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Article

Application of country classification methodology for enhancing the effectiveness of official development assistance (ODA) policies: Utilization of decision tree analysis

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Abstract: Objective: As the scale and importance of official development assistance (ODA) continue to grow, the need to enhance the effectiveness of ODA policies has become more critical than ever before. In this context, it is essential to systematically classify recipient countries and establish tailored ODA policies based on these classifications. The objective of this study is to identify an appropriate methodology for categorizing developing countries using specific criteria, and to apply it to actual data, providing valuable insights for donor countries in formulating future ODA policies. **Design/Methodology/Approach:** The data used in this study are the basic statistics on the Sustainable Development Goals (SDGs) published annually in the SDGs Report. The analytical method employed is decision tree analysis. **Results:** The results indicate that the 167 countries analyzed were classified into 10 distinct nodes. The study further limited the scope to the five nodes representing the most disadvantaged developing countries and suggested future directions for aid policies for each of these nodes.

Keywords: classification of developing countries; decision tree analysis; ODA effectiveness

1. Introduction

1.1. Research background and necessity

Official Development Assistance (ODA) has become a significant tool in promoting economic and social development and reducing poverty in developing countries. With the growing emphasis on supporting sustainable development in developing countries, donor nations have been making concerted efforts to establish more systematic and effective ODA policies.

However, for ODA to achieve tangible results, it is essential to carefully analyze the economic, social, and political environment of recipient countries and develop tailored aid strategies based on this analysis. Since each developing country differs in its level of economic development, political stability, and socio-cultural background, a one-size-fits-all approach to aid policies has inherent limitations (Addison et al., 2009; Collier and Hoeffler, 2004; Deaton, 2013; Kim and Davis, 2023; Osei and Miller, 2022).

Given that approximately 140 developing countries are the main recipients of ODA in the international community, formulating aid strategies that reflect the specific circumstances of each country presents a considerable challenge. This can lead to inefficient allocation of resources during the aid provision process and hinder the practical effectiveness of ODA. Thus, there is a need for a systematic approach that classifies recipient countries according to a set of criteria based on their diverse characteristics and establishes effective aid policies tailored to each category (Castells, 1999; Heston et al., 2012; Kosack and Tobin, 2006; Nguyen and Wilson, 2022; Patel, 2023; Rodriguez et al., 2022; Todaro and Smith, 2011). This approach can maximize the effectiveness of ODA, enable more efficient allocation of limited resources, and promote sustainable development by proposing policies that are suited to the specific conditions of each country group.

Although many previous studies have emphasized the need for aid policies that reflect the unique characteristics of developing countries, few have systematically applied such classifications to typologize countries and define specific policy directions for each type (Cheney and Syrquin, 1975; Easterly, 2006; Garcia and Johnson, 2023; Knack, 2004; Kharas and Rogerson, 2012; Kaufman et al., 2009; United Nations, 2015). Particularly, there is a lack of research that comprehensively reflects the characteristics of recipient countries, classifies them systematically, and derives efficient and effective aid strategies based on this classification. Therefore, this study aims to present a methodology for classifying countries that considers the unique traits of recipient countries, thereby enhancing the effectiveness of ODA for developing countries.

1.2. Research objectives

The purpose of this study is to maximize the effectiveness of official development assistance (ODA) for developing countries by comprehensively analyzing the economic, social, and political characteristics of recipient countries and establishing a classification system that can guide aid policy directions. The specific objectives of this study are as follows: First, to identify the characteristics of each recipient country by comprehensively analyzing their level of economic development, political stability, and socio-cultural background, and to categorize them using statistical methods such as Decision Tree Analysis. By grouping countries based on these analyses, this approach aims to enable a strategic approach that respects the individual specificities of each country while maintaining a cohesive overall strategy.

Second, based on the classification of countries into different groups, to suggest strategic directions for establishing effective aid policies that are suitable for each group. This approach will support ODA donor countries in formulating systematic and efficient aid policies, enhancing the effectiveness of ODA by reflecting the unique characteristics of recipient countries.

Third, to derive concrete policy implications so that the classification methodology proposed in this study can be utilized in actual ODA policy-making processes. The aim is to provide donor countries with guidelines for developing more sophisticated aid strategies, thus supporting sustainable development in developing countries and strengthening international cooperation.

This study is expected to enhance the effectiveness of ODA policies through the classification of recipient countries based on their characteristics, ultimately contributing to the self-sustained development of developing nations. Furthermore, the country classification methodology proposed in this study can serve as essential foundational data for the formulation of future aid policies in various developing countries and function as a valuable policy tool for maximizing the practical outcomes of ODA.

2. Theoretical discussion and review of previous research

Official Development Assistance (ODA) for developing countries is a key instrument of international development cooperation aimed at promoting economic and social development, reducing poverty, and improving the quality of life in recipient countries. For the successful implementation of ODA, a systematic approach that reflects the economic, political, and social characteristics of recipient countries is required (Williamson, 1990).

To achieve this, it is crucial to classify recipient countries based on specific criteria and design effective aid policies tailored to each classification (Alesina and Dollar, 2000; Collier, 2008; Collier and Dollar, 2002; Hansen and Tarp, 2001). A one-size-fits-all approach that does not consider the unique characteristics of each country may not adequately address the development needs of recipient countries and may lead to inefficient use of aid resources. Therefore, research that categorizes recipient countries and derives differentiated aid strategies for each category is vital for enhancing the effectiveness of ODA policies.

2.1. Significance and importance of enhancing oda policy effectiveness through country classification

Research on ODA policies that utilize country classification methodologies has primarily emphasized the need for tailored approaches that align with the specific characteristics of recipient countries. These classifications should comprehensively consider factors such as the developmental stage, economic structure, political stability, and institutional conditions of recipient countries. By designing aid policies suitable for each classified group, the effectiveness of ODA can be maximized (Angelsen and Wunder, 2003; Baneajee and Dufli, 2011; Fernandez and Ahmed, 2023; Moyo, 2009; Sen, 1999; Smith and Brown, 2023). Recently, the paradigm of international development cooperation has shifted away from mere financial assistance toward strengthening the self-sustained development capabilities of recipient countries. As a result, the significance of customized aid policies based on country classification has become even more pronounced.

2.2. Research trends in other countries

Internationally, research on country classification to enhance the effectiveness of ODA policies has been actively conducted (Lee et al., 2022; OECD, 2021; Pritchett and Woolcock, 2004; Ravallion, 2011; United Nations, 2015; World Bank, 2006). Major ODA donors such as the United States, the European Union (EU), and Japan have been making continuous efforts to classify recipient countries according to their specific characteristics and to develop strategic approaches tailored to these classifications to formulate their aid policies accordingly.

