sustainability

Article

Identification of Perceived Challenges in the Green Energy Transition by Turkish Society through Sentiment Analysis

Ugur Bilgin * and Selin Soner Kara

Department of Industrial Engineering, Graduate School of Natural and Applied Sciences, Yildiz Technical University, 34349 Istanbul, Turkey; ssoner@yildiz.edu.tr
* Correspondence: ugur.bilgin@std.yildiz.edu.tr

Abstract: Green energy refers to energy derived from renewable sources such as solar, wind, hydro, and biomass, which are environmentally sustainable. It aims to reduce reliance on fossil fuels and mitigate environmental impacts. In the Turkish context, alongside positive sentiments regarding the establishment of energy plants, there are also prevalent negative perspectives. Societal responses to the transition towards green energy can be effectively gauged through the analysis of individual comments. However, manually examining thousands of comments is both time-consuming and impractical. To address this challenge, this study proposes the integration of the Transformer method, a Natural Language Processing (NLP) technique. This study presents a defined NLP procedure that utilizes a multi-labeled NLP model, with a particular emphasis on the analysis of comments on social media classified as "dirty text". The primary objective of this investigation is to ascertain the evolving perception of Turkish society regarding the transition to green energy over time and to conduct a comprehensive analysis utilizing NLP. The study utilizes a dataset that is multi-labeled, wherein emotions are not equally represented and each dataset may contain multiple emotions. Consequently, the measured accuracy rates for the risk, environment, and cost labels are, respectively, 0.950, 0.924, and 0.913, whereas the ROC AUC scores are 0.896, 0.902, and 0.923. The obtained results indicate that the developed model yielded successful outcomes. This study aims to develop a forecasting model tailored to green energy to analyze the current situation and monitor societal behavior dynamically. The central focus is on determining the reactions of Turkish society during the transition to green energy. The insights derived from the study aim to guide decision-makers in formulating policies for the transition. The research concludes with policy recommendations based on the model outputs, providing valuable insights for decision-makers in the context of the green energy transition.

Keywords: transformer; NLP; green energy; sentiment analysis; multi-label

Citation: Bilgin, U.; Soner Kara, S. Identification of Perceived Challenges in the Green Energy Transition by Turkish Society through Sentiment Analysis. *Sustainability* **2024**, *16*, 3367. https://doi.org/10.3390/su16083367

Academic Editor: Antonio Caggiano

Received: 13 March 2024
Revised: 5 April 2024
Accepted: 15 April 2024
Published: 17 April 2024

1. Introduction

Green energy is considered energy derived from sustainable sources with minimal impact on the environment and is recognized as a non-depletable energy resource. These sources include solar energy, wind energy, hydroelectric power, biomass energy, and geothermal energy. Solar energy harnesses the power of sunlight using photovoltaic cells or solar panels, while wind energy utilizes wind turbines to generate electricity. Hydroelectric power is generated by capturing the energy of flowing water in rivers or dams, while biomass energy is derived from organic materials such as wood, crop residues, and animal waste. Geothermal energy utilizes heat from the Earth's core to produce electricity or heat buildings. With its environmentally friendly characteristics, green energy provides an energy solution that contrasts with fossil fuels. Traditional energy sources are finite resources that deplete over time. In contrast, green energy sources are limitless and continually replenished in nature. This characteristic emphasizes green energy sources as a sustainable and long-term energy solution. Moreover, the transition to green energy aligns with global priorities for environmental sustainability and energy efficiency [1].

Green energy sources inflict less harm on the environment compared to traditional energy production methods. Environmental issues such as air and water pollution caused by fossil fuels significantly diminish with the utilization of green energy. Moreover, green energy sources play an effective role in combating climate change by reducing greenhouse gas emissions. Consequently, recent years have witnessed a rapid increase in global interest in electric vehicles, driven by incentive policies. This interest seeks to reduce dependence on fossil fuels, mitigate air pollution, and promote the use of green energy [2]. Electric vehicles continue to offer an environmentally friendly transportation solution when charged with green energy [3]. Green energy emerges not only as a preference for the current generation but also as a crucial choice to safeguard the quality of life for future generations and ensure environmental sustainability.

The importance of transitioning to green energy is increasingly recognized worldwide due to various reasons, such as environmental sustainability, combating climate change, ensuring energy security, and promoting economic development [4]. Major economies like the European Union (EU) are adopting policies to promote the transition to green energy and increase the use of renewable energy sources. For instance, the EU's Green Deal aims to reduce carbon emissions, increase the use of renewable energy sources, and enhance energy efficiency [5]. However, the significance of transitioning to green energy is not limited to Europe alone; it is also acknowledged in other regions across the globe. The United Nations Sustainable Development Goals aim to ensure sustainable and accessible energy worldwide [6], encouraging all countries to focus on transitioning to green energy to balance energy security with environmental sustainability. Moreover, transitioning to green energy sources is recognized as crucial for enhancing energy security. Reducing dependence on traditional energy sources contributes to diversifying the energy supply and increasing energy security, which is critical for maintaining a stable energy supply. Furthermore, the urgency and necessity of transitioning to green energy are increasing. Combating climate change and ensuring environmental sustainability require the reduction of carbon emissions. The use of renewable energy sources can reduce greenhouse gas emissions released into the atmosphere through a reduction in the use of fossil fuels and mitigate the effects of climate change [7]. In conclusion, transitioning to green energy is becoming increasingly important in Turkey, Europe, and other regions worldwide due to environmental, economic, and strategic reasons. The urgency and necessity of transitioning to green energy have drawn the attention of policymakers at national and international levels, leading to various measures being taken in this direction.

Until the early 2000s, Turkey, which largely met its energy demand from fossil fuels, initiated policies and took initial steps towards green energy, driven by environmental concerns and energy security needs. The transition to green energy, ongoing since the 2000s, represents a significant strategic move for Turkey. Due to its geographical location, climate conditions, and energy needs, Turkey holds substantial potential in the field of green energy. In Turkey, the share of green energy in the total energy mix was 35.71% in 2011, increased to 51.39% in 2020, and reached 55.40% by the end of 2023. As of December 2023, hydroelectric power plants constitute 30% of the installed capacity in Turkey, wind energy plants account for 11.1%, solar energy plants contribute 10.6%, geothermal energy plants represent 1.6%, and biomass energy plants make up 2.1% [8]. Turkey has made significant progress in transitioning to green energy; however, the success of this transition depends not only on technical and economic factors but also on the thoughts and attitudes of society. While the transition to green energy brings numerous benefits, such as combating climate change, achieving energy independence, and environmental protection, the views and attitudes of society play a crucial role in the success of this transformation and the formulation of policies.

The transition towards green energy represents a significant shift in energy production and consumption habits, guided by environmental concerns, energy security, and sustainability objectives. The success of this transition is heavily reliant on societal awareness of green energy. Societal awareness, encapsulating the collective sentiments, attitudes, and opinions of communities, significantly influences the adoption and acceptance of green energy initiatives. Therefore, comprehending the dynamics of societal awareness and its impact on green energy is crucial for effective policy formulation and successful implementation strategies. Research indicates that societal awareness significantly affects the adoption rates of green energy. Societal awareness of green energy can have both positive and negative effects on adoption. Positive awareness, characterized by support, enthusiasm, and belief in the benefits of green energy, accelerates momentum towards renewable energy projects and encourages investment in clean energy technologies, fostering a culture of sustainability within communities. Conversely, negative awareness, fueled by skepticism, misinformation, or resistance to change, can impede progress in green energy adoption, leading to delays or even opposition to renewable energy initiatives. Numerous factors influence societal awareness towards green energy adoption. These factors include the impact of social media, cultural norms, socioeconomic status, level of environmental awareness, access to information, trust in institutions, political support, and perceptions of risk and benefit associated with renewable energy technologies. Understanding the complex interplay of these factors is crucial for developing targeted interventions and communication strategies aimed at promoting the adoption of green energy and fostering public support [9–11].

Public attitudes towards the transition to green energy are a critical factor in the success of this transformation. The acceptability and feasibility of green energy policies depend on the public's thoughts on this matter. Decision-makers should consider society's opinions and concerns when formulating energy policies. Surveys are commonly used as a research method for gauging public opinion. However, over time, surveys have become less popular due to various factors. These include their potential to be misleading and biased, the manner in which survey questions are phrased, the challenge of accurately measuring emotional responses to complex issues [12], the limited capacity to capture evolving societal views [13], and participants' tendency to withhold their true thoughts [14]. Considering these challenges, social media analysis emerges as one of the most important tools for obtaining societal opinion today. Social media analysis provides access to a broad user base, enabling rapid and large-scale data collection [15], and users' emotional responses, thoughts, and opinions can be directly observed [16]. However, despite its advantages, social media analysis encounters challenges such as the reliability and accuracy of social media data [17] and the lack of representation of all types of users [18,19], which can hinder effective data analysis. To overcome this disadvantage, sentiment analysis is employed. Sentiment analysis serves as a reliable and powerful tool to better understand users' sentiments and opinions [20].

According to a study conducted in Turkey, approximately 66% of the participating students spend more than one hour on social media, and during the pandemic period, about 64% of this group experienced an increase in social media usage [21]. With the increase in social media usage, the importance of obtaining useful and usable information has also grown. Examining the comments and thoughts of thousands of people, which is called "dirty text", is not only time-consuming but may also be unfeasible [22]. The term "dirty text" is commonly used in academic discourse to denote irrelevant, inappropriate, or nonsensical textual content found on social media platforms. It refers to messages or comments that may include spam, hate speech, offensive language, or other forms of undesirable content. In scholarly research focusing on sentiment analysis, content moderation, or data mining of social media data, "dirty text" serves as a descriptor for noise or clutter that can hinder the extraction of meaningful insights or analysis. By identifying and filtering out such content, researchers aim to enhance the quality and reliability of their data analysis. For instance, in studies examining public opinion or sentiment towards certain topics on social media, the term "dirty text" helps researchers differentiate between relevant and irrelevant content, ensuring the accuracy and validity of their findings [23]. With the increase in social media data, the need for automatically extracting useful information from large amounts of text has significantly increased, and advanced technologies such as natural language processing and text mining have come into play at this point [24]. These technologies can rapidly scan thousands of comments, identify keywords and trends, and analyze differences in attitudes among different groups [25]. Particularly, the integration of the deep learning model, called Transformer, enables rapid progress in this field [26]. This method stands out with its ability to process large datasets and identify keywords and trends in text mining [27]. Therefore, the Transformer method is employed to determine and analyze the challenges perceived by society in the process of transitioning to green energy in Turkey. Understanding and analyzing how the transition to green energy is perceived by society is critically important for shaping future energy policies. Given the potential to shed light on efforts to make the transition to green energy more sustainable and community-friendly in Turkey and similar countries, this study is considered of great significance.

