alphanumeric
https://alphanumericjournal.com/

Volume 13
Issue 01
Year 2025

Research Article

Data-Driven Insights into Climate Change and Technological Levels: Data Mining Visualization and TOPSIS Approach

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Abstract

According to the 2024 Global Risks Report prepared by the World Economic Forum, the risk of misinformation and disinformation in the technology category and extreme weather events in the environmental concerns category are shown to be the biggest risks threatening the world both in the short term of two years and in the long term of ten In the long term, the negative consequences arising from artificial intelligence technologies have also been added to the technology category. Environmental and technological factors pose major challenges to global stability. The fight against environmental and technological global risks is not limited to the field of environmental science or technology experts. It should be accepted that every individual, every sector, and every nation has responsibilities on these risks and that these risks should be evaluated with an interdisciplinary academic perspective. In this study, both the countries fight against climate change and their technological studies were considered together, and these two risks were evaluated together on a national scale. The primary objective of this research is to determine the relationships between combating climate change and technology use areas and to position and rank countries according to these characteristics. In order to achieve this goal, exploratory data analysis, principal component analysis, multidimensional scaling, and TOPSIS methodologies were applied. As a result of the study, the basic relationships between countries' climate change combat and technology use sub-indicators were determined, and a ranking was obtained with a detailed understanding of how countries are aligned with these global risks.

Keywords Data mining, Visualization, TOPSIS, Climate change, Technology level

Jel Codes C38, C44, C63

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2025.13.01.OR.02

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Timeline

Submitted	Feb 27, 2025
Revision Requested	Apr 04, 2024
Last Revision Received	Apr 17, 2024
Accepted	May 06, 2025
Published	Jun 30, 2025

Citation

Doğruel, M. (2025). Data-Driven Insights into Climate Change and Technological Levels: Data Mining Visualization and TOPSIS Approach, *alphanumeric*, 13 (1), 13-35. https://doi.org/10.17093/alphanumeric.1647858

1. Introduction and Related Studies

The Global Risks Report 2024 published by the WEForum (2024) provides an analysis based on the perceptions of nearly 1,500 international experts regarding global risks. Environmental risks, notably extreme weather events, emerge as the most probable to precipitate a significant global crisis over the next decade. These weather events are also ranked as the second most significant immediate risk for the next two years. The report further warns of an escalating digital divide caused by advancements in artificial intelligence and other leading technologies, which could exacerbate disparities in economic, educational, and health outcomes between higher- and lower-income countries. This divide poses a substantial risk of leaving vulnerable communities further behind. Additionally, the report highlights the acute risks posed by the ongoing cost of living crisis and the proliferation of misinformation and disinformation about AI, which is identified as one of the top short-term risks.

The phenomenon of climate change, primarily driven by global warming, is identified as the leading cause of extreme weather events. This change occurs over extended periods, spanning several millennia, and has the capacity to increase global temperatures, alter precipitation patterns, and redistribute water resources worldwide (Demirbaş & Elmaslar Özbaş, 2024).

The implications of climate change extend beyond environmental and natural sciences, affecting various disciplines including geography, sociology, psychology, and political science. It impacts critical sectors such as health, agriculture, energy, tourism, construction, finance, and media, necessitating a broad interdisciplinary approach to understanding and addressing its effects (Karacaoğlu & Akbaba, 2024).

The climate change performance index (CCPI) is a scoring system designed to increase transparency in national and international climate policies. It is followed academically and administratively.

Martin (2025) conducted a study on climate change indicators. The indicators in the study were detailed as the International Monetary Fund, in collaboration with other international organizations, divided them into six categories to demonstrate the impact of economic activity on climate change: (1) greenhouse gas (GHG) emissions; (2) mitigation; (3) adaptation; (4) transition to a low-carbon economy; (5) climate finance; and (6) climate and weather. Additionally, the European Central Bank case study is presented.

Caglar et al. (2024) investigated the impact of green innovation, green investment, economic growth, and natural resources on ecological sustainability in the five best performing European Union countries in terms of the Climate Change Performance Index using an econometric analysis. For this, the EU-5 countries with the highest CCPI scores from 1995 to 2020 (Germany, Sweden, Portugal, the Netherlands and Denmark) were included in the list. The study suggests specific policies to achieve the Sustainable Development Goals, especially targeting target 13.

Puertas & Marti (2021) aimed to evaluate the performance profiles of countries in combating climate change using information from the 2021 Climate Change Performance Index and to verify the link between actions and achievements. According to their empirical analysis, it was found that concern about the need to limit climate change does not depend on the wealth of countries and that no common pattern is observed in geographically close regions. Additionally, this study presented statistical evidence on the link between climate change policies, the use of renewable energy in electricity supply, and the reduction of harmful gas emissions.

Addressing the misinformation and disinformation concerning artificial intelligence is also critical, as these are among the dominant risks of 2024, with significant economic and technological implications expected in the near future.

The Networked Readiness Index (NRI) is an index that provides a performance score regarding the use of information technologies within a country. Similar to the CCPI, this index is used both in academic studies and managerial fields.

Qazi (2025), examines the relationships between regulatory factors and various socioeconomic outcomes using Bayesian Belief Network models and Network Readiness Index 2023 data for 134 countries. The main conclusion of the study is that regulatory quality and e-commerce legislation from the sub-pillars of NRI emerge as central determinants that directly or indirectly impact economic development, societal well-being and sustainability objectives.

In their study, Bánhidi & Dobos (2024) provide a viable alternative framework to the equal weights scheme of the original NRI scoring model using the Data Envelopment Analysis (DEA) Without Explicit Input (WEI) method and the Common Weight Analysis (CWA) method.

Silva et al. (2022) have revealed the indicators that most significantly affect the economic and social impact pillars of NRI based on the Least Absolute Shrinkage and Selection Operator (LASSO) analysis of NRI for 2013-2016.

It is very important to conduct a multidisciplinary investigation into the risk factors and their relationships with each other in the two major global risks: climate change and technology. It would be appropriate to articulate the objectives of this investigation through the subsequent inquiries. Which of the technological sub-elements of the countries are effective in combating climate change? Which countries are in a good position both for combating climate change and for technological development? Can these country positions be visually made? How can countries be ranked when evaluated in terms of these two features when evaluated?

The process of data visualization involves the transformation of intricate data sets into visual representations, such as charts, graphs, maps, word clouds, networks, arcs, and alluvial diagrams, with the aim of facilitating the comprehension and interpretation of the underlying data and information (Muhammad & Hazelton, 2024). Visualization encompasses more than mere visual representation; it has the potential to render intricate scientific information more comprehensible, memorable, and credible to lay individuals (Saka et al., 2019). Data visualization facilitates cognitive processing by transforming abstract data into a more comprehensible form. In this manner, it enables individuals to swiftly identify trends, outliers, patterns, and correlations in data that may otherwise be concealed within numerical data (Muhammad & Hazelton, 2024). For some writers, visualization is like “a picture speaking a thousand words” (Mathaisel, 2024).

Although tables, graphs, and maps have actually been used in very difficult areas since the 17th century, thanks to technological developments such as open source programs such as R and Python that can easily visualize big data, “data visualization” is considered a relatively modern development in statistics (Mathaisel, 2024)

Exploratory Data Analysis (EDA) is a fundamental step in data investigation, utilizing visual methods to understand data structures and extract significant insights. This approach is instrumental in identifying key variables, detecting outliers, and developing models, and it is often the precursor to more complex analyses such as clustering, principal component analysis, and factor analysis (Miranda-Calle et al., 2021; Nielsen, 2022). It is often the first step in this investigation to display the data in a graph and observe how frequently each value for the variable occurs. Multivariate exploration techniques include clustering (hierarchical or non-hierarchical), principal component analysis (PCA) and factor analysis (FA) (Nielsen, 2022).

