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The political economy of coal across 12 countries: Analysing qualitative interviews with topic models

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Abstract

Understanding the ongoing investments in coal-fired power plants requires an analysis of the political economy. Here, we conduct a computational analysis of 212 interviews from 12 countries on the political economy of coal using topic modelling (TM). Our study highlights relevant topics by actor group and country. While most topics are similarly distributed across all actor groups, we find distinct clusters of countries in which similar topics play important roles. For example, in Indonesia and India, sustaining low electricity tariffs is brought forward as a reason to invest in coal, whereas in South Africa and Kenya the civil society is considered instrumental in the choice of coal or alternatives. To validate our findings, we compare them to outcomes of qualitative case studies and to papers grouping countries based on quantifiable factors. As this study is among the first to apply TM to interview data, we thereby highlight strengths and challenges for such application and the interpretability of results. We argue that topic models are effective supplements to qualitative case studies, particularly when analysing large amounts of text.

Keywords: Topic modelling, Political Economy, Coal, Qualitative Interviews, Country Comparison, Low-Carbon Transition

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1. Introduction

Coal is the primary source of global CO_2 emissions [1]. To limit global warming to well below 2°C, unabated coal use in the power sector needs to be rapidly phased out [2]. Nevertheless, globally there is still 2,074 GW of coal capacity in operation and another 457 GW in the pipeline [own calculations based on 3]. Scholars increasingly uncover the important role of political economy factors for the ongoing construction and usage of coal-fired power plants to identify entry points for feasible and effective climate policies.

Methodologically, many studies in energy social science use qualitative interviews to conduct country case studies. Case studies allow to ask "how" or "why" questions [4], to explore and generate hypotheses [5], and to produce context-specific knowledge [6]. Interviews are a useful tool to capture different perspectives from different actors and to improve understanding on a specific matter without requiring a-priori hypotheses [5,7]. In the case of coal, they thus help to better understand the underlying reasons for the persistence of coal mining and coal-fired power generation. Yet, there are only a few studies that generate cross-country evidence on the political economy of coal. In addition, cumulative quantities of text render manual analysis of interviews increasingly challenging.

At the same time, the rapid development of Natural Language Processing (NLP) tools helps to generate insights about large text collections. As they are getting better and more versatile, their usage in academia and energy social science increases [8]. For example, Topic Modelling (TM) [9] identifies latent topics in texts to compare documents. So far, however, there seems to be only one study – not limited to energy social science – that applies TM on interviews, more specifically on one focussed group discussion [10]. To our knowledge, no study has yet applied TM to semi-structured interview data.

In this paper, we analyse 212 semi-structured expert interviews on the political economy of coal in 12 countries that together cover about 30% of global coal power capacity and coal consumption (60% without China). The interviews were conducted for country case studies jointly published in a book [11]. We assume that the interviews do not only reflect interviewees' individual focus but – taken together – also provide insights into the expert-driven debates on coal in each country. We do not test or use preconceived hypotheses or theories, but follow grounded theory with a focus on rigorous data analysis [12]. Using topic modelling, we pose two major research questions, one content-related and one methodological: First, what are similarities and differences among actor groups across countries in terms of the political economy of coal? Second, how reliable are results from comparative computational analysis for analysing qualitative interviews?

We aim to answer our research questions by comparing actor groups and clustering countries with respect to dominant topics in the interviews. Our results can inform cross-country policy learning and help to better adapt policies to national specificities. Our methodological contribution is to scrutinize the benefits, challenges, and limitations of TM applied to interview data. By comparing our results to insights from qualitative and comparative studies, our analysis can help to better evaluate the usage of TM on interviews in the future.

We find similarities among countries in terms of the political economy of coal. Some similarities are also obtainable by comparing data on coal production and consumption as well as plant capacity, such as recent coal declines in Germany, the UK, and the US. Others require in-depth, country-specific knowledge, which is commonly derived from case studies. For example, debates about phase-out policies in Germany and the UK are similar, whereas the debates in the US have a stronger focus on markets, which can be linked to the different drivers of the respective coal phase-out. We also uncover the large role of the civil society in South Africa and Kenya or the importance of energy sector planning for Vietnam, Pakistan, and the Philippines. We argue that TM is an effective supplement to qualitative case studies and comparative statistical analyses, especially when analysing large sets of texts and comparing different groups.

The study is structured as follows: First, we provide an overview of the literature. Second, we describe the materials and methods applied in this study. Third, we highlight the most important findings from the results. Fourth, we compare our findings to available studies and highlight the strengths and limitations of the method. Finally, we draw conclusions on coal policies and method development. Additional information is provided in the Supplementary Information (SI).

2. Related Literature

Our paper contributes to two strands of literature. The first discusses the political economy of coal. Following the literature, we understand 'political economy' as the interaction of stakeholders with given vested interests that explains, why political decision making does not necessarily target societal well-being. Associated articles in the context of coal mining and power generation analyse different stakeholder configurations in combination with external political and economic factors that explain why coal is phased-out – or not. The second strand relates to NLP and in particular TM, which is applied to different sources of text in multiple fields.

The necessary developments, barriers, and drivers of coal phase-outs are increasingly analysed by several authors in the energy transition literature: Cherp et al. [13] show the diversity of this literature and demonstrate that transitions are analysed using several perspectives: techno-economic, socio-technical, and political. An influential framework often applied in case studies on transitions is the Multi-Level Perspective (MLP) framework [14]. It originally focused on technology before Geels developed it further, e.g., by including aspects of the political economy to explain regime resistance [15]. MLP is also applied to explain coal transitions, highlighting the importance of regime destabilization and theory-building in Germany [16] or long-term transition strategies in China [17]. Diluiso et al. [18] examine historical coal transitions worldwide and demonstrate that applying a political economy lens helps to explain these past transitions.

Congruously, a growing body of literature explicitly examines the political economy of coal in specific countries. A set of studies use the AOC ('Actors, Objectives, Context') political economy framework [19]. Jakob et al. [11] collect 15 case studies all following this framework. Also using the AOC framework, Dorband et al. [20] explain how the Communist Party in Vietnam uses coal to legitimize its power; Montrone et al. [21] and Manych and Jakob [22] discover large industry conglomerates as the main driving forces of coal in India and the Philippines, respectively; Ordonez et al. [23] highlight the importance of coal royalties for the government in Indonesia; and Hanto et al. [24] find incumbents supporting coal to increase energy availability and the profitability of the coal sector in South Africa. A comparison of relevant actors based on an expert survey finds differing objectives across countries related to coal [25]. Other authors explicitly analyse the role of coal regimes, inter alia, in the Philippines [26], in Japan [27], and in Poland [28], or explain the importance of political motives for coal, e.g., in Kenya [29] or Tanzania [30]. Some articles highlight the importance of international finance for the development of coal plants [31] and discuss the political economy of overseas investment in the energy or specifically the coal sector, especially from China [32–35]. In summary, the literature on the political economy of coal is small but growing with different focus areas. While some studies use statistical methods, surveys, or media analyses, many rely on data from expert interviews.

At the same time, a growing number of studies use computational techniques from the NLP toolbox to analyse text in energy social science, predominantly TM [36]. Traditional discourse analysis methods are often applied in energy research [37]. Over the last years, several studies were published using computational methods that considers text as data [8]. Examples from this journal cover, for example, social policy debates related to ethanol production in Brazil [38], coal in stories in the US [39], frames among global renewable energy institutions [40], and the coal debate in the German parliament [41].

Even though we see a large number of studies employing interviews and an increasing number of articles using NLP, we hardly find any overlap. To the best of our knowledge, there exists one sentiment analysis on the views of millennials and managers across different industries based on 18 interviews [42], and one case study on energy externalities in India applying TM on transcripts of one focussed group discussion [10].

