Analysing Energy Outcomes Based on Countries' Development Levels (2010-2020) with Visual Analytics Approach

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Abstract—With the sustainable development goals proposed by the UN, this study aims to address the energy-related aspects–accessibility, efficiency, renewable energy, and emissions–based on countries' development levels with 2015 data. The analysis involves clustering countries, examines energy outcomes in 2015, and explores trends from 2010 to 2020. The analysis approach combines statistical methods, human judgment, and visualisations to address complex questions. Findings reveal significant variations in energy-related aspects across different development groups. Positive trends in accessibility, narrowing urban-rural gaps, and improved energy efficiency are observed. While positive trends are observed, concerns also arise in all four aspects. Predictions for 2030, indicate a gap from UN goals. Real-world challenges further complicate achieving these goals.

1 Problem Statement

In 2015, the United Nations (UN) proposed 17 sustainable development goals (SDGs)[1], aims to accomplish by 2030. SDG7 focuses on energy accessibility, efficiency, and sustainability. A 2023 United Nations report[2] reveals that over 2 billion people still lack clean cooking energy, nearly 700 million people do not have access to electricity, and less than 20% of renewable energy consumption of all energy. At the same time, electricity consumption and greenhouse gas emissions in developed and developing countries are increasing at an unprecedented rate.

It would be naive to think that the challenges faced by every country are the same. It is more suitable to conduct further analysis based on the country's level of development. This study will use 2015 data to classify countries according to their development levels and answer the following energy-related questions, which are divided into four aspects: energy accessibility, energy efficiency, renewable energy, and emissions.

1. In 2015, how did the indicators of each group perform? What specific aspects of each group need to focus on?

2. What was the performance of each group in the five years before and after 2015, and what were the trends from 2010 to 2020? Additionally, what expectations can be set for 2030?

The World Bank database[3] supplies two sets of data: one related to countries' development levels in 2015, and the other is the countries' energy-related indicators from 2010 to 2020. These can help us understand the relationship between indicators and their performance within each group.

2 State of the Art

The literature on energy consumption, environment, economic growth and sustainability is highly extensive. The focus of this section will be based on the two dimensions of the analytical problems we want to solve. First, we take a look at clustering countries according to their development level. Second, we explore the methods to analyse energy-related outcomes and present their relationships.

Other than traditional approaches such as income or geographic region[4] for country classification, Basel et al.[5] adopted another way by using values from four aspects, including social, sustainability, economic, and institution, to cluster the countries' development levels. Using data from the World Bank database and UNESCO Institute of Statistics, the study applied K-means and grey relational analysis to cluster 102 countries into four different groups. Employed two-way ANOVA to further analyse the variations within and between groups, finding that none of the groups has the lowest score across all four aspects. This result indicated that only using a singular perspective to decide countries' development levels might not be enough to understand global development dynamics.

The study by Bonjour et al.[6] investigates the clean energy accessibility for cooking, given the high health risks associated with unclean energy use. This paper mainly focuses on middle or low-income countries, the study used the WHO household energy database, including 155 countries from 1974 to 2010. Applying multilevel/mixed-effects models for trend analysis. Compared to linear regression, it offers advantages by considering other outcome-related variables like income or population density etc. into the model. The results reveal that there is still a high percentage of individuals in Africa or South-East Asia lacking access to clean energy. Despite an annual decrease in overall percentage, the total number of affected people remains high due to population growth.

Herman et al.[7] explore the correlation between green policies and actual green growth within the G7 countries. The study used data from the OECD stat website and considered data from four aspects, including policy, environment, economics, and productivity, with 28 indicators in total. To manage the abundance of indicators, they applied k-means clustering and decided to focus on seven indicators within the same cluster. Correlation analyses are conducted separately for each G7 country. Although these are all developed

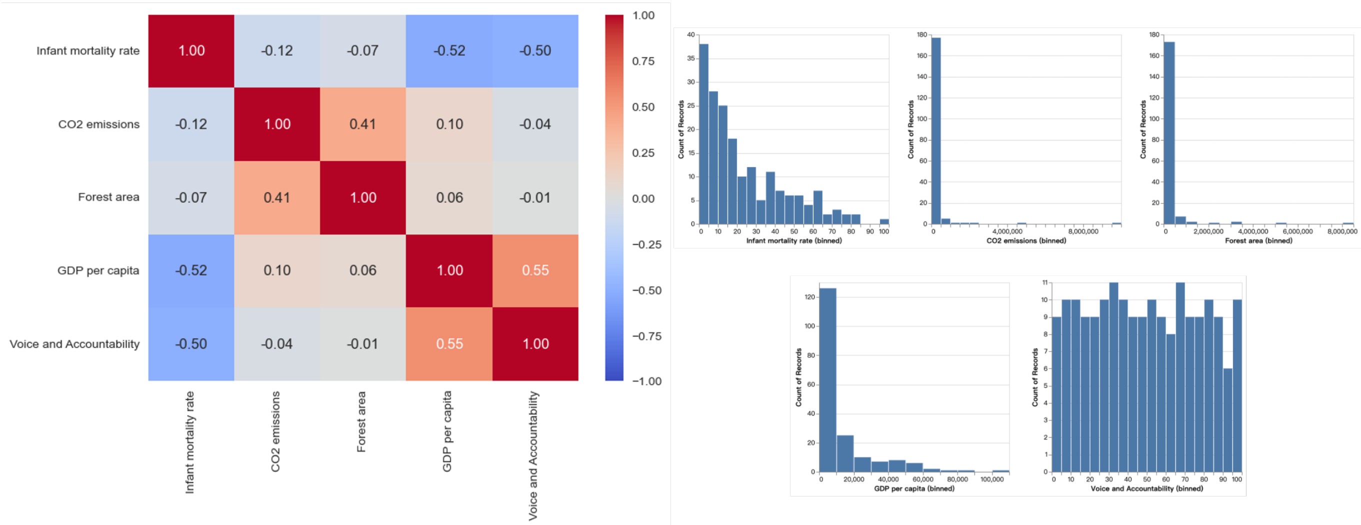


Fig. 1. Correlations and histograms in development dataset.