2.2.1. Case of the United States

The United States Agency for International Development (USAID) sets its development cooperation goals on a country-by-country basis and implements ODA policies using a country classification system that comprehensively considers the development levels and cooperation needs of recipient countries. For instance, USAID categorizes recipient countries into low-income, middle-income, and high-income countries based on their economic development levels and devises corresponding policy responses.

For low-income countries, USAID focuses on infrastructure development and institutional reforms aimed at reducing poverty and fostering economic self-reliance. In contrast, for middle-income countries, the primary objectives are to promote economic and social development through technical cooperation and capacity-building initiatives.

2.2.2. Case of the European Union (EU)

The European Union, in its revised European Consensus on Development policy of 2017, clearly outlines the need for a tailored aid approach that reflects the diverse characteristics of recipient countries. The EU classifies recipient countries based on criteria such as economic growth rates, political stability, and social development indicators, and strives to propose effective development cooperation plans tailored to each classification. Furthermore, the EU considers the levels of human rights, democracy, and governance as critical factors in its country classification, thereby ensuring that its development cooperation policies are reflective of the unique characteristics of each recipient country.

2.2.3. Case of Japan

The Japan International Cooperation Agency (JICA) analyzes the development challenges and plans of each recipient country and categorizes them into groups such as "Development Strategy-Oriented" and "Cooperation Enhancement-Oriented." Through this classification, Japan aims to strengthen technical cooperation and human resource development support tailored to the specific needs of recipient countries, thereby promoting efficient allocation of aid resources. Additionally, JICA evaluates the resource utilization capacity and policy commitment of recipient countries to set future cooperation directions, placing emphasis on enhancing the self-sustained development capabilities of these countries.

2.3. Review of previous studies and differentiation of this study

This study categorizes the existing research into three main groups for review to clarify how its methodology differs from prior country classification studies and how it intends to overcome the limitations of existing research. Through this review, the study aims to establish its unique contribution to the field and highlight the practical implications of its approach for ODA policy-making.

2.3.1. Studies on country classification based on economic indicators

The most common approach in existing country classification studies is to categorize countries based on economic indicators. For instance, the World Bank classifies countries into low-income, middle-income, and high-income categories based on Gross National Income (GNI) per capita (United Nations, 2014; World Bank, 2006). This classification allows for an easy comparison of countries based on their economic development levels and assists in setting priorities for economic support during policy formulation.

However, this approach has limitations due to its focus solely on economic indicators, failing to adequately reflect the social, environmental, and institutional characteristics of countries. For example, classifications based on GNI per capita or GDP do not consider factors such as economic inequality, population distribution, or social development, making it challenging to achieve comprehensive country typologies. Furthermore, such economically centered classifications have limited policy implications and may not be effective in designing aid policies that account for the diverse characteristics of recipient countries.

2.3.2. Studies on country classification based on political and institutional factors

The second group of studies focuses on categorizing countries based on political and institutional factors such as political stability, rule of law, and institutional capacity (Collier and Hoeffler, 2004). For example, research that utilizes the Political Stability Index or the Worldwide Governance Indicators (WGI) classifies countries according to their levels of political stability and institutional efficiency (World Bank, 2023; World Bank, 1998). This type of classification is useful for assessing whether a particular country has the absorptive capacity to effectively utilize aid, highlighting the importance of considering institutional capabilities for ODA policies to achieve practical outcomes.

However, such an approach also tends to overlook the economic, social, and environmental characteristics of recipient countries by focusing exclusively on political factors. Even if a country demonstrates strong political stability or institutional capacity, it may still face significant economic or social development challenges. Therefore, a classification based solely on political indicators may have limitations in enhancing the overall effectiveness of aid policies.

2.3.3 Studies on country classification based on social and environmental factors

The third group of studies categorizes countries primarily based on social and environmental factors. Such research often utilizes indicators like the Human Development Index (HDI), Environmental Sustainability Index (ESI), education levels, and health status to classify countries (UNDP, 2022). For example, the United Nations Development Programme (UNDP) categorizes countries into high, medium, and low human development groups using HDI, which is helpful for understanding the overall social development status of countries.

However, this approach has its limitations as it does not adequately reflect the interactions between social and environmental factors across different countries. Additionally, by excluding economic and political indicators, this type of classification may not provide a comprehensive view of a country's overall development status. Using only HDI or ESI for country classification fails to capture the complex interrelationships between social and environmental factors and does not clearly explain how these factors interact with a country's economic development or political stability.

2.3.4. Rationale for using SDGS as key indicators in country classification

In this research paper, the Sustainable Development Goals (SDGs) indicators have been chosen as the primary independent variables for classifying countries due to their comprehensive nature in reflecting a nation's overall development status. The

SDGs, established by the United Nations in 2015, cover a broad spectrum of development aspects, including economic growth, social inclusion, and environmental sustainability. Each of the 17 SDGs encompasses multiple indicators that collectively evaluate the development conditions and capacities of countries across various domains. By using these SDGs indicators, this study aims to provide a more holistic and nuanced understanding of the development status of each country compared to traditional single-variable classification methods.

Therefore, the SDGs indicators are not only theoretically justified as key classification variables but also practically essential for developing a robust and comprehensive country classification model. This study's approach, which combines SDGs with GDP per capita in a Decision Tree Analysis, overcomes the limitations of previous research that relied on single-variable classifications. It establishes a stronger foundation for designing aid policies that are better aligned with the diverse development needs of recipient countries.

The names of each SDG and the sample indicators included in each SDG are presented in the **Table 1** below.

Table 1. Names of SDGs and their sample indicators.

SDG No.	SDG Name	Key areas	Sample indicators
1. SDG 1	1. No poverty	2. Eradication of extreme poverty	3. Proportion of population below the international poverty line
		4. Social protection coverage	5. Coverage of social protection systems, including social floors
		6. Access to basic services	7. Proportion of population living in households with access to basic services
2. SDG 2	8. Zero hunger	9. End hunger and ensure access to safe, nutritious food	10. Prevalence of undernourishment
		11. Agricultural productivity and sustainability	12. Agricultural productivity, food production per unit of labor
		13. Food security and malnutrition	14. Prevalence of moderate or severe food insecurity
3. SDG 3	15. Good health and well-being	16. Maternal and child mortality	17. Maternal mortality ratio, under-5 mortality rate
		18. Communicable and non-communicable diseases	19. Incidence of HIV, malaria, tuberculosis, cardiovascular diseases
		20. Universal health coverage	21. Coverage of essential health services
4. SDG 4	22. Quality education	23. Access to education	24. Participation rate in early childhood education, primary and secondary education
		25. Literacy and numeracy	26. Proportion of youth and adults with literacy and numeracy skills
		27. Quality of education systems	28. Proportion of teachers who are trained in education
5. SDG 5	29. Gender equality	30. End discrimination against women and girls	31. Proportion of seats held by women in national parliaments
		32. Gender-based violence	33. Proportion of women subjected to violence
		34. Equal access to leadership and economic resources	35. Proportion of women in managerial positions, access to financial resources

Table 1. (*Continued*).