3. Materials and Methods

3.1. Data Sources

We analyse interview material from 12 countries: Germany (DE), the UK (UK), Chile (CL), Colombia (CO), the US (US), Kenya (KE), South Africa (ZA), Indonesia (ID), India (IN), Vietnam (VN), the Philippines (PH), and Pakistan (PK).[1] They cover a significant amount of the global coal capacity, both operating and in the pipeline, as well as global coal production (see **Table 1** for details). All interviews were conducted according to the AOC framework [19]. Interviews were semi-structured, with interview guidelines being harmonized in joint workshops across all interview teams. Interviews for 11 countries also fed into peer reviewed book chapters collected by Jakob and Steckel [11]. Underlying interviews for the case of Pakistan followed the same framework and process but are not yet used for a publication. All interviews were carried out between 2018 and 2021 by different research teams in every country. Each single interview was expected to take 45-60 min. The interviewees are experts on the energy sector in their respective countries, with knowledge of either technical, interpretative or procedural origin [43]. The case study authors targeted experts across different fields, including politics, the private sector, and academia. The selection of experts followed a snowballing approach, where interviewees were asked to recommend other experts. The interviews in each country thus cover a wide range of opinions and expertise. More information on the interviews can be found in the SI (Table S1) as well as in Jakob and Steckel [11].

Table 1 | Share of the 12 countries covered in this study for the capacity of the operating and planned coal fleet, coal production, and consumption. *Operating and pipeline capacity as of July 2022; coal production and consumption is the sum for the years 2010-2020. Data from [3] and [44].*

	Total capacity in GW (Operating and Pipeline) or coal energy in exajoules (Production and Consumption)			Share of the 12 covered countries in %	
Type	**World**	**World w/o China**	**12 sudied countries**	**Of World**	**Of World w/o China**
Operating	2074	1009	632	30.5	62.6
Pipeline	457	206	125	27.4	60.6
Production	1749	908	572	32.7	63.0
Consumption	1714	829	483	28.2	58.4

[1] The order of countries throughout the paper is according to the clusters we find in our analysis. This is to ensure comparability.

3.2. Text Processing and Coverage

We first prepared the interviews manually, including translation into English for transcripts from Colombia and Chile. We proofread all interviews and removed all information that was not spoken text, e.g., timestamps or comments added during the transcription. We further removed unrelated text, such as welcoming small talk. To improve accuracy of the model, we merged each reply with the respective question into a text item, usually called “document” in topic modelling. A question might have a short reply without using the keywords that would enable to understand the content. Merging thus increases the number of text items we can use and contextualises the reply. Each question and answer pair was tagged with markers to signal its beginning and end.

The question-answer pairs were pre-processed in Python using standard procedures, which is briefly explained hereafter and more detailed in the SI (section 2). Pre-processing includes removing punctuation, dropping stopwords consisting of a pre-defined list to which we added words manually (e.g., ‘or’, ‘any’, and ‘say’) and lemmatization, i.e., converting words into their base form. We further use n-grams, which are contiguous sequences of words in a sentence. Examples for 2-, 3-, and 4-grams are ‘renewable energy’, ‘ministry of energy’, and 'coal fired power plants', respectively. The text items are then turned into vectors of word counts using the ‘bag-of-words’ approach. It discards information on the order of words and simply counts how often a word appears in a question-answer pair.

We dropped short question-answer pairs below a certain word limit because some consist of only a handful of words (see SI section 3 for details). They are lacking enough details to infer topics and might overproportionally bias the topic distributions. The literature did so far not produce a clear proposal for word limits, but an emerging convention is to have documents that are at least 100-200 words in length [45]. Given the nature of interviews, it is difficult to apply a word limit to the original texts, as some question-answer pairs purely consist of stopwords. We therefore consider the word count of the ‘cleaned’ text. We see a trade-off between keeping as many question-answer pairs as possible and dropping those with a word count below the limits proposed in the literature. The former is not common in the literature – with the exception of Debnath et al. [10], who treat each sentence as a unique text item regardless its length – and might lead to biased results. The latter implies a loss of information and can result in a country bias in remaining text items because average question-answer pair length varies considerably by country. We therefore analysed the remaining and lost information for different lengths of the cleaned items. We decided to drop pairs that have 10 or less words after removing stop words. This reduces the total number of text items in our corpus from 5,392 to 4,986, i.e., by 8%, but the total number of words by only 1%.

We analyse a total number of 1,197,630 words belonging to 212 interviews from 12 countries. The number of interviews, question-answer pairs, and words differ between countries as **Table 2** shows. The number of interviews per country ranges from 11 for Vietnam and the US to 25 for Chile and Indonesia. As a result, the number of question-answer pairs and words per country vary considerably, as does the average number of pairs and words per interview. For Vietnam, we find 36 question-answer pairs per interview, for Kenya only 17. This implies that on average the interviewers in Vietnam asked more than twice as many questions per interview as compared to the ones in Kenya. The average words per interview range from 1619 for Pakistan to 7568 for Colombia, which mirrors the length of the interviews. Similarly, Pakistan has the lowest number of words per question-answer pair with only 97 words, while for South Africa there are 383 words on average. It is important to keep these variations between countries in mind for the interpretation of results of the topic model.

***Table 2 | Overview of interviews by country**. The number of interviews, question-answer pairs, and words is shown in addition to the number of average pairs and words per interview and the average word count per document. This table considers only those question and answer pairs above the word limit of 10 words after removing stop words.*

		Per country			Per interview		Per question-answer pair
Country		Interviews	Question-answer pairs	Words	Average question-answer pairs	Average words	Average words
DE	Germany	17	353	104,694	20.8	6158.5	296.6
UK	United Kingdom	18	305	92,789	16.9	5154.9	304.2
CL	Chile	25	447	141,782	17.9	5671.3	317.2
CO	Colombia	20	485	151,363	24.2	7568.2	312.1
US	United States	11	234	52,048	21.3	4731.6	222.4
KE	Kenya	17	284	91,618	16.7	5389.3	322.6
ZA	South Africa	19	330	126,505	17.4	6658.2	383.3
ID	Indonesia	17	474	87,208	27.9	5129.9	184.0
IN	India	25	898	170,338	35.9	6813.5	189.7
VN	Vietnam	11	396	55,411	36.0	5037.4	139.9
PH	Philippines	20	579	104,449	29.0	5222.4	180.4
PK	Pakistan	12	201	19,425	16.8	1618.8	96.6
TOTAL		212	4,986	1,197,630	23.5	5649.2	240.2

The data does not only allow to compare countries, but also actor groups. Seven different groups were recommended for conducting interviews with in the case studies. However, few studies covered them all. For our analysis, we decided to cluster the actors into four larger types that were found in most countries: 'economic actors' (such as company and lobby group representatives), 'political actors' (politicians and workers in ministries), 'societal actors national' (representatives from NGOs and unions), and 'societal actors international' (representatives from international cooperation agencies and multilateral development banks). **Table 3** gives an overview of the interviews by actor group. Most interviews were conducted with societal national actors (72), least with societal international (27). As compared to the different countries, the actor groups do not differ much with regards to the number of average question-answer pairs, words per interview, and words per pair.

***Table 3| Overview of interviews by actor group**. The number of interviews, question-answer pairs, and words is shown in addition to the number of average pairs and words per interview, and the average word count per document. This table considers only those question-answer pairs above the word limit of 10 words after removing stop words.*

	Per actor group			Per interview		Per question-answer pair
Actor groups	Interviews	Question-answer pairs	Words	Average question-answer pairs	Average words	Average words
Economic	50	1133	271,059	22.7	5421.2	239.2
Political	63	1507	335,473	23.9	5325.0	222.6
Societal international	27	673	151,207	24.9	5600.3	224.7
Societal national	72	1673	439,891	23.2	6109.6	262.9
TOTAL	212	4986	1,197,630	23.5	5649.2	240.2

The number of interviews with specific actor groups is distributed heterogeneously among countries (see SI Table S1). For some countries, there are no interviews with actors belonging to the group 'Societal international', namely Germany, the US, and Pakistan; for the UK and Chile there is only one. In some countries, more than 40% of interviews are conducted with one specific actor group, e.g., 'Societal national' in Germany and 'Economic' in South Africa. These large differences in the numbers and shares of interviews by actor group and country need to be taken into account when interpreting the topic modelling results.