The study of data mining falls under the purview of Machine Learning (ML). ML teaches the computer to perform tasks without human intervention. The objective of ML is to detect patterns and acquire skills in making predictions and recommendations through the processing of data and experiences, as opposed to receiving explicit programming instructions. The field of ML is primarily concerned with EDA and the acquisition of knowledge pertaining to pattern recognition.

Multidimensional Scaling (MDS) was developed to analyze the data of a group of objects according to their similarities and differences. MDS attempts to model this data according to distances between points in a geometric space. The primary purpose of this is to present the data structure graphically. Even if the relationships between the objects are not known, if the distances between the objects can be calculated, the relationship between the objects can be revealed by using these distances. The representation of the objects in a low-dimensional space helps to better understand the data (Aydın & Yalçın, 2017).

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is one of the most widely used methods in the literature for multi-criteria decision making. The TOPSIS method is based on the idea that among the most preferred alternatives, not only the closest to the positive ideal solution, but also the one farthest from the negative ideal solution, is the alternative (Karaman & Kazan, 2015).

2. Bibliometric Survey

In this section, literature reviews and bibliometric researches of the two indexes used, CCPI and NRI, and the analysis methods, EDA, PCA, MS and TOPSIS, will be included. The word clouds related to the information of the relevant keywords taken from the Web of Science database were visualized with VOSviewer for this purpose. In addition, the publication numbers of the relevant words over the years are shown in the form of column charts according to the analysis results obtained from the Web of Science database.

The first subheading contains bibliometric research on indexes.

2.1. Climate Change Performance Index (CCPI)

The Climate Change Performance Index (CCPI) has served as an autonomous evaluative mechanism since 2005, monitoring the climate protection efforts of 63 countries along with the European Union. The 2024 edition of the CCPI evaluates the climate mitigation actions of 67 countries, which collectively contribute over 90% of worldwide greenhouse gas emissions. This assessment is conducted across four distinct categories: greenhouse gas (GHG) emissions, renewable energy, energy usage, and climate policy. The CCPI is collaboratively published by Germanwatch, the New Climate Institute, and the Climate Action Network (Burck et al., 2024).

When searching the Web of Science database using quotation marks ("climate change performance index"), only 32 publication results are obtained. The search without quotation marks appears in Figure 1. Upon examination of Figure 1, it is evident that the terms climate, sustainable development objectives, regional climate modeling, and energy efficiency are notable.

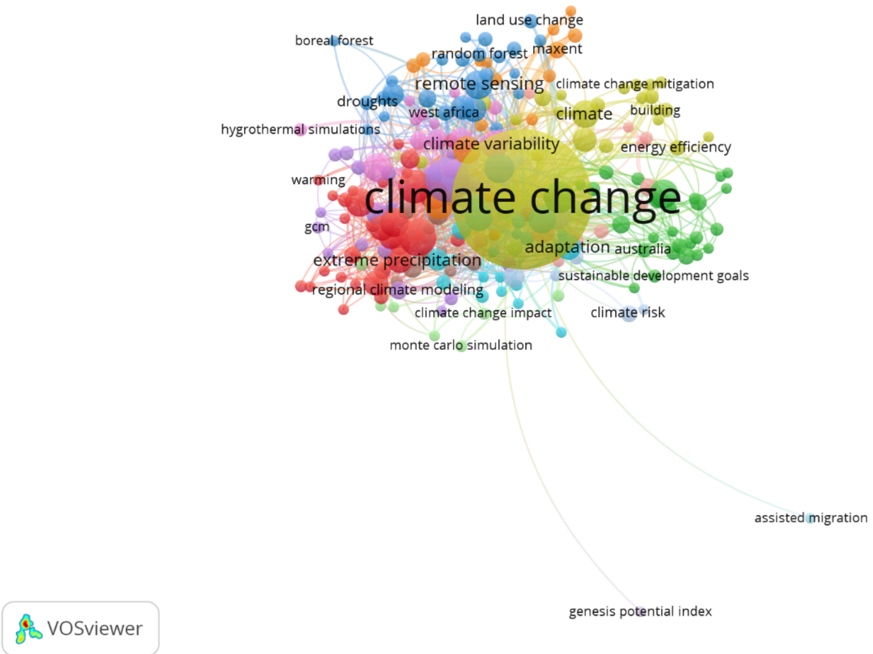

Figure 1. Keywords related to climate change

Figure 2 shows that studies on CCI have steadily increased over the years.

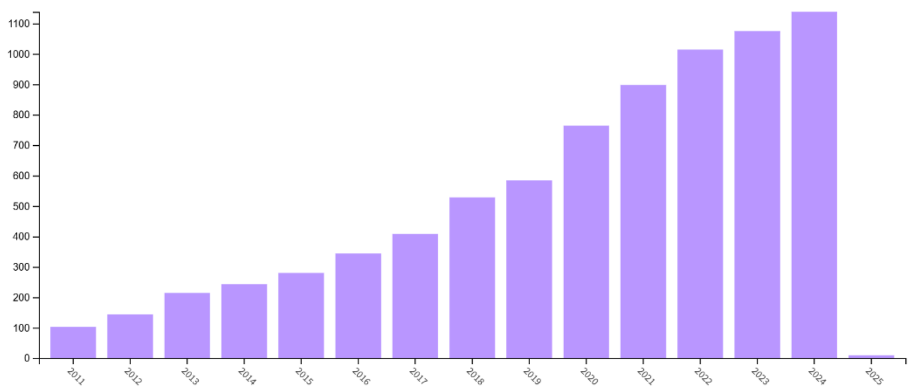

Figure 2. Climate Change Index publication years

2.2. Network Readiness Index (NRI)

The NRI was first published by the World Economic Forum in 2002, and has been under the auspices of the Portulans Institute since 2019. The 2024 report is the sixth edition, and includes data from

133 countries, and the main indicators are Technology, People, Governance, and Impact (Dutta & Lanvin, 2024).

When searching the Web of Science database using quotation marks ("network readiness index"), only 42 publication results are obtained. The search without quotation marks appears in Figure 3. The analysis of Figure 3 reveals that the word cloud visual is notably straightforward, demonstrating a significant association with terms such as "ICT," "e-government," and "e-readiness".

Figure 3. Keywords related to Network Readiness Index

When Figure 4 is examined, it is understood that although there are only very few publications with network readiness index keywords annually, the increase after 2020 is significant.

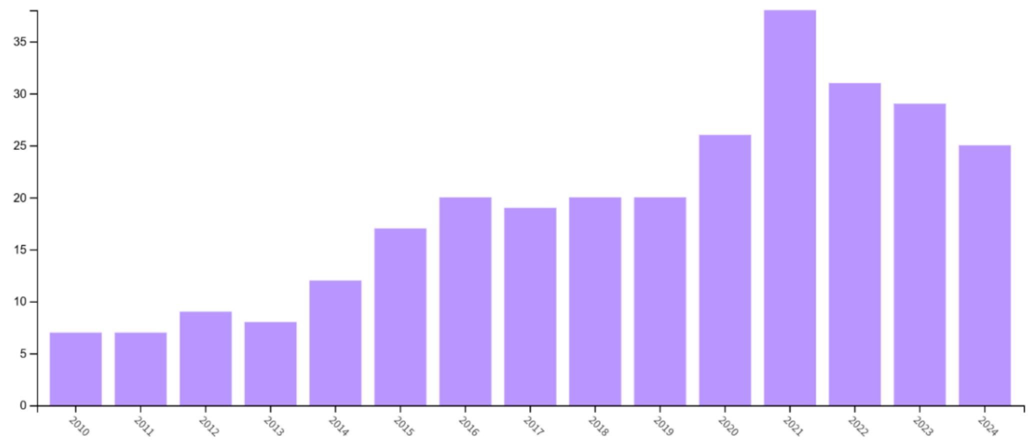

Figure 4. Network Readiness Index publication years

2.3. Analysis Methods

This subheading contains bibliometric analysis studies for the analysis methods EDA, PCA, MS, and TOPSIS.