The objectives of the study are as follows:

- Measuring the reactions and acceptance level of Turkish society regarding the transition to green energy by analyzing YouTube comments containing individual remarks that are produced from news articles featured in international, national, and local media videos and individual videos (shorts).
- Developing a tool to measure the evolving perceptions of society over time for each transition to a green energy source. Identifying the reasons behind changing perceptions and developing policy recommendations accordingly.

The structure of the study is as follows: Section 2 explains relevant studies and methods regarding how social media influences human behavior. Section 3 describes the methodology; Section 4 presents the dataset and experimental results; Section 5 discusses the findings; and finally, Section 6 provides the conclusions.

2. Materials and Methods

2.1. Natural Language Processing

The field of Natural Language Processing (NLP) pertains to the interaction between computers and humans through the utilization of natural language. Recently, NLP has experienced tremendous growth, driven by the increasing volume and accessibility of data. The significance of NLP lies in its ability to transform the manner in which humans and computers interact, thereby facilitating more intuitive and human-like communication. The primary goals of NLP involve the interpretation, analysis, and processing of natural language data using various algorithms, tools, and methods. Initially used for text preprocessing [28], NLP applications have become increasingly popular. They rely heavily on statistical and probabilistic computations, along with machine learning techniques. In previous periods, machine learning techniques such as Naive Bayes, k-nearest neighbors, hidden Markov models, conditional random fields (CRFs), decision trees, random forests, and support vector machines were extensively used; however, neural architectures have emerged as predominant in more recent times [29]. Initially employed for tasks such as image categorization and visual representation analysis, Convolutional Neural Networks (CNNs) have subsequently been expanded to encompass Natural Language Processing (NLP) applications, including sentence classification, sentiment analysis, text categorization, text abstraction, machine translation, and semantic relationship identification. Recurrent Neural Networks (RNNs) have been extensively investigated for sequential data analysis, spanning various domains such as textual, temporal, financial, auditory, and visual data [30]. Long Short-Term Memory (LSTM), a modified iteration of RNNs, has been specifically used in scenarios necessitating the prolonged retention of essential information [31]. As a simplified version showing better results than regular LSTMs, a gated recurrent unit (GRU) has been developed [32]. Common applications of NLP include machine translation, question-answering systems, chatbots, and sentiment analysis, among others. Multi-task NLP models, often based on transformer architectures, have emerged as key components, with notable examples, including ULMFiT, Transformer, GPT-2, BiGRU, BERT, Transformer-XL, and XLNet [33]. Significant advancements in NLP have been achieved through the use of attention mechanisms and transformers [34]. The self-attention mechanism, widely employed in transformer models, allows words in a sentence to receive varying degrees of attention based on their contextual significance, leading to improved performance in tasks such as language modeling, translation, and text generation [35]. Models like Bidirectional Encoder Representations from Transformers (BERT) and their successors have also played a crucial role in NLP [36].

2.2. The Use and Impact of Social Media

In comparison to surveys, social media appears to be a more suitable source for a better and more comprehensive understanding of public perception. This is because surveys tend to represent the perspective of a small group of individuals rather than capturing the overall public opinion or societal views [37]. Additionally, due to the time and high capital costs involved in the data collection process for surveys, the quantity of data is often limited. With the parallel increase in the use of mobile phones and the internet, social media usage has also surged, making it easier to access desired data through social media. Recently, social media platforms such as LinkedIn, Twitter, Facebook, and YouTube have become extremely popular, especially during the pandemic era. This popularity stems from people connecting and interacting with each other by sharing images, comments, or videos. The rise in social media usage has made sentiment analysis using social media data crucial in determining public opinions. The utilization of social media as a data source to gauge societal views addresses fundamental methodological limitations of traditional surveys, such as representative sampling, the hierarchical structure of opinion formation, and challenges in obtaining time-series data [38,39]. Opinions shared on social media platforms are recorded in real-time, providing more temporally sensitive results regarding public opinions on specific policies and events [40]. In European countries such as Italy and Switzerland, studies have found that national and regional political support plays a significant role in the societal acceptance of transitioning to local energy communities [41]. Similarly, it has been noted that citizens' perceptions and expectations regarding energy technologies and strategies are influenced by the strategic flow of information in the media [42,43]. The importance of the media in implementing climate policies has also been emphasized [44]. Consequently, it appears that social media could also help predict similar situations in the future. These advantages encourage researchers to use social media as a data source instead of surveys. Despite these advantages, there are challenges in ensuring the relativity of data, barriers to honest and open information sharing, and concerns about the reliability and validity of data reprocessing that arise from the use of social media in collecting public opinions [45]. Considering all these factors, the accessibility and ease of use of data on platforms like Facebook, YouTube, Instagram, Twitter, Weibo, and others have made sentiment analysis in Natural Language Processing (NLP) increasingly popular. Facebook and Twitter are the two main online social media platforms, and researchers prefer conducting research using the data from these platforms on social media. However, due to concerns about user privacy and company policies, Facebook has waned in popularity over time, with Twitter taking the forefront [46]. Many published studies predominantly focus on Twitter messages for sentiment analysis because the platform hosts a wide and diverse population that expresses their opinions daily on almost every topic [47]. Instagram data are rarely used in studies, both due to API usage requirements and privacy policies. When examining 115 studies related to sentiment and content analysis published between 2010 and 2022, it is observed that only 30 of these studies are related to sentiment analysis, and a total of 36 studies used YouTube comments [37]. In our study, data were collected from YouTube due to the abundance of technical comments, the absence of character limits, and the ease of accessing past data related to the topic.

2.3. Green Energy and Public Opinion

The term "green energy" describes the idea that energy derived from naturally occurring renewable resources—such as sunlight, wind, rain, tides, plants, algae, and geothermal heat—has little to no adverse effects on the environment. In an effort to promote renewable energy, this idea was first presented in 2006 [41]. Given sustainability and efficiency concerns, diversifying energy sources and effectively utilizing local resources are essential. Policymakers and industry leaders aim to accelerate the transition to green energy by increasing its share in electricity production. Technological advancements have made public acceptance and endorsement crucial in expediting this transition. In a study conducted in China, the attitudes of the public towards electric vehicles, considered a step-in transitioning to green energy, were examined based on data collected from Weibo. The findings from the analysis provided guidance to policymakers in formulating policies to promote the use of electric vehicles [42]. Another study discussed global energy needs and renewable energy technologies for domestic use and sought to identify public opinions on renewable energy using data collected from Twitter. The study revealed that a lack of public awareness is a significant barrier to the acceptance of renewable energy technologies [43]. The media assists individuals in forming attitudes based on the most salient and, therefore, most accessible thoughts when making decisions [48]. With this in mind, online news data related to energy communities at Telpress International were analyzed to understand public awareness and the significance of this topic in the media. The study identified possible steps to promote a low-carbon energy transition [44]. In Europe, studies conducted across 23 different countries/regions were examined to determine the local and general societal acceptance trends of renewable energy projects. The aim was to create a framework that would reduce the likelihood of renewable energy systems encountering public opposition [49]. Another study examined research conducted in Europe, focusing on Greece, to investigate public preferences and attitudes towards investments in renewable energy projects and the use of new energy technologies in daily life. The study found that the relationship between household characteristics and public preferences is beneficial for designing better energy policies and increasing demand for reliable energy sources [50]. In a study conducted in Qatar, unlike other studies, survey results were examined to determine public attitudes towards renewable energy and the environment. Although the study yielded limited results due to its small sample size, it was considered appropriate to extend the study to a larger population for a more comprehensive analysis [51]. These similar studies collectively suggest that in today's world, where green energy is crucial, the success of transitioning to green energy is directly proportional to the level of acceptance by all stakeholders. Policymakers also emphasize the importance of real-time detection of the common societal view through social media-based analysis studies.

2.4. Deep Learning and Transformers

Deep learning is popularly used as a method for sentiment analysis due to its ability to learn representations of text data. The advantage of deep learning models in sentiment analysis is that they do not rely on manually designed feature extraction methods, as ideal features can be automatically extracted. Hence, deep learning models do not require domain expertise, making sentiment detection in societal views more accessible. In these methods, text data are first preprocessed and then encoded using pre-trained embedding models such as GloVe and word2vec. These embedding models are then fed into deep learning models such as CNN, RNN, LSTM, GRU, and transformer-based models for learning and classification. The transformer model used in our study was first proposed by Vaswani et al. [35]. This model has enabled researchers to approach textual data with novel methods and has become increasingly popular over time due to its effectiveness in acquiring contextual word representations, leading to numerous studies in this area. Upon reviewing the literature, it is evident that many studies typically focus on various aspects of transformer models, including their architecture, efficiency, computational power, memory efficiency, and the development of fast and lightweight variants [52]. On the other hand, in other studies, various NLP applications have been explored, including visualization of transformers for NLP [53], examination of pre-training methods used in transformer models [54], usage of transformers for text summarization tasks [55], application of transformer models for detecting different sentiment levels from text-based data [56], and using transformers for extracting useful information from large datasets [57]. In our study, however, unlike the existing research, the aim was to detect the general perception in society regarding newly established/green energy systems and to assist decision-makers in policymaking. To achieve this goal, we developed a transformer-based model and used a multi-labeling approach for the analysis and prediction of the collected data.

In Turkey, the transition to green energy has been accelerated since the 2010s due to the country's lack of fossil fuel reserves and its emphasis on a clean environment. In this study, to achieve this, comments under YouTube videos related to green energy, which represent a previously unexplored dataset, were analyzed to bring together all stakeholders involved in the transition to green energy, including environmentalists, consumers, energy companies, politicians, and public institutions. The objective was to evaluate the level of acceptance or resistance to the transition to green energy within society, recognizing that different stakeholders may have divergent perspectives. Additionally, the primary motivation of this study is to determine how public opinion has evolved during the recent green transformation process. The aim is to discern whether this change is solely related to shifts in public sentiment or if it is influenced by the effectiveness of implemented policies. The findings of this study will be essential for policymakers to formulate inclusive policies that address the needs of all stakeholders and promote the transition to green energy within society. Additionally, the developed dynamic framework will serve as a reference for future studies on similar topics.

