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FROM FOSSIL FUELS TO RENEWABLES :JOB LOSSES RISK AND JUST TRANSITION IN ELECTRIC UTILITIES COMPANIES

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RESUME :

La transition mondiale vers la durabilité et la décarbonisation, telle qu'énoncée dans l'Accord de Paris, nécessite une transformation qui peut engendrer à la fois des gagnants et des perdants en termes d'emploi. Une mauvaise gestion de cette transition peut entraîner des inégalités sociales. Alors que la transition énergétique offre des opportunités d'emploi, elle entraîne également des pertes d'emplois dans les secteurs des combustibles fossiles. Par conséquent, il est essentiel de garantir une transition juste et équitable qui soutienne les travailleurs à risque de perdre leur emploi afin d'accélérer la transition énergétique et d'atteindre les objectifs de l'Accord de Paris. Cet article présente une analyse statistique exploratoire des indicateurs de transition juste développés par la World Benchmarking Alliance. L'objectif de cette étude est d'examiner en profondeur la contribution des entreprises de services publics électriques dans la transition juste. En regroupant 50 entreprises de services publics électriques et en analysant les caractéristiques de chaque groupe, cette recherche fournit des informations sur les différents niveaux de risques de perte d'emplois auxquels sont confrontés les travailleurs de ces entreprises. Notre analyse confirme que les pertes d'emplois sont une réalité pour les travailleurs de ces entreprises, avec des degrés de risque différents. Les résultats de cette étude fournissent des informations précieuses aux décideurs et aux gestionnaires du secteur des services publics électriques afin de comprendre les risques de perte d'emplois pour les travailleurs et de développer des stratégies visant à minimiser de tels impacts.

Mots clés: Transition énergétique, Transition juste, Entreprises de services publics électriques, Risque de perte d'emplois, Classification hiérarchique sur l'analyse en composantes principales.

ASTRACT:

The global transition towards sustainability and decarbonization, as outlined in the Paris Agreement, requires a transformation that can create both winners and losers in terms of employment. Inadequate management of this transition can lead to social inequalities. While the energy transition offers employment opportunities, it also leads to job losses in the fossil fuel sectors. Therefore, it is crucial to ensure a fair transition that supports workers at risk of losing their jobs in order to accelerate the energy transition and achieve the goals of the Paris Agreement. However, there has been limited empirical research on just transition for high-emitting companies, particularly concerning their workers. This article presents an exploratory data analysis of just transition indicators developed by the World Benchmarking Alliance. The main objective of this study is to deeply examine the contribution of

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electric utilities companies to the just transition. By grouping 50 electric utilities companies and analysing the characteristics of each group, this research provides insights into the different levels of job loss risks faced by workers in these companies. Our analysis confirms that job losses are a reality for workers of these companies with varying degrees of risk. The findings of this study offer valuable insights to policymakers and managers in this sector, enabling them to understand the risks of job losses for workers and develop strategies to minimise such impacts.

Key words: Energy transition, Just transition, electric utilities companies, Risk of jobs loss, Hierarchical clustering on principal components analysis.

INTRODUCTION

Climate change is a complex and multifaceted problem that presents significant challenges to societies and economies worldwide[1], [2], [3]. It poses a substantial threat to human well-being, with wide-ranging and potentially irreversible consequences, making it one of the most urgent issues of the 21st century[4], [5] . The scientific consensus on the causes and impacts of climate change is widely recognized, with research indicating that human activities, particularly the burning of fossil fuels for electricity generation, are the primary drivers of this phenomenon. The combustion of fossil fuels, such as coal, oil, and gas, to produce electricity and heat is a major source of greenhouse gas emissions. Despite efforts to transition to renewable energy sources, the majority of electricity production still relies on the burning of fossil fuels. This highlights the need for further action to address the environmental impacts of electricity generation and accelerate the shift towards sustainable and low-carbon alternatives[6], [7].

The electricity sector plays a significant role in global pollution and greenhouse gas (GHG) emissions due to its heavy reliance on fossil fuels. The Intergovernmental Panel on Climate Change (IPCC) states that the world generates around 10 gigatonnes, or roughly 37% of global emissions, come from the production of electricity[8].

To address these challenges, a transition towards sustainable and low-carbon energy sources is imperative. This involves gradually reducing our reliance on fossil fuels and adopting cleaner alternatives, such as renewable energies like solar, wind power. This transition helps to decrease GHG emissions, minimise environmental impacts, and promote long-term sustainability[9].

In recent years, many electric utilities companies have set targets to reduce their carbon emissions and have invested in renewable energy sources. However, there are still many electric utilities companies that rely heavily on fossil fuels for electricity generation[10].

Electric utilities companies, as the primary players in electricity generation, have a significant role to play in this energy transition. Given the high global greenhouse gas emissions caused by electricity supply and demand, it is essential for electric utilities companies to embrace renewable energy technologies and energy efficiency measures[11]. Their role is pivotal in this transition, as they bear the responsibility of generating and distributing energy to residential, commercial, and industrial consumers[12].

As the energy transition progresses and the demand for renewable energy increases, the need for fossil fuel-based power generation decreases. This shift affects electric utility workers who are employed in these sectors and puts workers in traditional power plants at risk of losing their jobs[13].

The workers employed in fossil fuel industries often possess specialized skills and experience that may not directly translate to the renewable energy sector. Consequently, the decline of traditional fossil fuel industries creates a pressing need for electric utilities to address the potential job losses and provide support to these workers.

In this context, electric utilities are navigating a multifaceted challenge: transitioning to cleaner and more sustainable energy sources while ensuring a just and inclusive transition that considers the social impact on their workforce and communities. The social dimension of the energy transition presents several critical issues that must be addressed to mitigate potential disparities and ensure a fair distribution of benefits.