Upon examination of Figure 5, it can be observed that the notion of exploratory data analysis is closely associated with concepts such as exploratory factor analysis, confirmatory factor analysis, big data, visual analytics, and interactive visualization. It is evident that EDA is most closely associated with the notions of exploratory and visuality.

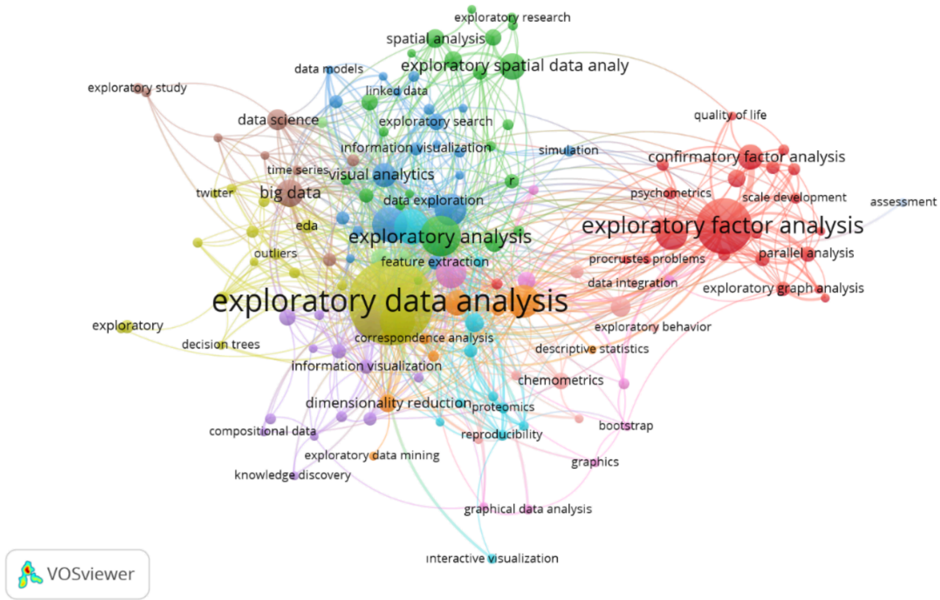

Figure 5. Keywords related to exploratory data analysis

It can be seen from Figure 6 that there is a general increasing trend in publications related to EDA, and the increase is especially evident after 2020.

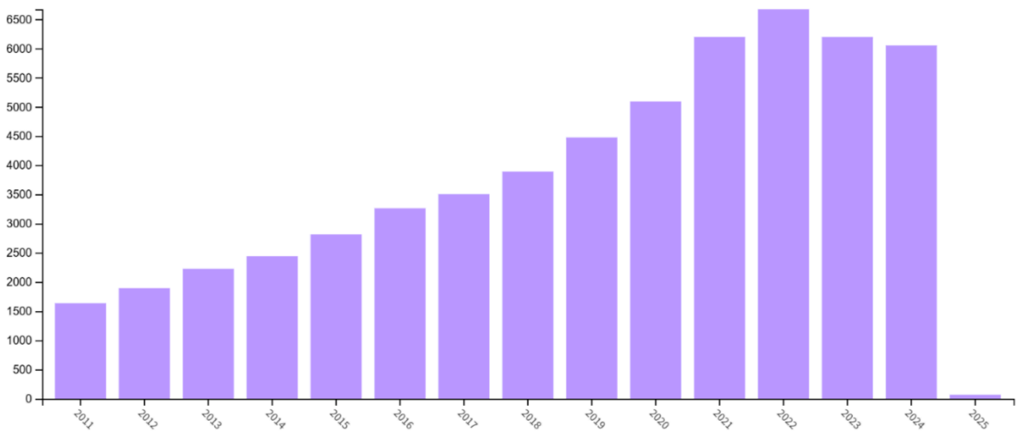

Figure 6. Keywords related to exploratory data analysis

As shown in the Figure 7, the concept of principal component analysis is related to concepts such as dimension reduction, feature extraction, cluster analysis, fault detection, and evaluation.

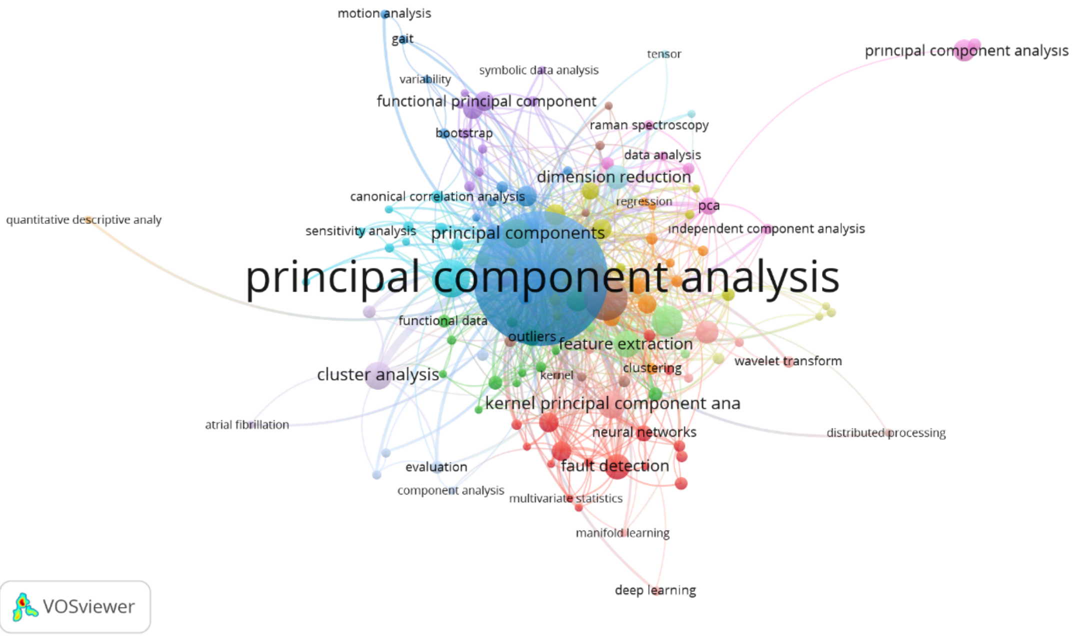

Figure 7. Keywords related to exploratory data analysis

As evident from Figure 8, the quantity of publications on PCA persists with modest increments.

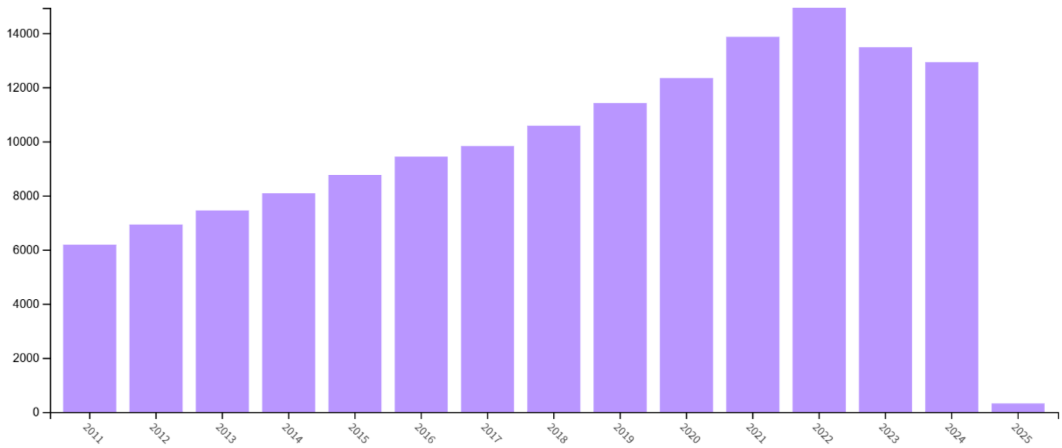

Figure 8. Principal component analysis publication years

It is evident from Figure 9 that a relationship exists between the notion of multidimensional scaling and various concepts such as visualization, confirmatory factor analysis, and feature.

