sustainability

MDPI

Article

'I Tweet about Our #GreenEnergy'—Automated Classification of Social Identity and Opinion Mining of the Dutch Twitter Discourse on Green-Energy Technologies

Romée Lammers *, Sikke R. Jansma, Bernard P. Veldkamp, Anna K. Machens, Matthias de Visser and Jordy F. Gosselt

Faculty of Behavioral, Management and Social Sciences, University of Twente, Drienerlolaan 5, 7522 NB Enschede, The Netherlands
* Correspondence: r.lammers-1@utwente.nl

Abstract: Understanding the complexities of public opinion is crucial for a green-energy transition. This present study examines the sentiment of public opinion towards various energy technologies on Twitter during the Dutch 2021 general elections. A dataset comprising 186,822 tweets and profile descriptions was analyzed using two automated text classifiers to explore how individuals with different self-proclaimed identities perceive green-energy technologies. The analysis involved the application of the sentiment and social identity classifier models, followed by a frequency and co-occurrence analysis. The findings revealed a negative overall sentiment towards green-energy technologies in the Twitter discourse. It further showed that perceptions may differ depending on a technology's development stage, with emerging technologies generally receiving more favorable views compared to established ones. Furthermore, it was found that, although there is a general trend of negative sentiment based on political identity, and positive sentiment based on occupational identity, this trend did not consistently apply to specific energy technologies. This discrepancy can likely be attributed to varying implementation effects and contextual situations associated with the technologies. The findings suggest that personalized communication strategies for specific social groups may be beneficial for understanding and addressing public opinions, needs, and concerns within the energy transition. The complexity of understanding public opinion in the context of green-energy highlights the need for a nuanced approach in future research.

Keywords: green energy technologies; public opinion; sentiment analysis; social identity; natural language processing; machine learning

check for updates

Citation: Lammers, R.; Jansma, S.R.; Veldkamp, B.P.; Machens, A.K.; de Visser, M.; Gosselt, J.F. 'I Tweet about Our #GreenEnergy'—Automated Classification of Social Identity and Opinion Mining of the Dutch Twitter Discourse on Green-Energy Technologies. *Sustainability* **2023**, *15*, 16106. https://doi.org/10.3390/su152216106

Academic Editor: Thomas A. Clark

Received: 25 September 2023
Revised: 13 November 2023
Accepted: 15 November 2023
Published: 20 November 2023

1. Introduction

1.1. Background

The Paris agreement has established ambitious targets for the transition to renewable and low-emission energy technology options, often referred to as green-energy technologies [1]. Past research has indicated that public opinion plays a crucial role in the successful implementation of this technological transition; however, in practice, developers of green-energy technology projects often encounter significant challenges in understanding and addressing the diverse opinions of the public that influence acceptance [2–4]. Despite efforts to increase public acceptance, opposition to green-energy technologies persists due to skepticism regarding their financial benefits, system reliability, placement considerations, and concerns about potential conflicts of interest [5]. In current initiatives that aim to increase public acceptance of the technologies, the public is generally approached as a relatively homogeneous group [6]. However, within processes of technological change, multiple social groups are involved, each characterized by distinct demographics, perspectives on the challenge at hand, reform objectives, and preferred approaches to pursue [7,8].

Consequently, it becomes evident that there is no one-size-fits-all solution within public acceptance initiatives.

Previous studies have shown that social identity plays a significant role in affecting environmental behaviors and opinions [9–11]. Social identity guides actions that align with the norms of the social group in which membership is held [12]. Consequently, individuals who belong to groups where pro- or anti-environmental beliefs and behaviors are the social norm, are likely to adopt these views and behaviors themselves [13]. In the context of green-energy, studies examining opinion and acceptance based on social identity have mainly relied on surveys and interviews to gauge differences amongst the public [14]. Surveys and interviews allow for the collection of individual-level demographic information, which can influence perceptions of green-energy technologies [14]. However, as social identity is a mostly subconscious phenomenon that does not exist separately from social interaction [15,16], these more traditional methods alone may not fully capture the relationship between social identity and opinion toward green energy technologies without incorporating explicit self-report measures or observer involvement [14,17]. This limitation introduces potential bias in how social identity is expressed, thereby making it challenging to fully understand the impact of implicit social identity. For example, the social desirability bias, as outlined by Krumpal [17], can distort how individuals present their social identities in these more traditional methods. Respondents, instead of spotlighting genuinely salient identities, might foreground more socially acceptable ones or downplay identities that might be seen as controversial in a research setting, thereby overshadowing the true hierarchy of social identities they would naturally uphold [17].

Considering the limitations of traditional methods, this research adopts a different approach by harnessing social media data related to green-energy technology to gain a deeper understanding of public opinion and social identity. Social media has become a prevalent avenue for individuals to voice socio-political views [18,19], thereby enabling personal expression of opinions and identities, including in the green-energy technology discourse [5,20]. Thus, the present research aims to provide a clear-cut, yet thorough, understanding of the relation between opinions towards green-energy technologies and social identity within the Dutch Twitter public discourse.

To gain this understanding, this paper employs three sub-objectives with corresponding research questions. First, it seeks to evaluate public opinion via sentiment orientation and target analysis, specifically on the envisioned green-energy mix technologies in the Netherlands, including solar, wind, biomass, geothermal, hydrogen, hydropower, and nuclear energy, using Twitter data, thus, utilizing the sub question 'How is sentiment expressed towards green-energy technologies within the Dutch Twitter discourse?' Twitter, a microblogging platform, is opted for as the primary data source for this study due to its rich repository of user-generated content, which is particularly abundant with respect to socio-political discourse [21]. This characteristic renders Twitter a valuable resource for researchers to tap into a crowd-sourced pool of sentiments embedded within public opinion toward green-energy technologies [21]. The second goal of this study is to comprehend opinion holders through their social identity expressions, using Twitter profile description data from the Netherlands. In pursuit of this goal, the following sub question is posed: 'How are social identity categories expressed among Dutch Twitter users within green-energy technology Twitter discourse?' This is opted for as Twitter allows users to create profile descriptions, which are frequently used to represent online social identities [20,22,23]. This means that Twitter generates extensive data about individuals' social identities, which can be used for identity analyses embedded within the energy discourse without direct interference. The paper's final goal is to determine how the sentiment components of public opinion, towards green-energy technologies, vary across social identity expressions among Dutch Twitter users, employing the sub question 'How does sentiment regarding green-energy technology types vary among social identity categories among Dutch Twitter users?' This will allow for a better understanding of how individuals' social identity relates to expressed opinions within energy technology discourse and to enhance acceptance practices with the potential of being more inclusive.

1.2. Public Opinion and Sentiment in the Online Energy Discourse

During the Dutch House of Representatives elections in March 2021, green-energy technologies gained considerable attention, becoming focal points of discussion as they were assessed as potential solutions to meet the government's target of generating 27% sustainable energy by 2030 [24]. Specifically, solar, wind, biomass, nuclear, the more emerging technologies of geothermal and hydrogen energy, and hydropower to some extent, were discussed on a grand scale [25,26]. The potential integrations of these green-energy technologies within current energy systems may have profound implications on societies' economic, political, and social systems, meaning that the topic often prompts public response [27]. The opinions shared by the public in response represent a multitude of perspectives and are usually quite complex to grasp [27]. Thoroughly understanding these opinions is crucial for both researchers and policymakers, given that public opinion can shape, or even hinder and halt, the acceptance and deployment of green energy technologies [28]. Consequently, scholars have called for the establishment of a concrete, yet nuanced, comprehension of public opinion, as this would aid in developing more meaningful acceptance initiatives, as well as expanding the comprehension of potential policy obstacles [14,29,30]. Past research has focused on understanding public opinion on green-energy technologies by analyzing the public discourse, which encompasses the exchange and deliberation of viewpoints and opinions among individuals within the wider public dialogue [29,31–33]. The emergence of digital media, particularly social media platforms, has ushered in a new era of public opinion and discourse research [5,34]. These platforms have offered individuals unparalleled opportunities to express themselves and participate in discussions [35,36], which has led to a more diverse and dynamic public conversation, allowing a wide range of opinions, including on socio-political matters, to be freely expressed and debated [21]. Twitter in particular has become a crucial platform for socio-political deliberation [18,37], particularly on topics of general interest such as climate change [38], sustainability [39], and energy systems [14]. This has resulted in Twitter serving as a space where socio-political public opinions, including those related to green-energy technologies, are discussed, and partially reflected [14,18]. Utilizing the Twitter discourse to study public opinions has been shown to be particularly advantageous surrounding the opinion component of sentiment [40,41].