3. Methodology

This section describes the stages of collecting, labeling, standardizing, processing, and applying the Transformer model to user comments obtained from social media. These stages are schematically presented in Figure 1.

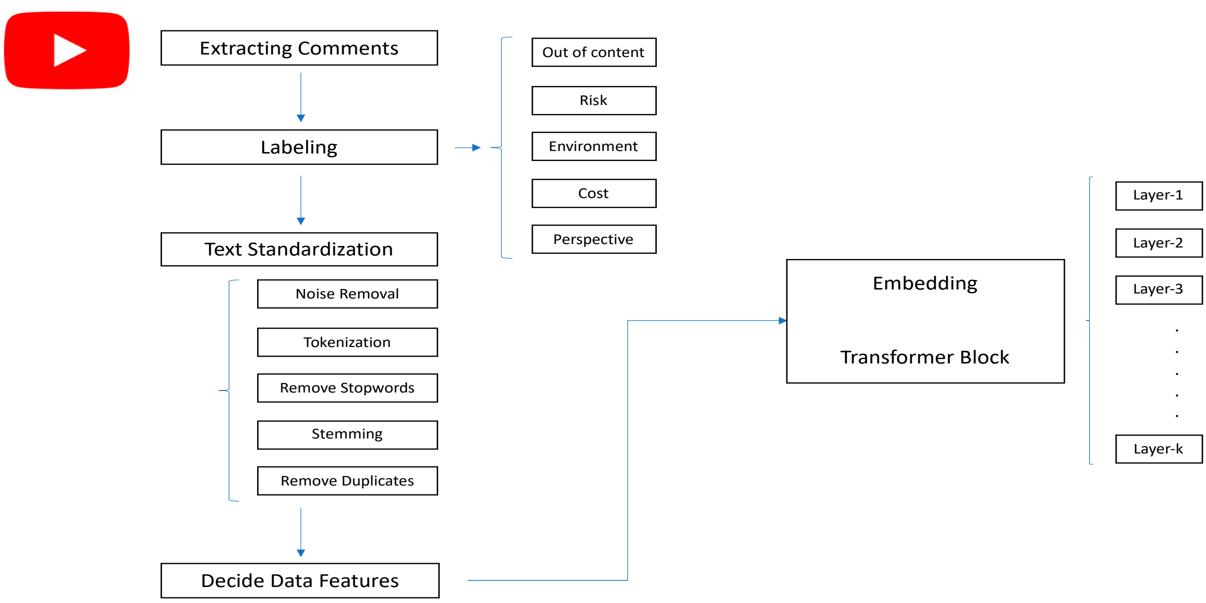

Figure 1. Methodological framework for processing data.

The Transformer method was introduced by a team at Google Brain in 2017 [35]. The Transformer has replaced recurrent neural network (RNN) models, such as Long Short-Term Memory (LSTM), as the model of choice for handling NLP problems over time [58]. The Transformer is a deep learning model that uses the self-attention mechanism, which assigns varying weights to the various components of the input data. The Transformer is made to handle sequential input data, like natural language, for tasks like text summarization and translation, much like recurrent neural networks (RNNs). But the Transformer processes the whole input all at once, unlike RNNs. The model can create relationships between words at any point in the input sequence thanks to the attention mechanism. As stated differently, not every word needs to be processed by the Transformer at every stage. Compared to RNNs, this enables more parallelization, which shortens training times [35]. The effectiveness of the Transformer algorithm in our study can be attributed to its structure, which enables training on larger datasets and shorter training times.

Prior to Transformer, the majority of cutting-edge natural language processing (NLP) systems depended on neuronal networks with additional attention mechanisms, such as long short-term memory (LSTMs) and gated recurrent units (GRUs). Unlike RNNs, the Transformer lacks a recurrent structure, even though it makes use of attention mechanisms as well. This implies that attention mechanisms alone can achieve performance close to RNNs, provided there is enough training data [35]. Transformer handles every token at once. It uses a non-sequential attention mechanism to compute attention weights between layers in sequential layers. Faster training speeds are achieved because the attention mechanism can be computed for all tokens in parallel, as it only uses information from other tokens in lower layers.

Transformers usually go through an unsupervised pre-training phase and then a supervised fine-tuning phase that involves self-supervised learning. Pre-training is typically carried out on a larger dataset due to the scarcity of labeled training data. Language modeling, next sentence prediction, question answering, reading comprehension, sentiment analysis, paraphrasing, and other tasks are frequently included in pre-training and fine-tuning sessions [59]. Numerous studies have shown the Transformer architecture's proven ability to support large-scale training datasets with adequate parameters. Transformer is frequently demonstrated to perform better with large amounts of training data due to its larger capacity compared to CNNs and RNNs. Transformer's primary benefit lies in its utilization of the self-attention mechanism to represent global dependencies among nodes within the input data.

Looking at the process, after collecting comments related to green energy (nuclear power plants, hydroelectric power plants, wind energy power plants, solar energy power plants, biomass energy power plants, and geothermal energy power plants) on YouTube, the comments are labeled, and then text standardization steps are applied to the collected unstructured text data. These include transformations such as converting to lowercase, data cleansing (removing numerical values, punctuation marks, web addresses, and unnecessary spaces), removing stop words (common conjunctions, etc.), and deleting duplicate comments. During the tokenization stage, the text is segmented into individual words, allowing for the analysis of word variety and frequency. After the text standardization stage, decisions are made regarding the data characteristics, including the diversity of vocabulary and the standard length of comments. Once the vocabulary diversity is determined, the length of each comment is adjusted to meet a standardized length. It is preferred that the length value be smaller than the maximum word length in the comments but larger than the average word length. This value affects the model's performance. If the specified length value is greater than the number of words in some comments, the missing part is filled with a value of 0. Some comments may contain more words than the specified length value. In this case, the words between the first word and the specified numerical value are encoded, and the remaining words are removed from the dataset. At this stage, some information is lost, but in return, processing speed and accuracy are increased. As detailed in Section 4, for this study, the word diversity is set to 20,000, and the maximum word length is determined to be 60.

The Embedding and Transformer Block are detailed in Figure 2. All words are encoded as numerical values in the embedding section. This enables all data to be mathematically usable. The embedded data are processed using the transformer block.

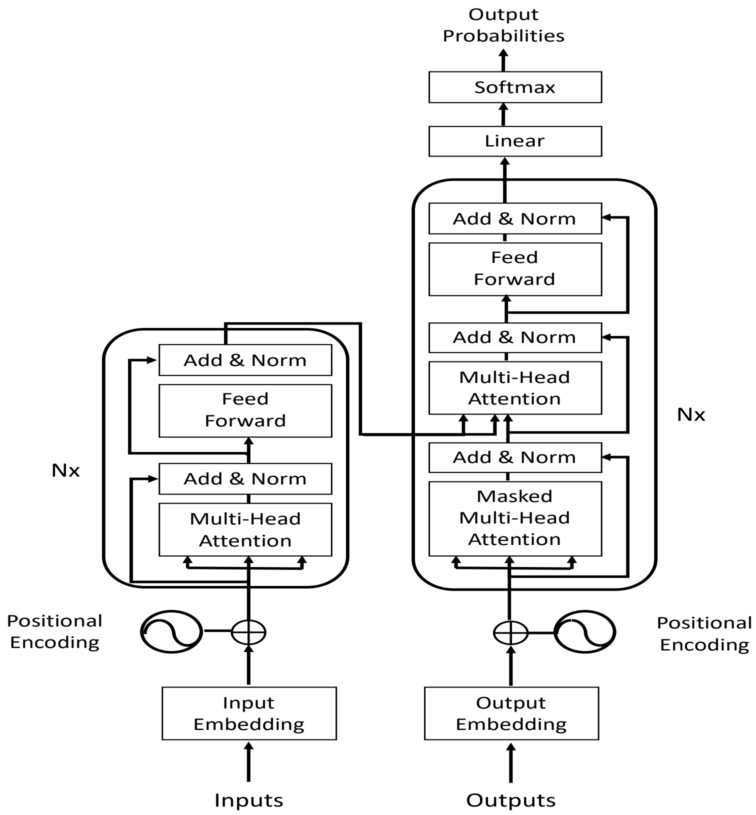

Figure 2. Structure of Transformers method [35].

Encoder: The Encoder consists of two fundamental layers: Feed-Forward layer and Multi-Head Attention layer. Additionally, there are two Add and Norm layers. Encoder takes the data as input and converts it into a numerical code using its internal function. This code is referred to as the 'context vector' in NLP, storing information about the entirety of the input.

Decoder: The Encoder and Decoder modules are similar. Furthermore, the Decoder incorporates Masked Multi-Head Attention layers in addition to the Encoder module. The Decoder uses the attention mechanism twice: once to find attention between the encoding inputs and the targeted output, and again to compute attention between targeted output elements. After that, each attention vector is sent through the feed-forward unit to improve the comprehensibility of the decoder's output. Using its functions, the decoder converts the numerical code produced by the encoder into the intended output.

The encoder and decoder layers each incorporate a feed-forward neural network. These layers feature residual connections and include steps for layer normalization. The reason for encoding in the Transformer architecture is the necessity for neural networks to have fixed and pre-known dimensions for input and output data. This is because a single neural network cannot take variable-sized input and produce variable-sized output. In this architecture, the encoder learns to reduce variable-sized input to a fixed-size vector, and the decoder learns to interpret and perform the desired task with the encoded information.