To achieve sustainable development goals, particularly in the area of social sustainability, it is important to consider the social aspects of the energy transition. This includes providing support to workers who may lose their jobs due to the transition.

The concept of a "just transition" has become increasingly popular, driven by ethical and strategic considerations. Scholars from diverse fields have explored just transition solutions to mitigate the negative effects of the energy transition on fossil fuel workers and their communities. For companies, a just transition emphasizes the importance of social dialogue between employers and workers, enabling collaborative planning and implementation of decarbonization efforts while safeguarding employment opportunities[14].

Employment is a crucial concern for policymakers, particularly in the context of the energy transition. There is a limited amount of comprehensive global research that specifically investigates the empirical aspect of just transition for electric utilities companies, except for the work carried out by the World Benchmarking Alliance (WBA) [15]. To address this research gap and contribute to the existing literature on the empirical aspects of the just transition, our paper aims to conduct a deeper statistical analysis of the just transition indicators developed by the WBA. Specifically, we will focus on examining the contribution of electric utilities companies to the just transition, with a particular emphasis on understanding the potential risk of job losses for their employees.

The primary objective of this paper is to conduct a comprehensive analysis of the performance of electric utilities companies in terms of a just transition. This analysis will provide a clearer understanding and enable us to draw conclusions regarding the potential risk of job losses for these companies during the energy transition. The study involves grouping 50 electric utilities companies into clusters and examining the characteristics of each cluster. This approach will help us gain insights into the challenges and the varying degrees of job loss risks faced by workers in the evaluated companies.

Specifically, this paper addresses the following research questions:

- What are the distinctive characteristics of each cluster obtained through Ascending Hierarchical Classification analysis for electric utilities companies?
- What are the key factors that help to minimise the risk of job losses for each cluster?

In order to address these research questions, we employed the Hierarchical Clustering on Principal Components (HCPC) analysis [12]. This method was selected due to its compatibility with our variables and its ability to address the research objectives effectively. Through the HCPC analysis, we grouped the electric utilities companies into distinct clusters and identified the specific characteristics of each cluster. This allowed us to determine which indicators are relevant for each group of companies in order to minimise the risk of job losses during the energy transition.

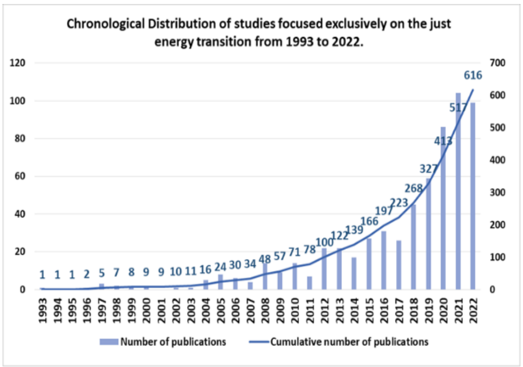
The structure of this paper is as follows: Section two provides a comprehensive review of previous academic research on the just transition framework for fossil fuel workers in the context of climate change. In Section three, we describe the material and methods employed in this study. Section four presents and discusses the results of our analysis. Finally, in Section five, we present our conclusion.

I LITERATURE REVIEW

The concept of a just transition has gained increasing attention in recent years as scholars and researchers recognize its significance in the transition towards sustainable and clean energy sources. The growing literature on a just transition reflects a broader understanding of the need to ensure that the energy transition is not only environmentally sustainable but also socially inclusive and equitable. This recognition emphasizes the importance of considering the fair distribution of costs, benefits, and opportunities associated with the transition among different social groups and communities.

The research conducted by Soleil de Zhonggen et al. [16] highlights a prominent trend in the field of the just transition, focusing on the scholarly literature dedicated to this topic. The study reveals an interesting pattern in the publication of research papers over time. Prior to 2002, there were only a limited number of publications, totaling just 10. However, starting from 2012, there was a noticeable increase in scholarly interest, resulting in 100 publications on the subject. The most substantial growth in literature related to the just transition occurred after 2018, indicating a significant rise in attention and engagement from researchers and scholars. By 2022, the cumulative number of publications had reached an impressive milestone of 616, indicating a substantial expansion of knowledge and research in this field. These findings highlight the increasing recognition of the importance of investigating and addressing social equity and justice in the context of the energy transition.

Fig.1.Temporal distribution of studies related to the just transition (1993–2022)



Source : [16]

One research study by Hägele et al.[17] emphasized the need for a radical change to achieve the goals of the 2030 Agenda and the 2015 Paris Agreement, ensuring that no one is left behind. They developed a conceptual framework and conducted a comparative analysis of two coal-dependent countries (Germany and South Africa) to explore the just transition in the energy sector. Galgóczi [18] examined the implications of the European Union's Paris targets on the labor market, highlighting the need for policies that support a just transition.

Hess et al. [19]made a significant contribution by emphasizing the role of civil society groups in defining and promoting a just transition, particularly in situations where government players oppose transition policies.

Heffron and McCauley [20]analysed the development of just transition policies between 2015 and 2020 and found that phased plans to phase out the fossil fuel industry may impede the development of low-carbon economies globally. They emphasized the importance of proactive policies and stakeholder involvement. Heffron (2023)[21] argued for large-scale organizational reform within multinational and state-owned energy companies to achieve a just transition to a low-carbon economy. This requires decisive actions to align with the goals of the Paris Agreement.

Vona [22] analyzed case studies and found that job losses resulting from climate policies can impact support for those policies, particularly in regions and social groups heavily impacted by economic challenges.

Carley and Konisky[23] explored the distributional impacts of the energy transition, highlighting disparities in the benefits and costs among specific communities and socio-economic groups.