According to Liu and Zhang [42], sentiment, or sentiment orientation, is one of four the underlying components of the concept of opinion, namely, sentiment orientation, sentiment target, time, and opinion holders. Sentiment orientation refers to the evaluative disposition associated with an opinion, and can be classified as positive, negative, neutral, or ambiguous depending on the valence of the sentiment expressed. The sentiment target, on the other hand, represents the matter that is evaluated or assessed, towards which the sentiment is directed. The time component reflects the temporal dimension of the sentiment, indicating when it was or is expressed. Finally, the opinion holder component refers to the individual, community, or organization expressing the sentiment [42]. In accordance with this framework, all components of opinion should be taken into account to gain nuanced comprehension of public opinions within socio-political Twitter discourses. When taking this approach, an understanding can be created in terms of what green-energy technologies are targeted with what sentiment in the timeframe of the Dutch 2021 elections, and, very crucially, who is expressing the sentiments that underly public opinions.

1.3. Online Social Identity Classification

The field of social psychology offers insight into grasping the identities of those sharing their green-energy opinions, by examining the concept of social identity [43]. Within social identity research, two main lines of theory have been central, namely self-categorization theory [44,45], and identity theory [46]. Self-categorization theory illustrates how individuals categorize themselves into groups based on personal interpretations, while identity theory focusses on intergroup behavior and particularly on the distinctions and biases of in-group ('us') versus out-group ('them') dynamics [16,45,46]. From the integration of both theories, social identity can be defined as the sense of self derived from social categories and social roles based on membership to social groups, which is formed and/or expressed in a social setting [43].

Due to the growing usage of social media platforms to connect with others, express oneself, and share opinions, social identity has become increasingly apparent online [34]. In the case of Twitter specifically, users are able to form profile descriptions, which are often utilized to communicate online social identities [20,22,23]. For example, a Twitter profile description may look like the following: "Father, accountant, liberal, from Rotterdam", highlighting different dimensions of the user's social identity and how they present themselves accordingly. In online settings, the choices individuals make about which identities to display are informed by the concept of identity salience. Stryker and Serpe [47] posit that choices have to be made concerning which identities are relevant to perform in a given situation, as social identities are extensively multitudinous. For this, individuals maintain a subconscious hierarchy of their identities [23,47]. Within this structure, identities perceived as the most salient and valuable for a given context are brought to the forefront and expressed [23,47]. In the context of Twitter, the restriction of 160 characters in profile descriptions necessitates individuals to deliberate about the identities they wish to express [23]. As such, the identities reflected in these descriptions can be seen as the most pertinent to the users' self-concepts within this online discourse, while other identities are downplayed. This suggests that Twitter offers a space to comprehend the most salient social identities individuals uphold, and how they participate in public discourse through these identities.

The understanding of identities within Twitter biographies has been the subject of several studies, including those conducted by Beller et al. [48], Pathak et al. [22], Priante et al. [20], and Semertzidis et al. [49], who pinpointed linguistic indicators of social identity roles, including relational identities tied to family, gender, fandom, and community. These works also noted lexicon reflecting occupational-based roles such as those related to work, education, and hobbies. Next, Priante et al. [20] and Rogers and Jones [21] emphasize the presence of lexicon specifically tied to political affiliations and their aligning roles that construct the overall category of political identities. Lastly, lexicon linked to geography, ethnicity, and religion, classified as cultural identities, was observed by Beller et al. [48], Priante et al. [20], and Semertzidis et al. [49]. As such, these studies consistently reveal the presence of four primary categories of social identities within user profiles, which are duly considered in the scope of this study, namely, relational identities, occupational identities, political identities, and cultural identities.

Firstly, relational identity pertains to how individuals define themselves in relation to others through interpersonal relationships and social roles [20,22,48,49]. Previous research has demonstrated that individuals who perceive themselves as being oriented towards their relationships are more likely to have a positive attitude towards sustainable solutions compared to those who do not define themselves based on relational identity [50]. This could extend to energy technologies as well, as people who identify with relational roles saliently may feel a greater sense of responsibility towards the impact of their behaviors on the lives of others [50]. Second, occupational identity refers to an individual's identity that is based on their engagement and roles in various activities, such as professions and careers, but also hobbies and interests [20,22,48,49]. Action-orientation, a psychological trait associated with occupational identity that is characterized by a strong drive towards action, has been found to strengthen perceptions, both positively and negatively, towards environmental solutions such as sustainable energy systems due to perceived utility [9]. It can thus be argued that this embedded trait may relate to the opinions held by people who hold salient occupational identities [9,51]. Third, political identity is based on affiliation with political parties, groups, causes and movements [20,23]. This identity has been shown to lead to strong convictions of opinions and engagement in political affairs, regardless of the type of political identity held [23]. This can also be applied to the socio-political context of environmental issues, where it can be argued that individuals who express political identity show generally stronger and more entrenched opinions towards topics like green-energy technologies. Fourth, cultural identity relates to the membership that one holds within geographic, ethnic, and religious groups and communities [20,48,49]. Cultural identity has been shown to affect the perceptions that people have towards green-energy solutions [50]. Studies have shown that individuals with strong cultural identities are more likely to develop stronger place attachments, nature orientations, and worldviews [50]. These factors can influence their opinions of green-energy technologies, which can vary based on the specific implementation of these technologies and their impact on ecosystems [50,52].

When relational, occupational, political, or cultural identities are saliently expressed, they can lead to strong convictions of opinions and engagement within their respective dimensions [23,37]. Salient political identities, for instance, whether as activists, party-members, or along the conservative–progressive spectrum, foster entrenched stances on political issues [23,53]. Meanwhile, those who do not hold politics as a salient part of their identity may engage politically but are more likely to retreat when discomfort arises [23]. Focusing on salient identities, as such, can be relevant in understanding how social identity relates to public opinion in the field of green-energy technologies. This is the case as expressing a particular identity online explicitly, implies a set of beliefs, values and norms that are generally aimed to be upheld [23,47]. Hence, this study explores the interplay of relational, occupational, political, and cultural social identities with Twitter users' opinions of green-energy technologies.

2. Methods

2.1. Sentiment and Social Identity Classification on Twitter

In the past, researchers have increasingly turned to Twitter as a valuable resource for evaluating public discourse through opinion mining [40,41]. Opinion mining involves the automated analysis of opinions, attitudes, perceptions, and sentiment expressed within textual data [54]. A specific aspect of opinion mining is sentiment analysis, which aims to categorize text based on various linguistic features that express sentiment orientations [14,54]. Within this study, this type of analysis was opted for through the categorization of positive, negative, neutral, and ambiguous sentiments towards green-energy technologies as sentiment targets. Furthermore, to grasp the social identities to which Twitter users subscribe, profiles tweeting about green-energy technologies were analyzed as well. This analysis involved classifying the users' profile descriptions, using an online social identity classification approach that draws inspiration from studies by Beller et al. [48], Pathak et al. [22], Priante et al. [20], and Semertzidis et al. [49], and it employs the social identity classifications of relational, occupational, political, and cultural identities. In this study, the sentiment and social identity classifications were carried out using natural language processing (NLP) through automated text classification. Within this approach, two machine learning models were developed for the sentiment and social identity classifications using supervised learning methods (Figure 1).

2.2. Data Collection, Dataset and Pre-Processing

Data were collected from tweets posted between the 1st of January and the 7th of May 2021. This timeframe represents the range of approximately two months before and after the Dutch parliamentary elections. The period was chosen due to the active public debate occurring around the elections on topics such as the environment and the energy transition on social media platforms like Twitter [55]. For this reason, Dutch election-period tweets and corresponding profiles mentioning the envisioned energy-mix technologies of solar, wind, biomass, geothermal, hydrogen, hydropower, and nuclear energy, were collected using a Twitter Application Interface (API). For the tweet collection, a total of 58 keywords relating to the various energy technologies and their spelling variants were employed in search queries. The search queries per energy technology were first selected through a process of discourse and concourse evaluation, involving a researcher panel comprised of four data science, social science, and environmental researchers. This was followed by several rounds of pilot searches, employing a trial-and-error approach, to fine-tune the search queries. During this process, keywords were added and removed based on their ability to generate additional tweets. As an example, for nuclear energy, the Dutch translations of the final search terms: 'nuclear power', 'nuclear energy', 'nuclear power plant', 'nuclear power plants', 'atomic power', and 'atomic energy' were used (see Appendix A). Using these search queries, the API was used to stream tweets that were perceived as 'relevant' according to the Twitter algorithm. The scraping of these tweets resulted in a dataset containing a total of 196,159 tweets, excluding retweets.

