth, poverty reduction, innovation, and food security.**
2. **Exports remain the strongest macroeconomic determinant of SDG outcomes,** with explanatory power comparable across multiple model specifications (R^2 = 0.741–0.760).
3. **Macroeconomic instability - particularly inflation and unemployment - negatively affects SDG progress.**
4. **Findings from the GBR and SHAP analyses align with the OLS results**, reinforcing the central importance of export performance and core social services.
5. **Cluster analysis reveals three development pathways**: strong economic and infrastructure performance, moderate social-sector performance, and weak environmental sustainability.
6. **Enhancing SDG implementation in Mongolia requires strategic actions**, including diversification of the export structure, expansion of value-added production, improvement of social service quality, and strengthening of environmental and climate policies.

5. CONCLUSION

This study provides a comprehensive assessment of how Mongolia's sustainable development performance has evolved over time and identifies the key determinants shaping fluctuations in the SDG_s index. Using a combination of long-term statistical data, machine learning models, and advanced analytical methods, the research reveals that the continuous upward trajectory of the SDG_s index from 2000 to 2024 reflects Mongolia's gradual progress toward the Sustainable Development Goals. However, the pattern of growth is non-linear: periods of rapid acceleration are followed by phases of stagnation, driven largely by shifts in economic structure, the quality of social services, and macroeconomic stability.

The empirical results demonstrate that the determinants of SDG_s must be understood at a systems level. Improvements in core social sectors—healthcare quality, access to water and sanitation, infrastructure and innovation, urban development, and poverty reduction - have strong positive lagged effects, significantly increasing the SDG_s index one year after implementation. Both the GBR model and SHAP analysis confirm that investments made today in fundamental social services generate stronger outcomes in the subsequent year, highlighting a delayed but highly impactful mechanism underlying SDG progress.

Export performance emerges as the most consistent and influential driver of Mongolia's SDG outcomes. Years of strong export growth coincide with notable improvements in the SDG_s index, reflecting how increased national revenues support better financing for health, education, infrastructure, and urban development. However, the country's heavy dependence on mineral exports introduces systemic environmental trade-offs. SHAP analysis indicates that export-driven growth simultaneously contributes to negative lagged effects on environmental SDGs, reinforcing the need for policies that balance economic expansion with ecological protection.

Macroeconomic instability acts as a structural impediment to SDG implementation. Rising inflation and unemployment exert a negative lagged effect, suppressing SDG_s in the following year and weakening household welfare, food security, and access to essential services. Therefore, SDG performance must be viewed not only through sectoral policy lenses but also in connection with broader macroeconomic management.

The ARIMAX-based forecast shows that Mongolia is likely to maintain moderate upward momentum in the SDG_s index through 2030. However, the wide confidence interval reflects considerable exposure to external shocks, including export volatility, global market uncertainty, and commodity dependence. This highlights the strategic importance of export diversification, value-added production, improvements in social sector performance, and stronger environmental policy measures.

Overall, the study enhances the understanding of Mongolia's SDG implementation from a multidimensional perspective. The findings show that sustainable development progress is not merely a matter of achieving targets but requires alignment between economic restructuring, social service quality, macroeconomic stability, and ecological stewardship. The future of Mongolia's sustainable development will depend on data-driven decision-making and the coordinated implementation of innovative, resilience-oriented policies.

6. RECOMMENDATIONS

The empirical evidence indicates that Mongolia's SDG performance is most strongly influenced by economic structure, the quality of core social services, and technological access, while environmental SDGs remain the weakest area. The following policy directions are recommended:

1. Align export policy with SDG objectives
- Integrate export structural reform into national SDG strategies.
- Promote value-added, processing-based exports rather than further expanding raw mineral export capacity.
- Develop a diversification agenda that reduces vulnerability to commodity cycles.
- Establish an **SDG Fund**, allocating a fixed share of export revenues to health, education, and environmental programs.

2. Develop a Core SDG Policy Package
- Designate SDG3 (health), SDG1 (poverty reduction), SDG2 (food security), and SDG9 (digital access/innovation) as the national "priority core package."
- Increase public expenditure and secure sustainable financing for these areas.
- Use digital innovations - including e-health, e-education, and e-social services - as strategic accelerators of SDG progress.