Newell and Mulvaney[24] focused on the political economy of the just transition and emphasized the importance of creating "decent" job opportunities for fossil fuel workers. Normann and Tellmann [25]highlighted the potential of the just transition concept to reconcile the conflict between jobs and climate change, emphasizing the need for policies that promote new industries while providing support and compensation for affected workers.

Kolde and Wagner[26] proposed policy measures for a just transition based on a case study in Germany's lignite mining sector, emphasizing the negative impact on service and supply companies. Banerjee and Schuitema[27] explored the practical implementation of the just transition concept, emphasizing the importance of applying theoretical justice principles and involving all stakeholders in inclusive transition programs.

II MATERIAL AND METHODS

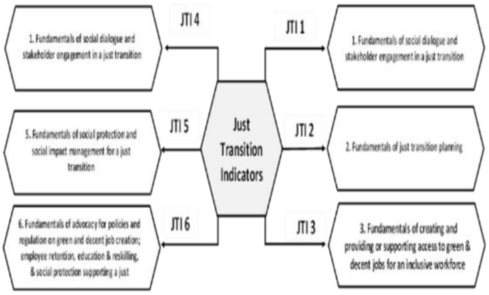
A Material and data description

The statistical analyses in this study were conducted using R (version: 2023.09.1+494), a widely used programming language in academic research for data analysis and visualization[28].

We analysed the just transition indicators (JTI) for 50 electric utilities companies. These indicators were developed by the World Benchmarking Alliance and are the first of their kind to be publicly accessible[29]. Data were collected over a two-year period, from 31/08/2018 to 31/08/2021, and published in December 2021 based on publicly available information[30]. Each JTI is scored on a scale of 0 to 2 points and consists of four elements (a to d), with each element worth 0.5 points. For example, meeting elements (a) and (b) but not (c) and (d) would result in a score of one point out of a maximum of 2. The sample was selected based on specific criteria, among which the top 50 electric utilities companies with the highest emissions worldwide were chosen.

With the exception of JTI 1 and JTI 2, which pertain to stakeholder participation and just transition planning, respectively, each JTI will be individually weighted. However, due to the relative importance of these indicators, JTI 1 and JTI 2 will be given double weight, meaning that the maximum of 2 points available for these indicators will represent 4 points. Each JTI follows a specific format, including the indicator text, indicator elements, indicator guidance, sources, scores available, and weighting. Each indicator is accompanied by a set of expectations that outline what companies should be doing and describe the desired outcomes[29].

Fig.2 Just Transition Indicators description



Source : Authors

Figure 2 provides an overview of the six just transition indicators. Each indicator addresses a crucial aspect of a just transition:

Just Transition Indicator 1 (JTI 1) evaluates a company's commitment to social dialogue and stakeholder engagement in the just transition process. It looks at whether the company engages in ongoing and meaningful discussions with stakeholders, discloses the categories of stakeholders involved, and respects labor rights.

Just Transition Indicator 2 (JTI 2) focuses on the company's planning for a low-carbon transition and its efforts to mitigate social impacts on workers, stakeholders, and business relationships. It emphasizes the importance of social dialogue and stakeholder engagement in the development of just transition plans.

Just Transition Indicator 3 (JTI 3) assesses the company's commitment to creating or supporting access to green and decent jobs for an inclusive workforce. It looks at whether the company discloses risks related to employment displacement and ensures gender balance and inclusivity for vulnerable groups.

Just Transition Indicator 4 (JTI 4) highlights the company's commitment to re- and/or up-skilling workers affected by the transition. It emphasizes gender balance and inclusivity for vulnerable groups in the company's efforts to retain and enhance the skills of its workforce.

Just Transition Indicator 5 (JTI 5) examines how the company identifies the impact of the low-carbon transition on social protection for workers and affected stakeholders. It also considers the company's contribution to social protection within the areas it operates.

Just Transition Indicator 6 (JTI 6) focuses on the company's advocacy efforts for policies and regulations on green and decent job creation, employee retention, education and reskilling, and social protection. It requires disclosure of any misalignment with just transition policies and measures taken to address such misalignment.

B Methods

To effectively address our research question, we used an Exploratory Data Analysis (EDA) techniques, specifically Hierarchical Clustering on Principal Component Analysis[31]. This method allows us to gain insights into the similarities and differences among companies. PCA is applied as a pre-processing step to reduce the dimensionality of the dataset and transform variables into uncorrelated principal components. This simplifies the data and enhances the efficiency of clustering algorithms. It also facilitates the visualization of high-dimensional data. We determined the optimal number of dimensions to retain for clustering by examining the scree plot, which shows the eigenvalues and indicates where the variability levels off or decreases significantly.

Next, we utilized agglomerative hierarchical clustering (AHC) to identify clusters within the AHC is used to iteratively merge clusters based on similarity, resulting in a dendrogram that represents the hierarchical relationships among clusters. Ward's criterion is commonly used to merge clusters, aiming for compact and homogeneous groups.

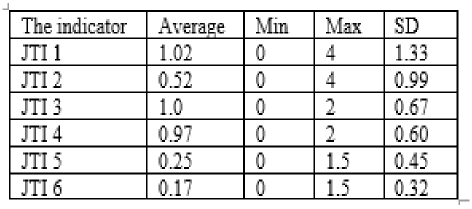
The initial partition obtained from the hierarchical tree is then used as a starting point for the K-means algorithm, which refines and enhances the partition through multiple iterations. This integration of K-means with HCPC improves the robustness and stability of cluster assignments.

III RESULTS AND DISCUSSION

In this section, we share the findings of our analysis using hierarchical clustering on principal components (HCPC) analysis on a dataset of 50 electric utilities companies.

A Descriptive statistics for the Just Transition assessment

Table 1.Average, minimum, maximum, standard deviation (SD) of the Just Transition Indicators (JTI).