Multi-Head Attention: The main contribution of the Multi-Head Attention module to the model is determining the contextual placement of the transformer. Multi-head attention enables the model to collectively attend to information from different parts of the input sequence. This adjustment is used to distinguish words that have the same spelling but may have different meanings in a sentence. This approach enabled the formation of a self-attention architecture instead of the attention mechanisms used in earlier models [46]. The neural network was able to learn and capture various features of the sequential input data more easily with the use of multi-head attention, which improved the representation of the input contexts. Mathematically, the multi-head attention function is expressed as shown in Equation (1):

$$\begin{aligned} MultiHead\ (Q,\ K,\ V) &= Concat\ (head_1,\ \ldots,\ head_i) \\ W^O head_i &= Attenation\left(QW_i^Q,\ KW_i^K, VW_i^V\right) \end{aligned} \tag{1}$$

where

$$W_i^Q \in \mathbb{R}^{d_{model}\ x\ d_k},\ W_i^K \in \mathbb{R}^{d_{model}\ x\ d_k},\ W_i^V \in \mathbb{R}^{d_{model}\ x\ d_v},\ W^O \in \mathbb{R}^{hd_v\ x\ d_{model}}$$

Matrices Q and K represent the Query and Key vectors, respectively, both having a dimension of d_k, while the matrix V represents the Value vectors, which have a dimension of d_v [35]. In this study, we utilize $h = 5$ parallel attention layers, or heads. For each of these, we use $d_k = d_v = d_{model}/h = 64$.

Feed Forward: The number of layers of the Feed Forward in the Transformers model is another decision for the study. Additionally, a linear activation function, ReLU, is used for this layer.

Add § Norm: The network outputs are normalized with a normalization layer after the feed-forward and multi-head attention mechanisms. The similarity of vectors in a lower-dimensional space is calculated by reducing their dimension.

Some labels in the dataset have a high frequency, leading to rapid learning, while low-frequency labels experience delayed learning. A single epoch value is determined when running the model, and for this study, it is set to 10. Selecting a high epoch value may lead to overfitting of some labels. Additionally, the number of layers (Nx) for this study is set to 60.

Analyzing thousands of user comments on the transition to green energy is not always feasible due to time and resource constraints. To overcome this challenge, our application integrates the Transformer method, aiming to achieve more successful results in a shorter time compared to other deep learning methods. The Transformer method was coded in the Python programming language, trained by labeling the data from 2011 to 2022, and utilizing this trained data to predict the 2023 data.

4. Results

4.1. Data Description

With the purpose of detecting the challenges perceived by society in the green energy transition in Turkey through natural language processing, comments on YouTube videos related to green energy (nuclear power plants (NPP), hydroelectric power plants (HPP), wind energy power plants (WPP), solar energy power plants (SPP), biomass energy power plants (BPP), and geothermal energy power plants (GPP)) with news content were collected. For data collection on other social media platforms, API codes are required. However, manual data collection is not possible when accessing historical data. Additionally, even when using API codes, accessing private accounts is not possible. This results in limited data acquisition. Therefore, data were collected from YouTube due to the abundance of technical comments, the absence of character limits, and easy access to historical data related to the subject. In particular, challenges in collecting data using API codes and privacy-related limitations on other social media platforms are common problems encountered in such analyses. It is considered that a detailed analysis of this dataset will be an important step in understanding the public's perception of green energy and anticipating possible challenges.

Between 2011 and 2023, a total of 6431 comments were collected as raw data from YouTube videos with news content related to green energy. After removing duplicate comments, the raw dataset consisted of 6224 unique comments. Standardization was applied to the dataset consisting of comments made by Turkish society in Turkish. In this context, punctuation marks were removed, and all texts were converted to lowercase. As a result of these processes, there were 24,163 distinct words, the longest comment consisted of 376 words, and the average word count of the comments was 16 with a standard deviation of 19. To determine the optimal values to be used in our model (minimum word count, maximum word count, and word diversity), our model was run in different variations, and the values yielding the highest 'Roc Auc Score' were considered optimal values for the model. The values obtained from running the model in different variations are presented in Table 1, showing that a word diversity of 20,000, a maximum word length of 60, and a minimum word length of 3 were adopted as the basis for our model.

Table 1. Alternatives to the model parameter.

			Roc Auc Score of Categories				
Count of Word Diversity	**Count of Max Word**	**Count of Min Word**	**Out of Content**	**Risk**	**Environment**	**Cost**	**Perspective**
20,000	50	3	0.799	0.895	0.891	0.908	0.71
20,000	60	3	0.811	0.896	0.902	0.923	0.736
20,000	70	3	0.79	0.94	0.901	0.878	0.709
15,000	50	3	0.803	0.899	0.88	0.903	0.707
15,000	60	3	0.81	0.894	0.881	0.865	0.714
15,000	70	3	0.842	0.913	0.919	0.882	0.739
10,000	50	3	0.816	0.927	0.904	0.874	0.736
10,000	60	3	0.807	0.899	0.883	0.874	0.73
10,000	70	3	0.799	0.887	0.848	0.894	0.729

The distribution of the number of words is shown in Figure 3, and it can be seen that the minimum and maximum number of words cover 91.95% of all comments.

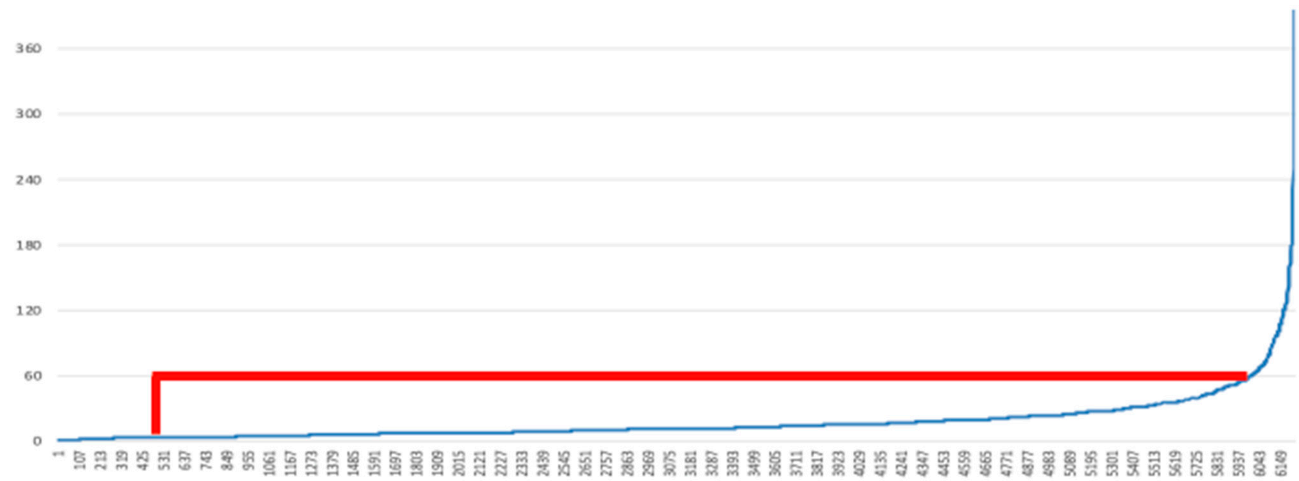

Figure 3. Distribution of Word Count in Comments.

The collected comments were labeled with 9 tags (out of content, low risk, high risk, negative impact on the environment, positive impact on the environment, low cost, high cost, negative perspective, and positive perspective). After labeling the comments, five main clusters were formed for obtaining meaningful results, namely, out of content, risk, environment, cost, and perspective. From the analysis of the data sample since its collection, it is evident that these four emotions, excluding out of content data, are predominantly considered by society. These emotions serve as a common denominator for stakeholders in the energy sector, including consumers, sellers, companies, environmentalists, public authorities, and others. It is observed that decision-makers need to formulate policies addressing these four emotions to bring all stakeholders together at the same decision-making point. Given that these emotions are dominant in the decision-making process overall, our study also measures these four emotions accordingly.

Label-1 (Out of Content): Comments under the relevant videos that do not relate to the six energy types addressed in the study are categorized under this label. These comments may include deviations from the main topic, personal conversations, advertisements, or comments about different videos. Without this label, a comment not related to Risk, Environment, Cost, or Perspective would have been inevitably assigned to one of these categories during the comment prediction stage. This label is used to prevent this misclassification.

Label-2 (Risk): This label is used to indicate the level of danger posed by the implementation of energy types. Comments where society assesses the possible risks or dangers of a specific action, product, or event are included in this category. It is divided into two subcategories: high-risk and low-risk or risk-free.

Label-3 (Environment): Reactions from the community regarding the environmental impact of energy types are gathered under this heading. These comments evaluate the environmental effects, natural resources, or impacts on nature related to the discussed topic. There are two subcategories: positive or negative impact of the energy type on the environment.

Label-4 (Cost): Comments regarding the cost-effectiveness of energy sources, including factors such as initial investment costs and operational costs, are addressed under this label. There are two themes related to whether the energy type is cost-effective or not.

Label-5 (Perspective): To determine how society approaches the transition to green energy, two themes are considered: positive and negative perspectives. Comments are classified under the relevant label based on their perspective.

The distribution of comments collected from YouTube into the five main categories is presented in Figure 4, and the distribution of comment counts by energy types and labels is provided in Figure 5. A comment can contain multiple emotions, and this aspect has been considered in this study. This means that a comment may contain multiple different labels.

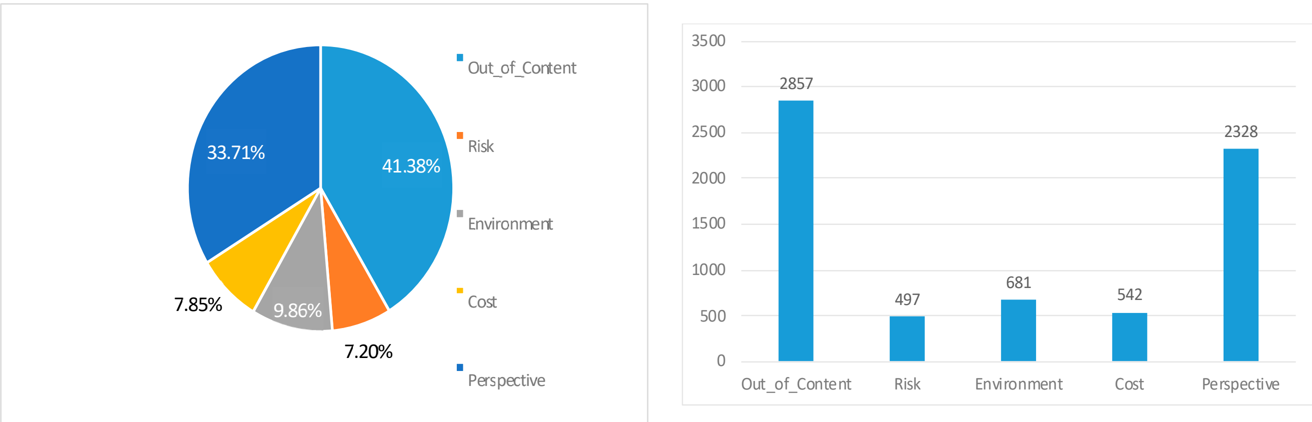

Figure 4. Comment counts and percentages according to labels.