SDG No.	SDG Name	Key areas	Sample indicators
6. SDG 6	36. Clean water and sanitation	37. Access to safe and affordable drinking water	38. Proportion of population using safely managed drinking water services
		39. Sanitation and hygiene	40. Proportion of population using safely managed sanitation services
		41. Water quality and scarcity	42. Freshwater withdrawal as a proportion of available freshwater resources
7. SDG 7	43. Affordable and clean energy	44. Access to affordable, reliable, sustainable energy	45. Proportion of population with access to electricity, reliance on clean energy sources
		46. Energy efficiency	47. Energy intensity measured in terms of primary energy and GDP
		48. Renewable energy	49. Renewable energy share in total final energy consumption
8. SDG 8	50. Decent work and economic growth	51. Employment and decent work	52. Unemployment rate, labor force participation rate
		53. Economic growth	54. Annual growth rate of real GDP per capita
		55. Productive employment and decent work for all	56. Proportion of informal employment in non-agriculture sectors
9. SDG 9	57. Industry, innovation, and infrastructure	58. Resilient infrastructure	59. Proportion of rural population who live within 2 km of an all-season road
		60. Promote inclusive industrialization	61. Manufacturing value added as a proportion of GDP
		62. Innovation and research	63. Expenditure on research and development as a percentage of GDP
10. SDG 10	64. Reduced inequality	65. Income inequality	66. Income share held by lowest 40% of the population
		67. Social, economic, and political inclusion	68. Proportion of population living below 50% of median income
		69. Equal opportunity and reduce inequalities	70. Policies to reduce inequality of outcome, including social protection systems
11. SDG 11	71. Sustainable cities and communities	72. Access to safe housing	73. Proportion of urban population living in slums or informal settlements
		74. Sustainable transportation	75. Proportion of population that has convenient access to public transportation
		76. Urbanization and sustainable development	77. Proportion of urban area covered by forests or green spaces
12. SDG 12	78. Responsible consumption and production	79. Sustainable consumption and production patterns	80. Material footprint, material footprint per capita, and material footprint per GDP
		81. Waste reduction and recycling	82. National recycling rate, tons of material recycled
		83. Sustainable management of resources	84. Sustainable public procurement policies
13. SDG 13	85. Climate action	86. Mitigate climate change	87. CO2 emissions per capita, adaptation strategies to climate risks
		88. Strengthen resilience to climate-related disasters	89. Number of countries with national disaster risk reduction strategies
		90. Climate financing	91. Mobilized amount of USD per year starting in 2020 accountable towards the $100 billion commitment

Table 1. (*Continued*).

SDG No.	SDG Name	Key areas	Sample indicators
14. SDG 14	92. Life below water	93. Conservation and sustainable use of oceans, seas, and marine resources	94. Proportion of fish stocks within biologically sustainable levels
		95. Marine pollution	96. Proportion of wastewater safely treated
		97. Protection of marine and coastal ecosystems	98. Coverage of protected areas in relation to marine areas
15. SDG 15	99. Life on land	100. Protection and restoration of terrestrial ecosystems	101. Forest area as a proportion of total land area
		102. Combat desertification and halt biodiversity loss	103. Proportion of important sites for terrestrial and freshwater biodiversity
		104. Sustainable use of terrestrial ecosystems	105. Red List Index, Proportion of land that is degraded over total land area
16. SDG 16	106. Peace, justice, and strong institutions	107. Reduce violence and conflict	108. Homicide rate per 100,000 population
		109. Access to justice	110. Proportion of unsentenced detainees as a proportion of overall prison population
		111. Inclusive, participatory decision-making	112. Proportion of population satisfied with their last experience of public services
17. SDG 17	113. Partnerships for the goals	114. Strengthen global partnerships for sustainable development	115. Amount of total official development assistance (ODA) contributed
		116. Mobilize financial resources for developing countries	117. Proportion of countries reporting progress in multi-stakeholder development effectiveness monitoring
		118. Enhance technology and innovation capacity	119. Number of countries with national development plans aligned with SDGs

Source: 2023 sustainable development report (2023).

2.4. Differentiation of this study from previous research

This study aims to overcome the limitations of the three research groups mentioned above and present a more comprehensive and systematic methodology for country classification. While previous studies have often focused on classifying countries based on specific factors—such as economic, political, or social indicators—resulting in limited applicability to tailored aid policy formulation, this study utilizes indicators from Sustainable Development Goals (SDGs) 1 through 17 as independent variables to capture a wider range of country characteristics.

The SDGs comprehensively reflect the economic, social, environmental, and institutional development of countries, enabling a more in-depth analysis of each country's development status and unique attributes.

Moreover, unlike previous studies that relied heavily on economic indicators (e.g., GDP per capita, GNI) or a single political indicator (e.g., Political Stability Index) for country classification, this study employs a machine-learning-based Decision Tree Analysis, using SDG indicators and GDP per capita as dependent variables. By applying machine learning techniques, this study systematically analyzes the interrelationships among various variables, leading to a more sophisticated and inclusive classification of recipient countries. This approach stands apart from earlier studies that depended on single-variable classifications or simple statistical methods, providing a more comprehensive reflection of recipient countries' characteristics and establishing a robust foundation for formulating more effective aid policies tailored to each group.

Therefore, this study distinctly differentiates itself from existing research by enhancing the effectiveness of ODA policies through a country classification system that considers a broader spectrum of recipient country characteristics. Ultimately, it aims to support the sustainable development of developing countries, making a meaningful contribution to the existing body of research on ODA policy-making.

3. Research methodology

This study aims to enhance the effectiveness of Official Development Assistance (ODA) policies for developing countries by proposing a country classification methodology that reflects the unique characteristics of recipient countries. To achieve this, the study employs Decision Tree Analysis, a machine learning technique, to categorize recipient countries and propose effective aid policy directions for each category. This section provides a detailed explanation of the research's target countries and data, variable settings, analytical methods, and tools used for the analysis.

3.1. Target countries and data

The primary target countries for analysis are those that receive development assistance; however, it is deemed more appropriate to classify all countries, including both developed and developing ones, based on the same criteria before narrowing the focus to developing countries. Therefore, the study includes 167 countries worldwide for which Sustainable Development Goals (SDGs) indicators are available. The target countries for analysis are those listed in the 2023 edition of the SDGs REPORT 2023. Countries with missing data or a lack of usable SDGs indicators were excluded from the study. Consequently, a total of 167 countries were selected as the final analytical subjects, and the classification of these countries was carried out based on the SDGs indicators.

The data used in this study is based on the Sustainable Development Report 2023: Implementing the SDG Stimulus (Dublin University Press, 2023), which provides indicator values for the 17 Sustainable Development Goals (SDGs) of each country (**Table 2**).

Table 2. Descriptive statistics of 17 SDGs variables.