The indicator	Average	Min	Max	SD
JTI 1	1.02	0	4	1.33
JTI 2	0.52	0	4	0.99
JTI 3	1.0	0	2	0.67
JTI 4	0.97	0	2	0.60
JTI 5	0.25	0	1.5	0.45
JTI 6	0.17	0	1.5	0.32

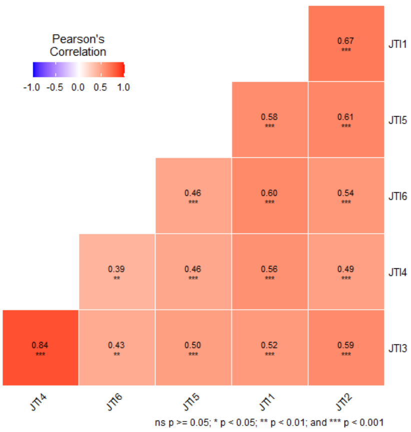
Source : Authors using R software.

Table 1 provides the descriptive statistics for the just transition indicators. The results indicate a moderate level of homogeneity among the indicators, as all indicators have a minimum value of 0. However, JTI1 and JTI2 have higher maximum values due to their double weighting, reflecting their greater significance in the analysis. JTI1 and JTI3 exhibit higher average scores compared to the other indicators. Moreover, most indicators have low standard deviations, suggesting that their values are closely concentrated around their means. However, JTI1 and JTI2 have relatively higher standard deviations, indicating a greater dispersion of values around their means.

B *Bivariate analysis*

Correlation analysis is a valuable method for examining the relationship between multiple variables. It is essential to conduct this analysis before performing multivariate analyses to ensure that the variables show some level of correlation. The Pearson correlation coefficient is used to assess the strength of the linear relationship between two variables and ranges from -1 to 1.

Fig.3. Correlation matrix (Pearson coefficient)



Source: Authors using R software.

According to Figure.3, the analysis of the Pearson correlation coefficients reveals a positive association between the just transition indicators. Specifically, JTI4 and JTI3 exhibit a strong positive correlation, with a Pearson correlation coefficient of 0.84. Furthermore, JTI2 is positively correlated with JTI1 and JTI5, with correlation coefficients of 0.67 and 0.61, respectively.

C *Multivariate Analysis - Hierarchical Clustering on Principal Components Analysis- of Just Transition Indicators*

- *Bartlett's test of Sphericity*

Before conducting the PCA analysis, it is recommended to perform Bartlett's test of sphericity. This test examines the null hypothesis that the variables are independent or orthogonal, meaning that the correlation matrix is an identity matrix. The alternative hypothesis suggests that the variables are not orthogonal and that the correlation matrix significantly differs from the identity matrix. If the p-value of the test is less than 0.05, the null hypothesis is rejected, indicating that factor analysis is appropriate for the dataset. In our case (referring to Appendix-Table A.1), the highly significant p-value of 2.2e-16 suggests that factor analysis is suitable for our dataset.

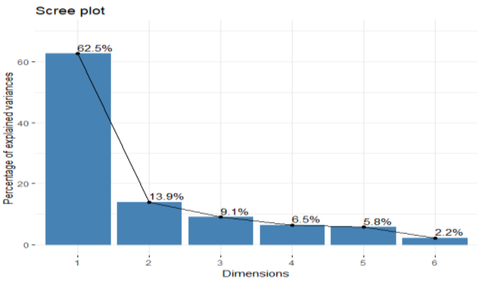
- *Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy*

The KMO measure is employed to assess the adequacy of partial correlations between variables and indicates how well factors explain each other. KMO values closer to 1.0 are considered ideal, while values below 0.5 are deemed unacceptable[32]. In our study (referring to Appendix-A.2), the KMO value of 0.79 falls within the moderate range of 0.7 to 0.8, indicating a good factorial solution.

- *Principal components selection*

A scree plot is a useful tool for determining the appropriate number of principal components (PCs) to retain in a PCA analysis. It visually represents the amount of variation each principal component extracts from the data. The x-axis of the scree plot represents the number of components, while the y-axis displays the corresponding eigenvalues. By examining the inertia of the first few dimensions, we can determine if there are strong relationships between variables and identify the number of dimensions that should be further studied.

Fig.4. Scree plot for 6 just transition indicators.



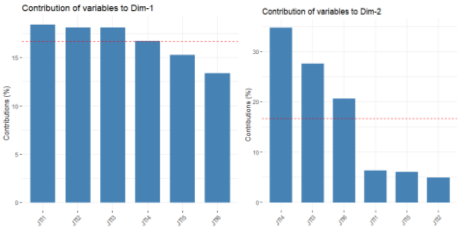
Source: Authors using R software.

According to the results shown in Figure.4, we selected the first two dimensions of analysis (which are just before the line flattens out). They represent 76.4 % of the total dataset inertia. This indicates that these two principal components together contain the majority of the information in the data (76.4%). Therefore, we can safely disregard the remaining dimensions without losing any significant insights.

- *Highlight the most contributing just transition indicators to each principal dimension (Dim-1 and Dim-2)*

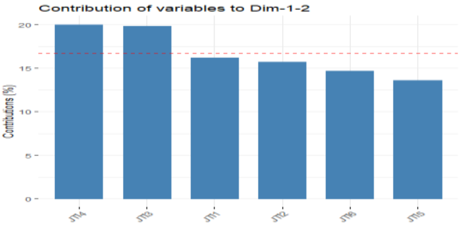
Figure.5 displays the percentage contributions of the just transition indicators (JTI) in defining the primary axes. The indicators associated with Dimension-1 and Dimension-2 are particularly influential in explaining the variability in the dataset. The red line depicted in the graph represents the average expected contribution.