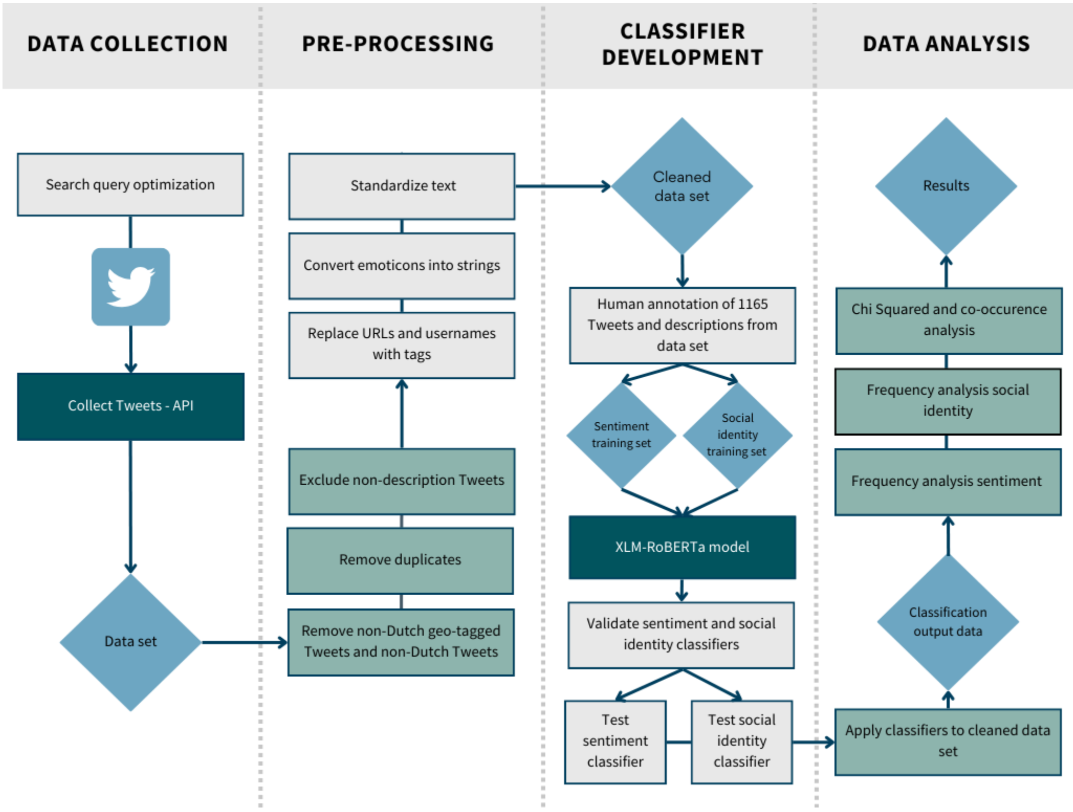

Figure 1. Flowchart for Automated Sentiment and Social Identity Classification and Analysis.

Through pre-processing, the raw data set was cleaned by removing inconsistent and missing values, as well as by removing redundant information to allow for more accurate training of the classification models. The initial step removed tweets geo-tagged outside the Netherlands. However, tweets referencing foreign green-energy practices were retained due to their relevance in shaping the sentiment and discourse within the Dutch context [39]. Next, any tweets that included languages other than Dutch were filtered out and duplicate tweets were removed. Thereafter, tweets originating from profiles without profile descriptions were removed, as tweets from such accounts have often been shown to belong to bot profiles, troll accounts, or other types of automated or spammy content [56,57]. These accounts may not accurately represent genuine user sentiment or contribute to the overall discourse in a meaningful way. Furthermore, anonymity online, such as through incomplete profiles, has been linked to increased hostility and negativity, as well as diminished accountability and legitimacy of public opinions, thereby posing challenges to the quality of participation in online social and political discussions [58–60]. Additionally, the absence of these data points can introduce noise into automated text classifier models [61], hindering social identity classification. Finally, the textual data underwent further cleaning by replacing URLs and usernames with tags, converting emoticons into strings, transforming uppercase characters into lowercase, and standardizing punctuation marks.

As delineated in Table 1, after the pre-processing phase a total of 186,822 Dutch tweets and corresponding Dutch or English profile descriptions remained. In this final data set, a total 215,172 mentions of the aforementioned energy technologies occurred, indicating that some tweets included multiple energy technologies. Specifically, wind energy represented 25.9% of the mentions. Nuclear and solar energy followed with 22.6% and 22%, respectively. Biomass energy accounted for 16.1% of the mentions. Hydrogen and geothermal energy were observed at 5.9% and 5.2%, respectively, while mentions of hydropower energy constituted 0.4%.

Table 1. Green-energy Technology Mentions.

	Number of Mentions	**Percentage of Total Mentions**
Wind	55,816	25.9%
Nuclear	48,674	22.6%
Solar	47,430	22%
Biomass	3486	16.1%
Hydrogen	12,493	5.9%
Geothermal	11,109	5.2%
Hydropower	938	0.4%
Total	215,172	100%

2.3. Classifier Development

2.3.1. Human Annotation

To develop classifiers for sentiment and social identity, labelled data are required for model training purposes. The labelling of this dataset commenced with two rounds of annotation by two coders, a step taken to ensure coding reliability. The coders met in sessions to construct a codebook, which served as a guide for manual annotation. The codebook consisted of two components, the first of which revolved around sentiment, and was employed for annotating the sentiment orientation within a tweet. Two labelling categories were used for sentiment classification: positive and negative sentiment. Since both positive and negative sentiments can occur within a single tweet, both could be assigned. If both sentiments were present, the tweet would be considered 'ambiguous'. However, if neither positive nor negative sentiment was discernible, the tweet would be regarded as 'neutral'. Only tweets explicitly mentioning the energy technologies of interest were considered. For instance, in the case of reply tweets, sentiment was evaluated based on the reply alone, without considering the original tweet. This approach provided insights into the overall sentiment expressed in the discourse about green-energy technologies. The second component of the codebook involved the classification of social identity according to previously described categories. During the annotation process, Twitter profile descriptions were coded based on the presence or absence of social identity categories of relational, occupational, political, and cultural identity. Given that social identity categories are not mutually exclusive, multiple categories could be attributed to a single profile description.

To assess the inter-rater reliability, a Cohen's Kappa was calculated based on 210 double annotations during the first round of coding. However, for this round, the Cohen's Kappa was insufficient for sentiment (0.66) and social identity (0.65). Based on these results, the unclear components in the codebook were further specified. In the second round of coding, involving 335 annotations, the Cohen's Kappa values were deemed sufficient for both sentiment (0.82) and social identity (0.84). After confirming the inter-rater reliability, 1165 tweets were annotated to create the labelled dataset that was used to train the text classification model for sentiment and social identity.

2.3.2. Automated Text Classifiers

For the automated text classification modelling in this study, two separate binary classifiers were developed using the manually labeled tweets and profile descriptions as input. The 1165 annotated tweets were used to make up the training (64%), validation (16%), and test (20%) sets.

The separate classification models for sentiment and social identity were based on the pretrained transformer XLM-RoBERTa. Transformer models parallelize language processing, meaning that all words in a dataset are analyzed simultaneously, rather than in progression [62]. This allows a model to grasp the contextual meaning of a data-point, such as a tweet, rather than merely comprehending at the word level. XLM-RoBERTa is a type of transformer model that is pretrained on a large amount of data in 100 different languages, thereby reducing the amount of training data needed to fine-tune the model to a specific domain of interest [62]. Hence, XLM-RoBERTa was chosen as the base model for this research because it allows for state-of-the-art building of text classifiers.

2.3.3. Classifier Model Evaluation

For the development of the sentiment classifier, the XLM-RoBERTa base model was fine-tuned using the manually labeled tweets. This was done with the use of two categories: positive and negative sentiment. These were labeled using a multi-label classification. To evaluate the prediction quality of the positive and negative categories within the classifier, the precision, recall, and F-scores of the categories were calculated. The positive sentiment category achieved an accuracy of 75%, a precision of $P = 0.619$, a recall of $R = 0.907$, and an F-score of $F = 0.736$. The negative sentiment category achieved an accuracy of 83%, a precision of $P = 0.659$, a recall of $R = 0.879$, and an F-score of $F = 0.753$.

Furthermore, for the development of the social identity classifier, the XLM-RoBERTa base model was fine-tuned using manually labelled profile descriptions. The four social identity categories of relational, occupational, political, and cultural identity were labelled using a multi-label classification. Firstly, for the relational identity category, the model achieved an accuracy of 96.4%, a precision of $P = 0.957$, a recall of $R = 0.846$, and an F-score of $F = 0.898$. Secondly, the occupational identity category showed an accuracy of 80.6%, a precision of $P = 0.816$, a recall of $R = 0.827$, and an F-score of $F = 0.821$. For the political identity category, the model achieved an accuracy of 84.9%, a precision of $P = 0.708$, a recall of $R = 0.548$, and an F-score of $F = 0.618$. Furthermore, the cultural identity displayed an accuracy of 82.7%, a precision of $P = 0.559$, a recall of $R = 0.679$, and an F-score of $F = 0.613$.