Variable	N of countries	Min	Max	Mean	Std
sdg1	151	0	100	75.23	31.17
sdg2	166	19.81	83.4	59.8	10.62
sdg3	166	12.95	97.12	69.69	20.35
sdg4	166	1.23	99.76	76.51	23.18
sdg5	166	13.05	94.02	63.29	16.4
sdg6	166	32.6	95.06	66.71	14.09
sdg7	166	8.7	99.55	61.41	20.36
sdg8	166	39.54	93.38	71.95	10.59
sdg9	166	1.65	99.13	51.6	26.56
sdg10	149	0	100	62.92	27.35

Table 2. (*Continued*).

Variable	N of countries	Min	Max	Mean	Std
sdg11	166	13.83	99.86	72.18	18.22
sdg12	166	37.73	98.81	79.78	16.09
sdg13	166	0	99.93	82.12	21.18
sdg14	126	36.58	90.39	65.49	11.48
sdg15	166	26.48	97.85	66.64	14.18
sdg16	166	29.44	93.84	61.55	15.52
sdg17	166	29.35	94.03	60.95	12.99

The SDGs serve as a comprehensive set of indicators that evaluate the economic, social, and environmental development levels of each country. In this study, these SDG indicators are used as independent variables to categorize countries based on their specific characteristics. The 17 SDG goals include objectives such as reducing poverty (SDG 1), ending hunger (SDG 2), ensuring quality education (SDG 4), and combating climate change (SDG 13), among others. Each SDG goal consists of detailed sub-indicators designed to measure various aspects of a country's development status.

3.2. Variable settings

To comprehensively evaluate the development status of each country, the following variables were set:

Independent Variables: The independent variables are the indicator values based on SDGs 1 through 17. Each indicator measures the economic, social, environmental, and institutional development levels of a country. The data values provided in the SDGs REPORT 2023 (e.g., achievement rates for each goal, level of improvement) were used for these indicators. These SDG indicators serve as the primary variables for classifying countries in this study.

Dependent Variable: The dependent variable used in this study is Gross Domestic Product (GDP) per capita of each country. GDP per capita is a representative indicator of the economic level of a country, and it is used as a benchmark for evaluating the economic development status of each nation. By examining the relationship between SDG indicators and economic development levels, this study aims to identify the characteristics of each country that influence economic development.

3.3. Analytical method

This study employs Decision Tree Analysis, a machine learning technique, for country classification. Decision Tree Analysis is well-suited for visualizing the relationships between independent and dependent variables and for clearly presenting the classification criteria of variables (Freund and Mason, 1999; Gehrke et al., 2000). In particular, Decision Tree Analysis can be applied regardless of data distribution and effectively reflects complex interactions among variables (Wang and Thompson, 2022). Using Decision Tree Analysis, this study aims to categorize countries based on SDG indicators and analyze the relationship between these categories and economic development levels (GDP per capita).

The specific procedure for Decision Tree Analysis is as follows (Gama et al., 2003; Ho, 1988; Kass, 1980). First, the independent variables (SDG indicators) and dependent variable (GDP per capita) are defined. Next, classification criteria for each independent variable are established, and a decision tree is constructed to ensure that countries are assigned to specific nodes (classified groups). Based on this classification, the characteristics of each group are identified, and the economic development level of countries within each group is evaluated.

3.4. Analytical tools

The analysis in this study was conducted using IBM MODELER 18. MODELER is a software tool for data mining and machine learning analysis, allowing for the easy application of various analytical methods and effective execution of processes such as data preprocessing, analysis, and visualization. In this study, IBM MODELER 18 was used to classify countries based on SDG indicators and to derive country-specific characteristics using the Decision Tree model. Additionally, various visualization tools within MODELER were utilized to present the analytical results more intuitively and to extract policy implications.

Through this analytical process, the study proposes a systematic country classification methodology based on SDG indicators and suggests differentiated ODA policy directions for each category. This approach differs from conventional country classifications that rely solely on economic indicators and contributes to the development of tailored aid policies that comprehensively reflect the diverse characteristics of recipient countries.

4. Analysis results

4.1. Decision tree analysis results

The structure of the Decision Tree Analysis resulted in a tree-shaped diagram, as shown below. This structure visually represents the process of dividing the dataset into multiple groups based on specific criteria, with each node and branch holding distinct meanings (Kohavi and Sommerfield, 1998; Langley and Sage, 1994; Last et al., 2002; Lim et al., 2000).

The Root Node is the node located at the top of the tree and represents the independent variable and classification criteria that serve as the basis for the entire dataset. The root node is the initial point where the dataset is first divided, using the most significant variable and classification criteria to split the data. For example, as shown in Figure 1 below, if SDG Indicator 9 (Industry, Innovation, and Infrastructure) is set as the root node, the dataset would be divided into two groups based on a specific value of SDG Indicator 9 (e.g., a score of 83.936). This indicates that the first division of the dataset is made according to whether each country's value for SDG 9 is above or below 83.936.

The branches extending from the root node represent further subdivisions based on other independent variables and their corresponding criteria. Each branch leads to additional child nodes that reflect progressively finer classifications, ultimately resulting in leaf nodes—the final nodes where countries are categorized into distinct groups. This hierarchical structure enables a detailed analysis of the characteristics of each group, providing insights into how different variables contribute to the classification of countries.

By interpreting the tree structure, it is possible to understand the relative importance of various SDG indicators in distinguishing between countries and to identify which specific indicators most strongly influence the classification. This analytical approach offers a comprehensive view of the relationships among the SDG indicators and their impact on economic development levels (GDP per capita) across different country groups.

The internal nodes are located in the middle of the tree and provide criteria for further subdividing the data. Each internal node is divided based on one independent variable, resulting in the creation of new groups. The branches represent data groups that are divided according to the classification criteria of the root node and internal nodes. Each branch is generated based on a single classification criterion and serves to connect subgroups of data according to specific conditions.

As illustrated in **Figure 1** below, the decision tree structure visually separates the data and provides a clear understanding of how each group is formed. This structure helps in identifying how specific groups are composed of data with distinct characteristics (Lopez de Maritras, 1991).

Through this visual representation, it becomes easier to interpret the distinct characteristics of each node, the criteria used to differentiate the groups, and how each country fits into the respective classifications. This level of detail allows researchers to understand the underlying logic of the classification process and the significance of each variable in determining the final groupings.