3.3. Topic Modelling (TM)

Topic models are computational approaches to find latent topics in a collection of texts, often called documents or – in this paper – question-answer pairs. A frequently used method for TM is Latent Dirichlet Allocation (LDA) [46]. LDA models word counts in a corpus of documents by assigning each document to a distribution of 'topics'. In turn, these topics each consist of a distribution of words. The algorithm iteratively improves topic distributions and topics to best match the desired corpus using assumptions about the shape of underlying probability distributions. Mathematically, the corpus is represented by a document-term matrix with rows corresponding to different words from a dictionary of terms in the corpus and columns representing the documents [47].

The topic model requires setting some parameters for training, most of which have a default value that can be adjusted. We varied the following main parameters: The a-priori belief of the document-topic distribution α, which is related to the expected number of topics per document [36], and the number of topics K. The decision for parameter values is an iterative process, which we explain in detail in the SI (section 4). It comprises comparison of results for different parameter values quantitatively, using, for example, the coherence score, which quantifies the goodness of the learned topics, and qualitatively by looking at the top keywords and overlap between the resulting topics. The latter also implies comparing similarities and differences between topics for different model runs and examining the interpretability. For our final results, we chose the following parameter settings: $\alpha = 0.01$ and $K = 22$.

Based on each topic's keywords and question-answer pairs with highest topic shares, we labelled topics and assigned them to categories. Labelling topics is commonly applied in TM to give meaning to the topics by finding the common content of texts and keywords. This helps to better understand and analyse the results of the topic model. We therefore extracted the 20 keywords with the highest contribution for each topic as well as the keywords that make a topic exclusive. We additionally considered the 20 most representative question-answer pairs for each topic, i.e., the text items with the highest contribution for each topic. We added this information to a table, which provides the basis for the manual, iterative labelling in a first step and the assignment to categories in a second step. All three authors individually conducted those tasks, followed by a joint discussion. We finally assigned the topics to four overarching categories.

We clustered the countries based on the topic contributions to highlight similarities and differences. Each country is thus considered a 22-dimensional vector representing the 22 topics. To extract the groups, we applied hierarchical clustering [48], which uses the topic shares for each country to compute the similarity between them and merges most similar data points into clusters. We drew a dendrogram, illustrating how countries cluster. It represents a tree with a root node and the countries as leaves. The clusters are determined by cutting the tree at a certain height. We additionally produced two maps illustrating the position of countries and question-answer pairs in the 22-dimensional topic space (see SI section 7). To display them in 2D, we use a dimensionality reduction algorithm called t-distributed stochastic neighbour embedding (t-SNE) [49]. All three methods display congruent findings.

Rigorous model validation is critical when conducting TM analyses [8]. Internal validation, i.e., the coherence and interpretability of topics, should complement external validation, i.e., comparing and discussing results to existing studies. For internal validation, we examine the results of the topic model in detail. This implies comparing topic coherence and exclusivity. We consider key words and labels per topic, and additionally the question-answer pairs with the highest contribution for each topic for each country. We also tested the robustness of our results by comparing models with different numbers of topics and the resulting country clusters (see SI, section 4). We additionally validate the results externally in the Discussion. First, we compare the main content identified in this study based on TM results and a qualitative analysis of the underlying question-answer pairs to traditional content analysis gathered in [11]. Second, we compare the country clusters. Studies by Jakob and Steckel [11,50,51] produced country clusters for the political economy of coal including for the 12 countries we analyse in this study. We explain their approach and highlight differences to our method, drawing on individual case studies from [11].

4. Results

We present the results of our study in four subsections. First, we discuss the topics identified by the topic model and the respective categories we assigned to them. Second, we look at the differences in topics between actor groups and, third, between countries. Finally, we cluster the countries based on the differences in topics and discuss each cluster's characteristics.

4.1. Topics and Categories

The model identifies 22 topics in the interviews, their contribution, and keywords. **Figure 1** shows them together with the labels and categories assigned by the authors.

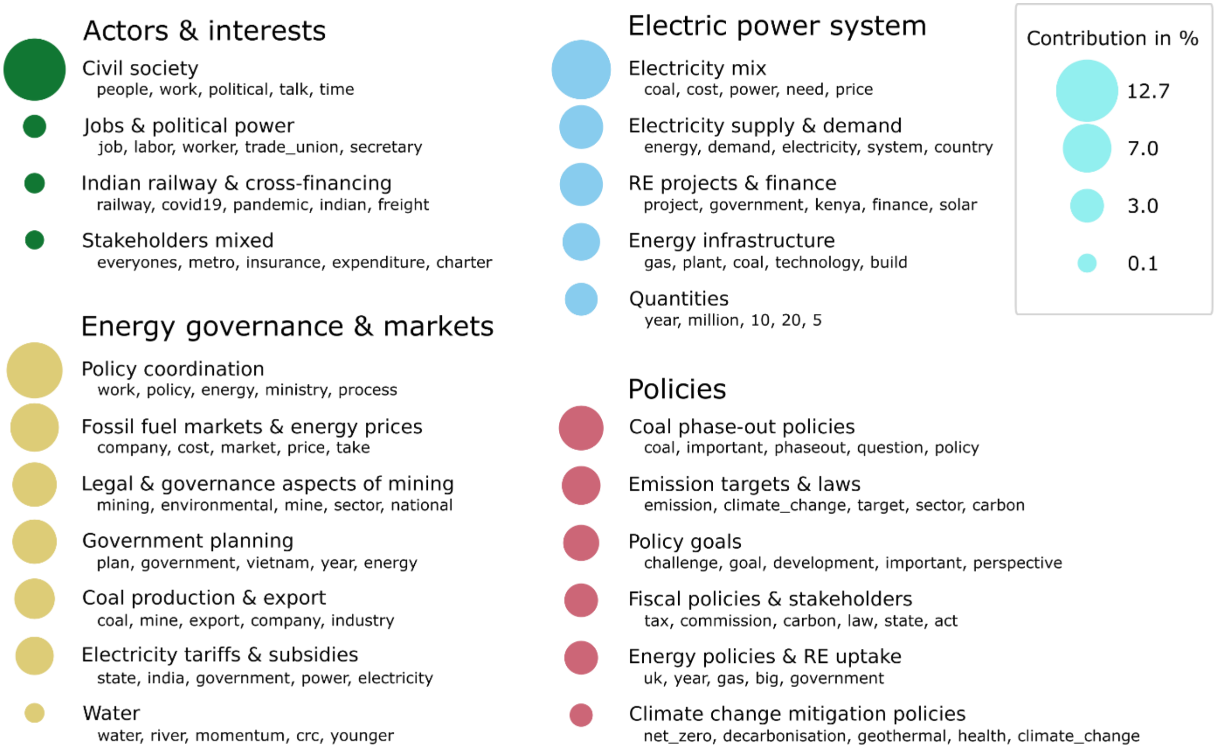

Figure 1 | The 22 topics identified by the topic models with labels, contribution, and categories. *The topic model identifies the topics, their contribution to the corpus, and the respective keywords, of which we display the 5 words with the highest contribution. The topic contribution describes the share of the total corpus assigned to a topic. The scores for topic contribution range from 0.1% to 12.7%. The large variation implies that the occurrence of the topics is distributed unevenly. The authors decided on the topic labels and the four categories. The keyword 'crc' for the topic 'Water' stands for the Central Electricity Regulatory Commission in India.*

We assign the topics to four categories: 'Actors & interest', 'Electric power system', 'Energy governance & markets', and 'Policies'. 'Actors & interest' covers discussions of a wide range of stakeholders and their specific interests. These are mostly civil society actors, e.g., communities and unions, but also political and economic actors, e.g., companies. This category is highly concentrated on the topic 'Civil society'. The four topics discussed in this category contribute to 14% of all topics, the lowest value of all categories. 'Electric power system' covers the path of the electricity from the generation facility to the end user, e.g., plants and transmission, including supply and demand of electricity. The category's contribution is 29 %. 'Energy governance & markets' combines topics on policy coordination and government planning with topics on export and import of coal and other fossil fuels. It has the largest contribution at 38%. The contribution of the group's topics is rather homogenous, with the topic 'Water' being an outlier. 'Policies' includes topics on energy, mitigation and coal phase-out policies, and on policy goals and emission targets. The contribution of this category is 20%. These four categories allow to easily detect what content the respective topics cover, e.g., policies, technology, or governance.