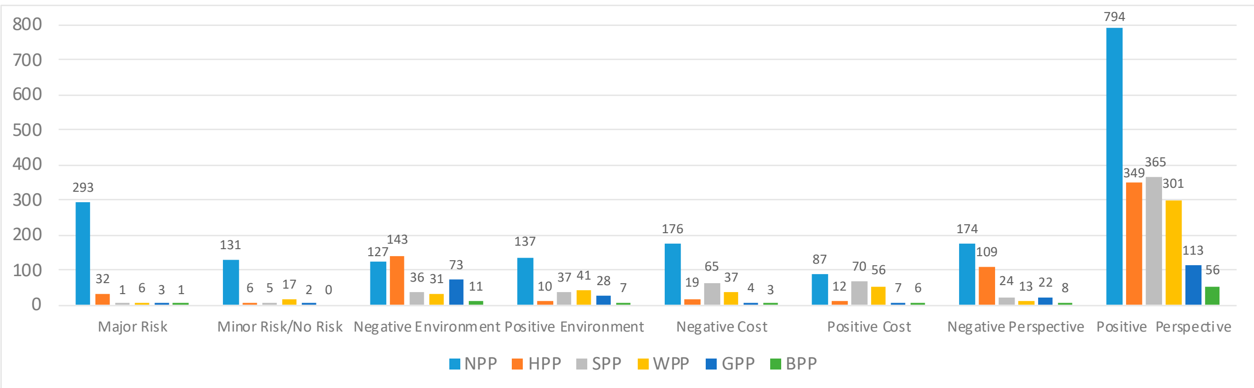

Figure 5. Distribution of comment counts by energy types and labels.

When examining the distribution of these eight labels, it is observed that the perspective category contains more comments compared to others. This situation indicates that people's emotional reactions to green energy outweigh factors such as risk, environmental impact, and cost related to the subject. The significant increase in comments made, especially from 2020 onwards, demonstrates that the topic is increasingly gaining attention and being discussed in society.

Furthermore, there are noticeable differences in the public's interest in and perception of different energy sources. Particularly, the higher number of comments on nuclear power plants indicates that this topic is closely monitored by a broad segment. The discussions related to nuclear energy are observed to resonate more in society and encompass various opinions.

The substantial portion of comments on hydroelectric power plants, solar, and wind energy plants also indicates the popularity of these energy types. However, when looking at the number of comments on geothermal and biomass energy plants, it suggests that the scarcity of news and comments on these energy types on YouTube indicates that these two energy types are not widely embraced. This distribution reflects the diversity of societal interests and concerns regarding different green energy sources. These data are considered important for understanding the public perception of each energy type and assessing potential challenges in the transformation process.

4.2. Experimental Results

As seen in Figure 6, when 497 comments related to risk are examined, approximately 68% of the comments contain the theme of high risk. When the distribution of risk comments by energy types is considered, nuclear power plants are perceived as high-risk by users. The analysis of comments reveals that, particularly due to the effects of the Chernobyl disaster, this energy type is considered high-risk. Additionally, the perception that the region with the nuclear reactor carries earthquake risk and the belief that the technological infrastructure for the operation of this energy type is not sufficient has led to the perception of high risk for nuclear power plants in cases of chemical pollution leakage.

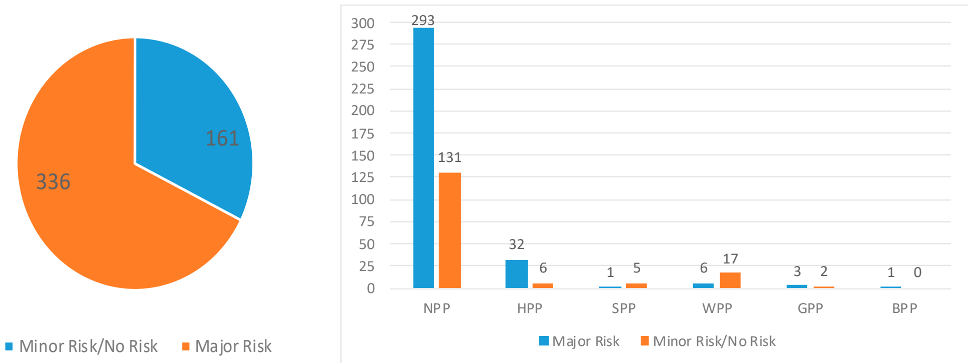

Figure 6. Distribution of risk comment counts by energy types.

The perception that hydroelectric power plants entail high risk comes in second place. This is attributed to factors such as controlling large water masses, flood risks, and environmental changes. Solar energy plants, wind energy plants, geothermal energy plants, and biomass energy plants are perceived as the least risky energy types by the public. This finding is important in highlighting that renewable energy sources are generally perceived as safer and less risky.

However, these perceptions may not always align completely with objective risk analyses. In some cases, public perception may not directly align with real risks. For example, although renewable energy sources like solar and wind are typically perceived as less risky, it should not be forgotten that these energy types can also cause environmental impacts or harm local ecosystems under specific conditions. Factors such as lack of information, media influence, and emotional responses play a significant role among the factors shaping the public's perception of energy types. Thus, supporting the public's perception of energy source risks with accurate information and objective analyses is crucial.

Analysis of 681 comments related to the environment reveals that approximately 62% of them express negative environmental concern. Figure 7 shows the distribution of environmental comments by energy types, revealing that hydroelectric power plants, nuclear power plants, and geothermal power plants are perceived by the public as having a greater negative impact on the environment.

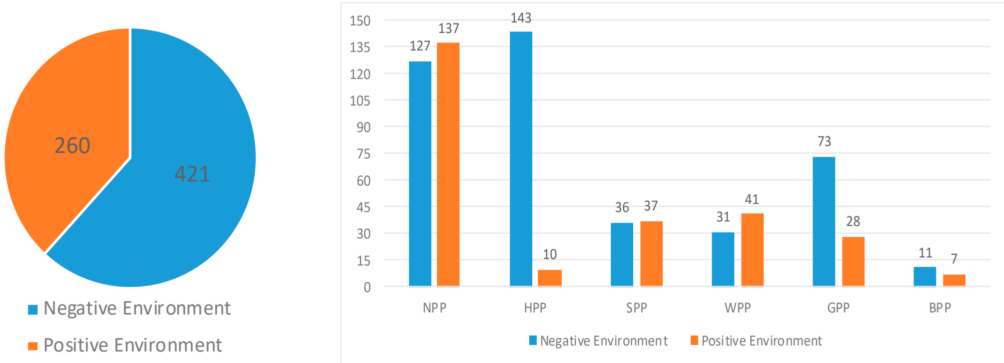

Figure 7. Distribution of environmental comment counts by energy types.

Hydroelectric power plants are notably associated with the most adverse environmental impact, primarily attributed to factors such as their widespread usage, water resource management practices, impacts on ecosystems, potential flood risks, and particularly observed negative effects on communities. Nuclear power plants raise environmental concerns due to potential risks such as radioactive leaks, nuclear waste management, and reactor accidents. However, it is worth noting that there is also a perception of nuclear power plants having positive effects among the public. This perception is believed to be influenced by publications about nuclear energy and examples from developed countries, which highlight the efficiency and continuity of energy production associated with nuclear power. The positive aspects of nuclear energy, such as its efficiency and continuity in energy production, are considered to play a role in shaping this perception.

The environmental impacts of geothermal power plants are generally perceived with a negative connotation. The effects of geothermal energy plants on local ecosystems and water resources lead to increased concerns in society. In particular, drilling and energy production in geothermal areas have the potential to create lasting effects on natural ecosystems. The decrease in underground water levels poses a risk to the natural life in the environment and can also affect agricultural activities. This situation may lead local communities and environmental advocates to adopt a more sensitive approach to geothermal energy.

There is a lack of clear distinction between the positive and negative effects of solar and wind energy plants on the environment. While solar energy plants are generally seen as a clean and renewable source, there are some concerns about the environmental impacts of installation processes and panel production. These concerns often focus on the extraction and processing of materials used in panel production. Wind energy plants are also considered a clean energy source. However, concerns about potential impacts on birds and wildlife, noise pollution generated by rotating blades, and visual pollution of the landscape may result in negative feedback. The lack of a clear positive or negative perception of these energy types in the public indicates the necessity for more information and detailed evaluations regarding their environmental impacts. Renewable sources like solar and wind energy play an important role in a cleaner and more sustainable energy future. However, it is essential to acknowledge that these energy types also have their own environmental impacts.

Bioenergy plants are generally perceived as more environmentally friendly compared to other green energy sources. However, it is important to remember that each energy source has its own environmental impacts that need to be carefully evaluated. Especially, in the collection and processing of biomass resources, the preservation of natural balance and the sustainability of biodiversity should be considered. Additionally, the use of bioenergy resources is observed to be related to issues such as food security and the use of agricultural land. Thus, the sustainability and environmental impacts of the resources used in bioenergy production should be considered when shaping energy policies, addressing them with a balanced approach.

When the distribution of cost comments in Figure 8 is examined, it is observed that approximately 56% of the comments form a negative perception about costs. There is no conclusive evidence regarding whether green energy is inherently costly or cost-effective. Although green energy is generally considered a cleaner and more environmentally friendly option compared to fossil fuels, drawing definitive conclusions about cost-effectiveness presents a significant challenge. The costs of these energy sources are influenced by various factors, such as advancements in technology, investment costs, operating expenses, and subsidies. Renewable energy sources such as solar and wind have shown a decrease in costs with advancements in technology. However, installation costs, storage issues, and some local factors can influence these costs, complicating the assessment of overall cost-effectiveness.