Fig.5. The principal components (Dim-1, Dim-2) contributions for Just Transition Indicators.



(a)The first component **(b) The second component**

(c) The first and second components



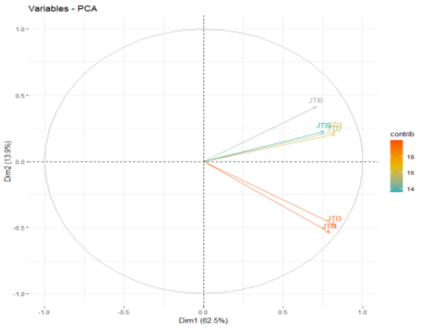
Source: Authors using R software.

Panel (a) illustrates that JTI1, JTI2, and JTI3 make the most significant contributions to the first dimension (Dim1), while Panel (b) demonstrates that JTI4, JTI3 and JTI6 contribute the most to the second dimension (Dim2). Additionally, Panel (c) indicates that JTI4, JTI3 have the most contributions to both the first and second dimensions (Dim1-Dim2).

- Correlation circle of just transition indicators

The correlation circle, which has a radius of 1, illustrates the correlations between all indicators. The first principal component (Dim-1) is represented on the horizontal axis, while the vertical axis shows the second principal component (Dim-2). The circle contains arrows of varying lengths pointing in specific directions. The length of each arrow represents how well that indicator explains the variance of the data on the factorial plane. This is referred to as the quality of representation of that indicator on the plane. Different colors are used to represent the contribution of the indicators to the principal components, the colors orange and blue represent strong and low contributions, respectively, of the indicators.

Fig.6. Projection of the contribution of Just Transition Indicators in the principal components (Dim-1, Dim-2).



Source: Authors using R software.

According to Fig.6, just transition indicators "JTI4", "JTI3, "JTI1" and "JTI2" are well represented (those that are close to the circle of correlation). This indicates that these indicators are well correlated with the two factors that form this plane. The angle between the indicators reflects their level of association.

A small angle on the factorial plane indicates a positive correlation between the two indicators' representations. On this factorial plane, as shown in Figure.5, there is:

- A strong positive correlation between (JTI3 & JTI4);

-A fairly strong correlation between (JTI1 & JTI2);

- A moderate positive correlation between (JTI 4 & JTI6) and (JTI3 & JTI6).

- *Biplot of electric utilities companies and just transition indicators*

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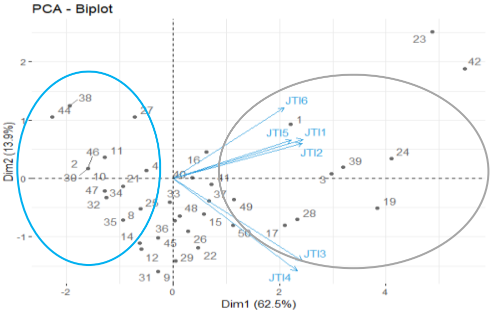
Fig.7. Biplot of electric utilities companies and just transition indicators.



Source: Authors using R software.

The dimension 1 opposes companies such as (23) Enel, (42) SSE , (24) ENGIE , (19) Électricité de France (EDF) , (39) RWE (to the right of the graph, characterized by a strongly positive coordinate on the axis) to companies such as (44) Taiwan Power Company , (38) Perusahaan Listrik Negara (PLN),

(27) Fortum , (46) Tohoku Electric Power (to the left of the graph characterized by a strongly negative coordinate on the axis).

Given that the "JTI1," "JTI2," "JTI3," and "JTI4" are the primary indicators contributing to the construction of the first principal component (Dim-1), their positive coordinates on axis 1 indicate their significance. Consequently, we can deduce that the correlation of these indicators is primarily driven by two distinct groups of companies depicted by the blue and grey circles in Figure.7. The companies positioned to the right of the axis exhibit high values for these indicators, while those on the left side demonstrate lower values.

- Hierarchical Clustering on Principal Components (HCPC) analysis

The HCPC (Hierarchical Clustering on Principal Components) analysis was conducted using two dimensions derived from Principal Component Analysis (PCA).

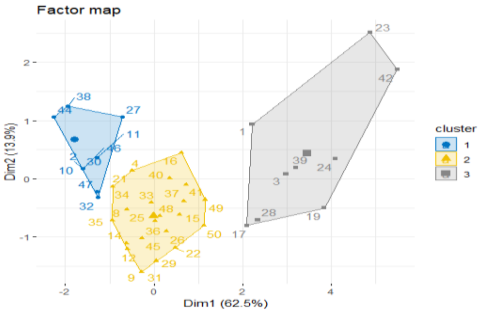
For the analysis, the first two dimensions obtained from PCA were retained, and the hierarchical clustering was performed using these two dimensions. The HCPC function indicates that three clusters provide an optimal level of division. This recommendation is supported by the inertia gain bar depicted in Panel (c), which indicates that the decrease in inertia from four clusters to three clusters is relatively smaller compared to reductions in other cluster configurations. The analysis suggests that dividing the data into three clusters is the most appropriate level of division.

To further validate our findings, we also applied the k-means algorithm, which yielded similar results to the hierarchical clustering. Consequently, we have confidence in the insights obtained from the hierarchical clustering analysis. This confirms that the hierarchical clustering method effectively captures the underlying clustering patterns in our dataset.

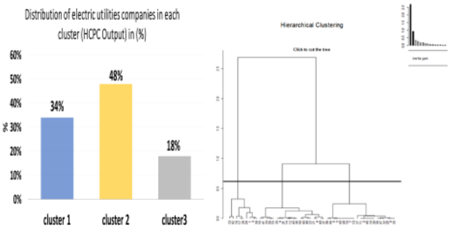
The output of the hierarchical clustering algorithm on principal components is presented in the form of a "factor map" (Panel a) and a "dendrogram" (Panel c), as shown in Figure.8.