The 22 topics vary greatly in their scope. In our manual review, we find that some topics are broader, e.g., 'Stakeholders mixed'. Others appear comparably narrow, e.g., 'Coal phase-out policies'. Therefore, we sometimes combine different content in the labels, e.g., 'Jobs & political power'. Some of the topics have quite different themes in the highest-ranking question-answer pairs, thus it was challenging to find a label fitting the content of all pairs equally well. A few topics are related to a specific country, e.g., 'Indian railway & cross-financing' to India and 'Energy policies & RE uptake' to the UK, while most others are overarching.

Figure 2 shows the similarities of question-answer pairs by reducing their positions in the 22-dimensional topic space to two dimensions (see section 3.3). Each dot represents one pair and is coloured according to its dominant topic. Question-answer pairs and topics closer to each other have a higher similarity in their topic distribution. The topic labels are placed in the centre (median) of the clusters of pairs associated with each topic. We slightly repositioned some to avoid overlapping. The graph thus indicates if topics are similar when their labels are close to each other.

We find that the dominant topic of a question-answer pair has a high impact on the total topic distribution. This is because many pairs have a high share of up to 100% for one topic, e.g., 'Legal & governance aspects of mining' and 'Emission targets & laws'. These question-answer pairs thus do not have a contribution of any other topic and are therefore located at the exact same x and y position in the graph. Some topics have only small contributions per document and are spread out widely across the graph, e.g., 'Stakeholders mixed' (max 36%), 'Water' (max 53%), and 'Indian railway & cross-financing' (max 44%). This implies that the remaining topic distribution for these question-answer pairs vary strongly.

In addition, **Figure 2** shows that topics cluster quite differently. For example, the question-answer pairs with the dominant topic 'Coal production & export' are separated from the rest. Other topics are located in clusters. A cluster on the top left pools pairs with dominant topics from the category 'Policies'. On the opposite site of the graph, one can see a cluster with topics from the category 'Energy governance & markets'. All four topics of the category 'Actors & interests' are located on the centre-left side of the graph. The placement of question-answer pairs on this figure thus also confirms that the manually assigned categories are consistent with the topic model results.

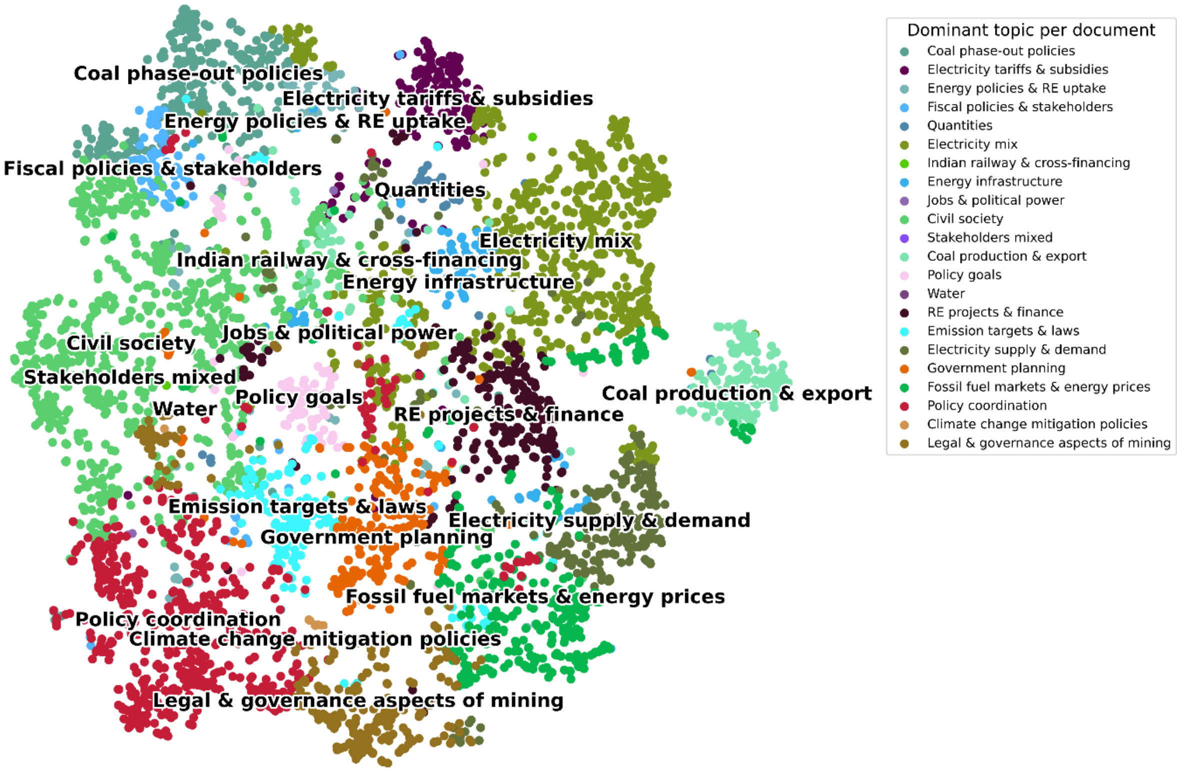

Figure 2 | Similarities between question-answer pairs using a t-SNE embedding of topic distributions. *The colour indicates the dominant topic per document. The topics are annotated at their median x- and y-values. The order of the legend follows the y-value for each topic.*

4.2. Actor Groups

We analyse differences in topics between the actor groups by merging the contribution of topics from question-answer pairs belonging to each group. This can be seen in the heat map in **Figure 3**, where the colour of each square represents its value, with a darker colour implying a higher share. The graph highlights two different patterns.

First, by comparing the squares in one column, we learn which topics appear more frequently in the interviews belonging to a specific actor group as compared to the other groups. For economic actors for example, the topics 'Indian railway & cross-financing', 'Quantities', and 'Fossil fuel markets & energy prices' were particularly important. Political actors mostly mention topics allocated to the category 'Policies', such as 'Emission targets & laws' and 'Coal phase-out policies', while 'RE projects & finance' has a comparably low contribution. For societal actors there is a relevant distinction between international and national ones: International societal actors cover 'RE projects & finance', 'Government planning', and 'Policy goals', but not 'Fiscal policies & stakeholders' and 'Coal phase-out policies'. At the national level, societal actors focus more than other groups on 'Stakeholders mixed', 'Fiscal policies & stakeholders', and 'Coal phase-out policies'.

Second, by comparing the squares of each row, we learn in which actor group a topic is covered. Few topics are concentrated on individual actor groups, such as 'Indian railway & cross-financing' on economic actors, and 'RE projects & finance' and 'Government planning' on societal international actors. The topic 'Stakeholders mixed' is concentrated on the two groups societal national and international actors, 'Legal & governance aspects of mining' on political and societal national actors.

Most topics, however, have a less skewed distribution, which implies that each of the actor groups talks about them with similar frequency.