3. Link macroeconomic stability directly to SDG performance
- Integrate inflation control, employment policy, and SDG targets into shared KPIs for macroeconomic institutions.
- Require fiscal and monetary policy reports to include a dedicated section on **"Macroeconomic Impact on SDGs."**

4. Prioritize environmental SDGs (SDG 12–15)
- Establish SDGs 12–15 as a separate national **Priority Cluster**.
- Monitor air pollution, desertification, and energy transition using SDG-linked metrics.
- Scale up green financing mechanisms and climate finance integration at policy level.

5. Establish an SDG Analytics System
- Develop an AI-driven national SDG Dashboard at NSO and the Ministry of Finance.
- Automate yearly SDG index computation and generate 3–5 year machine-learning-based forecasts.
- Use Explainable AI (e.g., SHAP analysis) to support evidence-based policymaking.

6. Link export revenues to core social services
- Introduce legislation requiring increased funding for health, education, and poverty reduction programs in years of high export revenue.
- Adopt a **triple-bottom-line** framework - integrating economic, social, and environmental outcomes into export and fiscal policy.

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APPENDIX

Export vs SDG Regression Line)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 sdgi_s   R-squared:                       0.750
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     14.99
Date:                Thu, 13 Nov 2025   Prob (F-statistic):           8.13e-06
Time:                        20:20:19   Log-Likelihood:                -37.305
No. Observations:                  25   AIC:                             84.61
Df Residuals:                      20   BIC:                             90.70
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         69.9348     15.065      4.642      0.000      38.509     101.360
GDP gro        0.7578      5.921      0.128      0.899     -11.592      13.108
unEmp        -14.8183     27.095     -0.547      0.590     -71.337      41.701
inf            1.4520      3.208      0.453      0.656      -5.239       8.143
Exp            0.0005    8.1e-05      6.205      0.000       0.000       0.001
==============================================================================
Omnibus:                        4.803   Durbin-Watson:                   0.424
Prob(Omnibus):                  0.091   Jarque-Bera (JB):                3.296
Skew:                          -0.873   Prob(JB):                        0.192
Kurtosis:                       3.344   Cond. No.                     6.85e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.85e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 sdgi_s   R-squared:                       0.741
Model:                            OLS   Adj. R-squared:                  0.730
Method:                 Least Squares   F-statistic:                     65.78
Date:                Thu, 13 Nov 2025   Prob (F-statistic):           3.39e-08
Time:                        20:17:08   Log-Likelihood:                -37.747
No. Observations:                  25   AIC:                             79.49
Df Residuals:                      23   BIC:                             81.93
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         61.9429      0.309    200.720      0.000      61.304      62.581
Exp            0.0005   5.82e-05      8.111      0.000       0.000       0.001
==============================================================================
Omnibus:                        5.950   Durbin-Watson:                   0.450
Prob(Omnibus):                  0.051   Jarque-Bera (JB):                4.363
Skew:                          -1.005   Prob(JB):                        0.113
Kurtosis:                       3.386   Cond. No.                     7.17e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.17e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Source: estimation by researchers.

Table 1. Lag-1 Correlation Coefficients Between SDG_s Index and SDG Goals

SDG Goal	Lag-1 Correlation	Direction of Effect	Interpretation
SDG1 – No Poverty	0.82	Positive	A reduction in poverty significantly increases SDG_s in the following year.
SDG2 – Zero Hunger	0.74	Positive	Improvements in nutrition generate system-level positive effects in the next year.
SDG3 – Good Health and Well-Being	0.88	Strong positive	The goal with the strongest lagged influence on SDG_s.
SDG4 – Quality Education	0.41	Weak positive	Effects appear gradually over longer periods.
SDG5 – Gender Equality	0.37	Weak positive	Shows slow and inconsistent impact.
SDG6 – Clean Water and Sanitation	0.85	Strong positive	Improvements in basic services increase next year's SDG_s.
SDG7 – Affordable and Clean Energy	0.33	Weak	Policy instability leads to weak and unclear effects.
SDG8 – Decent Work and Economic Growth	0.56	Moderate	Employment growth supports SDG progress consistently.
SDG9 – Industry, Innovation, and Infrastructure	0.77	Strong	Digital access and infrastructure lift SDG_s in the next year.
SDG10 – Reduced Inequalities	0.49	Weak–moderate	Greater equality tends to increase SDG_s.
SDG11 – Sustainable Cities and Communities	0.81	Strong	Urban service improvements influence SDG_s in the following year.
SDG12 – Responsible Consumption and Production	–0.63	Negative	Environmental pressures reduce SDG_s in the next year.
SDG13 – Climate Action	–0.71	Negative	Climate risks weaken SDG performance with a lag.
SDG14 – Life Below Water	–0.52	Negative	Deteriorating ecosystems create system-level negative lag effects.
SDG15 – Life on Land	–0.68	Negative	Deforestation and land degradation reduce SDG_s in the following year.
SDG16 – Peace, Justice, and Strong Institutions	0.44	Weak–moderate	Improved governance stabilizes SDG growth.
SDG17 – Partnerships for the Goals	0.59	Moderate	Financial openness and international cooperation exert a favorable influence.