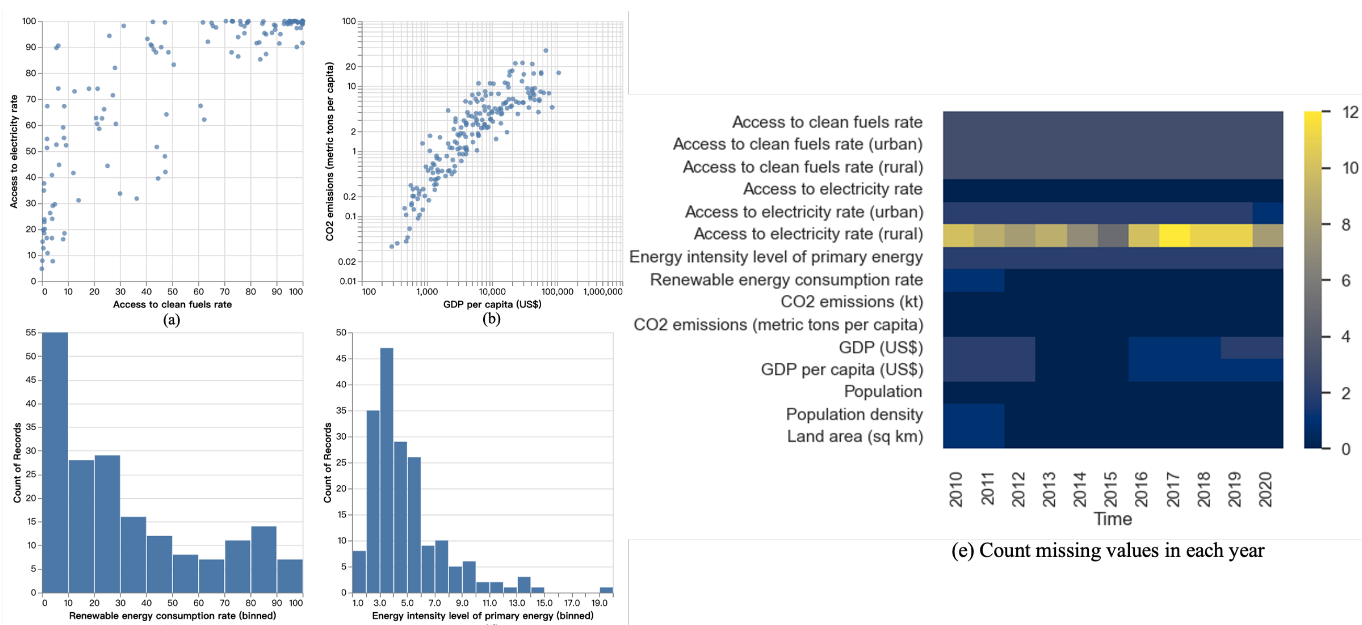
countries, the results still show that the relationship between these indicators differs across countries.

Combining the insights from [6] and [7], it becomes evident that the challenges faced by countries with different levels of development are very unique. This means that subsequent analysis should be conducted in depth in different aspects according to the degree of development.

3 Properties of the Data

The data is from the World Bank Open Data platform[3], which offers diverse global development data at country levels. This study will use two sets of data from 187 countries, including the indicators related to countries' development levels in 2015, and energy-related indicators from 2010 to 2020.

Based on the indicators used in [5], the first dataset consists of five of them. Since this report will focus on energy-related results, there will be more energy-related features, making them more suitable for our subsequent analysis after clustering. These features provide information about various aspects. "Infant mortality rate" reflects healthcare standards, "CO2 emissions, total kt" indicates energy use, "Forest area" signifies the sustainable development potential, "GDP per capita" shows economic status, and "Voice and Accountability" measures citizens' involvement in government. Fig. 1 shows their correlations



(e) Count missing values in each year

Fig. 2. Data evaluation for energy dataset.

through a heatmap and their distribution via histograms. With no high correlation between any two variables, the features are suitable for k-means clustering to group countries. The distribution of variables shows that there will require some transformation and scaling before applying K-means to the clustering.

To answer the questions in this study, the second dataset contains 15 indicators with five aspects related to energy outcomes across 11 years from 2010 to 2020, including energy accessibility, energy efficiency, renewable energy, emissions, and economic factors for each country. Energy accessibility is expressed through two indicators "Access to clean fuels rate" and "Access to electricity rate", with urban and rural data provided respectively. "Energy intensity level of primary energy" measures its energy efficiency, the lower the better. Renewable energy is measured by the "Renewable energy rate". Emissions are captured by "CO2 emissions" with total among and per capita. Economic is reflected in "GDP" also contains total and per capita. This dataset also includes some basic information about each country, such as "Population", "Population density", and "Land area" to reduce the influence of these variables on the outcomes.

In Fig. 2(a) to (d), we use data from 2015 to show the relationship and distribution of the main indicators. Fig. 2(a) shows the scatter plot between the two accessibility indicators. Overall, the accessibility of electricity is higher than the accessibility of clean fuels. Fig. 2(b) shows that the log-transformed CO2 emissions have a linear relationship with the log-transformed GDP. Fig. 2(c) and (d) show the distribution of energy efficiency and renewable energy consumption rate. In Fig. 2(e), we use a heatmap to show the missing values in different indicators for each year. Overall, there are not many missing values, with a maximum of only 12, which is less than 7% of the data. However, if the missing values are in the same cluster group, it may cause problems in further analysis. It's worth remembering this and taking care of this possibility while analysing.

4 Analysis

4.1 Approach

In this section, we will present the analysis approach used in this study to deal with three layers of questions. For each question, the process begins with applying suitable statistical analysis and identifying the points of interest. Using appropriate visualisation to present the information to make the conclusion or ask questions that may require more analysis. It would be like a loop between computer and human until the answer is served. The diagram of the approach is shown in Fig. 3[8].

A. Clustering: Countries' development levels

The first question is to cluster countries based on their development levels. The K-means algorithm will be performed after some feature transformation and scaling. Later, the elbow method and silhouette scores are applied as a guide to select the range of cluster numbers. Combined with

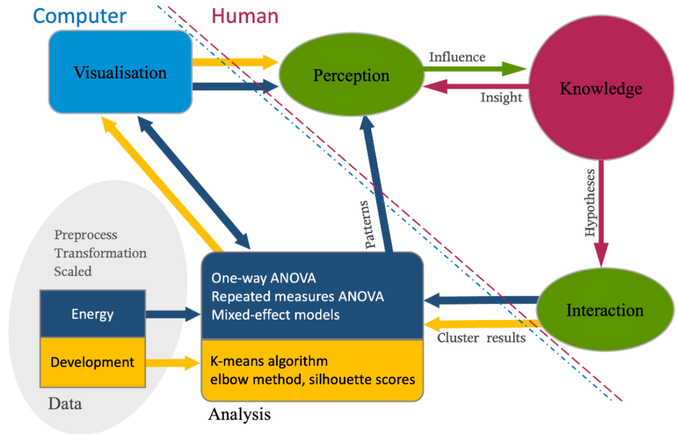


Fig. 3. Analysis approach diagram[8].

human knowledge, including whether each group is different in terms of geography, economy, culture, religion etc., and through some suitable visualisation, such as showing cluster results on a map, or showing the relationship between different indicators on plots to decide the final results.