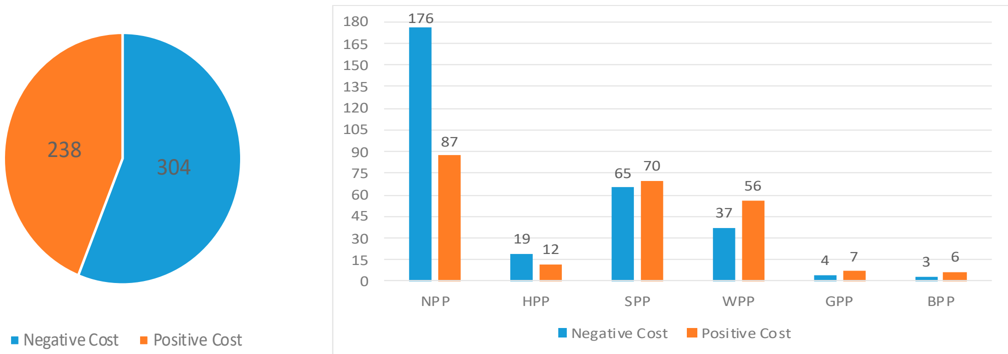

Figure 8. Distribution of cost comment counts by energy types.

Such uncertainties can also influence public perceptions of costs. Negative perceptions about the cost of green energy sources are often due to concerns about the high initial investment cost and the perceived lengthy payback period. Nevertheless, the benefits, such as lower operating and maintenance costs eventually, reduction of environmental impacts, and increased energy independence, should not be overlooked. Continuous technological innovations and decreasing cost trends in the energy sector indicate that green energy may become more competitive in the future, suggesting that society's negative perceptions in this area may gradually change, allowing wider adoption of green energy.

When the distribution of cost comments is examined by energy types, it is understood that comments on hydroelectric energy, geothermal energy, and bioenergy costs constitute approximately 10% of total cost comments, making it difficult to reach a positive or negative opinion on costs. Hydroelectric energy generally has a high initial investment cost due to infrastructure costs and the fact that it requires large-scale projects. However, factors such as low operating and maintenance costs and a long lifespan can eventually make hydroelectric energy more advantageous in terms of cost. The limited number of cost comments for these energy types is generally due to the complexity of their cost structures. In particular, the different geographical, technological, and local factors associated with each energy source make it difficult to make a general comparison.

Upon examining comments regarding the cost of nuclear power plants, the prevailing opinion is that they are not considered cost-effective. The high initial installation cost and the high unit sales cost to the public, as stipulated in agreements, have created a negative perception of the cost of this energy type among the public. However, some debates try to expand cost analyses by considering aspects such as the efficiency and continuous energy production of nuclear energy. With technological advances and innovations in the energy sector, it is considered that views on the cost-effectiveness of nuclear energy will change.

When comments related to perspectives are examined, as seen in Figure 9, approximately 85% of society exhibits a positive attitude towards the transition to green energy across all six investigated energy types. When classified by energy types, nuclear energy is observed to be more widely embraced by the public, particularly due to its efficiency and continuous energy production aspects, especially in the long term. Despite the risks, environmental concerns, and costs associated with nuclear energy, its perceived efficiency and sustainability contribute significantly to shaping the preference for green energy. Hydroelectric power, solar energy, and wind energy are generally the next most embraced energy types after nuclear energy. These sources are generally more familiar, benefiting from advanced technologies and a clearer understanding of their environmental impacts. Limited comments have been made on geothermal energy and bioenergy, possibly due to a lack of public awareness and insufficient promotion in these areas.

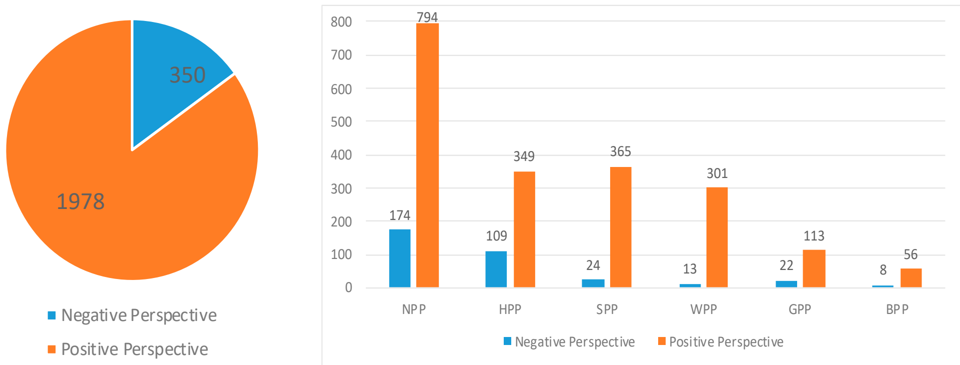

Figure 9. Distribution of perspective comment counts by energy types.

In the predictive stage, which is the second phase of our study, we employed the Python programming language along with the Keras library to implement a Transformers model. The Transformers model, a state-of-the-art architecture for natural language processing tasks, was chosen for its effectiveness in handling sequential data like textual comments. We fine-tuned the Transformers model using our labeled dataset, which consisted of 6431 comments collected from YouTube between 2011 and 2023. This dataset was divided into a 20% test set, a 70% training set, and a 10% validation set to ensure robust performance evaluation. By leveraging the power of the Transformers model, we aimed to accurately predict the categorization of comments into the five main categories established in our study. The values obtained by running the model are as shown in Table 2.

Table 2. Performance metrics of the multi-label model.

Label	Accuracy	Roc_Auc	Precision	Recall	F1_Score
Out of context	0.752	0.811	0.717	0.638	0.675
Risk	0.950	0.896	0.778	0.570	0.658
Environment	0.924	0.902	0.784	0.543	0.642
Cost	0.913	0.923	0.591	0.624	0.607
Perspective	0.708	0.736	0.611	0.558	0.583

The dataset used in this study exhibits class imbalance, as some emotions are not equally represented in the comments. Notably, there is a significant amount of out-of-content data, which can affect the model's ability to distinguish between different emotions. To evaluate the model's performance in handling this class imbalance, we employed the 'Roc Auc Score' metric. The performance metrics for each label are summarized in Table 2. We observed that while the risk, environment, and cost labels demonstrate good performance, the out-of-content and perspective labels, which have a higher volume of data, exhibit relatively lower performance. Furthermore, although the precision score for the risk and environment labels is satisfactory, the recall score is comparatively low. The moderate to low levels of F1 score across all labels can be attributed to the imbalance between the two classes (0 and 1) in the dataset. However, except for the 'perspective' label, achieving a Roc Auc Score greater than 0.80 indicates a successful performance of the model. Figure 10 depicts the roc curve of the multi-label model for the five different labels, along with the areas under the curves, providing a visual representation of the model's performance.

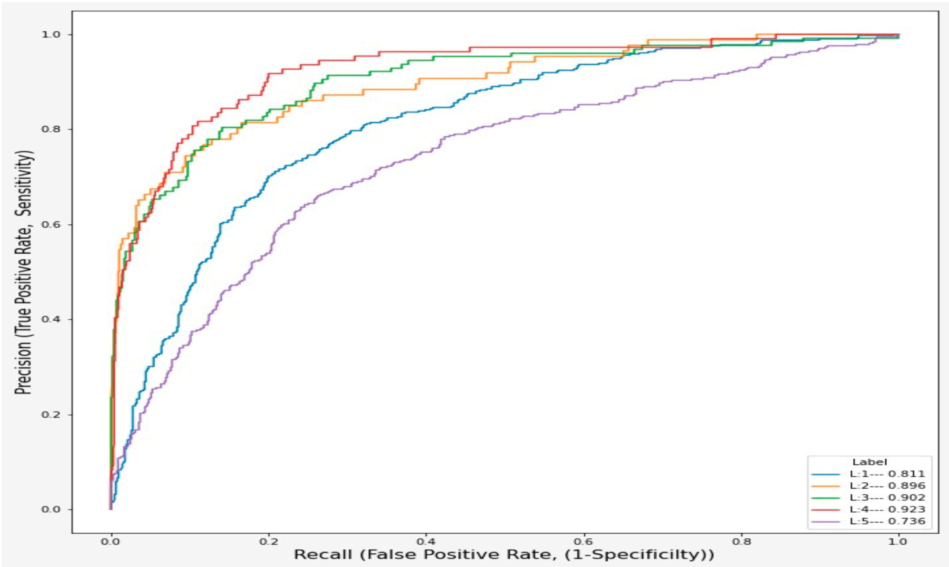

Figure 10. Roc Auc Score graph for multi-label model.

After training the model, predictions were generated for 2338 comments collected in 2023, utilizing the model's performance metrics discussed earlier. The prediction results are visualized in Figure 11.

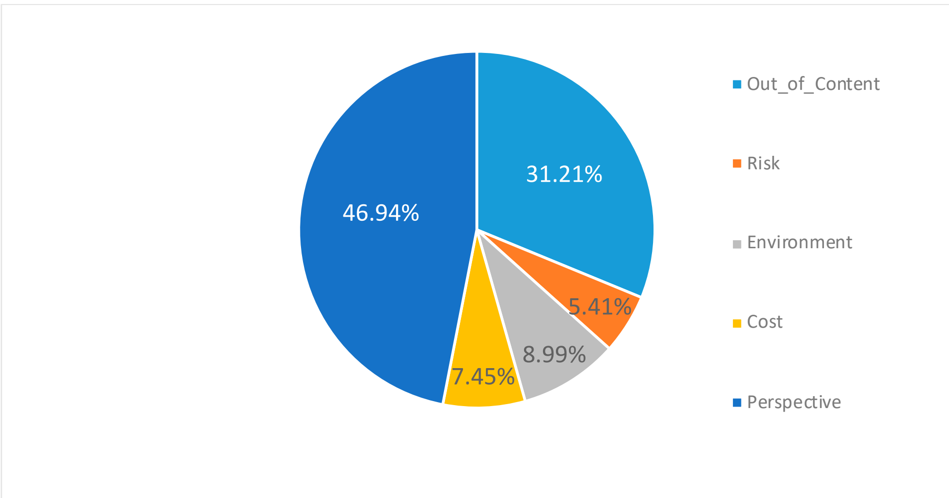

Figure 11. Distribution of predictions according to labels.

When comparing the labeled data from Figure 4 with the predicted data from Figure 11, a consistent trend was observed between the data collected and labeled between 2011 and 2023 and the data collected solely in 2023. Deviations of 2.4% for risk, 6.3% for environment, 22.8% for cost, and 43.09% for perspective were noted when comparing labeled and predicted data. Upon closer analysis of these deviation rates, it was found that the deviations for risk and environment were negligible, while the deviation for cost was deemed acceptable, indicating a high level of prediction accuracy for the model.