Fig.8. Ascending Hierarchical Classification of the electric utilities companies. (Panel (a), (b) and (c)).

(a)Hierarchical clustering on factor map (HCPC).



(b) Distribution of electric utilities companies in each cluster. (c) Hierarchical tree on the factorial map.



Source: Authors using R software.

Based on Panel (a) in Figure 8, our analysis revealed the presence of three distinct clusters, labeled as 1, 2, and 3.

Cluster 1, depicted in blue, consists of companies such as Fortum (27), Kyushu Electric Power (32), and Chubu Electric Power (18). (refer to Appendix Table A.3 for a comprehensive list).

Cluster 2, shown in yellow, comprises companies like Eletrobras (21), China Huaneng Group (8), and NTPC (34). (For a detailed list, see Appendix Table A.4.)

Cluster 3, represented in grey, includes companies such as ENGIE (24), Enel (23), and SSE (42). (Appendix Table A.5 provides additional information on the companies in this cluster).

- *Interpretation of specific characteristics within the electric utilities companies' clusters*

By applying the HCPC method to the electric utilities companies, we identified three distinct clusters. Cluster 1, which represents around 34% of the companies, exhibits important characteristics related to their performance in the just transition indicators.

Companies in Cluster 1 demonstrate low scores in indicators such as JTI3, JTI4, and JTI1. This indicates a lack of assessment or reporting of job displacement risks, limited efforts in creating environmentally and fair job opportunities, and a neglect of re-skilling programs for workers impacted by the energy transition. Moreover, a majority of companies in this cluster do not actively engage stakeholders in planning for a just transition, suggesting a lack of proactive measures to address social challenges. Additionally, all companies in this Cluster receive zero scores in indicators JTI2 and JTI5, indicating a failure to develop plans that support workers' rights and communities during the transition and a disregard for workers' social protection. Only one company, Fortum, stands out in Cluster 1 by supporting regulations for green jobs and retraining employees, although there are still areas where improvement is needed.

These findings highlight a concerning lack of effort from most companies in Cluster 1 to address the social challenges associated with the energy transition. This failure to contribute to the just transition raises significant concerns, particularly regarding the potential risk of job losses. Urgent action is necessary to mitigate these risks and ensure a more equitable and sustainable transition process.

Cluster 2, which represents 48% of the electric utilities companies, demonstrates higher values in certain just transition indicators. Specifically, most companies in this Cluster achieve high scores in indicators JTI3 and JTI4. This indicates that they actively assess and report job displacement risks and prioritize the creation of environmentally sustainable and quality job opportunities. They also prioritize retraining and upskilling workers affected by the energy transition. However, despite their strengths in JTI3 and JTI4, companies in Cluster 2 exhibit lower values in indicators JTI2, JTI5, JTI6, and JTI1. While some companies in this cluster meet two to three out of the four elements in these indicators, others receive zero scores. This suggests that a significant portion of these companies have not developed and implemented comprehensive just transition plans that respect the rights of workers, communities, and stakeholders (JTI2). Moreover, they fail to consider the impact of the energy transition on workers' social protection (JTI5) and do not actively advocate for regulations promoting green jobs and employee reskilling (JTI6). Additionally, there is a lack of meaningful engagement in social dialogue regarding a just transition (JTI1).

These findings indicate that companies in Cluster 2 make a relatively better contribution to the just transition compared to those in Cluster 1. Cluster 2 stands out with higher performance in just transition indicators related to job displacement risk assessment (JTI3) and the creation of sustainable and quality jobs (JTI4). This suggests that these companies recognize the importance of anticipating the social consequences of the energy transition. However, it's important to note that Cluster 2 still has room for improvement in other just transition indicators.

Cluster 3, accounting for 18% of the electric utilities companies, demonstrates exceptional performance across a majority of the just transition indicators. The companies in this cluster effectively address important aspects of a just transition, as evidenced by their strong scores in indicators such as JTI1, JTI3, JTI4, JTI2, and JTI5. All companies in this cluster actively engage in social dialogue and demonstrate transparency by disclosing stakeholder involvement in the just transition process. They prioritize assessing and reporting job displacement risks while working towards creating sustainable and quality employment opportunities. Additionally, these companies take concrete steps to retrain and upskill workers affected by the energy transition. A significant majority of companies in this cluster develop and implement just transition plans that respect the rights of workers, communities, and stakeholders. They also recognize the importance of social protection for workers during the energy transition. However, there is still room for improvement in advocating for regulations that promote the creation of green and decent jobs, as well as employee reskilling.

Based on these findings, it can be concluded that companies in Cluster 3 make a more positive contribution to the just transition compared to those in Cluster 1 and Cluster 2. They exhibit higher values in various just transition indicators, indicating a higher level of engagement in social dialogue, job displacement assessment, job creation, worker retraining, and just transition planning.

As we examined the clusters obtained through HCPC, a noteworthy observation emerged regarding the just transition indicators for electric utilities companies. As we move from cluster 1 to cluster 3 , there was a noticeable amelioration in the values of the just transition indicators for the majority of companies within each cluster.

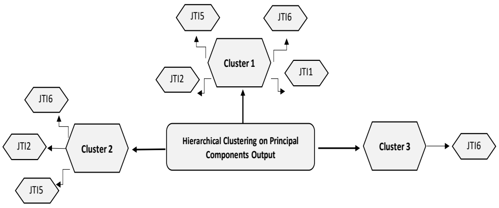
This allows us to observe that as we move from lower-scoring clusters to higher-scoring clusters (1 to 3), the risk of job losses decreases for electric utilities companies.