B. Energy Outcomes in 2015

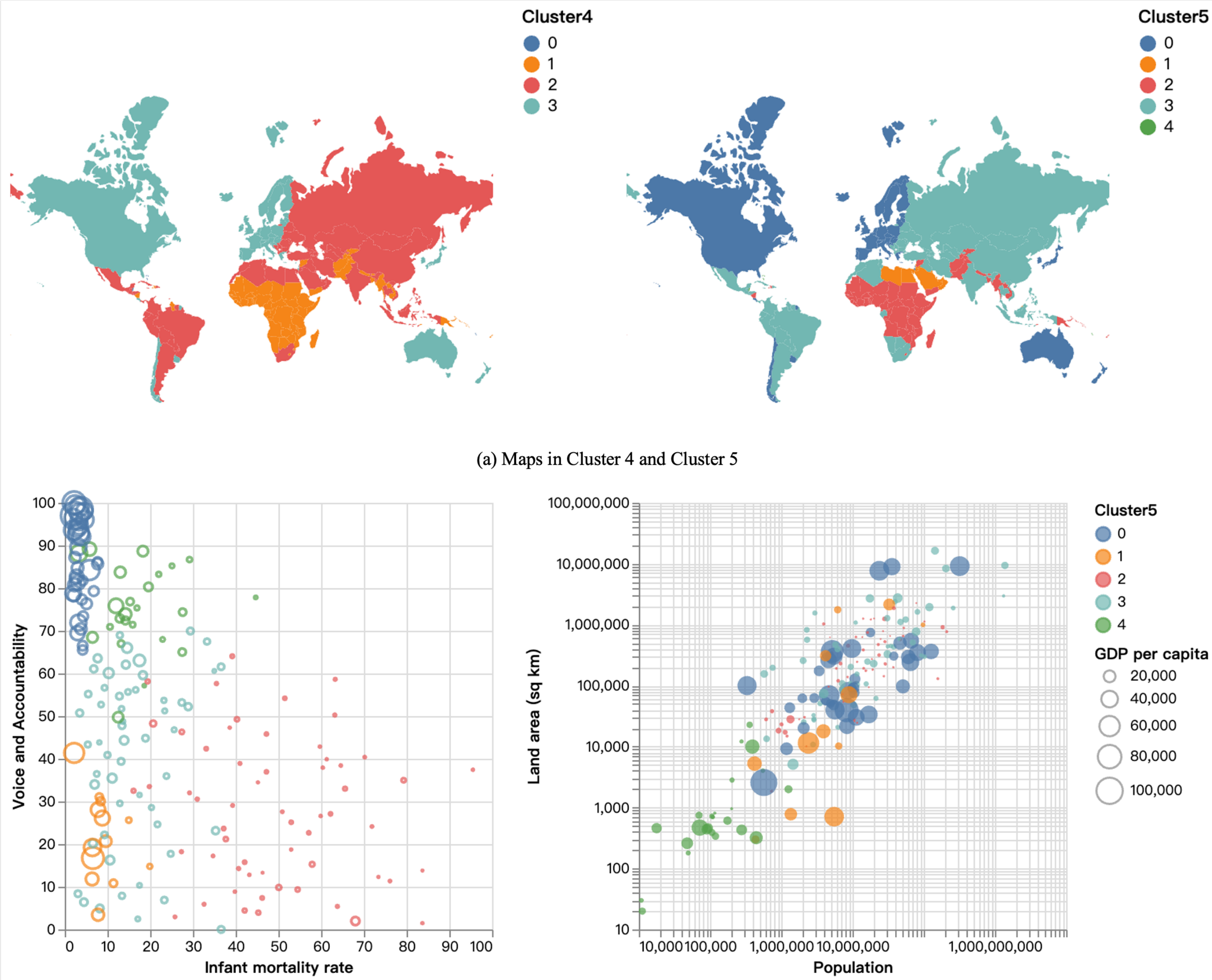
After clustering, the second question is to analyse the performance of different energy-related indicators within each group in 2015. This involves calculating the mean and standard deviation for each indicator to understand their distributions within groups. Applying one-way variance analysis (ANOVA) to see whether variances between groups are statistically significant, with Tukey's post hoc test for pairwise comparisons.

Based on these analysis results, see which results catch the attention. Which group scored highest and which scored lowest? Which group did not follow the usual pattern? Use graphs to display these results, and further analyse what situations may lead to such results. Is there any way I can prove these guesses based on the data I have? What questions do I want to answer in the next step of analysis?

C. Energy Outcomes Trend (2010-2020)

The last question is to examine the performance of each group in 2010, 2015, and 2020, and to calculate the trends in energy outcomes from 2010 to 2020. Repeated measures ANOVA are used to analyse the differences between the three years, while mixed-effect models are applied to capture trends over the decade. This analytical process provides us with the exact numbers in the specific year, and with coefficient from models enables us to estimate the approximate number for 2030.

Following the analysis, the focus shifts to the identified trends. Is there an improvement or decline in each indicator? Does this trend hold for every group? If not, what reasons might cause these results? Also, try to find the answer to the questions from the previous part. These might involve applying some statistical methods for deeper insights.



(a) Maps in Cluster 4 and Cluster 5

(b)

(c)

Fig. 4. K-means clusters results.

4.2 Process

In this section, the analysis is structured into three parts to show the process and human involvement. First, we use k-means to cluster countries according to their development levels, combining statistical methods and human knowledge to make the final decision. After clustering, this study will analyse and visualise the energy-related data in 2015, for understanding the overview of each group. Lastly, annual data is used for trend analysis to gain insights and future expectations.

A. Clustering: Countries' development levels

First, we need to perform a K-means cluster analysis based on the development level of each country. Before applying the K-means algorithm for clustering, the features must be transformed and scaled to ensure consistent scales for unbiased analysis. Using the elbow method and silhouette score, we can initially narrow down the number of clusters to 4 or 5. Later, combining with human judgement will help us decide the most suitable number of clusters for further analysis.

Fig. 4(a) shows the distribution of cluster 4 and cluster 5 on the map. From the map, we can see that in both clusters the two groups have similar distributions. One includes highly developed countries, including North America, Western Europe, Australia, Japan, etc. The other group is mainly located in some low-income or civil war areas in sub-Saharan Africa and Asia, usually classified as undeveloped countries. In addition, one of the groups in two clusters appears to have disappeared from the map. The main reason is that most of these countries are relatively small, or even islands. This can also be seen in Fig. 4(c). Their land area and population are relatively small, so their contribution to total CO_2 emissions or GDP is also small.