2.4. Data Analysis

The data analysis for this study began, after implementing the models, with a frequency analysis of both sentiment and social identity categorization. The social identity categorization analysis, specifically, involved a word frequency analysis, aimed at discerning the prevalence of a specific lexicon within distinct identity categories. This analysis was employed to gain insight into associations with specific identity categories. Additionally, the sentiment frequency analysis considered mutual exclusivity, while social identity frequencies considered non-mutual inclusivity, calculating frequencies based on the presence or absence of specific identity categories in data points. Both absolute and relative frequencies were calculated for all sentiment and social identity categories. This allowed for the observation of the overall data distribution, identification of the most common categories, and permitted the observation of data distribution in relation to other categories, thus enabling the identification of trends or patterns. A co-occurrence analysis of sentiment and social identity categories for each energy technology was conducted to understand the association between these constructs. This analysis facilitated a straightforward but thorough examination of the intersectionality of sentiment and social identity, and how they may impact each other in the context of energy technology tweets. An absolute and relative frequency analysis was initially conducted, taking mutual and non-mutual exclusivity into account. Subsequently, a chi-squared test was used to determine the significance of observed co-occurrence counts and whether they differed significantly from what would be expected by chance for each energy technology. As chi-squared tests assume category independence, non-mutually exclusive categories can cause inaccuracies. Therefore, the 16 possible combinations of social identity categories were treated as separate classes, along with the sentiment categories in the chi-squared co-occurrence test.

3. Results

Between January and May 2021, there were a few noticeable anomalies in the number of tweets sent out about various energy technologies. Figure 2 shows that a substantial increase in the number of tweets mentioning solar energy occurred in mid-January. This increase is most likely due to an article by the Dutch newspaper 'het AD', which reported that 79% of solar parks in the Netherlands are owned by foreign entities [63]. Furthermore, there was a general increase in tweets in March, just before the Dutch parliamentary elections when debates about the energy transition were in full swing. Specifically, nuclear energy and wind energy were the technologies with the biggest increase in discourse during this time. Following the elections, during the beginning to the middle of March, the number of tweets discussing energy technologies decreased substantially.

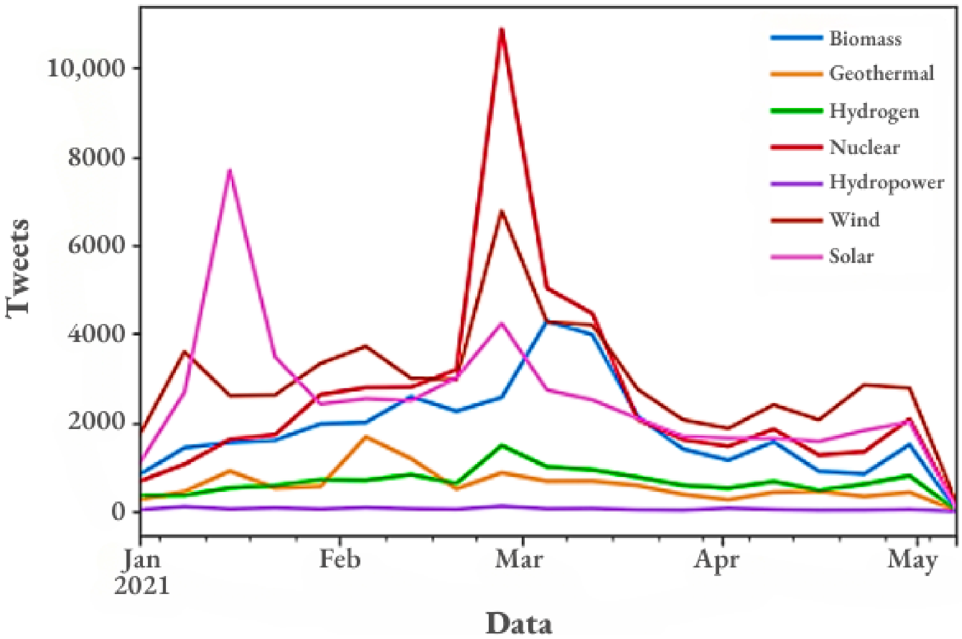

Figure 2. Frequency of Energy Technologies in Tweets Time Frame.

3.1. Sentiment per Energy Technology

As is shown in Figure 3, while following the general curve of the tweets put out in the time frame, the sentiment of the tweets collected is negative (117,793 tweets) above all. In the peaks, while more tweets are put out, the difference between the amounts of negative sentiment and the other sentiments becomes larger. Meaning that during those peak times relatively more negative tweets are tweeted when compared to positive, neutral, and ambiguous tweets. From the remaining three sentiments positive tweets (40,266 tweets) are most frequent, followed by neutral tweets (26,552 tweets). Few ambiguous tweets (2211 tweets) are detected.

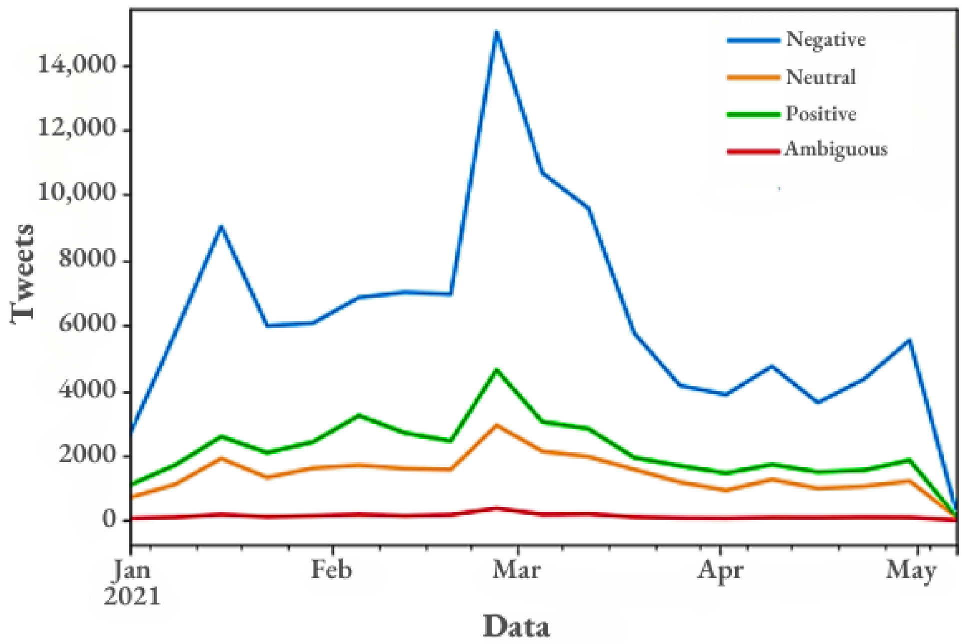

Figure 3. Frequency of Sentiment Classifications in Tweets Time Frame.

When looking at Table 2, it can be seen overall that negative sentiment is most prominent in terms of absolute frequency for biomass, nuclear, hydropower, wind, and solar energy. This is especially evident for biomass energy and wind energy. On the other hand, geothermal and hydrogen energy technologies appear with more positive sentiment. When considering a relative perspective, among the negative tweets, biomass (78%), wind (75.6%), and nuclear energy (60.6%) are mentioned most frequently. In contrast, hydrogen energy has the fewest number of negative tweets (32%). Furthermore, positive tweets are relatively more commonly tweeted about geothermal (49.5%) and hydrogen energy (46.6%), while wind energy (11.9%) and biomass energy (8%) receive the least positive tweets. In tweets categorized as neutral, hydrogen (19.8%), and hydropower (17.1%) are mentioned most often, while geothermal (11%) is mentioned least. Lastly, when it comes to ambiguous tweets, geothermal (2.6%) and nuclear energy (1.9%) are the most frequently mentioned, while biomass receives the least mentions (0.6%).

Table 2. Sentiment Classification and Energy Technology Frequencies.

	Biomass	**Geothermal**	**Hydrogen**	**Nuclear**	**Hydropower**	**Wind**	**Solar**	**All Technologies**
Negative	26,979 (78.0%)	4113 (37.0%)	4003 (32.0%)	29,489 (60.6%)	463 (49.4%)	42,199 (75.6%)	27,144 (57.2%)	117,793 (63.1%)
Positive	2755 (8.0%)	5494 (49.5%)	5822 (46.6%)	11,751 (24.1%)	306 (32.6%)	6625 (11.9%)	12,807 (27.0%)	40,266 (21.6%)
Neutral	4645 (13.4%)	1218 (11.0%)	2478 (19.8%)	6490 (13.3%)	160 (17.1%)	6516 (11.7%)	6826 (14.4%)	26,552 (14.2%)
Ambiguous	207 (0.6%)	284 (2.6%)	190 (1.5%)	944 (1.9%)	9 (1.0%)	476 (0.9%)	666 (1.4%)	2211 (1.2%)

3.2. Social Identity per Energy Technology

Over the course of January through March, the number of Twitter profiles tweeting about energy technologies logically follows the general curve of tweets posted during that time frame, as depicted in Figure 4. It is apparent that in the classification of social identity, the model most often did not identify any of the distinct identity categories (95,677 profiles). However, when the identity categories were recognized, the occupational classification (66,009 profiles), was most prominent. This is followed by the three other categories with a substantial gap. Cultural identity (30,078 profiles) is detected the most among these three, followed by the political (23,183 profiles), and finally, relational identity classifications (18,359 profiles).