- *Identification of key indicators for minimising the risk of job loss across different clusters*

The application of the HCPC method resulted in the identification of three distinct clusters for companies in the electric utilities sector. By examining the characteristics of each cluster, we were able to determine the specific indicators that should be prioritized to minimise the risk of job loss for companies in each cluster.

A visual representation of these key indicators for each cluster can be illustrated in Figure.9, providing decision-makers with a clear understanding of which indicators need to be prioritized for each electric utilities company. This proposition emphasizes the significance of identifying indicators that can help mitigate the risk of job loss, and highlights the HCPC analysis as an effective approach to grouping companies based on similarities and differences to facilitate this process.

Fig.9. Identification of key indicators for minimising the risk of job loss across different clusters



Source: Authors.

For companies in Cluster 1, it is crucial to concentrate on JTI 2, which emphasizes the importance of planning a transition to low-carbon activities while mitigating the social impacts on workers and stakeholders. Additionally, they should prioritize JTI 1, which highlights the significance of social dialogue and stakeholder engagement. JTI 5 is also significant, as it examines the impact of the transition on workers' social protection and emphasizes the company's contribution to social protection measures. Lastly, companies in Cluster 1 should ensure that their lobbying activities align with the principles of a just transition, as emphasized by JTI 6. This means conducting lobbying efforts in a manner that supports and promotes a fair and equitable transition to a sustainable economy.

In Cluster 2, where companies demonstrate a higher contribution to the just transition compared to Cluster 1, they should prioritize JTI 2 for effective transition planning, JTI 6 for aligning lobbying activities with just transition policies, and JTI 5 to examine the impact on social protection.

Lastly, companies in Cluster 3, which show the strongest contribution to the just transition among the clusters, should focus on JTI 6 to ensure the alignment of their lobbying activities with just transition policies.

These indicators provide guidance for each cluster to address specific challenges and risks related to job loss, enabling companies to develop targeted strategies that align with their unique circumstances and contribute to a more equitable and sustainable transition process.

IV CONCLUSIONS

In conclusion, this research paper highlights the importance of recognizing and addressing the social impact of the energy transition, particularly for workers in high-emitting companies like electric utilities. The study emphasizes the need for a just transition approach that supports and protects the livelihoods of these workers amidst the challenge of reducing reliance on fossil fuel sources. By conducting an exploratory data analysis on just transition indicators developed by the World Benchmarking Alliance, significant findings have been obtained for electric utilities companies.

The analysis identified three distinct clusters within the sector, each exhibiting specific characteristics and varying levels of contribution to a just transition. Moving from Cluster 1 to Cluster 3, there was an observable improvement in the values of just transition indicators, indicating a decrease in the risk of job losses. The study also identified key factors that help minimise this risk for each cluster, including effective transition planning, social dialogue and stakeholder engagement, social protection measures, and aligning lobbying activities with just transition principles.

It is important to acknowledge the limitations of this study. Firstly, the analysis relies on the just transition indicators provided by the WBA and may not consider all relevant factors that could influence the risk of job losses in the electric utilities sector, such as the political contexts of the countries where the companies operate. Further research that incorporates a broader range of factors is needed to enhance our understanding of just transition in the energy sector.

Furthermore, it is important to note that the sample size of 50 electric utilities companies used in the analysis may not represent the entire population of companies in the electric utilities sector. It is worth mentioning that the selection of these companies was based on specific criteria, including being among the top 50 high-emitting companies globally. As a result, the findings and conclusions of this study may not be applicable to all companies operating in the sector. To overcome this limitation, future research should aim to include a larger and more diverse sample of companies, allowing for a more comprehensive understanding of the industry as a whole.

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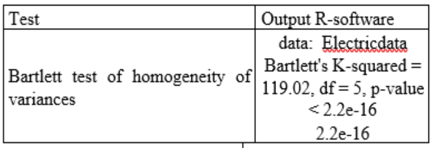
VI APENDICES

Appendix. A. Results-Electric utilities companies-

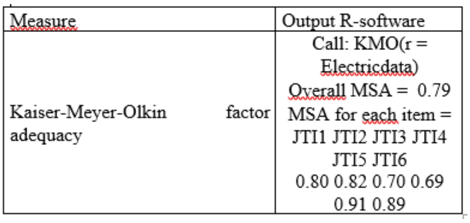
Table.A.1. Bartlett test.



Test	Output R-software
Bartlett test of homogeneity of variances	data: Electricdata Bartlett's K-squared = 119.02, df = 5, p-value < 2.2e-16 2.2e-16

Source: R software

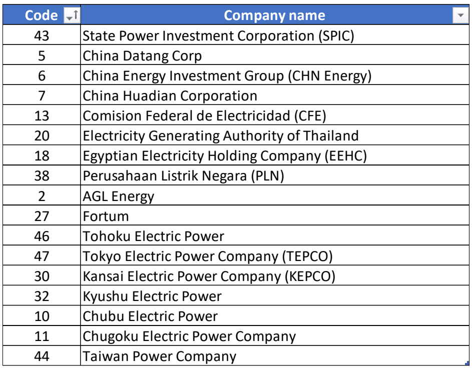
Table.A.2. KMO measure



Measure	Output R-software
Kaiser-Meyer-Olkin factor adequacy	Call: KMO(r = Electricdata) Overall MSA = 0.79 MSA for each item = JTI1 JTI2 JTI3 JTI4 JTI5 JTI6 0.80 0.82 0.70 0.69 0.91 0.89