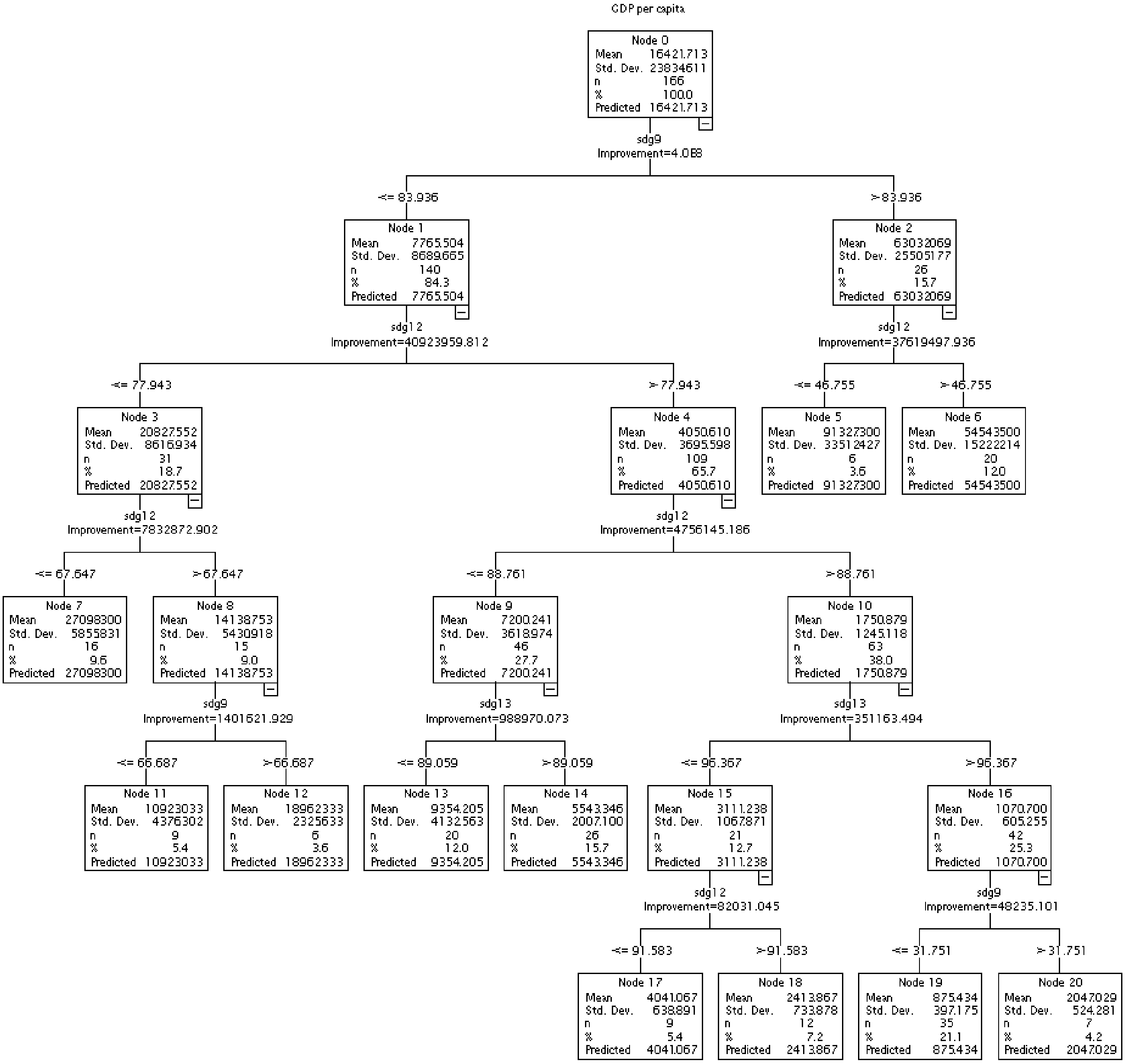

Figure 1. Results of the decision tree structure.

The following **Table 3** provides the number of countries included in each node and the average GDP per capita of the countries within each node. For instance, Node 2 consists of 26 countries, and the average GDP per capita for these countries, as of 2022, is USD 63,032.

This table helps illustrate the distribution of countries across different nodes and provides an overview of their economic status based on GDP per capita. Through such classification, the study aims to understand the economic characteristics of each group and analyze the relationship between various SDG indicators and the economic development levels of the countries included in each node.

Table 3. Number of countries and basic statistics for each node.

Node	*N*	Percent	Mean
2	26	15.7%	63032.0692
5	16	9.6%	27098.3000
10	6	3.6%	18962.333
12	6	3.6%	12254.9000
9	9	5.4%	10923.0333
11	40	24.1%	6442.0425
15	9	5.4%	4041.0667
16	12	7.2%	2413.8667
18	7	4.2%	2047.0286
17	35	21.1%	875.4343

Notes: dependent variable: GDP per capita.

Figure 2 below illustrates the Variable Importance graph resulting from the Decision Tree Analysis. This graph visually displays the significance of each variable in influencing the dependent variable (in this case, GDP per capita) within the decision tree model. The meaning of the graph can be explained as follows:

The *X*-axis represents the importance of each variable expressed as a percentile value. After ranking the variables based on their importance, the *X*-axis shows their importance scores on a scale from 0 to 100. A higher value on the *X*-axis indicates lower importance, whereas a lower value suggests that the variable has higher importance in the model.

The *Y*-axis indicates the magnitude of the influence that each variable has on the classification or prediction within the decision tree model. A higher value on the *Y*-axis means that the variable played a more critical role in classifying or predicting the dependent variable (GDP per capita).

In essence, this graph helps to identify which variables had the greatest impact on the model's performance, enabling a clearer understanding of the relative importance of each SDG indicator in determining the economic development levels of the countries classified in the analysis.

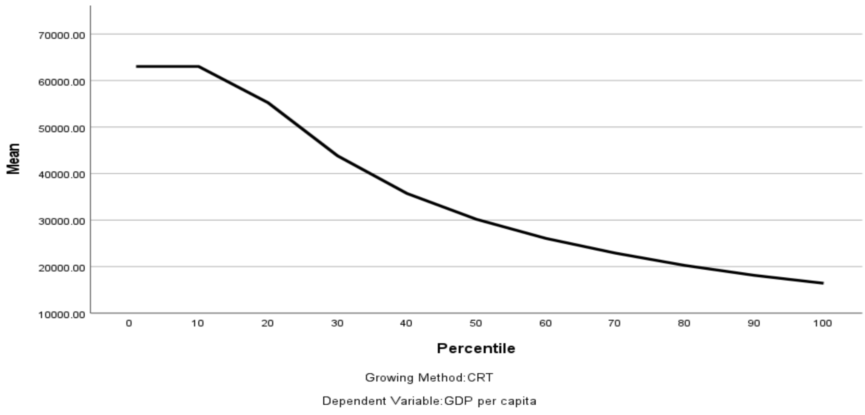

Figure 2. Variable importance graph.

The graph above illustrates the importance of each variable in predicting GDP per capita within the Decision Tree Analysis model. As shown, the first segment on the left side of the *Y*-axis with the highest values represents the most significant variables in the model. These variables had the strongest influence in predicting GDP per capita. The variables positioned between 0 and 10 on the *X*-axis exhibit relatively high importance and contribute significantly to explaining GDP per capita. In contrast, variables positioned beyond 50 on the *X*-axis, with lower *Y*-axis values, indicate those with low importance, meaning they had a relatively minimal impact on the model's predictions.