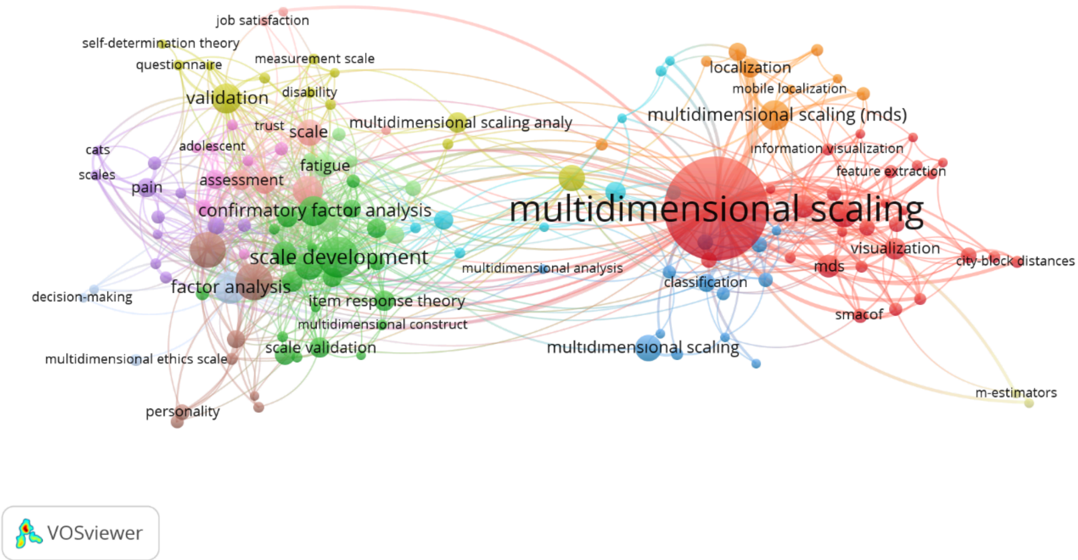

Figure 9. Principal component analysis publication years

Figure 10 shows that studies conducted with multidimensional scaling do not show a great deal of momentum, but they continue to increase.

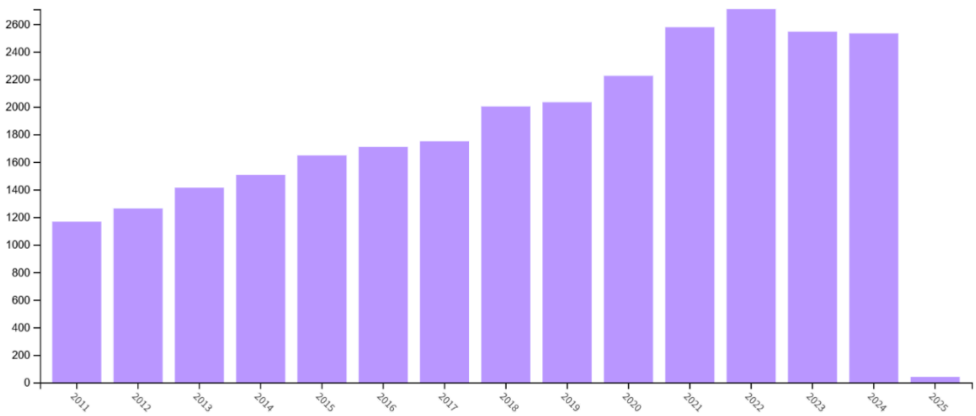

Figure 10. Principal component analysis publication years

As depicted in Figure 11, multi-criteria decision-making is associated with concepts such as sustainability, evaluation, entropy, weight, VIKOR, and genetic algorithm.

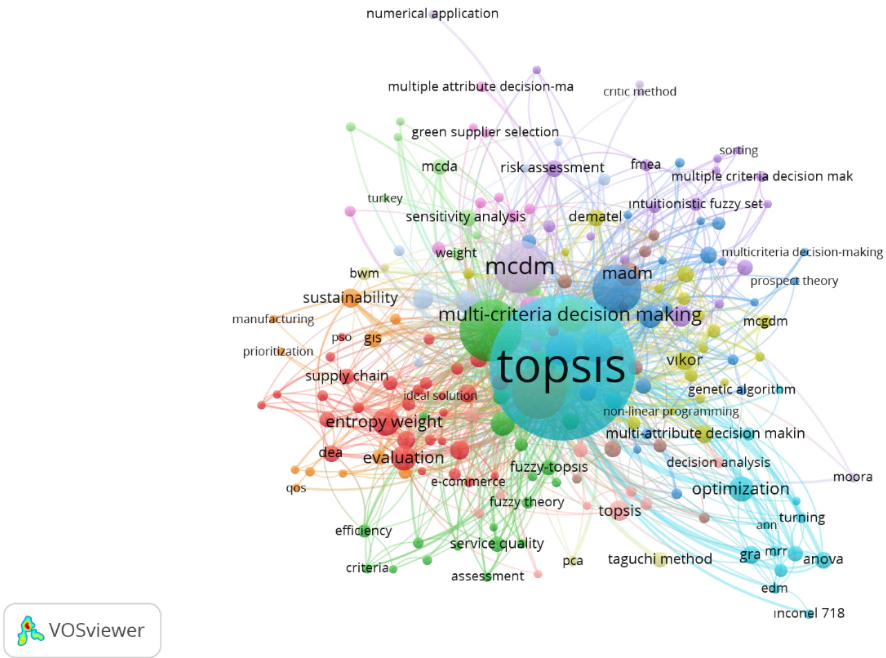

Figure 11. Principal component analysis publication years

As depicted in Figure 12, it can be observed that the number of publications related to TOPSIS increased until 2022, and a similar number of publications were produced every year thereafter

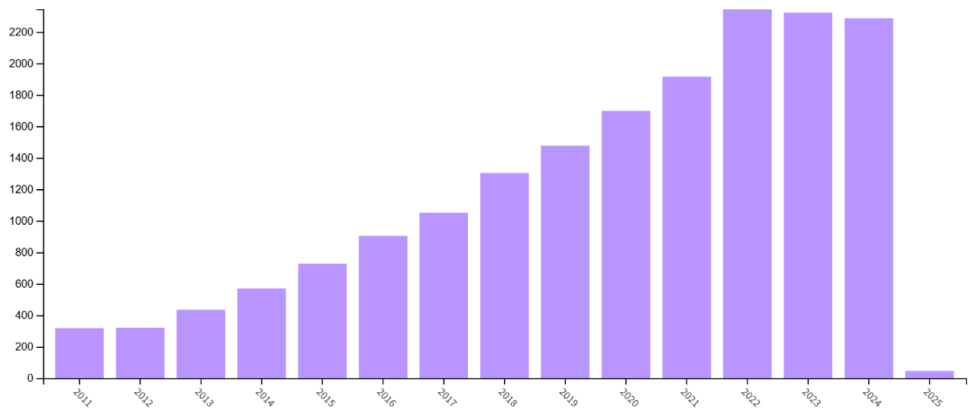

Figure 12. Principal component analysis publication years

3. Methodology

In the present research, Exploratory Data Analysis (EDA) serves as the foundational method for examining and visualizing the variables under consideration. Principal Component Analysis (PCA) is employed to determine the aggregation of these variables into principal components, while Multidimensional Scaling (MDS) facilitates the visualization of the relative positioning of various countries. Additionally, the TOPSIS is utilized to rank the countries based on their effectiveness in combating climate change and their technological advancements.

3.1. Exploratory Data Analysis (EDA)

EDA is typically the initial stage of data mining and is considered one of the most significant phases of the preprocessing process. It enables us to view data, understand it, and make hypotheses for further analysis. EDA revolves around the creation of a summary of data or insights for the subsequent phases of a data mining project. EDA effectively uncovers fundamental truths about the content without making any fundamental assumptions (Mukhiya & Ahmed, 2020).