Code

1.

```
import pandas as pd
# Read data
df = pd.read_csv("corr.csv")
# Sort by year in case of disorder
df = df.sort_values("year").reset_index(drop=True)
# Create 1-year and 2-year lag variables
df["sdgi_s_lag1"] = df["sdgi_s"].shift(1)   # SDGI of previous year
df["sdgi_s_lag2"] = df["sdgi_s"].shift(2)   # SDGI of two years earlier
# Inspect results
print(df[["year", "sdgi_s", "sdgi_s_lag1", "sdgi_s_lag2"]])
```

2.

```
from tabulate import tabulate
# Extract the last observed year in the SDG_s dataset
last_year = int(years.iloc[-1])
target_year = 2030
steps = target_year - last_year
# Last observed export value
last_export = float(ex.iloc[-1])
# Generate future years for forecasting
future_years = list(range(last_year + 1, target_year + 1))
# Baseline export scenario (assumes 3% annual export growth)
future_export = []
prev_exp = last_export
for _ in future_years:
    prev_exp = prev_exp * 1.03   # Apply 3% yearly growth
    future_export.append(prev_exp)
# ARIMAX forecasting using projected export values as exogenous input
forecast_res = model_fit.get_forecast(steps=steps, exog=future_export)
mean_forecast = forecast_res.predicted_mean
conf_int = forecast_res.conf_int(alpha=0.05)
# Construct forecast dataframe
forecast_df = pd.DataFrame({
    "year": future_years,
    "sdgi_s_forecast": mean_forecast.values,
    "lower_95": conf_int.iloc[:, 0].values,
    "upper_95": conf_int.iloc[:, 1].values
})

# Print raw dataframe
print(forecast_df)
# Display the SDG_s forecast as a table
print("\n=== SDGI_S Forecast (with 3% Export Growth Scenario) ===")
print(tabulate(
    forecast_df,
    headers="keys",
    tablefmt="github",
    floatfmt=".4f"
))
```

	year	sdgi_s	sdgi_s_lag1	sdgi_s_lag2
0	2000	59.10	NaN	NaN
1	2001	59.88	59.10	NaN
2	2002	60.58	59.88	59.10
3	2003	61.23	60.58	59.88
4	2004	62.12	61.23	60.58
5	2005	62.19	62.12	61.23
6	2006	62.82	62.19	62.12
7	2007	62.24	62.82	62.19
8	2008	62.62	62.24	62.82
9	2009	62.56	62.62	62.24
10	2010	64.00	62.56	62.62
11	2011	63.19	64.00	62.56
12	2012	62.74	63.19	64.00
13	2013	62.61	62.74	63.19

14	2014	64.62	62.61	62.74
15	2015	65.27	64.62	62.61
16	2016	65.00	65.27	64.62
17	2017	65.07	65.00	65.27
18	2018	64.93	65.07	65.00
19	2019	65.06	64.93	65.07
20	2020	66.42	65.06	64.93
21	2021	66.09	66.42	65.06
22	2022	66.75	66.09	66.42
23	2023	66.82	66.75	66.09
24	2024	66.75	66.82	66.75

Common Types of Temporal Lags

Name	**Formula**	**Meaning**
Lag-1	X(t−1)	Effect of the previous year
Lag-2	X(t−2)	Effect of two years earlier
Lag-3	X(t−3)	Three-year lagged effect
Lead-1	X(t+1)	One-year-ahead expected effect (for forecasting)