From both the graph and **Table 4** below, it is evident that SDG indicators 9 (Industry, Innovation, and Infrastructure), 12 (Responsible Consumption and Production), and 3 (Good Health and Well-being) were the most influential variables in this model, playing a critical role in explaining variations in GDP per capita across different countries. This indicates that these SDGs were the key determinants of economic development in the countries analyzed.

Table 4. Importance of independent variables.

Independent variable	Importance	Normalization importance
sdg9	442327107.6	100.0%
sdg3	397419302.4	89.8%
sdg12	394875516.9	89.3%
sdg16	332523286.6	75.2%
sdg13	314592397.4	71.1%
sdg11	254853723.4	57.6%
sdg1	251924070.5	57.0%
sdg8	237261047.7	53.6%
sdg4	201485401.1	45.6%
sdg5	190251964.9	43.0%
sdg6	125376609.7	28.3%
sdg7	68603741.46	15.5%
sdg17	38875752.94	8.8%
sdg15	33542842.62	7.6%
sdg2	15950591.67	3.6%
sdg10	6874748.076	1.6%
sdg14	1814088.876	0.4%

Notes: dependent variable: GDP per capita.

Figure 3 presents a graph that visually depicts the relative importance of the independent variables included in this model. As shown in the graph, SDG Indicator 9 (Industry, Innovation, and Infrastructure) has the highest impact, followed by SDG Indicator 3 (Good Health and Well-being).

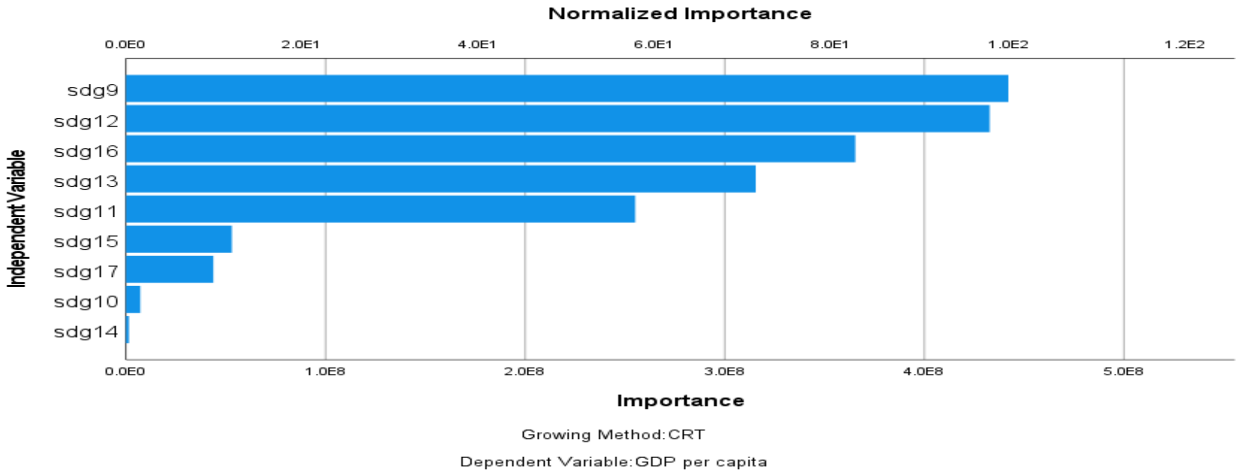

Figure 3. Variable importance graph for independent variables.

The following **Table 5** organizes the countries included in each node of the classification model. This table includes all the countries analyzed in the study, encompassing both developing and developed nations. However, the primary focus of this study is on lower-middle-income and low-income developing countries, which are in greater need of aid.

Table 5. Classification of countries by node.

Node ID	Number of Countries Included	Average GDP Per Capita	Main Characteristics	Countries included
2	26	63032.07	High GDP, high SDG 3, 9, and 8 scores. Includes primarily high-income countries.	Finland, Sweden, Denmark, Germany, Austria, France, Norway, United Kingdom, Switzerland, Spain, Ireland, Belgium, Netherlands, Japan, Italy, Canada, New Zealand, Iceland, Korea, Rep., Luxembourg, United States, Australia, Israel, Singapore, United Arab Emirates, Qatar
5	16	27098.3	Upper-middle income, high SDG 12 scores. Includes European countries.	Czech, Estonia, Slovenia, Latvia, Portugal, Greece, Lithuania, Malta, Cyprus, Barbados, Saudi Arabia, Brunei Darussalam, Kuwait, Bahrain, Trinidad and Tobago, Bahamas, The
9	9	10923.03	Medium GDP, relatively high SDG 8 and 12 scores. Includes Latin American and Eastern European countries.	Uruguay, Belarus, Bulgaria, Costa Rica, Montenegro, Maldives, Mauritius, Panama, Mongolia
10	6	18962.33	Upper-middle GDP, high SDG 8 and 12 scores. Includes Central European countries.	Poland, Croatia, Hungary, Slovak Republic, Chile, Oman
11	40	6442.04	Low GDP, high SDG 12 scores. Primarily lower-middle-income countries.	Moldova, Ukraine, Georgia, Thailand, Bosnia and Herzegovina, Brazil, Azerbaijan, Albania, Armenia, Fiji, Tunisia, North Macedonia, Bhutan, Dominican Republic, Peru, Kazakhstan, Türkiye, El Salvador, Ecuador, Colombia, Malaysia, Mexico, Jamaica, Iran, Islamic Rep., Paraguay, Cabo Verde, Turkmenistan, Suriname, Lebanon, Guyana, Nicaragua, Iraq, Belize, Namibia, South Africa, Gabon, Venezuela, RB, Botswana, Eswatini, Djibouti
12	6	12254.9	Medium GDP, high SDG 8 and 12 scores. Includes Eastern European and Latin American countries.	Romania, Serbia, Cuba, Russian Federation, Argentina, China

Table 5. (*Continued*).