The main objectives of EDA are as follows (Komorowski et al., 2016):

- Understanding the data's structure and delineating the issue as the primary objective of the analysis.
- Visualizing the relationships between variables in terms of direction and degree
- Detecting outliers and anomalies
- Making suitable variable selections for the analysis

3.2. Principal Component Analysis (PCA)

In 1901, Karl Pearson first described the PCA. Harold Hotelling's 1933 description of practical computing techniques came much later (Manly & Navarro Alberto, 2016).

PCA is a technique used for reducing the original variable space to a lower-dimensional principal component space. It is used for dimension reduction, feature selection, and visualization of measurements.

The basic steps of PCA are summarized below (Masnan et al., 2012).

$$\text{Compute Mean: } \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$\text{Standardize the Data: } \Phi_i = \frac{x_i - \overline{x}}{\sigma_x} \tag{2}$$

Form the matrix $A = \left[\Phi_1, \Phi_2, \ldots, \Phi_p\right]_{pxn}$, then compute:

$$C = \frac{1}{n}\sum_{i=1}^{n} \Phi_i' \Phi_i \tag{3}$$

$$\text{Compute the eigenvalues of } C: \lambda_1 > \lambda_2 > \ldots > \lambda_p \tag{4}$$

$$\text{Compute the eigenvalues of } C: u_1 > u_2 > \ldots > u_p \tag{5}$$

The linear transformation of the data initially in R_p performs dimensionality reduction by a linear projection onto R_q, where $q < p$.

3.3. Multidimensional Scaling (MDS)

MDS is the first metric learning algorithm, and it is likely the most widely used today (Peterfreund & Gavish, 2021).

Multidimensional Scaling (MDS) was originally utilized in the social sciences to assess the similarity ratings among pairs of stimuli, encompassing a diverse array such as tastes, colors, individuals, and nations. Additionally, it found application in archaeology for examining the similarities between two archaeological sites, and in various classification tasks to create confusion matrices for analyzing pairwise discrepancies. A significant application of MDS lies in dimension reduction. In the field of chemistry, MDS is employed to determine molecular conformations, which describe the spatial arrangement of molecules. Furthermore, MDS is also utilized in graph layout, an evolving field that resides at the confluence of discrete mathematics and network visualization (Buja et al., 2008).

MDS is equivalent to standard PCA, in which case the method is also referred to as ClassicMDS (CMDS). Nonetheless, MDS is significantly more versatile than conventional Principal Component Analysis and is capable of performing nonlinear dimension reduction as well (Shen et al., 2023).

The MDS methodology involves mapping the initial high-dimensional data (m dimensions) to a lower-dimensional data (d dimensions). The issue of constructing a configuration between the n points from the kxk matrix D is addressed, which is referred to as the distance affinity matrix if it is symmetric, i.e., $d_{ij} = 0$, and $d_{ij} > 0$, $i \neq j$ (Saeed et al., 2018). The MDS algorithm locates n data points $y_1, y_2, \ldots, y_n$ from the distance matrix D within a d-dimensional space, such that if d^{ij} is the Euclidean distance between y_i and y_j, then $\hat{D}$ resembles D. The MDS that is considered is

$$\min_y \sum_{i=1}^{k} \sum_{j=1}^{k} \left(d_{ij}^X - d_{ij}^Y\right)^2 \tag{6}$$

where $d_{ij}^X = \left\|x_i - x_j\right\|^2$ and $d_{ij}^X = \left\|y_i - y_j\right\|^2$.

The distance matrix D^X is transformed into a kernel matrix of inner product $X^T X$ by

$$X^T X = -\frac{1}{2} H D^X H \tag{7}$$

where $H = I - \frac{1}{t} e e^T$ and e is a column vector containing 1′s.

The above equation could be expressed as

$$\min_y \sum_{i=1}^{k} \sum_{j=1}^{k} \left(x_i^T x_j - y_i^T y_j\right)^2 \tag{8}$$

The solution is $Y = \wedge^{1/2} \vee^T$, in which $\vee$ represents the eigenvectors of $X^T X$ and $\wedge$ represents the d eigenvalues of $X^T X$.

3.4. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a well-known and significant classical multiple criteria decision analysis method, which was originally developed by Hwang and Yoon in 1981. TOPSIS has been extensively utilized in various domains, including but not limited to purchase decisions, outsource provider selection, manufacturing decision making, financial performance analysis, service quality assessment, educational selection applications, technology selection, material selection, product selection, strategy evaluation, and crucial mission planning (Chakraborty, 2022).

The TOPSIS method works on the shortest distance of the chosen alternative to the positive ideal solution and the farthest distance to the negative ideal solution. The basic steps can be summarized as follows (Han et al., 2024; Yu et al., 2020):

Determine the normalized decision matrix $R = (r_{ij})_{mxn}$ by utilizing Eq. 9:

$$r_{ij} = \begin{cases} \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} & \text{for } j \in I \\ \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} & \text{for } j \in J \end{cases}, \qquad i = 1, 2, ..., m \text{ and } j = 1, 2, ..., n \tag{9}$$

Find the positive ideal solution and the negative ideal solution using equations Eq. 10 and Eq. 11:

$$A^+ = \{r_1^+, ..., r_n^+\} = \{(\max_i r_{ij} \mid j \in I), (\min_i r_{ij} | \ j \in J)\} \tag{10}$$

$$A^- = \{r_1^-, ..., r_n^-\} = \{(\min_i r_{ij} \mid j \in I), (\max_i r_{ij} | \ j \in J)\} \tag{11}$$

Calculate the distance Δ_{ij} between the ideal solution value and each comparison value using the Euclidean distance, which is a widely used distance calculating formula, as Eq. 12 and Eq. 13:

$$\Delta_i^+ = \left\{ \sum_{j=1}^{n} \left(r_{ij} - r_j^+\right)^2 \right\}^{\frac{1}{2}}, i = 1, 2, ..., m \tag{12}$$

$$\nabla_i^- = \left\{ \sum_{j=1}^{n} \left(r_{ij} - r_j^-\right)^2 \right\}^{\frac{1}{2}}, i = 1, 2, ..., m \tag{13}$$

Determine the weighted distances from each alternative to the positive ideal solution and the negative ideal solution by the following Eq. 14 and Eq. 15:

$$d_i^+ = \sum_{j=1}^{n} w_j \Delta_{ij}^+, i = 1, 2, ..., m \tag{14}$$

$$d_i^- = \sum_{j=1}^{n} w_j \nabla_{ij}^-, i = 1, 2, ..., m \tag{15}$$

Calculate the relative proximity to the ideal solution. The relative proximity of the alternative X to Y and Z can be calculated using equation Eq. 16.

$$C_i = \frac{d_i}{d_i^+ + d_i^-}, i = 1, 2, ..., m \tag{16}$$

Position the alternatives in decreasing order.

4. Analysis and Findings

The research framework established to accomplish the objective of the study is depicted in Figure 13.

Figure 13. Research framework

When the data pertaining to countries common to the CCPI (Burck et al., 2024) and NRI 2024 reports are amalgamated, a dataset comprising 61 observations (countries) and 8 features was obtained, as depicted in Table 1.

Table 1. Condensed dataset

Country	CCPI GHG Emis.	CCPI Ren. Energy	CCPI Energy Use	CCPI C. Policy	NRI Tech.	NRI People	NRI Gov.	NRI Impact
Algeria	22.54	2.01	13.80	6.20	31.45	35.63	41.18	41.82
Argentina	18.77	4.13	15.33	7.16	39.53	44.28	59.48	55.82
Australia	23.20	5.57	8.04	8.90	59.97	64.37	86.88	70.23
Austria	24.43	8.92	10.95	13.87	60.19	63.74	81.98	70.61
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Vietnam	22.80	8.64	12.10	17.40	43.47	46.18	53.42	61.67

Other than TOPSIS, analyses are conducted in Python programming, and TOPSIS is conducted in MS Excel.

Within the purview of EDA, the correlation matrix, scatter plot, histograms, and violin graphs shown in Figure 14, Figure 15, Figure 16, and Figure 17 are examined.