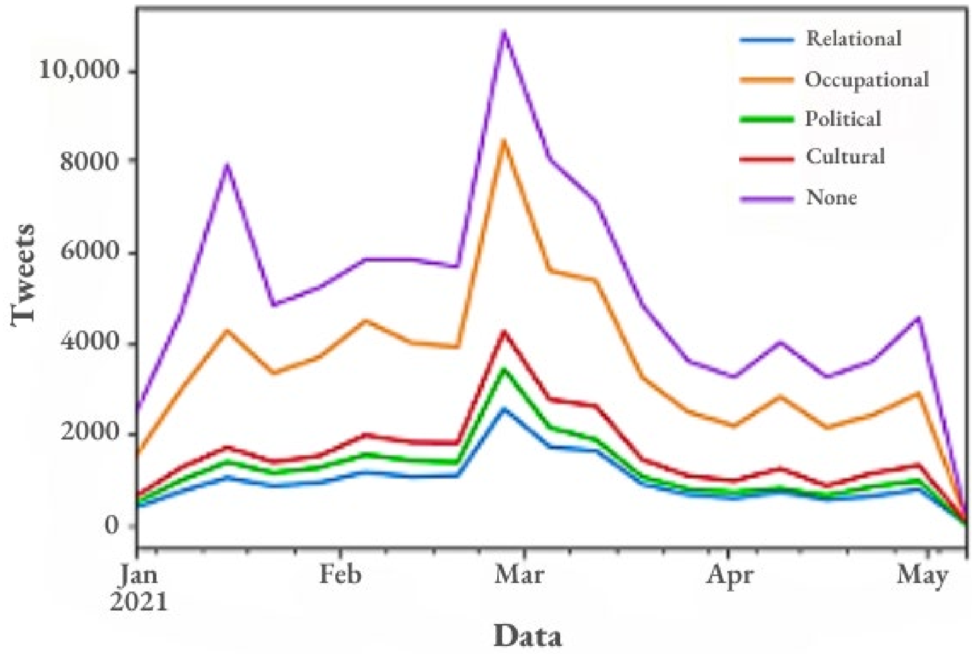

Figure 4. Frequency of Social Identity Classifications in Biographies Time Frame.

Furthermore, Figure 5 displays word cloud visualizations that represent the top fifteen most frequently occurring words for each social identity classification. To ensure clarity and focus on the relevant terms, default Dutch and English stop words defined in the R tm: Text Mining Package 'stopwords' library [64], were excluded from the analysis. Additionally, overlapping terms that exclusively pertained to other social identity categories were eliminated, taking into account the non-mutual exclusivity of the categories. Firstly, for relational identity the most common words include; 'vader' (father), 'moeder' (mother), 'getrouwd' (married), 'father' and 'echtgenoot' (spouse), among others. As such, this category most often employs words relating to immediate family. Next, for occupational identity the most common words include; 'ondernemer' (entrepreneur), 'manager', 'MSc', 'consultant' and 'senior', among others. As such, this category most often employs words relating to high-level education and white-collar professions. For political identity, the most common words include; 'politiek' (politics), 'rechts' (right), 'links' (left), 'lid' (member) and 'politieke' (political), among others. As such, this category most often employs words relating to general political interest, political orientation, and party memberships. Lastly, for cultural identity the most common words include; 'Dutch', 'Nederland' (The Netherlands), 'geboren' (born), 'Christen' (Christian), and 'Atheïst' (Atheist), among others. As such, this category most often employs words relating to the Dutch country or nationality, where one originates from, and religion.

When examining Table 3, it is evident that occupational identity is the most prominent in absolute frequency for each energy technology when social identity is perceived. However, when looking at relative frequency, Twitter profiles containing the relational identity category put out more tweets relating to nuclear energy (11.1%) and wind energy (10.1%), and least on hydrogen energy (8.8%). Furthermore, in the occupational category, relatively more tweets mentioning nuclear energy (41.8%), hydrogen energy (41.3%), and hydropower (40.2%) are put out. The least number of tweets are present in the biomass category (30.4%). When looking at political identity, relatively more tweets on nuclear energy (14.7%), wind energy (14%), and biomass energy (13.7%) are present, while hydrogen energy is present least (8.8%). Lastly, profiles with the cultural category relatively tweet most about wind energy (18.9%) and nuclear energy (17.9%). These profiles tweet least about hydrogen energy (11.7%). When no specific social identity can be detected, solar energy (57.1%) and biomass energy (54.4%) are discussed the most, while nuclear energy (43.3%) is discussed the least.

Relational Identity	Occupational Identity	Political Identity	Cultural Identity

Figure 5. Fifteen Most Frequent Words per Social Identity Category.

Table 3. Social Identity Classification and Energy Technology Frequencies.

	Biomass	**Geothermal**	**Hydrogen**	**Nuclear**	**Hydropower**	**Wind**	**Solar**	**All Technologies**
Relational Identity	3131 (9.1%)	1015 (9.1%)	1105 (8.8%)	5387 (11.1%)	84 (9.0%)	5610 (10.1%)	4352 (9.2%)	18,359 (9.8%)
Occupational Identity	10,513 (30.4%)	4125 (37.1%)	5154 (41.3%)	20,347 (41.8%)	377 (40.2%)	18,986 (34.0%)	14,857 (31.3%)	66,009 (35.3%)
Political Identity	4752 (13.7%)	1034 (9.3%)	1101 (8.8%)	7165 (14.7%)	87 (9.3%)	7839 (14.0%)	4849 (10.2%)	23,183 (12.4%)
CulturalIdentity	5116 (14.8%)	1575 (14.2%)	1458 (11.7%)	8694 (17.9%)	123 (13.1%)	10,533 (18.9%)	6649 (14.0%)	30,078 (16.1%)
None Detected	18,825 (54.4%)	5928 (53.4%)	6217 (49.8%)	21,052 (43.3%)	459 (48.9%)	28,163 (50.5%)	27,076 (57.1%)	95,677 (51.2%)

3.3. Co-Occurrence of Sentiment and Social Identity

A co-occurrence analysis was performed to examine how different social identity groups showcase sentiment overall. When observing absolute frequencies, it can be seen in Table 4 that all social identities showcase negative sentiment the most and ambiguous sentiment least. When perceived in a relative manner, it can be seen that for negative sentiment, political identity (67.9%) occurs most, and occupational identity (60.8%) occurs least. Furthermore, positive tweets are posted mostly by accounts containing occupational identity (23.8%) and least by accounts containing political identity (18.4%). For neutral sentiment, most often, no identity (14.8%), can be detected, while relational identity (12.6%) is detected least. Lastly, ambiguous sentiment occurs most with relational (1.4%) and occupational identity (1.4%) and occurs relatively least when no identity (1.1%) is detected.

Table 4. Co-occurrence Frequencies of Sentiment and Social Identity Overall.

	Relational	**Occupational**	**Political**	**Cultural**	**None**
Negative	11,803 (64.3%)	40,193 (60.8%)	15,740 (67.9%)	20,115 (66.8%)	60,080 (62.8%)
Positive	3982 (21.6%)	15,711 (23.8%)	4264 (18.4%)	5680 (18.8%)	20,382 (21.3)
Neutral	2310 (12.6%)	9195 (13.9%)	2876 (12.4%)	3901 (13.0%)	14,193 (14.8%)
Ambiguous	264 (1.4%)	910 (1.4%)	303 (1.3%)	382 (1.2%)	1022 (1.1%)

A chi-squared test of independence was performed to examine the relation between sentiment and social identity for all tweets and biographies, as well as for the tweets about separate energy technologies (Table 5). For this, all sixteen possible combinations of social identity were considered since social identity is not mutually exclusive. Based on the test of independence, the relation between sentiment and social identity was significant overall, χ^2 (45, N = 142.848) = 834.5, $p < 0.001$. This means that there is a significant difference in how sentiment is expressed by different social identity category combinations. This was also the case for all of the separate energy technology tweets, except for those concerning hydropower energy. For these, based on the test of independence, the relationship between sentiment and social identity was not significant, χ^2 (36, N = 750) = 33.6, $p > 0.01$. This means that there is no significant difference in how the different social identity category combinations express sentiment in tweets related to hydropower energy. Hence, from this point onward, hydropower energy was not considered for further co-occurrence analysis.

Table 5. Pearson Chi-Square test for Co-occurrence of Sentiment and Social Identity.

Sentiment × Social Identity	χ^2 Value	*df*	*N*	*p*	99% CI
Tweets overall	834.5	45	142,848	<0.001	[24.31, 73.17]
Biomass energy tweets	164.5	45	25,334	<0.001	[24.31, 73.17]
Geothermal energy tweets	110.7	45	8650	<0.001	[24.31, 73.17]
Hydrogen energy tweets	72.6	45	9349	<0.001	[24.31, 73.17]
Nuclear energy tweets	186.1	45	39,059	<0.001	[24.31, 73.17]
Hydropower energy tweets	33.6	36	750	0.599	[17.89, 61.59]
Wind energy tweets	230.9	45	43,030	<0.001	[24.31, 73.17]
Solar energy tweets	387.6	45	36,011	<0.001	[24.31, 73.17]

Note. CI = Confidence Interval.