Node ID	Number of Countries Included	Average GDP Per Capita	Main Characteristics	Countries included
15	9	4041.07	Low GDP, high SDG 12 scores. Includes Southeast Asian and North African countries.	Vietnam, Morocco, Algeria, Indonesia, Jordan, Egypt, Arab Rep., Sri Lanka, Honduras, Guatemala
16	12	2413.87	Low GDP, low SDG 9 scores. Includes Central Asian and South American countries.	Kyrgyz Republic, Uzbekistan, Bolivia, Philippines, Bangladesh, Cambodia, India, Lao PDR, Zimbabwe, Papua New Guinea, Congo, Rep., Angola
17	35	875.43	Very low GDP, low SDG 3 and 9 scores. Includes low-income countries in Africa and Asia.	Tajikistan, Sao Tome and Principe, Myanmar, Rwanda, Gambia, The, Syrian Arab Republic, Mali, Mauritania, Tanzania, Malawi, Togo, Sierra Leone, Cameroon, Benin, Uganda, Guinea, Lesotho, Ethiopia, Zambia, Burundi, Mozambique, Haiti, Burkina Faso, Comoros, Madagascar, Liberia, Afghanistan, Congo, Dem. Rep., Sudan, Niger, Somalia, Yemen, Rep., Chad, Central African Republic, South Sudan
18	7	2047.03	Low GDP, high SDG 12 scores. Includes West African and other low-income countries.	Nepal, Cote d'Ivoire, Senegal, Ghana, Kenya, Pakistan, Nigeria

4.2. Implications of the analysis results

Based on the country classification above, the countries that are in urgent need of aid are those in the five nodes with the lowest GDP per capita and the most challenging economic conditions. These countries are categorized under Node IDs 11, 15, 16, 18, and 17. Below is an overview of the economic, social, and regional characteristics of the countries in these nodes, along with suggested directions for aid policies from donor countries:

4.2.1. NODE ID 11

- Economic Characteristics: Countries in this node exhibit extremely low GDP per capita and face severe economic instability. They are characterized by weak industrial bases and a high dependency on agricultural and primary sectors.
- Social Characteristics: High poverty rates, limited access to education and healthcare, and high unemployment rates are prevalent in these countries.
- Policy Recommendations: Donor countries should focus on strengthening basic infrastructure, providing education and healthcare support, and enhancing agricultural productivity to improve food security and reduce poverty.

4.2.2. NODE ID 15

- Economic Characteristics: These countries show moderate economic growth potential but lack the necessary resources and capacities for sustainable development.
- Social Characteristics: Social development indicators, such as life expectancy and literacy rates, are relatively low. There is also a notable lack of access to clean water and sanitation.
- Policy Recommendations: Aid should be directed towards capacity building in human resources, improving access to basic social services, and promoting small and medium-sized enterprises (SMEs) to create job opportunities.

4.2.3. NODE ID 16

- Economic Characteristics: Countries in this node are primarily low-income, with economies that are vulnerable to external shocks due to their dependence on a narrow range of exports.
- Social Characteristics: High levels of income inequality and social exclusion are observed. These countries also face significant challenges in achieving gender equality and providing social protection.
- Policy Recommendations: Aid policies should focus on economic diversification, social protection programs, and gender equality initiatives to build resilience against economic fluctuations and promote inclusive growth.

4.2.4. NODE ID 18

- Economic Characteristics: This node includes countries with persistently low GDP per capita and limited access to international markets. They often experience high external debt and limited fiscal capacity.
- Social Characteristics: Countries in this group typically have low levels of education and health infrastructure, which hinders human capital development.
- Policy Recommendations: Donor countries should prioritize debt relief programs, support for health and education infrastructure development, and initiatives to facilitate market access and economic integration.

4.2.5. NODE ID 17

- Economic Characteristics: Countries in this node have low economic growth rates and limited investment in technology and innovation. They often struggle with high inflation and weak financial institutions.
- Social Characteristics: High youth unemployment and lack of skills development are key issues. Social services are often underdeveloped, leading to low social welfare levels.
- Policy Recommendations: Aid should be aimed at enhancing technical and vocational education and training (TVET), supporting economic policy reforms to stabilize inflation, and improving financial governance to attract investment.

By tailoring aid strategies according to these classifications and characteristics, donor countries can allocate resources more efficiently and design policies that are better suited to the specific needs of each group of developing countries, ultimately contributing to sustainable development.

5. Conclusion

Establishing effective aid policies for developing countries requires a systematic country classification that considers the economic, social, and regional characteristics of recipient nations. Conventional uniform aid approaches may fail to fully address the specific needs and developmental demands of each country, potentially diminishing the effectiveness of aid. To address this issue, this study applied Decision Tree Analysis, one of the machine learning methods, to classify various countries around the world—including developing nations—based on the scores of SDGs 1 through 17 and GDP per capita. Tailored aid policy directions were then proposed for each category. While the analysis included all countries, the interpretation of the results was focused on developing countries.

The analysis results classified developing countries into 10 nodes, each exhibiting distinct characteristics based on economic, social, and regional factors. Among these, countries in Node IDs 11, 15, 16, 17, and 18 were primarily lower-middle-income and low-income countries with low GDP and vulnerable social infrastructure. Based on the specific characteristics of these countries, the following policy directions are proposed for Korea's ODA strategy:

5.1. Support for economic self-reliance and strengthening of industrial foundations

For countries with low economic self-reliance, support should focus on expanding industrial infrastructure and fostering agriculture and small-scale manufacturing to strengthen the foundation for economic self-sufficiency. Particularly, for countries with agriculture-centered economies, technology transfer and educational programs aimed at modernizing agriculture and improving productivity are necessary to promote long-term economic growth

5.2. Enhancement of social services and poverty alleviation programs

For countries lacking basic social services, policies should aim to enhance education, healthcare, and welfare services to improve social stability and reduce poverty. Additionally, promoting human resource development through vocational education and skills training is critical for creating quality job opportunities.

5.3. Policy advisory and governance strengthening

In countries with high political and economic instability, policy advisory and support for strengthening governance capacities are needed. This can be achieved by providing educational programs to enhance public administration and governance capacities and supporting reforms aimed at increasing institutional transparency and efficiency. These efforts will contribute to the long-term development and stability of developing countries.

5.4. Emergency relief and humanitarian aid

For countries facing emergencies such as hunger, disease, or natural disasters, emergency relief and humanitarian assistance are essential. Such support should not only address immediate issues but also focus on strengthening disaster response capabilities to better prepare for similar situations in the future.

This study contributes to more effective and systematic formulation of Korea's ODA policies through customized aid strategies tailored to the characteristics of each type of developing country. Future research should explore country classification using additional variables and further refine detailed policy directions. By doing so, Korea's aid policies can contribute more effectively to the self-sustained development of recipient countries and to achieving the sustainable development goals of the international community.

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References

Addison, T., Hulme, D., & Kanbur, R. (2009). Poverty Dynamics: Interdisciplinary Perspectives. Oxford University Press.

Alesina, A., & Dollar, D. (2000). Who gives foreign aid to whom and why? Journal of Economic Growth, 5(1), 33-63.

Angelsen, A., & Wunder, S. (2003). Exploring the Forest—Poverty Link: Key Concepts, Issues and Research Implications. CIFOR Occasional Paper No. 40. Center for International Forestry Research.

Banerjee, A., & Duflo, E. (2011). Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty. PublicAffairs.

Burnside, C., & Dollar, D. (2000). Aid, policies, and growth. American Economic Review, 90(4), 847-868.