When the correlation matrix is examined Figure 14, it is observed that all indicators of NRI have a positive significant relationship with the renewable energy use indicator of CCPI, and a negative significant relationship with the energy use indicator of CCPI statistically significant negative relationship with the energy use of the CCPI. Another statistically significant correlation is observed between the impact indicator of NRI and the climate policy variable of CCPI.

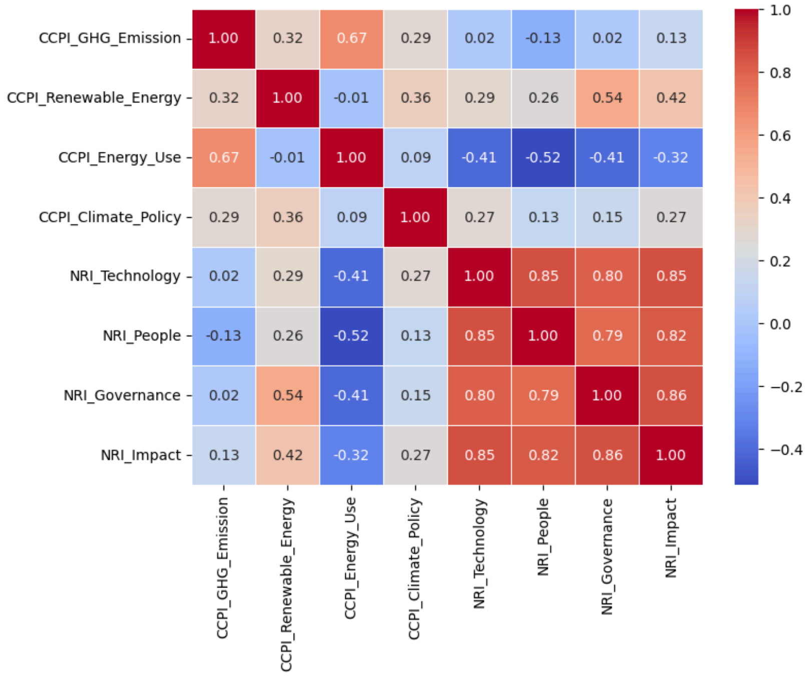

Figure 14. Correlation matrix

An analysis of the scatter plot graphs (Figure 15) reveals that the relationship between the NRI indicators and the CCPI indicators is not strongly linear. Additionally, the correlation matrix indicates that the levels of significant relationships are relatively modest.

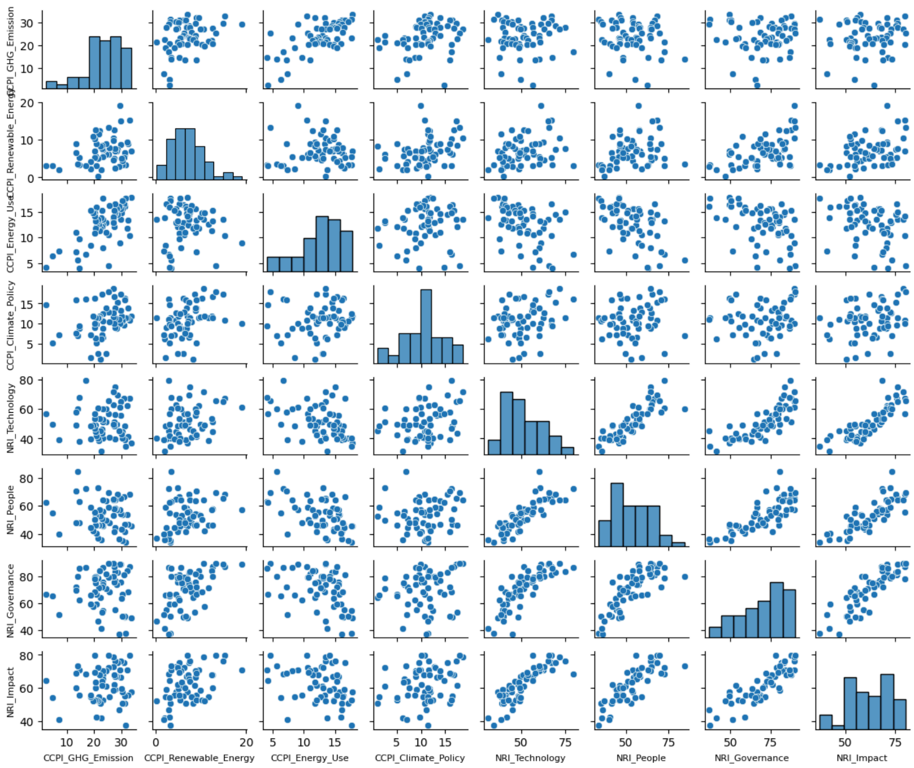

Figure 15. Scatter plots

Upon examination of the histograms depicted in Figure 16, it is evident that the variables exhibit asymmetric distributions instead of a completely normal distribution.

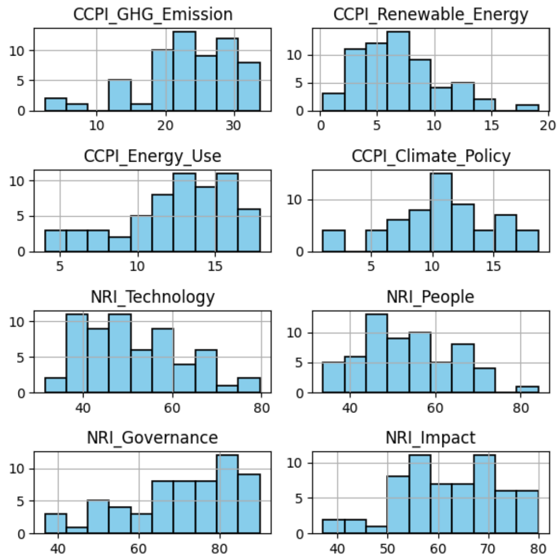

Figure 16. Histograms

Hintze and Nelson introduced the violin plot in 1998, based on Tukey's box plot with intensity traces. The violin graph represents the estimated density of scores falling within a certain range, not the raw data. A smoothed histogram of data density can be construed as the width of the violin plot. This approach has the advantage of keeping the graph accessible, with the possibility of incorporating visual representations of summary (Tanious & Manolov, 2022).

When the violin graphs in Figure 17 are examined, it is evident that the variables exhibit different patterns in terms of both density and summary statistics (such as mean, max-min, quartiles).

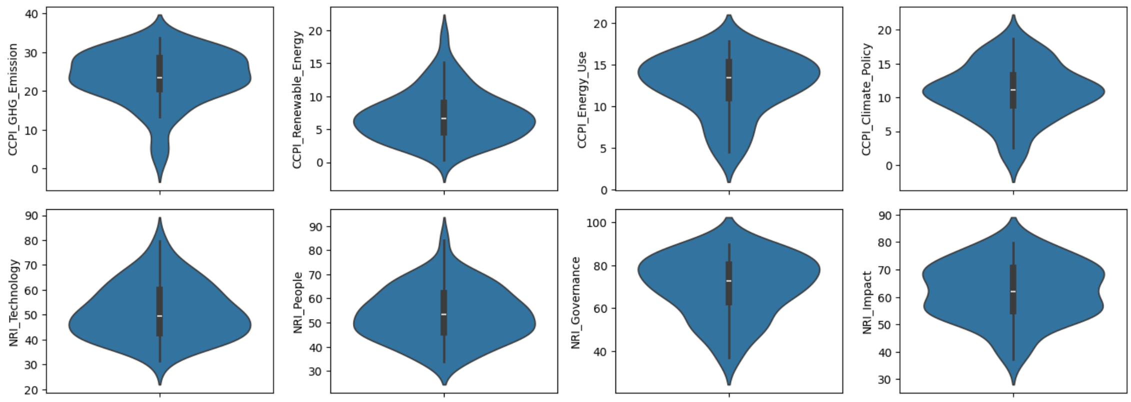

Figure 17. Violin Graphs

PCA will be executed subsequent to the analysis of scatter plots illustrating the correlation between variables, histograms displaying frequency distributions, and violin graphs from which both density and fundamental statistical values have been obtained.