3.3.1. Biomass Energy

When observing absolute frequencies for biomass energy, all social identities showcase negative sentiment the most, by a large margin, and ambiguous sentiment least. When perceived in a relative manner, for negative sentiment, cultural identity (79.4%) occurs most while occupational identity (75.8%) occurs least. Furthermore, positive tweets are posted mostly by accounts containing occupational identity (9.8%) and least by accounts containing political identity (7.2%). For neutral sentiment, most often, relational identity (13.9%) is detected, while political identity (12.2%) is detected least. Lastly, ambiguous sentiment occurs most with occupational (0.9%) and cultural identity (0.9%) and occurs relatively least when no identity (0.4%) is detected.

3.3.2. Geothermal Energy

When observing absolute frequencies for geothermal energy, all social identities showcase positive sentiment the most, except for political identity, which is more negative. Again, ambiguous sentiment is expressed least. When perceived in a relative manner, for negative sentiment, political (45.6%) occurs most while occupational identity (34.6%) occurs least. Furthermore, positive tweets are posted mostly by accounts containing occupational identity (53.4%) and least by accounts containing political identity (46.3%). For neutral sentiment, most often, no identity (12.3%) can be detected, while political identity (8.8%) is detected least. Lastly, ambiguous sentiment occurs most with relational (3.1%) and cultural identity (3.1%) and occurs relatively least when political (2.0%) is detected.

3.3.3. Hydrogen Energy

When observing absolute frequencies for geothermal energy, all social identities showcase positive sentiment the most. Again, ambiguous sentiment is expressed least. When perceived in a relative manner, it can be seen that for negative sentiment, relational (37.8%) occurs most while non-detected identity (30.7%) occurs least. Furthermore, positive tweets are posted mostly by accounts where no identity can be detected (47.4%), or when identity is detected, political identity is the most prominent (46.3%). On the other hand, relational identity occurs least (44.5%). For neutral sentiment, most often, no identity (20.5%) can be detected, while relational identity (15.2%) is detected least. Lastly, ambiguous sentiment occurs most with relational identity (2.4%) and occurs relatively least when no identity (1.3%) is detected.

3.3.4. Nuclear Energy

When observing absolute frequencies for nuclear energy, all social identities showcase negative sentiment the most. Again, ambiguous sentiment is expressed least. When perceived in a relative manner, for negative sentiment, none-detected identity (62.3%) occurs most, or when identity is detected, relational identity is the most prominent (60.9%). On the other hand, occupational identity (58.4%) occurs least. Furthermore, positive tweets are posted mostly by accounts with occupational identity (26.3%) and least by accounts where no identity can be detected (22.4%). For neutral sentiment, most often, no identity (13.4%) can be detected, while relational identity (12.1%) is detected least. Lastly, ambiguous sentiment occurs most with relational identity (2.4%) and occurs relatively least when no identity (1.8%) is detected.

3.3.5. Wind Energy

When observing absolute frequencies for wind energy, all social identities show negative sentiment the most by a big margin. Again, ambiguous sentiment is expressed least. When perceived in a relative manner, for negative sentiment, cultural identity (79.4%) occurs most while occupational identity (74.4%) occurs least. Furthermore, positive tweets are posted mostly by accounts with occupational identity (13.1%) and least by accounts where cultural identity is detected (9.5%). For neutral sentiment, most often, no identity (11.8%) can be detected, while relational identity (10.1%) and cultural identity (10.1%) are detected least. Lastly, ambiguous sentiment occurs relatively most when no identity (0.9%) can be detected and occurs relatively least when relational identity (0.7%) is detected.

3.3.6. Solar Energy

When observing absolute frequencies for solar energy, all social identities show negative sentiment the most. Again, ambiguous sentiment is expressed least. When perceived in a relative manner, for negative sentiment, political identity (67.4%) occurs most while none-detected identity (55.5%) occurs least. Furthermore, positive tweets are posted mostly by accounts with occupational identity (28.5%) and least by accounts where political identity is detected (19.4%). For neutral sentiment, most often, no identity (15.4%) can be detected, while political identity (11.2%) is detected least. Lastly, ambiguous sentiment occurs relatively most when political identity (1.9%) can be detected and occurs relatively least when no identity (1.2%) is detected.

4. Discussion

The present study aimed to evaluate public opinion toward energy technologies in the Netherlands, utilizing data from Twitter during the 2021 elections. It pursued the research question 'How is sentiment expressed towards green-energy technologies within the Dutch Twitter discourse?'. The findings of the study reveal that the overall sentiment of public opinion towards green-energy technologies is largely negative. This suggests a focus on the shortcomings, limitations, and negative side effects of energy technologies in the online public debate [65,66], rather than their potential opportunities. This result could be amplified by the negativity bias that is present on Twitter, as the platform is characterized by its outspoken and critical users [67], which could lead to overall more negative sentiment. Among the different types of energy technologies that are negative sentiment targets, biomass energy is most frequently discussed in a negative context. In the past, biomass energy has faced criticism for its reliance on the burning of organic matter, such as wood, which has been linked to deforestation and the release of carbon dioxide into the atmosphere, contesting the technology's sustainability [68,69]. These issues may have contributed to negative sentiment towards the energy technology in the Netherlands. On the other hand, geothermal and hydrogen energy are largely discussed positively despite negative sentiment orientation towards energy technologies in general. Geothermal energy is currently still in development in the Netherlands, with a focus on the implementation of private heat pumps [70]. The installation of heat pumps in individual buildings, such as homes, can lead to a sense of ownership of the technology, driving positive attitudes toward it [71]. Hydrogen energy technology is also currently being developed in the Netherlands, with the country aiming at the production of 500 megawatts of green hydrogen by 2024 [24]. The developmental stage of both geothermal and hydrogen energy, in comparison to more established technologies, may contribute to their perceived positivity. Developing energy technologies can be seen as offering potential for innovation and improvement in the energy transition process [72]. This could indicate dissatisfaction with currently feasible and concrete technologies, and a desire for potential options that lie in the future. This correlates with past research, which suggests that evaluating renewables on a more concrete level, as opposed to a more abstract level, decreases acceptance towards the technology [73].

The second research question of this study was 'How are social identity categories expressed among Dutch Twitter users within green-energy technology Twitter discourse?'. It was revealed that a majority of Twitter biographies could not be classified into a specific identity category. This is the case as these biographies may contain elements that pertain to value identity, such as quotes and citations, rather than to social identity. Moreover, users may include individual attributes or interests that do not specifically relate to social identity. Additionally, biographies might be used for self-promotion or linking to other social media accounts. When social identity was discernible, occupational identity was found to be the most prevalent. This prevalence might be attributed to the significance of this aspect of the social self and the ease of conveying it on social media platforms [20,74]. Moreover, occupational social identity was mainly described using words associated with highly educated and white-collar professions. This emphasis on professional status may stem from the importance placed on career achievements and the social status that accompanies these occupations, highlighting a certain level of expertise as well [75,76]. Additionally, the nature of these professions aligns with the discourse-driven and opinion-sharing nature of Twitter. As such, Twitter has been shown to be mainly employed by individuals who have engaged in higher education [75]. In contrast, relational identity was found to be least present, which may be due to it being considered more private or personal in nature [77]. Thus, it may be less likely to be included in a public profile on Twitter. This aligns with the fact that the identity type has mainly been described using words related to immediate family roles. This is likely because immediate family plays a crucial role in shaping social networks and overall sense of belonging [78–80]. Furthermore, the more moderately present cultural identities often related to Dutch nationality and Dutch place heritage. This reflects the significance placed on nationality and heritage as markers of belonging and inclusion within the Dutch political discourse [81]. Moreover, words relating to religion were also used to describe cultural identity. This might be the case as religious identities often shape an individual's value system, guiding their perspectives on various political issues, especially during elections [82]. Lastly, the moderately present identity category of political identity tended to be expressed through general political interest, party affiliations, and left-wing or right-wing associations. This is likely because both political interests and affiliations shape one's perspectives in the political discourse, making them central to one's self-identification in this context [23].

The paper's final research question was 'How does sentiment regarding green-energy technology types vary among social identity categories among Dutch Twitter users?'. The results of a co-occurrence analysis between sentiment and identity revealed that individuals with political identities tend to express the most negative sentiment towards green-energy technologies relatively. This can be attributed to pre-existing biases and agendas, as political identities are often closely aligned with specific political parties or ideologies [83]. As such, political identities have often become tribalized and polarized [84], and when an individual identifies saliently with one of these political identities, they may view those with differing opinions as not just wrong, but as a threat to their values and beliefs [84]. This may lead to increased hostility and animosity in online political discussions. Accordingly, previous research has shown that individuals who hold political identities saliently are more likely to engage in public discussions or debates on social media in an uncivil manner, resulting in a higher frequency of negative tweets about green-energy [85]. On the other hand, individuals with occupational identities tend to express the most positive sentiment towards green-energy relatively. An explanation could be that those with a salient occupational identity may be more concerned with maintaining a positive image and reputation within their professional field [86]. As a result, they may be more cautious about their online behavior and less likely to engage in negative behaviors, such as online arguments. Additionally, the action-orientation embedded within occupational identities may generate an amplified sense of empowerment when considering the prospects of green-energy technologies as practical and tangible solutions to energy issues [87].