The collected data underscores a growing positive sentiment towards green energy within society, which aligns with an increasing awareness and sensitivity towards environmental issues. This trend highlights the perceived environmentally friendly nature and sustainability of green energy compared to fossil fuels. However, to fully embrace these energy sources and promote their widespread adoption, initiatives such as education, awareness campaigns, and comprehensive knowledge sharing are essential.

Policymakers should prioritize addressing these issues with the insights gleaned from the data. By doing so, the transition to green energy can be accelerated and more widely accepted by society. This approach enables a broader segment of society to gain a more in-depth understanding of the benefits, operational principles, and environmental impacts of various green energy types, empowering them to make more informed energy choices.

5. Discussion

Sentiment analysis involves examining and analyzing the opinions, feelings, evaluations, attitudes, and emotions that people include in written documents on a given topic. Understanding the trends of topics that are of great interest to society, such as the transition to green energy, facilitates strategic decision-making by politicians, investors, and consumers. In our study, the analysis of societal reactions during the transition to green energy in Turkey was conducted using comments collected from YouTube. When the data collected from YouTube are analyzed, the identified points are as follows:

- Nuclear energy is the most important energy source on the agenda of Turkish society, followed by hydroelectric energy and solar energy.
- Political will and incentive policies play a significant role in society's orientation toward energy policies.
- Although there is no clear public opinion on the safety, waste management, and environmental effects of nuclear energy, the need for energy influences the public's acceptance of nuclear energy.
- Large-scale projects involving nuclear reactors, dams, solar panels, and wind turbines, supported by the government, are effective in promoting the public adoption of these energy types.
- Negative perceptions of nuclear energy include radiation hazards, environmental pollution, waste management, high investment, and operating costs; negative perceptions of hydroelectric energy include the cost of large dam projects, water management, and environmental impact; negative perceptions of solar energy include environmental and land use and technological risks; negative perceptions of wind energy include noise pollution and impacts on birds and wildlife; negative perceptions of geothermal energy include decreasing underground water levels and damage to agricultural areas; and negative perceptions of bioenergy include waste management and its impact on agricultural areas.
- Continuous, high-capacity energy production and efficiency are effective for nuclear energy, especially large dam projects; and high-capacity energy production for hydroelectric energy, the ability to install solar panels both publicly and individually; low operating costs for solar energy; low cost and low environmental impact for wind energy; long-term low operating and maintenance costs for geothermal energy, and the use of local resources for bioenergy.

The analysis of social media user comments enables the identification of public doubts regarding the transition to green energy. It is believed that decision-makers can steer society's perspective on green energy and potentially expedite the transition process with the assistance of these analyses. Changes in people's perspectives on green energy can be facilitated through planned educational and informative activities. As demonstrated in the study, data collected between 2011 and 2022 were used to predict 2023 data, resulting in a decrease of 2.4%

in risk comments, 6.3% in environment comments, and 22.8% in cost comments, while an increase of 43.09% was observed in perspective comments. The findings suggest that information dissemination, technological advancements, and education can lead to changes in societal perceptions over time. Ultimately, comparing data collected before and after the implementation of new policies allows for the evaluation of policy effectiveness.

In our study, unlike other studies [60–63], we used YouTube data instead of Twitter data due to reasons such as no character limit, easy access to historical data, and abundance of technical information. Considering the abundance of technical data related to the topic, it has been evaluated that YouTube data are more beneficial for analyzing important aspects of the energy transition, such as cost, risk, and environment. As with data from all social media platforms, it cannot be claimed that the data we used equally represent the entire population. When looking at the data collected from YouTube, it is observed that there are a scarcity of data on geothermal energy and biomass energy. To conduct a more comprehensive analysis of both these energy types and others, data can be collected from other social media platforms to expand the analysis. While single-labeled ternary classification models [61,64] are commonly used in previous studies, our study used a multi-labeled binary classification model (positive and negative). Considering the significant influence of political views on the acceptance of such large-scale projects by the public, it would be appropriate to consider political perspectives in future studies.

6. Conclusions

The most crucial part of this study is the ability to measure society's reaction during the transition to green energy. The influence of social media plays a significant role in shaping societal agendas. For a country like Turkey with diverse and extensive energy needs, transitioning to green energy represents a strategic step, although its adoption by society is not always easy. Therefore, the methodology used in this study holds significant importance in detecting, classifying, analyzing, and guiding decision-makers on society's response to the transition to green energy. The proposed methodology successfully achieved this emotional categorization using the raw dataset. It was observed that approximately 85% of society has a positive attitude toward the transition to green energy for all six energy types studied. To measure this significant aspect for decision-makers, comments on social media were analyzed using NLP. For these energy sources to be fully embraced by society, it is crucial for decision-makers to focus on education, awareness campaigns, and promotions.

An analysis of social media user comments reveals public perceptions and concerns regarding the transition to green energy. The results highlight the significance of political will and incentives in shaping public perceptions of energy policies. Despite uncertainties surrounding the security and environmental impacts of certain energy sources, public acceptance levels are significantly influenced by energy needs. Government-supported large-scale projects play a crucial role in promoting the public adoption of various energy types. Addressing negative perceptions associated with each energy source, such as environmental concerns and cost implications, is essential for fostering widespread acceptance. Additionally, the importance of continuous energy production and efficiency in driving the transition to green energy is emphasized. Ultimately, informed decision-making, technological advancements, educational initiatives, and the impact of social media are effective in influencing societal perspectives.

Author Contributions: Conceptualization, U.B. and S.S.K.; methodology, U.B. and S.S.K.; software, U.B.; validation, U.B. and S.S.K.; formal analysis, U.B.; investigation, U.B.; resources, U.B.; data curation, U.B.; writing—original draft preparation, U.B.; writing—review and editing, U.B. and S.S.K.; visualization, U.B.; supervision, U.B. and S.S.K.; project administration, U.B. and S.S.K.; funding acquisition, U.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in our study, gathered from YouTube, can be shared with the relevant individual upon request.

Acknowledgments: The authors would like to acknowledge that this paper is submitted in partial fulfillment of the requirements for a Ph.D. degree at Yildiz Technical University.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Androniceanu, A.; Sabie, O.M. Overview of Green Energy as a Real Strategic Option for Sustainable Development. *Energies* **2022**, *15*, 8573. [CrossRef]
2. International Energy Agency (IEA). *Global EV Outlook*; IEA: Paris, France, 2022.
3. International Renewable Energy Agency. Advantages of Green Energy. *Renew. Energy Rep.* **2020**, *32*, 45–58.
4. International Energy Agency (IEA). *Renewable Energy Market Update*; IEA: Paris, France, 2020.
5. European Commission. *The European Green Deal*; European Commission: Brussels, Belgium, 2019.
6. United Nations. *Sustainable Development Goals: Goal 7—Ensure Access to Affordable, Reliable, Sustainable and Modern Energy for All*; United Nations: New York, NY, USA, 2015.
7. International Renewable Energy Agency (IRENA). *Renewable Capacity Statistics*; IRENA: Abu Dhabi, United Arab Emirates, 2021.
8. Republic of Turkey Ministry of Energy and Natural Resources Website. Available online: https://enerji.gov.tr/bilgi-merkezi-enerji-elektrik (accessed on 2 February 2024).
9. Sovacool, B.K.; Dworkin, M.H. *Global Energy Justice: Problems, Principles, and Practices*; Cambridge University Press: Cambridge, UK, 2015.
10. Whitmarsh, L. Scepticism and Uncertainty About Climate Change: Dimensions, Determinants and Change Over Time. *Glob. Environ. Chang.* **2011**, *21*, 690–700. [CrossRef]
11. Poortinga, W.; Whitmarsh, L.; Suffolk, C. The Introduction of a Single-Use Carrier Bag Charge in Wales: Attitude Change and Behavioural Spillover Effects. *J. Environ. Psychol.* **2013**, *36*, 240–247. [CrossRef]
12. Converse, J.M. *Survey Research in the United States: Roots and Emergence 1890–1960*; University of California Press: Berkeley, CA, USA, 1987.
13. Tourangeau, R.; Rips, L.J.; Rasinski, K. *The Psychology of Survey Response*; Cambridge University Press: Cambridge, UK, 2012. [CrossRef]
14. Schuman, H.; Presser, S. *Questions and Answers in Attitude Surveys: Experiments on Question Form, Wording, and Context*; Sage Publications: Thousand Oaks, CA, USA, 1996.
15. Bruns, A.; Burgess, J. The Use of Twitter Hashtags in the Formation of Ad Hoc Publics. In Proceedings of the 6th European Consortium for Political Research (ECPR) General Conference, Reykjavik, Iceland, 24–27 August 2011.
16. Zagheni, E.; Weber, I.; Gummadi, K. Leveraging Facebook's Advertising Platform to Monitor Stocks. In Proceedings of the Eighth International Conference on Weblogs and Social Media, Ann Arbor, MI, USA, 1–4 June 2014.
17. Jungherr, A.; Jürgens, P.; Schoen, H. Why the Pirate Party Won the German Election of 2009 or The Trouble with Predictions: A Response to Tumasjan, A., Sprenger, T.O., Sander, P.G., & Welpe, I.M. "Predicting Elections with Twitter: What 140 Characters Reveal About Political Sentiment". *Soc. Sci. Comput. Rev.* **2012**, *29*, 229–234. [CrossRef]
18. Vosoughi, S.; Roy, D.; Aral, S. The Spread of True and False News Online. *Science* **2018**, *359*, 1146–1151. [CrossRef]
19. Tufekci, Z. Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls. *arXiv* **2014**, arXiv:1403.7400. [CrossRef]
20. Liu, B. *Sentiment Analysis and Opinion Mining*; Morgan & Claypool: San Rafael, CA, USA, 2012.
21. Parlak Sert, H.; Baskale, H. Students' Increased Time Spent on Social Media, and Their Level of Coronavirus Anxiety During the Pandemic Predict Increased Social Media Addiction. *Health Inf. Libr. J.* **2023**, *40*, 262–274. [CrossRef]
22. Garcia, M.N.M. Information Retrieval and Social Media Mining. *Information* **2020**, *1*, 578. [CrossRef]
23. Kim, W.; Choi, B.J.; Hong, E.K.; Kim, S.K.; Lee, D. A Taxonomy of Dirty Data. *Data Min. Knowl. Discov.* **2003**, *7*, 81–99. [CrossRef]
24. Babu, M.S.; Ali, A.A.; Rao, A.S. A Study on Information Retrieval Methods in Text Mining. *J. Eng. Res. Technol.* **2014**, *2*, 184–190.
25. Aftab, F.; Bazai, S.U.; Marjan, S.; Baloch, L.; Aslam, S.; Amphawan, A.; Neo, T.K. A Comprehensive Survey on Sentiment Analysis Techniques. *Int. J. Technol.* **2023**, *14*, 1288–1298. [CrossRef]
26. Kokab, S.T.; Asghar, S.; Naz, S. Transformer-Based Deep Learning Models for the Sentiment Analysis of Social Media Data. *Array* **2022**, *14*, 100157. [CrossRef]
27. Bach, M.P.; Kırstic, Z.; Seljan, S.; Turulja, L. Text Mining for Big Data Analysis in Financial Sector: A Literature Review. *Sustainability* **2019**, *11*, 1277. [CrossRef]
28. Sun, S.; Luo, C.; Chen, J. A Review of Natural Language Processing Techniques for Opinion Mining Systems. *Inf. Fusion* **2017**, *36*, 10–25. [CrossRef]
29. Daniel, W.O.; Julian, R.M.; Jugal, K.K. A Survey of the Usages of Deep Learning for Natural Language Processing. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *99*, 604–624. [CrossRef]