2015 Energy-Related Dataset	Group 0	Group 1	Group 2	Group 3	Group 4	ANOVA	Turky
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	p-values	post-hoc
Access to clean fuels rate	99.85 (0.92)	99.79 (0.60)	20.22 (23.55)	80.47 (19.68)	72.45 (34.82)	<.001	2<3,4<0,1
Access to clean fuels rate (urban)	99.95 (0.32)	99.95 (0.10)	36.11 (32.81)	90.71 (11.30)	79.99 (31.11)	<.001	2<0,1,3,4; 4<0
Access to clean fuels rate (rural)	99.58 (2.61)	99.70 (0.81)	10.53 (20.16)	65.72 (28.97)	64.80 (40.08)	<.001	2<3,4<0,1
Access to electricity rate	99.97 (0.11)	97.89 (7.23)	47.72 (26.97)	95.33 (8.76)	93.10 (12.22)	<.001	2<0,1,3,4
Access to electricity rate (urban)	99.99 (0.04)	99.93 (0.25)	73.66 (21.50)	98.14 (4.69)	96.05 (6.45)	<.001	2<0,1,3,4
Access to electricity rate (rural)	99.94 (0.38)	99.65 (0.68)	32.66 (30.73)	89.99 (17.82)	90.71 (16.72)	<.001	2<0,1,3,4

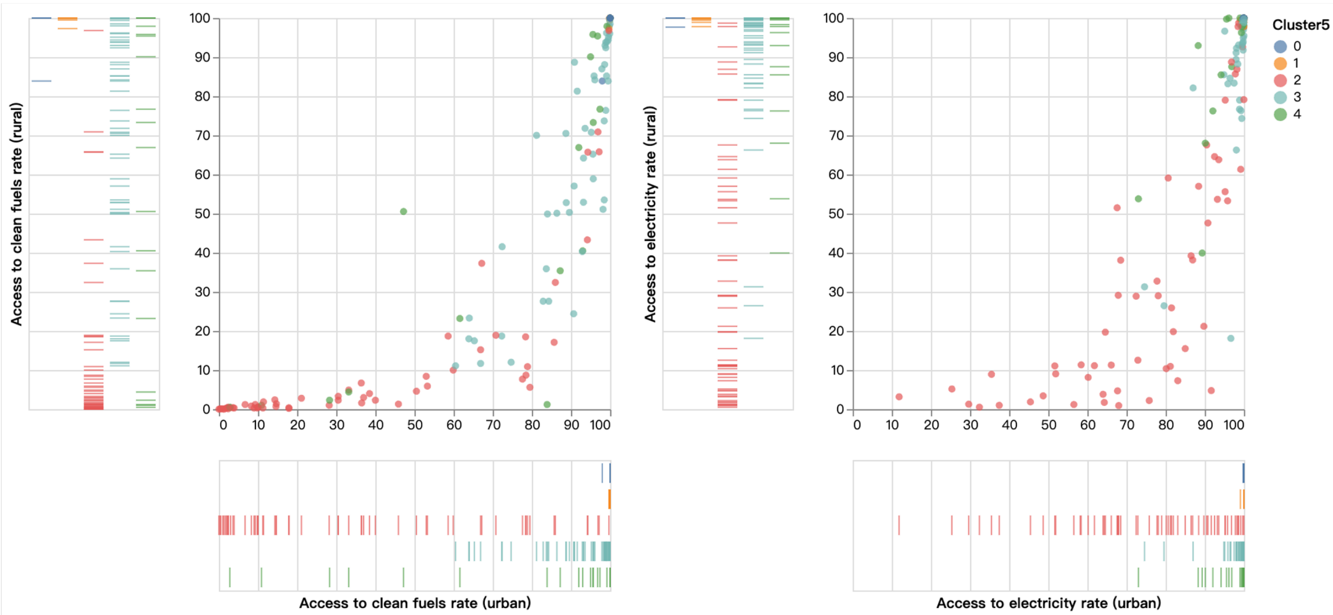


Fig. 5. Energy accessibility results in 2015.

Now let's look at the main differences between the two clusters. The main difference is that some countries in North Africa and the Middle East have been split into a new group. Fig. 4(b) presents the relationship between countries' infant mortality rate, Voice and Accountability, and their GDP per capita. The main focus is on the differences between Group 1 (G1) and Group 3 (G3). Compared with countries in G3, G1 has better healthcare levels, and significantly higher economic performance, but performs poorly in voice and accountability. These regions also have rich oil reserves which make the economy well and stable, but at the same time, it may lead to a lack of urgency in investing in renewable energy[9]. In summary, fundamental differences in geography, economy, culture, and religion distinguish this group from others. Combining these reasons, we will use the results in 5 clusters for subsequent analysis. There are 38, 13, 58, 54, and 24 countries in each group, respectively.

B. Energy Outcomes in 2015

After completing the cluster analysis, our next step is to analyse the performance of different indicators within each group in 2015. This aims to establish the basic understanding of each group, know the differences between them, and identify aspects that can be strengthened or improved. We first calculated the mean and standard deviation for each indicator in each group. Also, we applied one-way ANOVA to compare whether the variances between the groups were statistically significant and used Tukey's post hoc test to further analyse the differences between pairs of groups.

In terms of energy accessibility, G2 significantly fall behind other groups. Additionally, in G2 and G3 the gap between urban and rural areas was also really large, as shown in the dot-dash plot[10] in Fig. 5. As you can observe the density of dash parts in urban and rural areas perform differently in G2 and G3. Although G3 and G4 had performed well in the accessibility of electricity, there was still slight room for improvement in clean energy accessibility. G0 and G1 were both approaching 100%, positioned close to the upper right corner of the figure, indicating that this aspect will not be the primary focus for these two groups in the following analysis.

In terms of energy efficiency, both G1 and G2 performed worse than the other groups, despite their distinct performances in other aspects. In the renewable energy rate, the proportion for G2 was very high, but considering its performance in accessibility, this may be due to the lack of other stable power facilities. The performance of all groups was far from the UN's target of 33 to 38% in total[2]. It is worth noting that the performance of G1 in terms of economy and energy accessibility is closer to G0. Under normal circumstances, the performance of G1 should be closer to G0, but its performance was not ideal in terms of efficiency or renewable. Understanding the reasons for this result requires further investigation.