In line with the general trend, solar energy is perceived most negatively by users with political identities. This could be attributed to the prevailing discourse surrounding the "solar ladder" in the Netherlands [88], which represents a predefined hierarchy for the placement of solar systems in a policy context. Critics argue that this solar ladder is not being adhered to sufficiently, as the development of solar parks is perceived as being prioritized over the full utilization of roof-based solar panel installations [88,89]. Consequently, this lack of space optimization for solar energy installations has engendered concerns regarding the efficiency and effectiveness of solar energy initiatives within the national energy mix [88].

However, other energy technologies are perceived as relatively negative by users with other social identities. Both biomass and wind energy are both perceived as relatively most negative by Twitter users with cultural identities. This can be attributed to the fact that cultural or place-based identities are closely tied to issues of natural landscape conservation and sustainability [52], which are often key considerations in the development of biomass and wind energy projects [68,90]. For example, individuals with cultural identities may view biomass energy as having negative impacts on the local environment, leading to negative views on the topic. Similarly, wind energy may be viewed as a threat to the natural landscape and wildlife [90], leading to negative perceptions among those with cultural identities. Furthermore, nuclear energy is perceived as most negative by users with relational identity when an identity category is recognized. This might be the case as relational identities often involve a sense of shared responsibility and accountability [91], and the potential for accidents or disasters at nuclear power plants may be seen as a threat to the community as a whole [92]. Furthermore, relational identities may also be influenced by the experiences and perspectives of others within the group or community, and, if there is a shared negative perception of nuclear energy, this may further contribute to a negative attitude towards it [52].

Aligning with the general trend in positivity, geothermal energy is often discussed in a relatively positive light among individuals who identify with occupational roles. This is likely due to the emphasis on private heat-pumps within the Dutch discourse [93]. The heightened action orientation exhibited by individuals with occupational identities may contribute to their positive opinions regarding these private heat-pumps. This can be attributed to the proactive and solution-oriented approach commonly observed within this orientation, which fosters an empowered perception of this future-oriented solution at the individual level [94]. Conversely, discussions surrounding hydrogen energy tend to be most positive among individuals exhibiting political identities when identity categories are recognized. This can be attributed to the more national and communal orientation typically held and expressed by individuals with political identities, particularly during election periods [95]. Given that hydrogen energy is still in its developmental stage, with a primary focus on national-level implementation, concerns regarding its future implementation are more closely tied to national political considerations [96]. This stands in contrast to the more household or individualistic implementation of geothermal energy systems.

These co-occurrence results indicate that, even though there is an overall trend wherein Twitter users with political identities are generally the most negative, and users with occupational identities are predominantly the most positive, this trend does not translate across all specific energy technologies. This discrepancy is likely due to the varying specific implementation effects and circumstances surrounding these energy technologies. This underscores the importance of understanding the nuances and complexities of public opinion and its sentiment towards green-energy technologies and the role of social identity in shaping these perceptions.

Limitations and Suggestions for Future Research

Examining Twitter as a data source for machine learning research on the socio-political dimensions of green-energy technologies presents numerous opportunities but also limitations. One limitation is the potential overemphasis on the representativeness of Twitter data. Although Twitter offers a data-rich platform for exploring public opinion, it is crucial to acknowledge that its user base may not fully reflect the diversity of the general population. As has previously been shown, Twitter users are often skewed towards higher educated and higher income demographics [75]. Furthermore, the findings of the current study should be interpreted with consideration of the evolving nature of social media platforms. Since the completion of this research, Twitter, now known as 'X', has undergone significant changes under new leadership [97], which may influence user behavior, platform algorithms, and the overall discourse. Future research should take into account these platform changes when analyzing 'X' data to ensure the applicability of findings to the current state of public discourse.

In terms of machine learning methodology, the social identity classifier model used in this study employs broad categories that do not account for variations in identity orientations within each category. While providing a broader perspective, it fails to account for variations in identity orientations that may exist within each category. Consequently, the present study could be employed as a starting point for future investigations to benefit from by examining these identity orientations in greater detail. Another limitation is that the study does not differentiate between various forms of the energy technologies analyzed. For instance, there may be variations in sentiment towards solar energy depending on whether it relates to solar parks or private solar panels, due to differing perceptions of ownership [98]. Additionally, while this study focuses exclusively on green-energy technologies, future research could be enriched by comparing green-energy with more conventional energy technologies. Including such a reference could enhance the analysis by providing context for the relative sentiment of green-energy technologies. These limitations regarding the scope of energy sources and the depth of differentiation among technologies can be addressed in future research by utilizing topic modelling techniques to delve deeper into the social identity and energy technology spectra. Lastly, machine learning models in general have been shown to often face challenges in dealing with noise in datasets and nuanced forms of communication, such as irony and sarcasm [99,100]. The models tend to struggle to capture subtle cues and contextual nuances, leading to misclassification or misinterpretation [99]. Future research can mitigate these limitations by fine-tuning the models by incorporating larger and more diverse training datasets. By exposing the models to a wider and cleaner range of linguistic patterns and contextual variations, accuracy can be improved.

5. Conclusions

In conclusion, this study aimed to evaluate the sentiment of public opinion towards energy technologies in the Netherlands by utilizing data from Twitter. The findings revealed that the overall sentiment towards green-energy technologies among the online public is largely negative, with a dominant presence of "anti-voices" in the Dutch Twitter energy technology debate. Additionally, the study found that perceptions of specific technologies might depend on their stage of development. Technologies still under development were generally viewed in a more positive light compared to more established ones. This suggests a level of dissatisfaction with the currently available and applicable technologies, and a longing for potential options that lie in the future. The second goal of the study was to comprehend social identity expression using Twitter profile description data from the Netherlands. When the biographies could be classified into a specific identity category, occupational identity was expressed most prevalently, while relational identity was least present. The co-occurrence results indicate that although there is an overall trend of Twitter users with political identities being most negative and those with occupational identities being most positive, this trend does not translate to specific energy technologies in a relative sense. This is likely due to the variation in specific implementation effects and situations of the technologies. This highlights the importance of understanding the nuances and complexities of public opinion towards green-energy technologies and the role of social identity in shaping these perceptions. These findings have important implications for policymakers and stakeholders in the transition to green-energy, as they suggest that personalizing communication strategies through specific social group engagement may be beneficial in understanding their perspectives on energy technologies. Future research should also focus on the interaction between social identities, value identities, and public sentiment towards energy technologies, to provide a more comprehensive understanding of how these factors shape public opinion. Overall, this study highlights the complexity of understanding public opinion towards energy technologies and the need for a nuanced approach in future research.

Author Contributions: Conceptualization, R.L., S.R.J., B.P.V., J.F.G. and M.d.V.; methodology, R.L., A.K.M. and B.P.V.; software, A.K.M. and R.L.; validation, A.K.M., R.L. and B.P.V.; formal analysis, A.K.M. and R.L.; investigation, R.L.; resources, R.L.; data curation, R.L. and A.K.M.; writing—original draft preparation, R.L., S.R.J. and J.F.G.; writing—review and editing, R.L., S.R.J., B.P.V., J.F.G. and M.d.V.; visualization, R.L.; supervision, S.R.J., B.P.V., J.F.G. and M.d.V.; project administration, R.L.; funding acquisition, R.L., J.F.G., S.R.J. and M.d.V. 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 and python code presented in this study are available on request from the corresponding author. The data and python code are not publicly available due to the protection of privacy of Twitter users.

Acknowledgments: The authors would like to thank Robert Marinescu-Muster from the Behavioural Data Science Incubator (BDSi) at the University of Twente for their support in the data collection, and Maud Pfeiffer for their support in the machine learning model development. Furthermore, the authors would like to thank the reviewers whose suggestions helped improve and clarify this manuscript.

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

Appendix A

Table A1. Search String per Energy Technology.