30. Khurana, D.; Koli, A.; Khatter, K.; Singh, S. Natural Language Processing: State of the Art, Current Trends and Challenges. *Multimed. Tools Appl.* **2023**, *82*, 3713–3744. [CrossRef]
31. Greff, K.; Srivastava, R.K.; Koutnik, J.; Steunebrink, B.R.; Schmidhuber, J. LSTM: A Search Space Odyssey. *IEEE Trans. Neural Netw. Learn. Syst.* **2016**, *28*, 2222–2232. [CrossRef]
32. Chung, J.; Gulcehre, C.; Cho, K.; Bengio, Y. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. *arXiv* **2014**, arXiv:1412.3555.
33. Mathew, L.; Bindu, V.R. A Review of Natural Language Processing Techniques for Sentiment Analysis Using Pre-Trained Models. In Proceedings of the Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 11–13 March 2020. [CrossRef]
34. Bahdanau, D.; Cho, K.; Bengio, Y. Neural Machine Translation by Jointly Learning to Align and Translate. In Proceedings of the International Conference on Learning Representations, San Diego, CA, USA, 7–9 May 2015. [CrossRef]
35. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, L.; Polosukhin, I. Attention is All You Need. In Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA, 4–9 December 2017. [CrossRef]
36. Devlin, J.; Chang, M.W.; Lee, K.; Toutanova, K. Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Minneapolis, MN, USA, 2–7 June 2019. [CrossRef]
37. Alafwan, B.; Siallagan, M.; Putro, U.S. Comments Analysis on Social Media: A Review. *ICST Trans. Scalable Inf. Syst.* **2023**, *10*, 1–24. [CrossRef]
38. Murphy, J.; Link, M.W.; Childs, J.H.; Tesfaye, C.L.; Dean, E.; Stern, M.; Pasek, J.; Cohen, C.; Callegaro, M.; Harwood, P. Social Media in Public Opinion Research: Executive Summary of the Aapor Task Force on Emerging Technologies in Public Opinion Research. *Public Opin. Q.* **2014**, *78*, 788–794. Available online: http://www.jstor.org/stable/24545970 (accessed on 12 March 2024). [CrossRef]
39. Adams-Cohen, N.J. Policy Change and Public Opinion: Measuring Shifting Political Sentiment with Social Media Data. *Am. Politics Res.* **2020**, *48*, 612–621. [CrossRef]
40. McGregor, S. Social Media as Public Opinion: How Journalists Use Social Media to Represent Public Opinion. *Journalism* **2019**, *20*, 1070–1086. [CrossRef]
41. Kumar, S.; Darshna, A.; Ranjan, D. A Review of Literature on the Integration of Green Energy and Circular Economy. *Heliyon* **2023**, *9*, e21091. [CrossRef] [PubMed]
42. Wu, Z.; He, Q.; Li, J.; Bi, G.; Antwi-Afari, M.F. Public Attitudes and Sentiments Towards New Energy Vehicles in China: A Text Mining Approach. *Renew. Sustain. Energy Rev.* **2023**, *178*, 113242. [CrossRef]
43. Qazi, A.; Hussain, F.; Rahim, N.A.; Hardaker, G.; Alghazzawi, D.; Shaban, K.; Haruna, K. Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, and Public Opinions. *IEEE Access* **2019**, *7*, 63837–63851. [CrossRef]
44. Piselli, C.; Fronzetti Colladon, A.; Segneri, L.; Pisello, A.L. Evaluating and Improving Social Awareness of Energy Communities Through Semantic Network Analysis of Online News. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112792. [CrossRef]
45. Dong, X.; Lian, Y. A Review of Social Media-Based Public Opinion Analyses: Challenges and Recommendations. *Technol. Soc.* **2021**, *67*, 101724. [CrossRef]
46. Yue, L.; Chen, W.; Li, X.; Zuo, W.; Yin, M. A Survey of Sentiment Analysis in Social Media. *Knowl. Inf. Syst.* **2019**, *60*, 617–663. [CrossRef]
47. Rodriguez-Ibanez, M.; Casanez-Ventura, A.; Castejon-Mateos, F.; Cuenca-Jimenez, P.M. A Review on Sentiment Analysis from Social Media Platforms. *Expert Syst. Appl.* **2023**, *223*, 119862. [CrossRef]
48. Moy, P.; Tewksbury, D.; Rinke, E.M. Agenda-Setting, Priming, and Framing. In *The International Encyclopedia of Communication Theory and Philosophy*, 1st ed.; Wiley: Hoboken, NJ, USA, 2016; pp. 1–13.
49. Segreto, M.; Principe, L.; Desormeaux, A.; Torre, M.; Tomassetti, L.; Tratzi, P.; Paolini, V.; Petracchini, F. Trends in Social Acceptance of Renewable Energy Across Europe—A Literature Review. *Int. J. Environ. Res. Public Health* **2020**, *17*, 9161. [CrossRef] [PubMed]
50. Stigka, E.K.; Paravantis, J.A.; Mihalakakou, G.K. Social Acceptance of Renewable Energy Sources: A Review of Contingent Valuation Applications. *Renew. Sustain. Energy Rev.* **2014**, *32*, 100–106. [CrossRef]
51. Abdmouleh, Z.; Gastli, A.; Ben-Brahim, L. Survey About Public Perception Regarding Smart Grid, Energy Efficiency & Renewable Energies Applications in Qatar. *Renew. Sustain. Energy Rev.* **2018**, *82*, 168–175. [CrossRef]
52. Fournier, Q.; Caron, G.M.; Aloise, D. A Practical Survey on Faster and Lighter Transformers. *ACM Comput. Surv.* **2021**, *55*, 1–40. [CrossRef]
53. Brasoveanu, A.M.P.; Andonie, R. Visualizing Transformers for NLP: A Brief Survey. In Proceedings of the 24th International Conference on Information Visualisation (IV), Melbourne, VIC, Australia, 7–11 September 2020. [CrossRef]
54. Kalyan, K.S.; Rajasekharan, A.; Sangeetha, S. AMMUS: A Survey of Transformer-Based Pretrained Models in Natural Language Processing. *arXiv* **2021**, arXiv:2108.05542.
55. Wang, G.; Smetannikov, I.; Man, T. Survey on Automatic Text Summarization and Transformer Models Applicability. In Proceedings of the CCRIS: International Conference on Control, Robotics and Intelligent System, Xiamen, China, 27–29 October 2020. [CrossRef]

56. Acheampong, F.A.; Nunoo-Mensah, H.; Chen, W. Transformer Models for Text-Based Emotion Detection: A Review of BERT-Based Approaches. *Artif. Intell. Rev.* **2021**, *54*, 5789–5829. [CrossRef]
57. Gruetzemacher, R.; Paradice, D.B. Deep Transfer Learning & Beyond: Transformer Language Models in Information Systems Research. *ACM Comput. Surv.* **2022**, *54*, 1–35. [CrossRef]
58. Wolf, T.; Debut, L.; Sanh, V.; Chaumond, J.; Delangue, C.; Moi, A.; Cistac, P.; Rault, T.; Louf, R.; Funtowicz, M.; et al. Transformers: State-of-the-Art Natural Language Processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, Online, 16–18 November 2020. [CrossRef]
59. Wang, A.; Singh, A.; Michael, J.; Hill, F.; Levy, O.; Bowman, S. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, Brussels, Belgium, 1 November 2018. [CrossRef]
60. Ibar-Alonso, R.; Quiroga-García, R.; Arenas-Parra, M. Opinion Mining of Green Energy Sentiment: A Russia-Ukraine Conflict Analysis. *Mathematics* **2022**, *10*, 2532. [CrossRef]
61. Kim, S.Y.; Ganesan, K.; Dickens, P.; Panda, S. Public Sentiment toward Solar Energy—Opinion Mining of Twitter Using a Transformer-Based Language Model. *Sustainability* **2021**, *13*, 2673. [CrossRef]
62. Jain, A.; Jain, V. Sentiment Classification of Twitter Data Belonging to Renewable Energy Using Machine Learning. *J. Inf. Optim. Sci.* **2019**, *40*, 521–533. [CrossRef]
63. Li, R.; Crowe, J.; Leifer, D.; Zou, L.; Schoof, J. Beyond Big Data: Social Media Challenges and Opportunities for Understanding Social Perception of Energy. *Energy Res. Soc. Sci.* **2019**, *56*, 101217. [CrossRef]
64. Abdar, M.; Basiri, M.E.; Yin, J.; Habibnezhad, M.; Chi, G.; Nemati, S.; Asadi, S. Energy Choices in Alaska: Mining People's Perception and Attitudes from Geotagged Tweets. *Renew. Sustain. Energy Rev.* **2020**, *124*, 109781. [CrossRef] [PubMed]