2015 Energy-Related Dataset	Group 0	Group 1	Group 2	Group 3	Group 4	ANOVA	Turky
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	p-values	post-hoc
Energy intensity level of primary energy	3.84 (1.96)	5.27 (2.06)	5.89 (3.08)	4.79 (2.89)	4.13 (2.20)	0.004	0<2
Renewable energy consumption rate	23.40 (17.22)	1.38 (1.88)	61.80 (25.85)	20.76 (17.71)	13.10 (14.75)	<.001	1<0,3<2; 4<2
CO2 emissions (10,000 kt)	29.41 (82.19)	10.91 (15.07)	1.18 (2.66)	35.29 (1.37)	0.06 (0.09)	0.159	
CO2 emissions (metric tons per capita)	7.39 (3.71)	13.87 (10.12)	0.54 (0.62)	3.96 (2.92)	3.21 (2.54)	<.001	2<3,4<0<1
GDP (10e+11 US$)	11.90 (30.18)	1.71 (1.97)	0.36 (0.78)	4.51 (15.4)	0.02 (0.04)	0.008	2,4<0
GDP per capita (1,000 US$)	36.11 (21.88)	24.52 (20.05)	1.49 (1.43)	6.08 (3.25)	10.87 (9.69)	<.001	2,3,4<1<0; 2<4

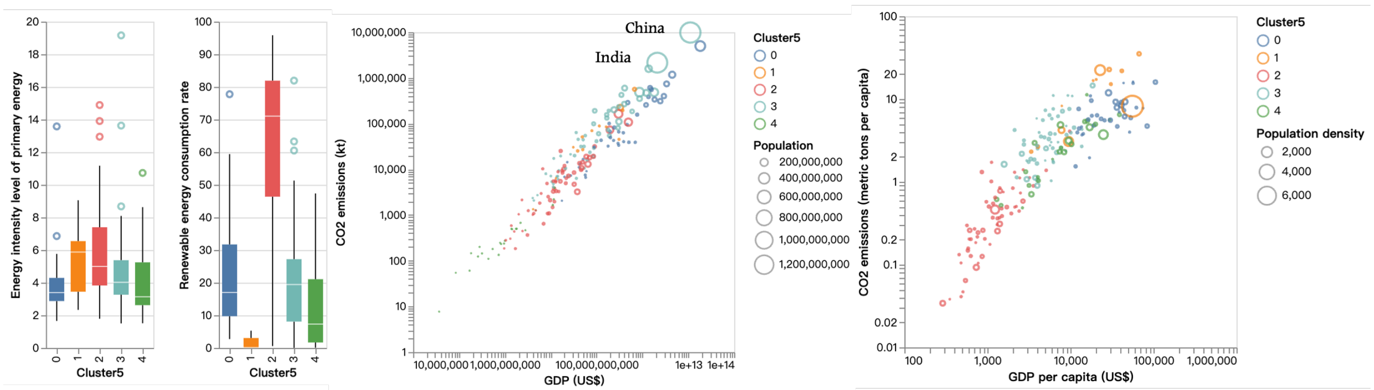


Fig. 6. Energy efficiency, renewability, and emissions results in 2015.

In CO2 emissions and GDP performance, the total amount of G3 is higher than other groups. This may be because several countries with a high population are in this group, including China and India. Regardless of the total amount or per capita, there were log-linear relationships between these two variables shown in Fig. 6.

Based on the above findings, we can initially summarize the differences between each group and highlight aspects for improvement. G0 primarily consists of developed countries, including North America, and Western Europe. Almost everyone in G0 had access to clean energy and electricity, and the energy efficiency was also the best. Although the proportion of renewable energy was not ideal, it still ranked relatively high. G1 had reached a certain level in terms of economic strength or energy access, but its performance in energy sustainability was at the bottom, which deserves continued attention in the following analysis. The performance of G2 in energy accessibility deserves attention and is also the focus of subsequent analysis. Except for the urban-rural gap in energy accessibility, the average performance of G3 and G4 was relatively similar. However, the composition of the countries is quite different. In G3, it contains countries with large areas and densely populated regions. In contrast, G4 is mainly composed of some small island countries. Perhaps the differences between the two can be observed in subsequent analysis.

C. Energy Outcomes Trend (2010-2020)

In this part, we applied repeated measures ANOVA to explore how each group performed in 2010, 2015, and 2020. Additionally, we examined the trends of each indicator within each group from 2010 to 2020, using a mixed-effect model to capture the temporal variations. Now, let's discuss more about the conclusion of the previous part.

Analysing energy accessibility, a positive trend is observed, especially for G2, G3, and G4. Overall, the situation was improving. In terms of electricity accessibility, even G2 is expected to reach 75% in 2030, with an estimated increase of 1.79 per year, almost double the level in 2010. However, progress in clean fuel accessibility had been relatively slow. Notably, differences emerge between G3 and G4 through this part. In rural energy, G3 was lower than G4 in 2010, but the situation reversed in 2020.

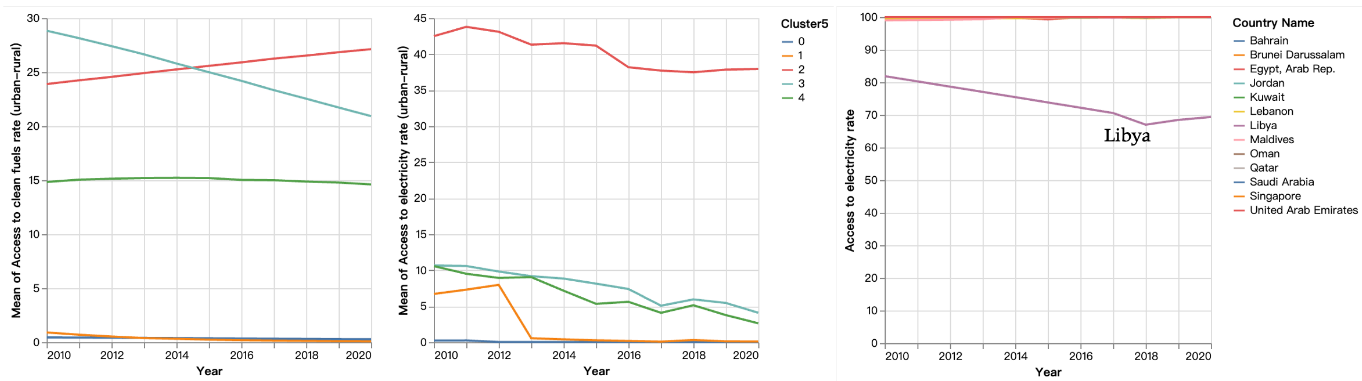
To further examine the urban-rural gap, we calculated the difference by using the urban value minus rural value and present the average of each group yearly in Fig. 7. Applying the mixed-effect model to analyse the trends in G2 and G3. G3 had significantly narrowed the gap between urban and rural areas in both indicators of energy accessibility. While G2 had significantly narrowed the gap in electricity accessibility, the values had expanded annually in clean energy. Considering that the overall rate of G2 was far from ideal, it is an understandable choice to develop urban areas first.