Castells, M. (1999). The Information Age: Economy, Society and Culture Volume III: End of Millennium. Blackwell Publishing.

Chenery, H. B., & Syrquin, M. (1975). Patterns of Development, 1950-1970. Oxford University Press.

Collier, P., & Hoeffler, A. (2004). Greed and grievance in civil war. Oxford Economic Papers, 56(4), 563-595.

Collier, P. (2008). The Bottom Billion: Why the Poorest Countries are Failing and What Can Be Done About It. Oxford University Press.

Collier, P., & Dollar, D. (2002). Aid allocation and poverty reduction. European Economic Review, 46(8), 1475-1500.

Deaton, A. (2013). The Great Escape: Health, Wealth, and the Origins of Inequality. Princeton University Press.

Easterly, W. (2006). The White Man's Burden: Why the West's Efforts to Aid the Rest Have Done So Much Ill and So Little Good. Penguin Press.

Fernandez, L. & Ahmed, S. (2023). Clustering Developing Countries: A Data-Driven Approach for Tailored ODA Strategies. Journal of Development Economics, 162, 102950.

Forman, E. H., & Gass, S. I. (2001). The analytic hierarchy process—An exposition. Operations Research, 49(4), 469-486.

Freund, Y., & Mason, L. (1999). The alternating decision tree learning algorithm. Proceedings of the Sixteenth International Conference on Machine Learning, Bled, Slovenia, pp. 124–133.

Gama, J., Rocha, R., & Medas, P. (2003). Accurate decision trees for mining high-speed data streams. Proceedings of 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 523–528.

Garcia, M. & Johnson, K. (2023). Cluster Analysis of Developing Countries: Implications for Aid Allocation. Development Policy Review, 41(3), e12609.

Gehrke, J., Ramakrishnan, R., & Ganti, V. (2000). RainForest—a framework for fast decision tree construction of large datasets. Data Mining and Knowledge Discovery, 4(2-3), 127–162.

Hansen, H., & Tarp, F. (2001). Aid and growth regressions. Journal of Development Economics, 64(2), 547-570.

Heston, A., Summers, R., & Aten, B. (2012). Penn World Table Version 7.1. Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Ho, T. K. (1998). The random subspace method for constructing decision forests. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20(8), 832–844.

Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. Applied Statistics, 29(2), 119–127.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2009). Governance matters VIII: aggregate and individual governance indicators 1996–2008. World Bank Policy Research Working Paper No. 4978.

Kharas, H., & Rogerson, A. (2012). Horizon 2025: Creative destruction in the aid industry. ODI Report.

Kim, H. & Davis, M. (2023). Reassessing the World Bank's Country Classification System: A Critical Analysis. Global Policy, 14(2), 228-241.

Knack, S. (2004). Does foreign aid promote democracy? International Studies Quarterly, 48(1), 251-266.

Kohavi, R., & Sommerfield, D. (1998). Targeting business users with decision table classifiers. Proceedings of the Fourth International Conference on Knowledge Discovery and Data Mining, AAAI Press, pp. 249–253.

Kosack, S., & Tobin, J. (2006). Funding self-sustaining development: The role of aid, FDI and government in economic success. International Organization, 60(1), 205-243.

Lee, S. et al. (2022). Beyond GDP: A Comprehensive Framework for Categorizing Developing Nations. World Development,

150, 105722.
Langley, P., & Sage, S. (1994). Oblivious decision trees and cases. Working Notes of the AAAI-94 Workshop on Case-Based Reasoning, Seattle, WA: AAAI Press, pp. 113–117.
Last, M., Maimon, O., & Minkov, E. (2002). Improving stability of decision trees. International Journal of Pattern Recognition and Artificial Intelligence, 16(2), 145–159
Lim, X., Loh, W. Y., & Shih, X. (2000). A comparison of prediction accuracy, complexity, and training time of thirty-three old and new classification algorithms. Machine Learning, 40(3), 203–228.
Lopez de Mantras, R. (1991). A distance-based attribute selection measure for decision tree induction. Machine Learning, 6, 81–92.
Moyo, D. (2009). Dead Aid: Why Aid is Not Working and How There is a Better Way for Africa. Farrar, Straus and Giroux.
Nguyen, T. & Wilson, E. (2022). Beyond Income: Multidimensional Poverty and Development Classification. Oxford Development Studies, 50(3), 321-339.
Osei, R. & Miller, G. (2022). Redefining Development Categories: An Analysis of Sub-Saharan African Nations. African Development Review, 34(3), 448-463.
Patel, N. (2023). Socioeconomic Indicators and Their Role in Developing Country Classification. International Journal of Social Economics, 50(7), 1022-1040.
Pritchett, L., & Woolcock, M. (2004). Solutions when the solution is the problem: Arraying the disarray in development. World Development, 32(2), 191-212.
Ravallion, M. (2001). Growth, inequality and poverty: Looking beyond averages. World Development, 29(11), 1803-1815.
Rodriguez, C. et al. (2022). A New Taxonomy of Developing Nations: Implications for Aid Effectiveness. Development and Change, 53(5), 1206-1234.
Sachs, J. D. (2005). The End of Poverty: Economic Possibilities for Our Time. Penguin Press.
Sen, A. (1999). Development as Freedom. Oxford University Press.
Smith, J. & Brown, A. (2023). Rethinking Development Classifications: A Multidimensional Approach. Journal of International Development, 35(4), 567-589.
Todaro, M. P., & Smith, S. C. (2011). Economic Development. Addison-Wesley.
United Nations. (2015). Transforming our world: the 2030 Agenda for Sustainable Development.
United Nations. (2014). World Economic Situation and Prospects. United Nations Publications.
Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. European Journal of Operational Research, 169(1), 1-29.
Wang, Y. & Thompson, R. (2022). Machine Learning Approaches to Classify Developing Countries for Targeted ODA. Data Science for Social Good, 7(2), 145-168.
Williamson, J. (1990). What Washington means by policy reform. In J. Williamson (Ed.), Latin American Adjustment: How Much Has Happened?. Institute for International Economics.
World Bank. (1998). Assessing aid: What works, what doesn't, and why. World Bank Policy Research Report.
World Bank. (2006). Global Monitoring Report 2006: Strengthening Mutual Accountability - Aid, Trade, and Governance. World Bank Publications.
World Bank. (2023). World Development Report 2023: Data for Better Lives.
OECD. (2019). Development Co-operation Report 2019: A Fairer, Greener, Safer Tomorrow.
OECD. (2021). Aid Effectiveness 2021: Progress in Implementing the Paris Declaration.
Sustainable Development Solutions Network. (2023). Sustainable Development Report 2023: Implementing the SDG Stimulus.
UNDP. (2022). Human Development Report 2022: Uncertain Times, Unsettled Lives.
UNCTAD. (2020). Trade and Development Report 2020: From Global Pandemic to Prosperity for All.