Figure 18, provides the explanation ratios for the components and the cumulative explanation ratios. It is observed that the first two components have a high variance explanation ratio, and together they have a variance explanation of approximately 75%.

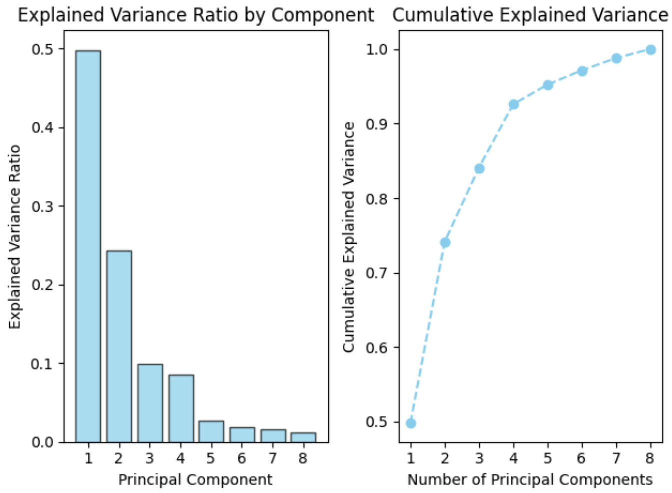

Figure 18. Explained variances for PCA

Figure 19 and Figure 20 indicate that variables belonging to NRI have dominant loadings on one factor, while variables belonging to CCPI have dominant loadings on one factor. This is a significant issue to verify the consistency of the data. Furthermore, the 2-factor high explanatory PCA demonstrates that when data reduction is desired, it is feasible to utilize two components.

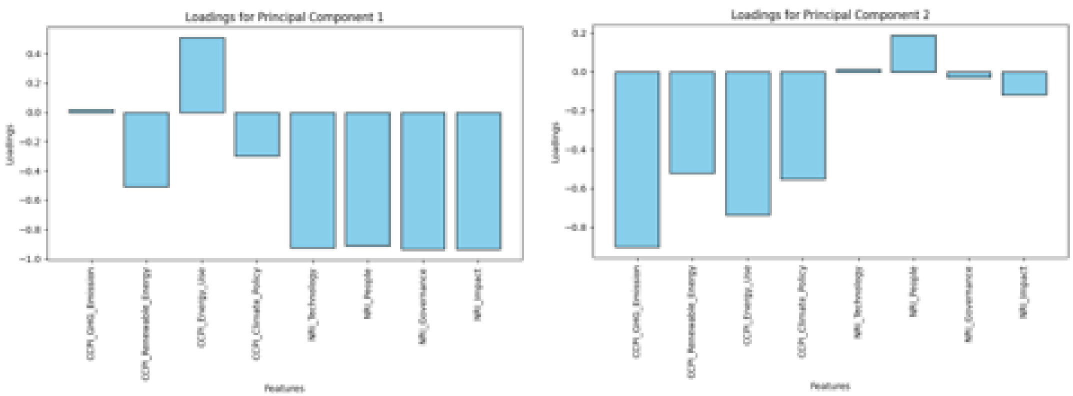

Figure 19. Loadings for Principal Component 1 and 2

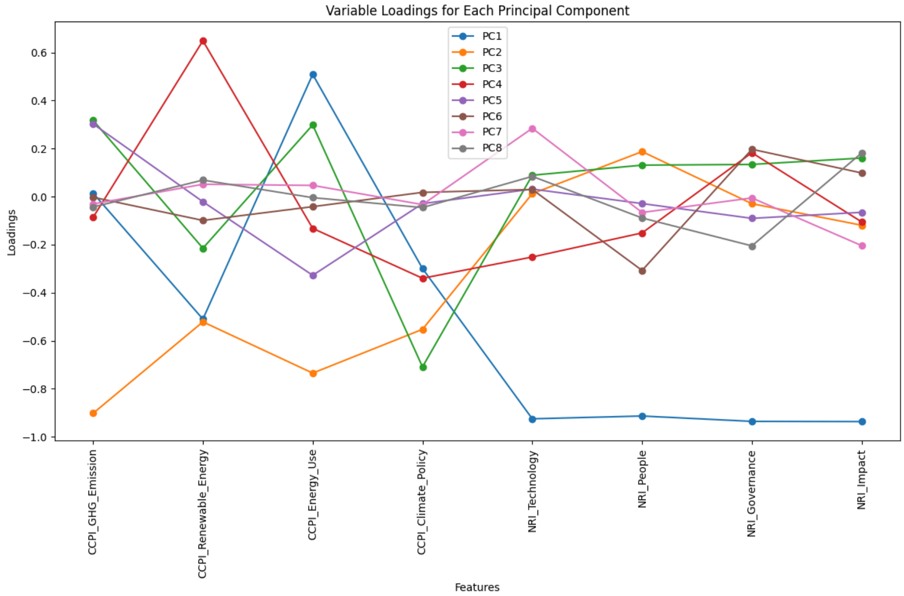

Figure 20. Variable loadings for each Principal Component

In the data set, which has a good explanatory power as two factors with PCA, the units, namely the countries, were subjected to MDS analysis in order to visualize their positions relative to each other in a two-dimensional graph. This visualization is illustrated in Figure 21.

When Figure 21 is examined, dimension 1 can be described as the CCPI and dimension 2 as the NRI dimensions. It is seen that the factors obtained from the Factor Analysis results and the dimensions obtained from the MDS analysis are consistent because the variables are collected in two factors and these factors consist of CCPI and NRI loadings. Based on Figure 21, the countries in the best position according to both dimensions are Sweden, Netherlands, Denmark and Norway. The Islamic Republic of Iran is perceived to be in a precarious situation in both regards. Despite the positive position of the United States, Republic of Korea, Canada, and China in dimension 2 (NRI), they are in a negative position in dimension 1 (CCPI). The Philippines, Morocco, Egypt, Pakistan, and Nigeria are examples of countries that are well positioned in dimension 1 (CCPI), but poorly positioned in dimension 2 (NRI). Countries such as the Czech Republic, Slovenia, Italy, and Poland are in an average position in both dimensions. The stress value obtained from the MS analysis is 5.53×10^{-6}, which is a commendable outcome for the reliability of the analysis.

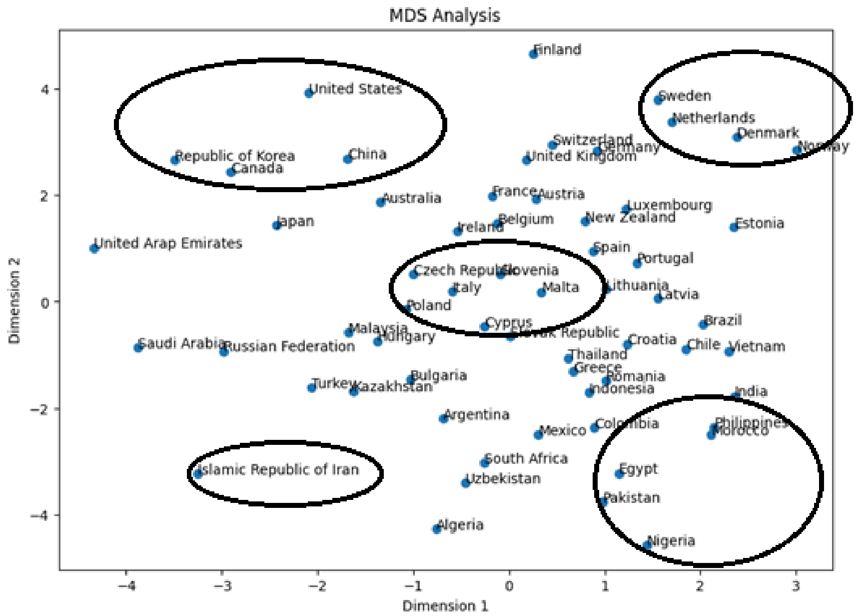

Figure 21. Variable loadings for each Principal Component

With the EDA, PCA, and MS applications completed to this stage, basic definitions of the data set, consistencies of the indices, and visual representations of the locations of the units in two-dimensional space can be obtained and interpreted.