Another thing worth further discussion is that the electricity accessibility rate in G1 was declining. To find out the reason, the annual performance of all countries in G1 is presented in Fig. 7. It can be seen that the performance of Libya was on a downward trend. This might be due to the long-term civil war.

Regarding energy efficiency, all groups, except G1, show a decreasing trend over ten years. For the renewable energy consumption rate, although G2 remains high overall, it should be excluded from further discussion in this aspect due to the energy use situation we already discussed in the previous part. Only G0 seems to be moving towards the goal among the other groups. However, with an estimated annual increase of 0.54%, it will only reach 32% by 2030, not to mention how

Access to clean fuels rate		2010	2015	2020
		Mean (SD)	Mean (SD)	Mean (SD)
Group 2	Overall	17.21 (21.87)	20.22 (23.55)	23.72 (25.14)
	urban	32.56 (32.32)	36.11 (32.81)	39.90 (33.38)
	rural	8.66 (18.13)	10.53 (20.16)	12.77 (22.07)
Group 3	Overall	76.26 (22.20)	80.47 (19.68)	83.59 (18.04)
	urban	88.63 (13.28)	90.71 (11.30)	91.92 (10.52)
	rural	59.79 (30.97)	65.72 (28.97)	70.89 (27.47)
Group 4	Overall	70.37 (35.70	72.45 (34.82)	73.70 (34.25)
	urban	78.25 (31.19)	79.99 (31.11)	80.59 (31.13)
	rural	63.42 (40.81)	64.80 (40.08)	65.98 (39.73)

Access to electricity rate		2010	2015	2020
		Mean (SD)	Mean (SD)	Mean (SD)
Group 2	Overall	39.64 (26.66)	47.72 (26.97)	57.09 (27.87)
	urban	67.74 (25.14)	73.66 (21.50)	80.30 (19.65)
	rural	28.01 (27.96)	32.66 (30.73)	42.34 (34.07)
Group 3	Overall	93.11 (11.01)	95.33 (8.76)	97.39 (7.63)
	urban	97.30 (5.87)	98.14 (4.69)	98.84 (3.99)
	rural	86.64 (18.77)	89.99 (17.82)	95.19 (14.48)
Group 4	Overall	89.17 (15.25)	93.10 (12.22)	95.75 (8.55)
	urban	94.77 (7.63)	96.05 (6.45)	97.70 (4.98)
	rural	84.02 (21.92)	90.71 (16.72)	95.06 (11.07)



(a) Urban-rural gaps in energy accessibility. (b) Access to electricity rate in G1.

Fig.7. Energy accessibility results in 2010-2020.

will the other groups perform. Fig. 8 shows that although CO2 emissions per capita were declining yearly, the total amounts still keep increasing, indicating that the control efficiency of greenhouse gas emissions cannot match the population growth rate. In the long run, it will still impact the climate.

4.3 Results

This study aims to address specific energy challenges based on countries' development levels using 2015 data. In 2015, each group performed vary in energy-related aspects. G2, G3, and G4 gain attention for energy accessibility, while G1 raises concerns for energy efficiency and renewable energy rates. Additionally, the overall performance seems to fall behind.

Examining data from 2010 to 2020 reveals positive trends in accessibility, particularly in G2, G3, and G4, with urban-rural gaps narrowing annually. Energy efficiency improves across most groups. However, the rise in total CO2 emissions poses potential long-term climate impacts.

Fig. 9 predicts the period from 2020 to 2030 using the coefficients from mixed-effect models. In 2030, clean energy accessibility is expected to reach 30, 91, and 77 in G2, G3, and G4, respectively. Electricity accessibility is projected at 75, 100, and 100. Energy intensity levels are expected to reach 2.61, 5.88, 5.20, 3.71, and 3.99 in each group. Renewable energy consumption rate will reach 32.1, 3.07,

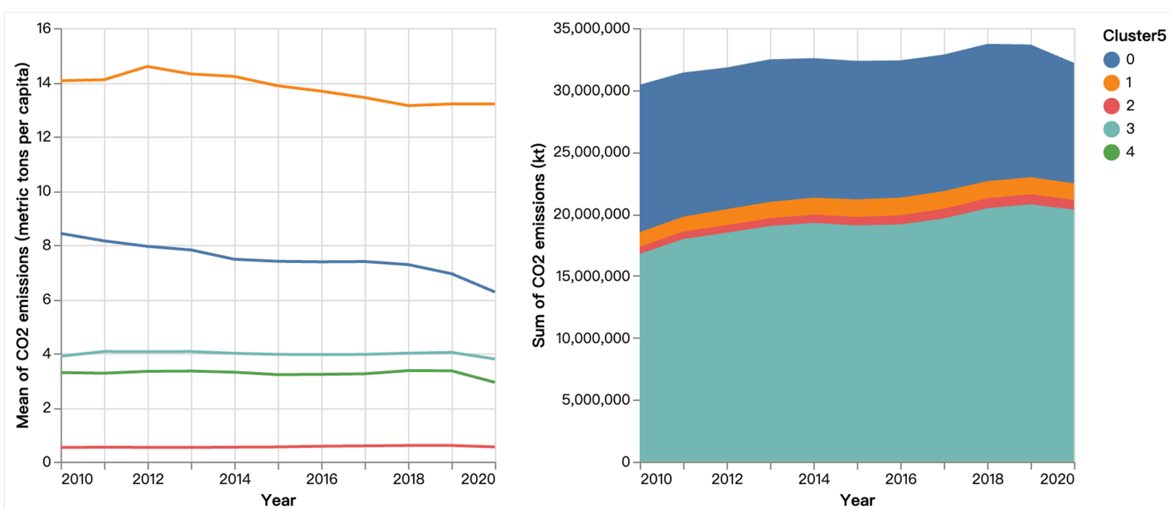


Fig.8. CO2 emission per capita and total results in 2010-2020.