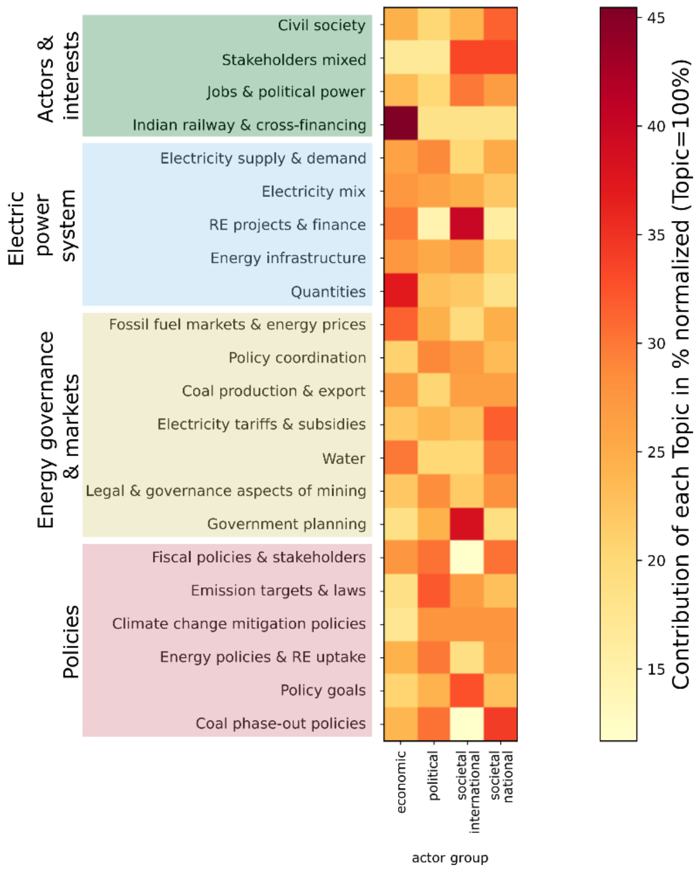

Figure 3 | Topic contribution by actor groups*. The colour of each square in the heat map shows the contribution of an actor group to a topic relative to the other groups. We calculate this contribution as follows: We first compute the contribution of each topic to each group (Group = 100%) before normalizing every value (Topic = 100%). This way, we account for both, a variation in total topic contribution and a variation in question-answer pairs per actor group.*

In summary, we find that only a few topics are specific to single actor groups – most topics are similarly distributed across actor groups. With respect to differences between actors some particularities are worth mentioning: economic actors more often talk about numbers, finance, and markets in their interviews as compared to the other groups. Political actors cover political topics. Societal international actors discuss REs and policy planning and goals; their national counterparts discuss different stakeholders and vested interests more frequently. This implies that the different experts in a country tend to stick to their domain but overall consider similar aspects important to the political economy of coal in their country.

4.3. Countries

We use the topic model to analyse which topics are mostly covered in each country. We do so by looking at the contribution of topics by country. In the heat map in **Figure 4**, the colour of each square represents a topic contribution per country and topic normalized by country and topic, similar to the heat map for the actor groups. Again, we consider two aspects.

First, by comparing the squares in one column, we learn which topics appear more frequently in the interviews belonging to a specific country as compared to the other countries. Germany and the UK have a comparably high share for political topics, e.g., 'Coal phase-out policies' (both), 'Fiscal policies & stakeholders' (Germany), and 'Energy policies & RE uptake' (the UK). Interviewees from Chile referred to 'Emission targets & laws' and, similar to those from Colombia, to the topics 'Fossil fuel markets & energy prices' and 'Legal & governance aspects of mining'. The US shows large shares for 'Coal production & export' and 'Electricity mix' compared to the other countries. In Kenya, 'RE projects & finance' and, similar to South Africa, 'Civil society' is covered. Indonesia as well as India show large shares for 'Electricity tariffs & subsidies' and 'Quantities'. The interviewees from Vietnam often talk about 'RE projects & finance' and 'Government planning'. The latter is also covered by interviewees from the Philippines and Pakistan.

Second, by comparing the squares of each row, we learn in which country a topic is covered. The graph shows that the coverage of some topics, such as 'Civil Society' and 'Policy goals' is rather equally distributed. Other topics are concentrated in few countries, e.g., 'Electricity Supply and Demand', 'Government Planning', or 'Coal phase-out policies'. Others again are concentrated in a single country, e.g., 'Fiscal policies & stakeholders' in Germany or 'Jobs & political power' in South Africa. We thus find that only few topics are equally prevalent in all countries, while most are specific to one or only few countries.

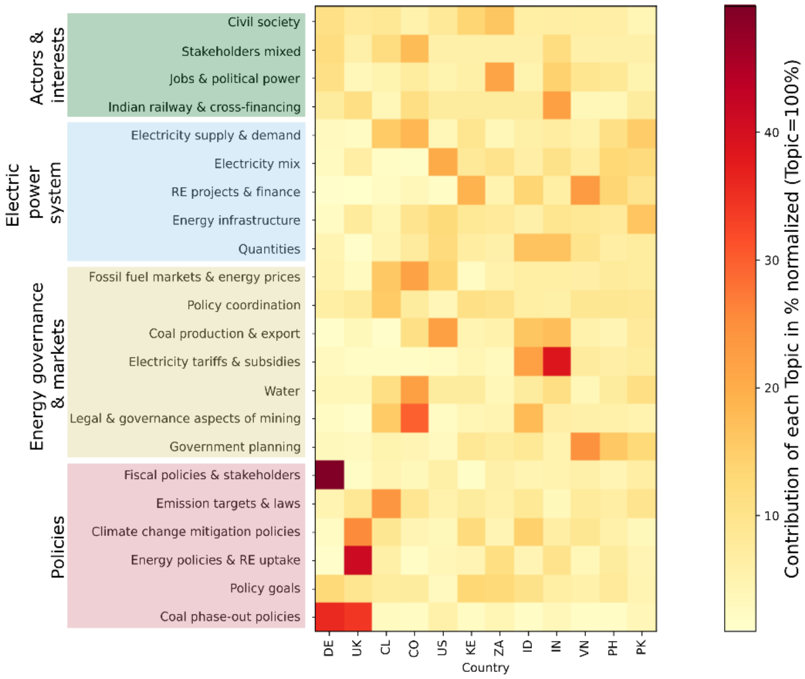

***Figure 4* | Topic contribution by country.** *The colour of each square in the heat map shows the contribution of a country to a topic relative to other countries. We first calculate the contribution of each topic to each country (Country = 100%) before normalizing every value (Topic = 100%). This way, we account for both, a variation in total topic contribution and a variation in question-answer pairs per country.*

Figure 5 shows the share of the four categories per country and the topics per category. It highlights big differences in the distribution of categories. Germany and the UK have large shares of 'Policies' (56% and 54%, respectively). In Chile and Colombia, topics belonging to the category 'Energy governance & markets' are dominant (47% and 56%, respectively). Kenya and South Africa have a comparably high share of 'Actors & interests' of more than 20%. The other countries, i.e., US, Indonesia, India, Vietnam, Philippines, and Pakistan, have similar shares for all four categories: 'Actors & interests' (7-14%), 'Electric power system' (29-43%), 'Energy governance & markets' (31-46%), and Policies' (12-15%). Comparing the share of categories already implies an emerging cluster of countries. However, shares of topics within the categories can vary strongly between countries, even if they have similar shares in categories.

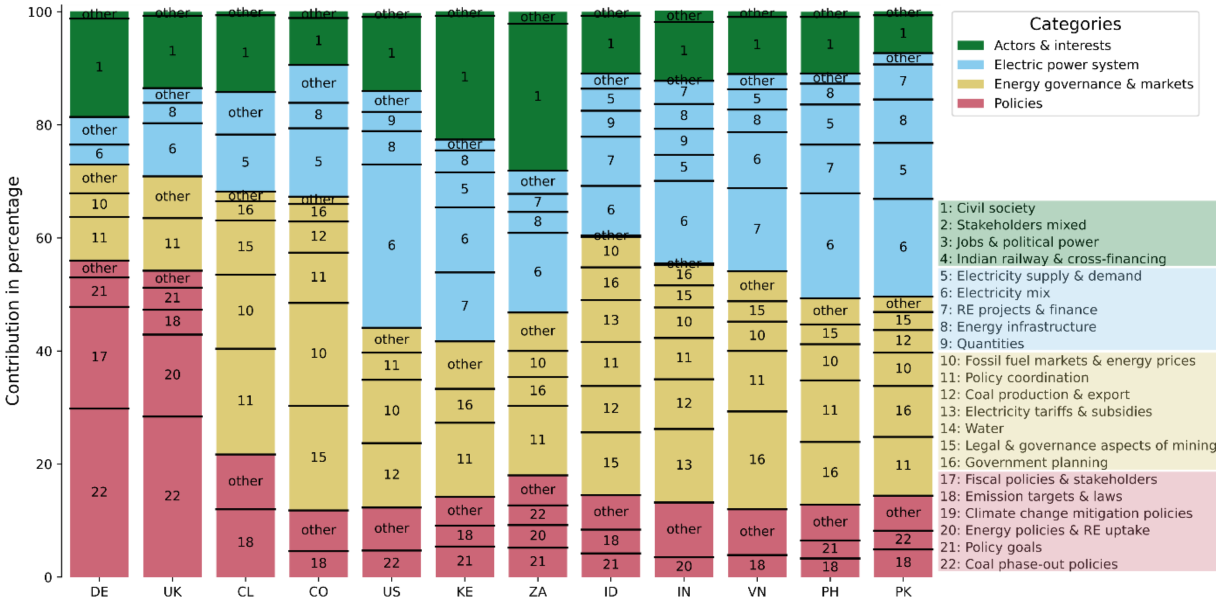

Figure 5* | *Topics and categories per country. *The graph shows the topics with a share of at least 3%. Topics with lower shares are grouped in 'other'. Topics are coloured according to the assigned category.*