Table 2 provides a ranking of 61 countries according to their TOPSIS scores, which are evaluated with equal weight (1/8 = 0.125) for eight indicators of climate change and technology level. According to the findings presented in Table 2, the top three countries in terms of climate change and technology level are Denmark, Sweden, and Norway, while the bottom three countries are Russia, Saudi Arabia, and the Islamic Republic of Iran. Among countries with average performance according to eight indicators of combating climate change and the level of technology, Greece is ranked 30th, Slovenia is ranked 31st, and Unitad State is ranked 32nd. It is evident that these rankings and the visual obtained according to the MDS analysis (Figure 21) give consistent results.

Table 2. The rankings of countries are based on the TOPSIS scores

Country	d_i^+	d_i^-	C_i	Rank	Country	d_i^+	d_i^-	C_i	Rank
Denmark	0.0126	0.0476	0.7911	1	United States	0.0373	0.0332	0.4707	32
Sweden	0.0173	0.0448	0.7214	2	Cyprus	0.0328	0.0286	0.4656	33
Norway	0.0193	0.0477	0.7125	3	Thailand	0.0353	0.0302	0.4606	34
Estonia	0.0187	0.0427	0.6959	4	Italy	0.0328	0.0280	0.4604	35
Netherlands	0.0196	0.0436	0.6901	5	Romania	0.0353	0.0299	0.4582	36
Finland	0.0217	0.0440	0.6702	6	Colombia	0.0356	0.0294	0.4524	37
New Zealand	0.0229	0.0366	0.6154	7	Australia	0.0346	0.0281	0.4481	38
Germany	0.0254	0.0385	0.6030	8	Slovak Republic	0.0360	0.0275	0.4330	39
Luxembourg	0.0253	0.0365	0.5901	9	Bulgaria	0.0349	0.0257	0.4246	40
Portugal	0.0256	0.0363	0.5862	10	Egypt	0.0402	0.0290	0.4187	41
Switzerland	0.0265	0.0367	0.5807	11	Czech Republic	0.0358	0.0255	0.4165	42
Latvia	0.0255	0.0352	0.5806	12	Japan	0.0383	0.0273	0.4165	43
Austria	0.0256	0.0349	0.5772	13	Nigeria	0.0423	0.0297	0.4124	44
Brazil	0.0262	0.0356	0.5763	14	Pakistan	0.0414	0.0277	0.4011	45
Lithuania	0.0259	0.0346	0.5714	15	Poland	0.0366	0.0241	0.3973	46
Chile	0.0283	0.0352	0.5543	16	Turkey	0.0381	0.0250	0.3960	47
Spain	0.0283	0.0345	0.5496	17	Hungary	0.0384	0.0249	0.3932	48
Croatia	0.0278	0.0330	0.5435	18	Mexico	0.0413	0.0267	0.3924	49
Indonesia	0.0284	0.0324	0.5328	19	Canada	0.0408	0.0251	0.3807	50
Vietnam	0.0297	0.0339	0.5327	20	Republic of Korea	0.0411	0.0253	0.3805	51
China	0.0293	0.0333	0.5320	21	Malaysia	0.0369	0.0224	0.3772	52
United Kingdom	0.0316	0.0350	0.5258	22	South Africa	0.0414	0.0239	0.3658	53
India	0.0320	0.0353	0.5246	23	United Arap Emirates	0.0435	0.0248	0.3625	54
Morocco	0.0331	0.0344	0.5103	24	Argentina	0.0405	0.0223	0.3553	55
Philippines	0.0329	0.0342	0.5094	25	Kazakhstan	0.0395	0.0201	0.3377	56
Belgium	0.0309	0.0314	0.5037	26	Uzbekistan	0.0460	0.0229	0.3321	57
Malta	0.0313	0.0314	0.5011	27	Algeria	0.0468	0.0195	0.2937	58
France	0.0325	0.0325	0.5002	28	Russian Federation	0.0465	0.0175	0.2734	59
Ireland	0.0309	0.0305	0.4960	29	Saudi Arabia	0.0467	0.0142	0.2334	60
Greece	0.0314	0.0309	0.4959	30	Islamic Republic of Iran	0.0491	0.0113	0.1864	61
Slovenia	0.0309	0.0295	0.4886	31					

5. Conclusion

This research aims to determine the relationships and sub-indicators between countries' fight against climate change and their use of technology, as well as to position and rank countries according to these two features. To achieve this, the study provides an insightful exploration of the links between climate change and technology through a comprehensive data-driven approach. Utilizing advanced analytical methodologies including exploratory data analysis (EDA), principal component analysis (PCA), multidimensional scaling (MDS), and the Similarity to Ideal Solution Rank Preference Technique (TOPSIS), the study elucidates the complex relationships between various national indicators of climate action and technological progress. Furthermore, the countries covered are positioned and ranked in terms of their climate change mitigation and technological progress.

Building upon the conclusions drawn from this comprehensive study, it is essential to further elaborate on the strategic implications and future directions for research and policy-making in the context of climate change and technological advancements.

Doğruel Anuşlu & Fırat (2020), in their study analyzing the impact of the Industry 4.0 level of countries on the Sustainable Development Goals, determined that in one of the models they investigated, a one-unit change in information and technology outputs caused a negative change of 0.531 in Environmental Health when other variables were held constant.

Energy, in addition to being the main element of development, also brings environmental risks and problems. If the current conventional energy production techniques are maintained, it is anticipated that a rise of 5°C will occur within the next century, potentially causing irreversible harm to the ecological system. This could cause irreversible damage to the ecological system. The source of the rapid climate change problem is CO_2 emissions, and 44% of these emissions occur during energy production. Therefore, it is recommended as a primary priority in action plans to change the preferences in energy production and switch from conventional energy technologies to renewable energy technologies (Sevim, 2011).

Fernández Fernández et al. (2018) stated that innovation, is an important component of technology, has a positive impact on the environment, but it is not enough to balance the negative impact of energy consumption. They also stressed the need to allocate additional resources to encourage innovation, both in the public and private sectors, and the need to take complementary measures for innovations that aim for sustainable development.

One of the most striking results of this study, which is conducted using various statistical techniques, is that the weakest factor in combating climate change in technologically advanced countries is energy use. It is apparent that this result makes similar inferences to the examples given in the literature. When preparing action plans for climate change, it is imperative to prioritize the consideration of renewable energy and energy use factors. Furthermore, it is possible to augment the weights of these indicators during the creation of an index for climate change.

Sweden, Netherlands, Denmark, and Norway are the best countries in terms of combating climate change and technological advancement. The Islamic Republic of Iran is one of the worst countries in terms of combating climate change and technological advancement. Countries that demonstrate a moderate level of progress in both combating climate change and technological advancement are the Chez Republic, Italy, Malta, Poland, and Cyprus.

The nuanced insights provided by the methodologies employed in this study, particularly through the use of TOPSIS, suggest that future research could explore alternative multi-criteria decision-making models that might offer different perspectives on ranking and evaluating national performances. In future studies, it can be possible to update the criteria weights when calculating country rankings. For this, either energy use and renewable energy criteria can be given greater weight, or weights can be determined after expert opinions using techniques such as AHP.

To encapsulate, the interdependence of technology and climate strategy within national frameworks is evident and critical for addressing the dual challenges of environmental degradation and technological disparity. Continued efforts in research are required to deepen our understanding of these relationships and to drive the formulation of more effective, integrated, and adaptive policies. As the world moves towards a more interconnected and technologically advanced future, it becomes all the more critical to ensure that these advancements are harnessed to foster not only economic growth but also environmental resilience and sustainability.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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