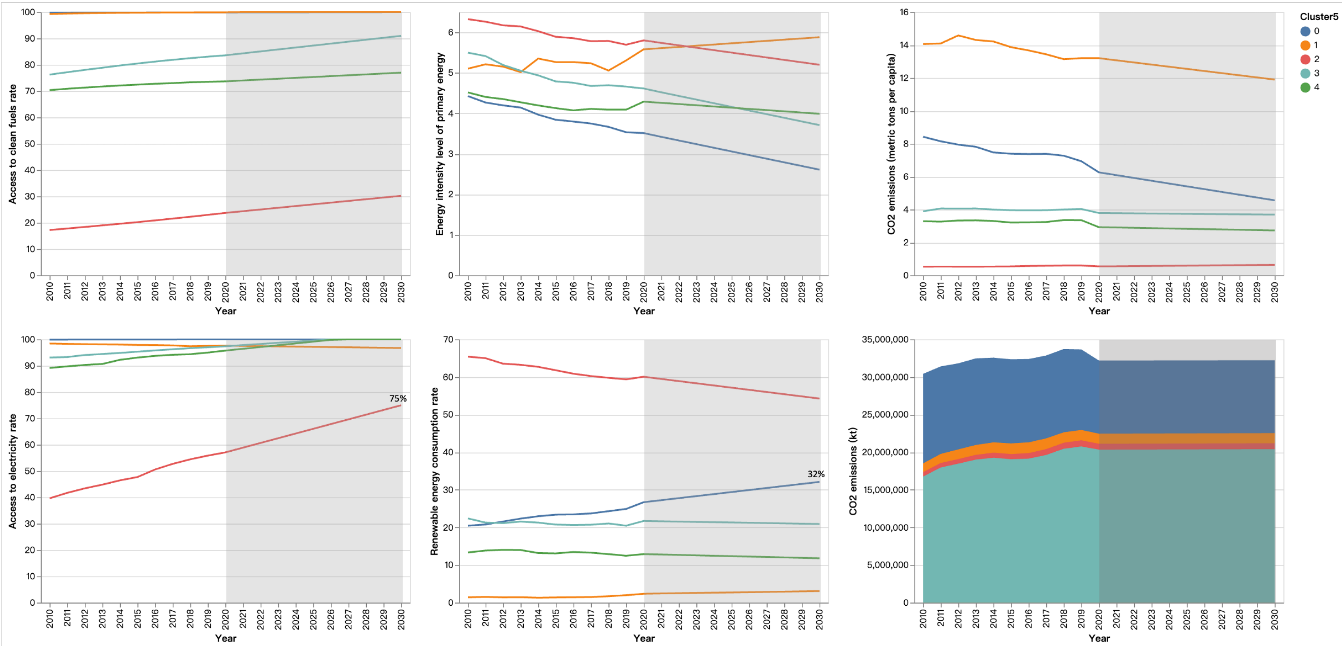


Fig. 9. Indicators' predictions.

54.27, 20.92, and 11.81, respectively. Although CO2 emissions per capita are expected to decline, the total CO2 emissions are forecasted to remain relatively stable in the next decade.

5 Critical Reflection

The analysis approach in this study combines statistical methods, human judgment, and visualisations to address questions. With each question built on the results of previous ones, the chosen approach navigates the complex layers of questions posed in this study.

In the clustering part, applying the K-means algorithm, elbow method, and silhouette scores provides an efficient way of grouping countries. However, the involvement of human knowledge gives meaningful insights to support the clustering results that help make sense for subsequence analysis. Visualisation plays a significant role, especially in this part. Without plotting cluster results on a map, the challenge emerges to compare differences between various cluster numbers. Moreover, the scatter plot with multiple features encoding, like healthcare levels and citizens' involvement in government on two axes, size representing income, and colours distinguishing different groups, making it more helpful to judge them.

The analysis of energy results for 2015 and trends from 2010 to 2020 involves calculating the mean and standard deviation within groups, supported by relevant statistical methods. The exact numbers and coefficients allow us to detect the unusual or noteworthy values in tables. Visualisations once again help us recognise patterns and give us evidence for our guessing.

However, there are still some challenges encountered. In the development levels dataset, relying on a singular indicator to represent one aspect may introduce potential bias. Combining it with suitable dimensionality reduction methods like PCA may help deal with this limitation. Additionally, we did not adjust the trend model with other random effects in this study. Without considering other random effects in the trends analysis, might cause the misestimation with variance.

Another issue is about the data in 2020. Looking closely at Fig. 9, the means performed a little differently in 2020, especially for indicators more related to finance. The reason may be due to the COVID-19 pandemic. However, the impact did not just happen in one year, the period spans years, and the effects might take longer to contain. Combined with ongoing wars, predicting the world becomes even more challenging. To validate the results without more data is difficult.

There also some questions remain unanswered with the dataset not included in this study. For example, why did the energy efficiency and renewable consumption rates perform so poorly in G1? How can we increase the renewable energy consumption rate? Additional features such as industrial activities, energy consumption patterns, or government policy may be necessary for answering these questions. This is certainly worth considering in future research.

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Supplementary Table for energy-related outcome from 2010-2020