4.4. Country Clusters

To systematically identify clusters of countries, we use hierarchical clustering in Python on the topic distributions for countries. **Figure *6*** shows the resulting six country clusters: (1) Germany and the UK, (2) Chile and Colombia, (3) the US, (4) Kenya and South Africa, (5) Indonesia and India, and (6) Vietnam, Philippines, and Pakistan. We quantitatively compare the contribution of the topics per country in each cluster, and the cluster to the other country groups. In addition, we qualitatively look into the relevant question-answer pairs for the three biggest topics per country to better understand the country specific content of each topic. The SI includes a graph showing all pairs by country and one showing all countries using t-SNE, which substantiate the results of the clustering (section 7). Additionally, it contains a detailed analysis of the material by individual countries (section 8). In the following, we synthesise this information and systematically discuss the characteristics of each cluster.

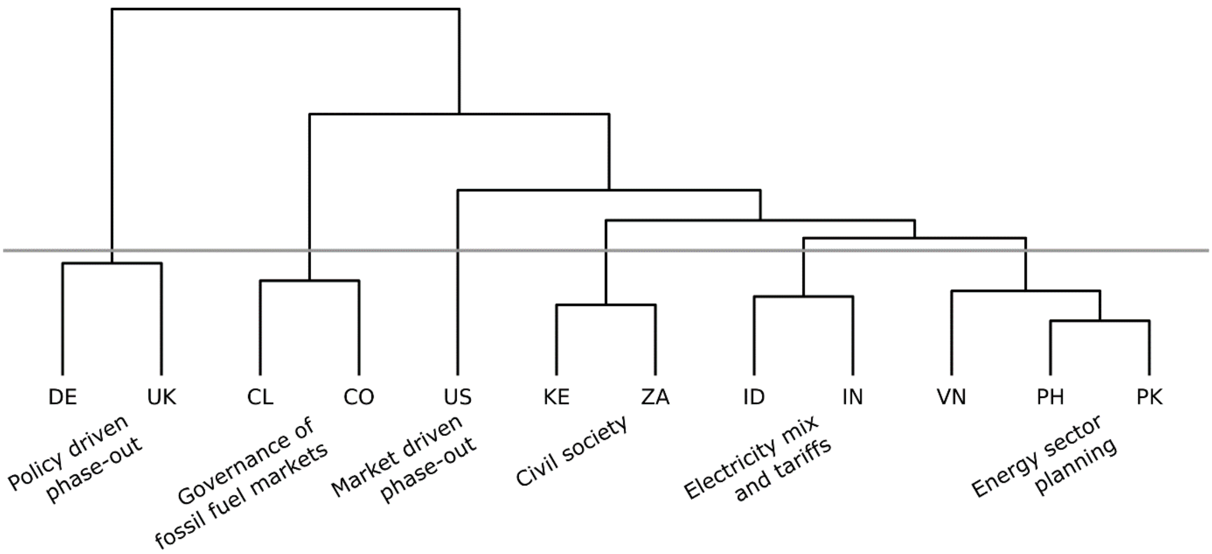

Figure 6* | *Hierarchical clustering of countries. *Countries are grouped based on their topic distributions. The tree is cut at the grey line, resulting in 6 country clusters.*

Policy driven phase-out

Germany and the UK form a distinct cluster. The two countries show highly similar shares for each category and have the biggest topic for each of the categories in common. They are also distinct from the other countries, e.g., with a share of the category ‘Policies’ above 54% while the other countries have a share below 22%. For the categories ‘Energy governance & markets’ and ‘Electric power system’ the two countries have the lowest shares among all countries. This cluster therefore displays a strong focus on policies. The topic ‘Coal phase-out policies’ has a contribution of around 1/3 for both countries. However, the exact content of this and other topics differs between the two countries. In Germany, the focus lies on the coal commission, involved political and societal actors, and its implications for the coal phase-out. In the UK, the interviewees discussed the development of the energy sector away from coal and drivers thereof, with a focus on actors and policies. This cluster can therefore be defined by a strong focus on the experienced and predicted policy driven coal phase-out.

Governance of fossil fuel markets

Chile and Colombia have the largest shares for the category ‘Energy governance & markets’ of all countries, 47% and 56%, respectively. They do share the biggest topic per category for each category except for ‘Energy governance & markets’. They differ from the other countries by having large shares of at least 10% for three topics that hardly any other country has: ‘Electricity supply & demand’, ‘Fossil fuel markets & energy prices’, and ‘Legal & governance aspects of mining’. When it comes to the category ‘Policies’, they both have ‘Emissions targets & laws’ as the most important topic. When we look at the topics per country qualitatively, we find that the interviews in Chile and Colombia have a strong focus on coordination of political and societal actors and private companies in the fossil fuel markets. This includes mining, prices for coal and other fossil fuels, and opportunities for energy companies. The overarching content in Chile and Colombia is thus fossil fuel markets and their governance.

Market driven phase-out

The US shows unique features. It has the largest share, namely 42%, for the category ‘Electric power system’ and for the topics ‘Electricity mix’ (29%, while all other countries have below 19%) and ‘Coal production & export’ (11%, others below 9%). Looking at the question-answer pairs of the largest topics we find the development of the electricity sector as the overarching theme. This is mainly related to the market driven downward trend of coal and its impact on communities, closely linked to the price of coal.

Civil society

The cluster consisting of Kenya and South Africa features the largest contributions of the topic ‘Civil society’ of all countries with 22% and 26%, respectively. Kenya and South Africa also have the second and third largest topics ‘Electricity mix’ and ‘Policy coordination’ in common, albeit in different order. The content of the three largest topics is considerably similar. The interviewees in both countries explain the reasons for coal plants and capacity in the respective country, with a focus on the relevant – mostly societal – actors, relevant policies, and vested interests.

Electricity mix and tariffs

Indonesia and India have similar shares for all four categories, with the highest contribution of the category ‘Energy governance & markets’ at 46% and 42%, respectively. In this category, both countries have high contributions of the topics ‘Electricity tariffs & subsidies’, ‘Coal production & export’, and ‘Quantities’. Both additionally display the topic ‘Electricity mix’ as the largest topic of the category

‘Electric power system’. We find this to be an overarching topic. In both countries the interviewees covered the electricity mix and reasons thereof, including interests of the civil society and vested interests in the mining sector, e.g., royalties. This is in both countries linked to electricity tariffs.

Energy sector planning

Vietnam, the Philippines, and Pakistan all have contributions above 35% for the two categories ‘Electric power system’ and ‘Energy governance & markets’. All three additionally have large contributions of the topics ‘Government planning’ (above 9%, while all other countries have below 6%) and ‘Policy Coordination’ (above 10%). None of the three has ‘Civil society’ as one of the top three topics, which is important in all other countries but Colombia. The qualitative analysis underpins the overarching characteristics of this cluster: a focus on policy planning and energy market regulations, the involved private and political actors, and how they shape policy making. This includes multiple energy and power development plans considering financial and technical aspects.