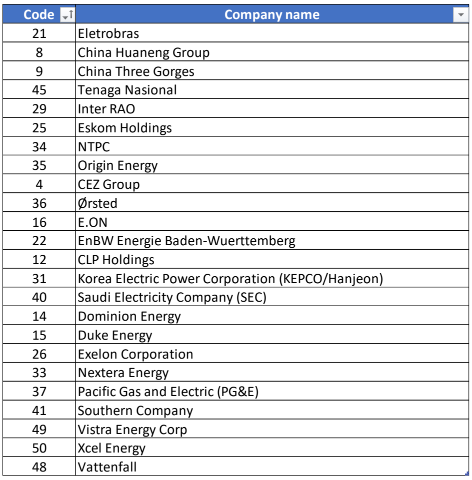
Source: R software

Table.A.3..HCPC output - cluster 1 listing



Code	Company name
43	State Power Investment Corporation (SPIC)
5	China Datang Corp
6	China Energy Investment Group (CHN Energy)
7	China Huadian Corporation
13	Comision Federal de Electricidad (CFE)
20	Electricity Generating Authority of Thailand
18	Egyptian Electricity Holding Company (EEHC)
38	Perusahaan Listrik Negara (PLN)
2	AGL Energy
27	Fortum
46	Tohoku Electric Power
47	Tokyo Electric Power Company (TEPCO)
30	Kansai Electric Power Company (KEPCO)
32	Kyushu Electric Power
10	Chubu Electric Power
11	Chugoku Electric Power Company
44	Taiwan Power Company

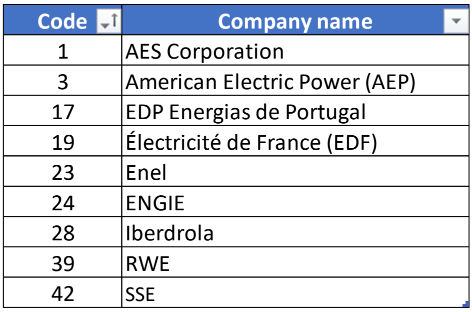
Table.A.4..HCPC output - cluster 1 listing



Code	Company name
21	Eletrobras
8	China Huaneng Group
9	China Three Gorges
45	Tenaga Nasional
29	Inter RAO
25	Eskom Holdings
34	NTPC
35	Origin Energy
4	CEZ Group
36	Ørsted
16	E.ON
22	EnBW Energie Baden-Wuerttemberg
12	CLP Holdings
31	Korea Electric Power Corporation (KEPCO/Hanjeon)
40	Saudi Electricity Company (SEC)
14	Dominion Energy
15	Duke Energy
26	Exelon Corporation
33	Nextera Energy
37	Pacific Gas and Electric (PG&E)
41	Southern Company
49	Vistra Energy Corp
50	Xcel Energy
48	Vattenfall

Source: R software

Table.A.5..HCPC output - cluster 1 listing



Code	Company name
1	AES Corporation
3	American Electric Power (AEP)
17	EDP Energias de Portugal
19	Électricité de France (EDF)
23	Enel
24	ENGIE
28	Iberdrola
39	RWE
42	SSE

Source: R software

A.6. Code R

```
##### Desctiptive statistics (mean, max,min, #####

summary.data.frame(Electricdata)

##### Desctiptive statistics  SD#####

ecart_type <- sd(Electricdata$JTI1)

print(ecart_type) ecart_type <- sd(Electricdata$JTI2)

print(ecart_type)

ecart_type <- sd(Electricdata$JTI3)

print(ecart_type)
```

```
ecart_type <- sd(Electricdata$JTI4)
print(ecart_type)
ecart_type <- sd(Electricdata$JTI5)
ecart_type <- sd(Electricdata$JTI6)
### Display of the correlation - Electricdata  is the name of the database- #####
> install.packages("metan")
> library(metan)
> corr1<-corr_coef(Electricdata [,1:6 ])
> plot(corr1)
        ##### The bartlett Test #####
        > bartlett.test(Electricdata)
        ##### The KMO Test #####
        > install.packages("psych")
        > library(psych)
        > KMO(Electricdata)
        ##### Principal Component Analysis (PCA) #####
        > install.packages("FactoMiner")
        > library(FactoMineR)
        > install.packages("Factoextra")
         > library(factoextra)
        > PCA(Electricdata,scale.unit = TRUE,ncp = 2,graph = TRUE)
        > res.pca <- PCA(Electricdata, graph = FALSE
        #### The PCA correlation Circle     #####
> fviz_pca_var(res.pca, col.var = "contrib", gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"), repel = TRUE)
 #### Display of variables and individuals in the same graph #####
> fviz_pca_biplot(res.pca, repel = TRUE, col.var = "#2E9FDF", col.ind = "#696969")

##### Contributions of variables to PC1 #####
> fviz_contrib(res.pca, choice = "var", axes = 1, top = 6)
         ##### Contributions of variables to PC2 #####
```

```
> fviz_contrib(res.pca, choice = "var", axes = 2, top = 6)

 ##### Contributions des variables à PC1 et PC2 #####

> fviz_contrib(res.pca, choice = "var", axes = 1:2 , top = 6)

##### Eigenvalues #####

> fviz_eig(res.pca, addlabels = TRUE, ylim = c(0, 70))

##### Hierarchical ascendant classification #####

 >install.packages("Factoshiny")

>library(Factoshiny)

>resshiny = PCAshiny(res.pca)

##### Hierarchical ascendant classification factor map graph affichage - dendogramme inertia bar #####

library(factoextra)

 library(FactoMineR)

res.pca <- PCA(Electricdata, ncp = 2, graph = FALSE)

res.hcpc <- HCPC(res.pca, graph = FALSE)

 fviz_cluster( res.hcpc, repel = TRUE, show.clust.cent = TRUE, palette = "jco", ggtheme = theme_minimal(), main = "factor map" )

##### Display the list of companies with their clusters #####

>head(res.hcpc$data.clust, 50)
```