	2010	2015	2020	ANOVA	2010-2020 trend test
	Mean (SD)	Mean (SD)	Mean (SD)	p-values	Coef. (95%CI)
Access to clean fuels rate	63.11 (39.15)	65.59 (38.37)	67.77 (37.49)	<.001	0.47 (0.43,0.50)
Group 0	99.80 (1.22)	99.85 (0.92)	99.89 (0.70)	0.373	0.01 (0.003,0.01)
Group 1	99.28 (2.10)	99.79 (0.60)	99.93 (0.18)	0.308	0.06 (0.03,0.09)
Group 2	17.21 (21.87)	20.22 (23.55)	23.72 (25.14)	<.001	0.65 (0.58,0.71)
Group 3	76.26 (22.20)	80.47 (19.68)	83.59 (18.04)	<.001	0.74 (0.64,0.83)
Group 4	70.37 (35.70)	72.45 (34.82)	73.70 (34.25)	0.031	0.33 (0.23,0.44)
Access to clean fuels rate (urban)	72.61 (35.84)	74.56 (34.84)	76.15 (33.80)	<.001	0.35 (0.31,0.39)
Group 0	99.94 (0.36)	99.95 (0.32)	99.95 (0.29)	0.373	0.001 (0.0004,0.002)
Group 1	99.87 (0.27)	99.95 (0.10)	99.96 (0.07)	0.149	0.01 (0.005,0.01)
Group 2	32.56 (32.32)	36.11 (32.81)	39.90 (33.38)	<.001	0.73 (0.64,0.83)
Group 3	88.63 (13.28)	90.71 (11.30)	91.92 (10.52)	<.001	0.32 (0.25,0.38)
Group 4	78.25 (31.19)	79.99 (31.11)	80.59 (31.13)	0.181	0.23 (0.12,0.33)
Access to clean fuels rate (rural)	54.69 (42.55)	57.22 (42.06)	59.61 (41.64)	<.001	0.49 (0.45,0.54)
Group 0	99.49 (3.13)	99.58 (2.61)	99.67 (2.03)	0.373	0.02 (0.01,0.03)
Group 1	98.96 (2.96)	99.70 (0.81)	99.87 (0.26)	0.318	0.08 (0.03,0.13)
Group 2	8.66 (18.13)	10.53 (20.16)	12.77 (22.07)	<.001	0.41 (0.34,0.47)
Group 3	59.79 (30.97)	65.72 (28.97)	70.89 (27.47)	<.001	1.12 (0.99,1.24)
Group 4	63.42 (40.81)	64.80 (40.08)	65.98 (39.73)	0.141	0.26 (0.15,0.37)
Access to electricity rate	77.77 (30.84)	81.40 (28.00)	85.23 (25.06)	<.001	0.76 (0.71,0.82)
Group 0	99.93 (0.21)	99.97 (0.11)	100 (0.02)	0.017	0.01 (0.004,0.01)
Group 1	98.44 (4.98)	97.89 (7.23)	97.63 (8.49)	0.511	-0.09 (-0.17,-0.02)
Group 2	39.64 (26.66)	47.72 (26.97)	57.09 (27.87)	<.001	1.79 (1.65,1.93)
Group 3	93.11 (11.01)	95.33 (8.76)	97.39 (7.63)	<.001	0.44 (0.39,0.50)
Group 4	89.17 (15.25)	93.10 (12.22)	95.75 (8.55)	<.001	0.68 (0.56,0.80)
Access to electricity rate (urban)	88.46 (20.30)	90.72 (17.01)	93.24 (14.25)	<.001	0.44 (0.39,0.48)
Group 0	99.96 (0.12)	99.99 (0.04)	100 (0.01)	0.012	0.003 (0.002,0.004)
Group 1	99.94 (0.14)	99.93 (0.25)	100 (0)	0.401	0.01 (0.003,0.01)
Group 2	67.74 (25.14)	73.66 (21.50)	80.30 (19.65)	<.001	1.14 (1.02,1.25)
Group 3	97.30 (5.87)	98.14 (4.69)	98.84 (3.99)	<.001	0.16 (0.13,0.19)
Group 4	94.77 (7.63)	96.05 (6.45)	97.70 (4.98)	<.001	0.29 (0.23,0.35)
Access to electricity rate (rural)	72.73 (35.50)	75.15 (35.14)	80.86 (32.36)	<.001	0.91 (0.83,0.99)
Group 0	99.72 (1.06)	99.94 (0.38)	99.99 (0.04)	0.116	0.02 (0.01,0.03)
Group 1	93.22 (22.77)	99.65 (0.68)	99.89 (0.34)	0.293	0.03 (-0.03,0.09)
Group 2	28.01 (27.96)	32.66 (30.73)	42.34 (34.07)	<.001	1.89 (1.69,2.09)
Group 3	86.64 (18.77)	89.99 (17.82)	95.19 (14.48)	<.001	0.77 (0.65,0.88)
Group 4	84.02 (21.92)	90.71 (16.72)	95.06 (11.07)	<.001	1.03 (0.83,1.24)

Supplementary Table for energy-related outcome from 2010-2020 (Conti.)

Energy intensity level of primary energy	5.38 (3.30)	4.88 (2.75)	4.78 (2.70)	<.001	-0.07 (-0.07,-0.06)
Group 0	4.43 (2.16)	3.84 (1.96)	3.51 (1.89)	<.001	-0.09 (-0.10,-0.08)
Group 1	5.10 (2.19)	5.27 (2.06)	5.58 (2.18)	0.087	0.03 (-0.003,0.05)
Group 2	6.33 (3.63)	5.89 (3.08)	5.80 (3.08)	0.004	-0.06 (-0.08,-0.05)
Group 3	5.50 (3.88)	4.79 (2.89)	4.61 (2.64)	<.001	-0.09 (-0.11,-0.07)
Group 4	4.52 (2.34)	4.13 (2.20)	4.29 (2.27)	0.119	-0.03 (-0.05,-0.02)
Renewable energy consumption rate	32.55 (29.99)	31.69 (28.64)	32.15 (27.76)	0.135	-0.10 (-0.14,-0.06)
Group 0	20.46 (16.79)	23.40 (17.22)	26.71 (17.57)	<.001	0.54 (0.47,0.60)
Group 1	1.42 (2.07)	1.38 (1.88)	2.37 (3.53)	0.106	0.07 (0.03,0.11)
Group 2	65.42 (25.47)	61.80 (25.85)	60.07 (25.38)	<.001	-0.58 (-0.66,-0.49)
Group 3	22.40 (19.38)	20.76 (17.71)	21.72 (18.52)	0.056	-0.08 (-0.16,-0.01)
Group 4	13.35 (15.56)	13.10 (14.75)	12.91 (13.65)	0.791	-0.11 (-0.19,-0.03)
CO2 emissions (metric tons per capita)	4.38 (5.44)	4.19 (5.06)	3.83 (4.65)	<.001	-0.05 (-0.05,-0.04)
Group 0	8.42 (4.37)	7.39 (3.71)	6.26 (3.12)	<.001	-0.17 (-0.19,-0.15)
Group 1	14.06 (10.37)	13.87 (10.12)	13.20 (9.73)	0.364	-0.13 (-0.19,-0.07)
Group 2	0.52 (0.81)	0.54 (0.62)	0.54 (0.54)	0.912	0.01 (0.001,0.01)
Group 3	3.89 (3.24)	3.96 (2.92)	3.79 (2.68)	0.362	-0.01 (-0.02,0.003)
Group 4	3.29 (2.70)	3.21 (2.54)	2.93 (2.21)	0.057	-0.02 (-0.03,0.002)
GDP per capita (US$) / 100	120.45 (170.36)	126.56 (176.23)	127.67 (178.77)	<.001	1.30 (1.11,1.50)
Group 0	342.05 (213.78)	361.13 (218.84)	372.59 (222.93)	<.001	4.55 (3.89,5.20)
Group 1	243.26 (188.55)	245.19 (200.49)	230.82 (194.45)	0.426	-0.97 (-2.28,0.35)
Group 2	14.33 (16.46)	14.86 (14.29)	14.40 (10.59)	0.652	0.03 (-0.06,0.12)
Group 3	53.32 (29.41)	60.84 (32.53)	61.57 (29.27)	<.001	1.02 (0.88,1.15)
Group 4	101.75 (97.22)	108.71 (96.91)	101.72 (85.18)	0.173	0.97 (0.57,1.37)