5. Discussion

To learn about the potential for TM on interviews in energy social science we validate our results and discuss limitations of our method. First, we compare country-level results to insights from qualitative case studies. Second, we compare our clusters to country groups derived with other methods. Third, we examine potential explanations for differences between our and external findings. Subsequently, we discuss the limitations of conducting TM on interviews.

5.1. Comparing TM results with case study content analyses

Table 4 provides an overview of the narratives per country and the main topics. The narratives were derived from the respective case studies. We identify the dominant content by looking at the category and topic distribution per country resulting from the topic model and at the underlying question-answer pairs. The table also shows example quotes from sections of the interviews, in which the most relevant topics for that country have a high share. A more detailed description of each country can be found in the SI (section 8).

While TM provides the most prevalent content from the interviews, e.g., “The set-up and impact of the coal commission” in Germany, the case studies use this material to reveal the narrative that dominated the political economy of coal at the time of the interviews (“The coal commission agreed on recommendations for the coal transition building on support across stakeholder groups”). The findings overlap for all countries; for none of the countries does TM produce results in terms of identified content that is not covered in the case studies. For some countries, however, the topic model puts emphasis on aspects not prominently explained in the case studies, e.g., the civil society in South Africa. The comparison suggests that TM allows researchers to yield similar results in terms of important content as compared to qualitative case studies – when using the same data – with some differences on the emphasis put on different aspects. It additionally points to differences between the methods as explained in section 5.3.

Table 4 |Comparison of results from traditional content analysis in case studies and TM. *The narratives were derived from the case studies published jointly in a book project [11].*

Country	Narratives found in case studies*	Dominant content derived from TM and representative quotes from interview sections
DE	The coal commission agreed on recommendations for the coal transition building on support across stakeholder groups [52]	**The set-up and impact of the coal commission** "[…] In your view, what were the main framework conditions for the Commission's negotiations, but also for the debate on the coal phase-out in general? - […] In this context, the question of jobs is of course a very decisive one for us. And in this context also the regional anchoring and the structural-political questions that arise from it."
UK	The ongoing coal phase-out is driven by effective climate policies following high political consensus [53]	**Actors and policies important to the coal phase-out** "And what was the role of the EU in driving the coal phase-out, in your opinion? You already mentioned a few EU policies. - Yes. So as mentioned, mainly I would say that the EU-ETS and a number of other, in particular environmental legislations, played a very, very important role in making that happen. […]"
CL	Civil society asserted pressure on the government to announce a coal phase-out plan which compensates companies [54]	**Influence of political and societal actors on fossil fuel policies** "In general, would you say how much coordination or synergy there is between the different actors in policy decision-making? […] - Of course, more from my experience, it depends on the minister on duty. There are ministers who have been more inclined to bring us all together at the table and hold these working groups. […]"
CO	The government plans to increase domestic coal consumption and coal exports due to revenues, employment, and private sector interests [55]	**Interests of coal mining companies and their influence on policy making** "Who are the ones, the government agencies or the actors that are currently influencing the formulation of public policies in this issue of the mining and energy sector? - Well, in addition to the Ministry of Mines and Energy, the Planning Unit, the DNP, but I don't really know who else is involved in construction... the presidency."
US	Coal interest groups cannot prevent the price-led decline of the coal industry [56]	**Market driven downward trend of coal and its impact on communities** "So if I'm asking you to give me your forecast, could you give me a number, specifically on how many percentage of electricity...? - I would expect coal to be less than 10% of the U.S. electric generation by the end of the decade."
KE	The construction of the country's first coal plant in Lamu County – supported by the government and the business elites – was forestalled by the civil society [57]	**Drivers and barriers of coal plants (e.g. Lamu), including the civil society and policies** "Maybe you could also say something about the anti-coal protest in the Lamu region […] - Basically what happens in some of these demonstrations, is that some of them are organized by politicians that are over there. […] sometimes you give up, because I think that people have more power, it's the power of the people, it's perceived their influence."
ZA	The government finds itself in the predicament of requiring coal for revenues and employment while acknowledging the need to diversify the energy sector [58]	**Reasons for coal plants and capacity additions with a focus on societal actors** "Do you have any solution for that in the short and medium term? - I don't know if it's a political will, then it's about leadership. There won't be any solution. Yeah, I think that's where you rely a little bit on civil society. To try and push, push, push, push, and then you also hope that as time goes on, people would understand the implications of business as usual, that it doesn't work."
ID	Coal exports and domestic usage is fostered by the Indonesian government due to royalties and vested interests – despite emission mitigation targets [59]	**Reasons for coal, such as royalties and tariffs** "But how would you keep the tariff low? - […] We need to refill the existing policy. What we can do to help PLN to reduce the cost. Maybe we can, for example, push PLN, don't use the old power plant, please make some improvement."
IN	The Indian government created a favourable policy environment for coal to ensure long-term cheap electricity supply, which has led to regional dependencies on coal [60]	**Electricity mix and reasons thereof, such as policy goals and profits** "Given the demand forecast, is that correct? - […] Given the demand forecast and what sort of plants should be built in the future. So if it there is a target of 175,000, then we said that is already going to supply some amount of energy. Only the remaining energy needs to be supplied by coal-based plants. All the other plants, Hydro whatever."
VN	The Communist Party envisaged a stark increase in coal capacity but decreasing prices for RE and the dependence on foreign investors might bring about change [61]	**Policy planning with a focus on the Power Development Plan** "[…] The power development plan […] what is its legal status if is not a law? - A government plan. It's a kind of plan, prepared by MOIT, but it has to be approved by the Prime Minister. But it also became of some kind of legal document. But it would not be law. So it would not be passed by the National Assembly. […] "
PH	Political and economic elites favour coal due to associated profits and economic development but face resistance from civil society actors [62]	**Actos relevant to energy decision making** "Who were the actors behind the policy formulation, and then who were the ones that are supposed to implement it but are lacking behind? - The renewable energy Law was by the law makers made from legislation, and the implement rules and regulations are to be developed by the National Energy Board. But they are just for recommendations, or whatever they come up, they submit it as a policy recommendation to the Department of Energy."
PK	Case study not yet published	**The electricity mix and reasons thereof, such as vested interests and technical difficulties** "Sir, what according to you is the ideal energy mix? […] – We're aiming for 30% wind and solar and 35% hydro, that makes around 65%. Rest will include nuclear, and then LNG. These are the cleanest fuels. We'll have coal to some extent. […]"

* Narratives represent the political economy of coal at the time of the interviews and might have shifted since.

5.2. Comparing country clusters

Three recent studies cluster countries based on their political economy of coal. They synthesise findings from the qualitative case studies shown in **Table 4** using the same interview base as we do [11,50] and numbers on coal capacity and coal export [51]. This enables comparison of results while drawing on the individual case studies from Jakob and Steckel [11]. The results of the three studies are almost identical and can be found in **Table 5** for the 12 countries covered in this article.

Table 5 | Country clusters for the political economy of coal from the literature. *This clustering is used in a Nature Comment [51]. In an earlier clustering [11,50], the Philippines were considered a phase-in country and Pakistan was missing.*

Cluster	Phase-out	Established	Phase-in	Export
Countries	United States	India	Vietnam	South Africa
	Germany	Philippines	Pakistan	Indonesia
	United Kingdom	[…]	Kenya	Colombia
	Chile		[…]	[…]
	[…]			

In the following, we merge our results with insights from individual country case studies to explain similarities and differences in country groups. We find our clusters strongly overlapping with two clusters from Steckel and Jakob [51], namely ‘Phase-out’ and ‘Phase-in’. Regarding the four countries in the cluster ‘Phase-out’, we can find a further specification using TM: Germany and the UK (‘Policy driven phase-out’) currently experience a mostly policy focused phase-out [52,53], whereas the US (‘Market driven phase-out’) experiences a market-led decline [56]. Interviewees from the cluster ‘Policy driven phase-out’ congruently focus on the coal commission and climate policies, while those from the cluster ‘Market driven phase-out’ describe the market driven downward trend and its impact on communities.

We find two out of the three countries from the cluster ‘Phase-in’, Vietnam and Pakistan, in our cluster ‘Energy sector planning’, together with the Philippines, which was considered a phase-in country in earlier papers as well [11,50]. The overarching content we find for this cluster is the focus on policy planning and the involved private and political actors and how they shape policy making. This includes multiple energy and power development plans. The respective case studies congruently highlight the interests of the Communist Party and incumbents in Vietnam [61] and the objectives of politicians and conglomerates in the Philippines [62] for energy policy making. The case study on Pakistan has not been published yet.

We find the three countries of the cluster ‘Export’, namely Colombia, South Africa and Indonesia, in separate clusters. Colombia and Chile (‘Governance of fossil fuel markets’) have a strong focus on governance and fossil fuel markets. In Chile, the government tries to reduce dependence on coal imports – currently accounting for around 90% of the consumed coal – stemming from high exploitation costs and low quality for the significant domestic coal reserves [54]. The Colombian government tries to reduce its reliance on coal exports by increasing domestic demand [55]. South Africa and Kenya (‘Civil society’) focus on the impact of different actors – especially societal – on the development of coal plants. Incumbent actors and societal stakeholders, including unions and affected regions, have a substantial impact on policy making in South Africa [58]. The case study however does not feature coal exports prominently, other than it being an important source of revenue expecting to decline. This is in line with relatively low shares of coal export averaging around 35 % between 2000 and 2021 [Own calculations based on 63]. In Kenya, companies with close ties to ruling elites and civil society organization are important players; the latter becomes evident in light of a recently cancelled coal plant project [57]. Indonesia forms the cluster ‘Electricity mix and tariffs’ with India, which in a similar fashion covers vested interests and how this affects the electricity mix. In this cluster, the focus however lies on economic and political actors. The two respective case studies highlight the incentives of state-owned enterprises and regional and central governments to favour coal due to profits and revenues [59,60]. Thus, while South Africa and Indonesia are technically speaking exporting coal, other aspects of the political economy made up a bigger part of the interviews.

5.3. Explaining differences in the results

The differences in the results are rooted in the underlying data and the characteristics of the different methods. TM does not rely on pre-defined and quantifiable factors, as is the case for the numeric clustering [51]. The other two studies synthesise knowledge from case studies [11,50]. Qualitative content analysis and computational text analysis show distinct characteristics. Qualitative case studies are characterized by the subjectivity of the researcher [5,10]. TM likewise relies on many decisions taken by the researchers, e.g., the specific steps in the text pre-processing and the number of topics. The hierarchical clustering in the end however is fully automated. The differences in the results thus point to strengths and weaknesses of computational text analysis versus qualitative case studies. Compared to Natural Language Processing (NLP), case studies go more into detail and analyse a specific question in depth. At the same time, the manual reading and coding of each document requires much time. Automated methods like TM can be scaled with increasingly large sets of documents. They reduce some level of subjectivity and allow for comparing single cases not on the results of each study, but directly on the underlying texts, e.g., interviews. However, TM cannot capture all specific details of the case studies (see limitations listed in section 5.4). It is thus especially useful to get an overview of the large text corpus and for the comparison of texts per country, actor group, or year. Computational text analysis including TM is therefore complementary to traditional qualitative approaches.

5.4. Challenges for TM with interview data

When applying TM to interview data, we encountered several general and specific challenges, some of which can inform further research methodology development. General limitations of TM are extensively discussed in the literature [41,45,64]. They include, for example, selection of adequate parameters for the model, the subjective bias when interpreting the model results, the loss of information when focusing only on word frequency, and the problem of confirmation bias. Challenges specific to the application of TM on interviews are explained hereafter, split into those commonly experienced by researchers working with interviews, and those emerging from the novel application of computational analyses on interviews.

Challenges rooted in the nature of interviews relate to the vulnerability to interviewer's bias [5,10,65], the transcription of interviews, and the selection of interviewees. The interviews are transcribed spoken language, which differs from written text in the terms used and on content. Interviewees have little time to respond and thus voice their opinion in a way they might not express in writing. For example, we find many colloquial terms, which can make comparison between interviews challenging. In addition, transcribing the interviews can alter the text and does not allow to read facial expressions or between the lines. Furthermore, interviews can be carried out by different researchers, potentially using different styles in questioning – as is the case in our paper for each country. This might lead to a bias that we cannot examine in this study, as we are not able to separate the influence of factors like language, country, length of interviews, and the interviewer. Also, transcriptions are commonly not available for all interviews, as is the case for our data. Some interviewees did not agree to recording, which can result in a bias regarding the analysed information, as does the selection of interview partners in the first place. Additionally, the raised questions often vary between interviews. This paper uses interviews following harmonized semi-structured interview guidelines, but questions can be specific to individual countries or actor groups. It is therefore difficult to compare the replies to the same question across interviews. However, we think that by looking at the occurrence of common and objectively identified themes we can find similarities regardless of the varying questions.

By applying TM on interviews we encounter additional challenges. First, removing short documents (in this paper called question-answer pairs) can introduce a bias because documents of countries and actor groups vary in length. Second, the number of interviews and the total and average numbers of documents and words differ greatly between countries. This can introduce some bias in the results, as countries with more documents have a stronger influence on the formation of topics. Finally, we merged questions and replies into documents, which consequently not only reflect the opinion of the interviewee. The interviewers however are experts of their respective countries as well and we thus assume that they inquire about the most important issues. The interviewees additionally could put forward their own subjects, as many questions were asked openly.

Topic modelling thus faces additional challenges to the ones characterising interviews. However, quantitative computational analyses can actually help to reduce some of the biases prevalent in traditional content analyses related to subjectivity [10], e.g., by providing a benchmark for manually extracted information, such as conclusions about dominant topics. Thus, the biases mentioned above should not discourage the use of TM on interviews, but spur further research on how they can be accounted for in research design and validation methodologies.

6. Conclusion and Policy Implications

This paper quantitatively analyses the differences in how experts describe the political economy of coal in their countries. While we do not find large differences in the topic contributions for actor groups, our findings indicate country clusters based on similarities in the content of the interviews for countries. One example is the group of Germany and the UK that covers policy driven coal transitions. By comparing the resulting main topics and groups to findings from other articles, we show that clustering countries based on their political economy of coal might benefit from looking more into the relevant topics in expert interviews in each country.

Our application of TM to interview data also yields methodological insights. Challenges include the difference in length of replies and specificities of spoken language. Nevertheless, we find that TM produces valuable information and allows comparing the content covered by different groups directly from the interviews. This is especially promising for large sets of data, where manual coding implies much effort. Based on the insights generated in thus study, we see TM as complementary to the traditional non-computational content analysis. The latter constitutes in-depth analysis of text, while TM provides insights on a broader scope with less bias from individual researchers. Computational analysis of interviews could be further extended using newly emerging techniques, such as argument mining, or by combining it with network analyses, e.g., discourse network analysis [66]. Thereby it can be an important part of energy transition design by allowing to analyse arguments for and against change from all available actors (that are willing to be interviewed) and to cluster these actors based on common narratives. Future work could cover topics such as renewable energy policies and just transition partnerships. Energy social science would thus benefit from more computational analyses comparing material generated in qualitative case studies.

The insights from this paper provide important implications for policy makers. We confirm previous findings that countries can be clustered based on their political economy of coal. Thus, policy makers can learn about the similarities from a country comparison using TM. For instance, we find that in Vietnam, the Philippines, and Pakistan, companies are highly important for the formulation of policies and that technical and financial aspects are relevant. Policy makers in these countries should try to improve the technical and financial system through laws while considering economic interests. The clustering allows governments to learn from policies enacted in other countries with similar characteristics regarding soft factors in their political economy of coal and beyond quantitative metrics like coal capacity and export trends.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data, i.e., the interviews, can unfortunately not be made available due to the affirmed anonymity of interviewees. The code for Python is available on GitHub:
https://github.com/niccoloMG/TM_coal_interviews

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Supplementary Data

Supplementary Information is published along with this paper.

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