	Dutch Search String	English Translation of Search String
Solar energy	("Zonneenergie" OR "Zonne-energie" OR "Zonne energie" OR "Zonnepaneel" OR "Zonnepanelen" OR "Zonnepark" OR "Zonneparken" OR "Solarenergie" OR "Zonneboiler" OR "Zonneboilers" OR "Zonnecollector" OR "Zonnecollectoren")	("Solar energy" * OR "Solar panel" OR "Solar panels" OR "Solar park" OR "Solar parks" OR "Solar boiler" OR "Solar boilers" OR "Solar collector" OR "Solar collectors")
Nuclear energy	("Kernenergie" OR "Kern energie" OR "Kerncentrale" OR "Kerncentrales" OR "Nucleaire-energie" OR"Nucleaire energie")	("nuclear power" OR "nuclear energy", "nuclear power plant" OR "nuclear power plants" OR "atomic power" OR "atomic energy")
Wind energy	("Windmolen" OR "Windmolens" OR "Windenergie" OR "Windturbine" OR "Windturbines" OR "Windpark" OR "Windparken" OR "Windmolenpark" OR "Windmolenparken" OR "Wind-energie" OR "Wind energie")	("Windmill" OR "Windmills" OR "Wind energy" ** OR "Wind turbine" OR "Wind turbines" OR "Wind park" OR "Wind parks" OR "Windmill park" OR "Windmill parks")
Hydrogen energy	("Waterstof" OR "Groene waterstof" OR "Waterstofcentrale" OR "Waterstofcentrales")	("Hydrogen" OR "Green hydrogen" OR "Hydrogen plant" OR "Hydrogen plants")
Biomass energy	("Bioenergie" OR "Bio energie" OR "Biomassa" OR "Bio massa" OR "Bio-energie" OR "Biomassacentrale" OR "Biomassacentrales" OR "Biogas" OR "Biocentrale" OR "Biocentrales" OR "Biomassa centrale" OR "Biomassa centrales" OR "Biobrandstof" OR "Biobrandstoffen")	("Bioenergy" OR "Biomass" OR "Biomass power plant" OR "Biomass power plants" OR "Biogas" OR "Bio plant" OR "Bio plants" OR "Biofuel" OR "Biofuels")
Hydropower energy	("Waterkracht" OR "Water kracht" OR "Waterkrachtcentrale" OR "Waterkrachtcentrales" OR "Getijdenenergie")	("Hydropower" OR "Hydropower plant" OR "Hydropower plants" OR "Tidal energy")
Geothermal energy	("Geothermie" OR "Geothermische" OR "Aardwarmte" OR "Warmtepomp" OR "Warmtepompen" OR "Aquathermie")	("Geothermal" *** OR "Ground heat" OR "Heat pump" OR "Heat pumps" OR "Aquathermal energy")

* "Zonneenergie", "Zonne-energie", "Zonne energie", and Solarenergie" are all variations that translate to "Solar energy" in English. ** "Windenergie" and "Wind-energie" are variations that translate to "Wind energy" in English. *** "Geothermische" translates to "Geothermal", but in English, it is often used as an adjective as in "geothermal energy". "Geothermal" alone can also be used as a noun in English to refer to the energy source.

References

1. Rogelj, J.; Elzen, M.; Höhne, N.; Fransen, T.; Fekete, H.; Winkler, H.; Meinshausen, M. Paris agreement climate proposals need a boost to keep warming well below 2 °C. *Nature* **2016**, *534*, 631–639. [CrossRef]
2. MacKinnon, D.; Karlsen, A.; Dawley, S.; Steen, M.; Afewerki, S.; Kenzhegaliyeva, A. Legitimation, institutions and regional path creation: A cross-national study of offshore wind. *Reg. Stud.* **2022**, *56*, 644–655. [CrossRef]
3. Memmott, T.; Carley, S.; Konisky, D. Who participates in energy activism? Profiling political engagement in the United States. *Energy Res. Soc. Sci.* **2021**, *77*, 102095. [CrossRef]
4. Neukirch, M. Protests against German electricity grid extension as a new social movement? A journey into the areas of conflict. *Energy Sustain. Soc.* **2016**, *6*, 4. [CrossRef]
5. Nuortimo, K.; Härkönen, J. Opinion mining approach to study media-image of energy production. Implications to public acceptance and market deployment. *Renew. Sustain. Energy Rev.* **2018**, *96*, 210–217. [CrossRef]
6. Smaliukienė, R.; Monni, S. A step-by-step approach to social marketing in energy transition. *Insights Into Reg. Dev.* **2019**, *1*, 19–32. [CrossRef]
7. Longhurst, N.; Chilvers, J. Mapping diverse visions of energy transitions: Co-producing sociotechnical imaginaries. *Sustain. Sci.* **2019**, *14*, 973–990.
8. Meadowcroft, J. Engaging with the politics of sustainability transitions. *Environ. Innov. Soc. Transit.* **2011**, *1*, 70–75. [CrossRef]
9. Fielding, K.S.; Hornsey, M.J. A Social Identity Analysis of Climate Change and Environmental Attitudes and Behaviors: Insights and Opportunities. *Front. Psychol.* **2016**, *7*, 121. [CrossRef]
10. Fritsche, I.; Barth, M.; Jugert, P.; Masson, T.; Reese, G. A Social Identity Model of Pro-Environmental Action (SIMPEA). *Psychol. Rev.* **2018**, *125*, 245–269. [CrossRef]

11. Jans, L. Changing environmental behaviour from the bottom up: The formation of pro-environmental social identities. *J. Environ. Psychol.* **2021**, *73*, 101531. [CrossRef]
12. Davis, J.L. Identity Theory in a Digital Age. In *New Directions in Identity Theory and Research*; Oxford University Press: Oxford, UK, 2016; pp. 137–164. [CrossRef]
13. Clayton, S.D.; Opotow, S. *Identity and the Natural Environment: The Psychological Significance of Nature*; MIT Press: Cambridge, MA, USA, 2004.
14. 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]
15. Ellemers, N.; Spears, R.; Doosje, B. Self and Social Identity. *Annu. Rev. Psychol.* **2002**, *53*, 161–186. [CrossRef] [PubMed]
16. Hogg, M.A.; Abrams, D. *Intergroup Relations: Essential Readings*; Psychology Press: Abingdon, UK, 2001.
17. Krumpal, I. Determinants of social desirability bias in sensitive surveys: A literature review. *Qual. Quant.* **2013**, *47*, 2025–2047. [CrossRef]
18. Labonte, D.; Rowlands, I.H. Tweets and transitions: Exploring Twitter-based political discourse regarding energy and electricity in Ontario, Canada. *Energy Res. Soc. Sci.* **2021**, *72*, 101870. [CrossRef]
19. Literat, I.; Kligler-Vilenchik, N. Youth collective political expression on social media: The role of affordances and memetic dimensions for voicing political views. *New Media Soc.* **2019**, *21*, 1988–2009. [CrossRef]
20. Priante, A.; Hiemstra, D.; Van Den Broek, T.; Saeed, A.; Ehrenhard, M.; Need, A. #WhoAmI in 160 Characters? Classifying Social Identities Based on Twitter Profile Descriptions. In Proceedings of the NLP + CSS 2016—EMNLP 2016 Workshop on Natural Language Processing and Computational Social Science, Proceedings of the Workshop, Austin, TX, USA, 5 November 2016; pp. 55–65. [CrossRef]
21. 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]
22. Pathak, A.; Madani, N.; Joseph, K. A Method to Analyze Multiple Social Identities in Twitter Bios. *Proc. ACM Hum. -Comput. Interact.* **2021**, *5*, 1–35. [CrossRef]
23. Rogers, N.; Jones, J.J. Using Twitter Bios to Measure Changes in Self-Identity: Are Americans Defining Themselves More Politically Over Time? *J. Soc. Comput.* **2021**, *2*, 1–13. [CrossRef]
24. Ministerie van Algemene Zaken; Ministerie van Economische Zaken en Klimaat. Duurzame Energie. Available online: https://www.rijksoverheid.nl/onderwerpen/duurzame-energie (accessed on 21 May 2021).
25. Lubbe, R. Tweede Kamerverkiezingen 2021. Opiniepanel Rapport. Available online: https://tweedekamer2021.stemwijzer.nl/#/ (accessed on 21 May 2023).
26. Van Vliet, L. Onderzoek: Kernenergie in Nederland. November. 2018, pp. 1–5. Available online: https://eenvandaag.assets.avrotros.nl/user_upload/PDF/Rapportage_kernenergie_panel.pdf (accessed on 21 May 2023).
27. Boudet, H.S. Public perceptions of and responses to new energy technologies. *Nat. Energy* **2019**, *4*, 446–455. [CrossRef]
28. Batel, S.; Devine-Wright, P. Towards a better understanding of people's responses to renewable energy technologies: Insights from Social Representations Theory. *Public Underst. Sci.* **2015**, *24*, 311–325. [CrossRef]
29. Isoaho, K.; Karhunmaa, K. A critical review of discursive approaches in energy transitions. *Energy Policy* **2019**, *128*, 930–942. [CrossRef]
30. 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]
31. Roberts, J.C.D. Discursive destabilisation of socio-technical regimes: Negative storylines and the discursive vulnerability of historical American railroads. *Energy Res. Soc. Sci.* **2017**, *31*, 86–99. [CrossRef]
32. Rosenbloom, D. Framing low-carbon pathways: A discursive analysis of contending storylines surrounding the phase-out of coal-fired power in Ontario. *Environ. Innov. Soc. Transit.* **2018**, *27*, 129–145. [CrossRef]
33. Zhang, S.; Li, Y.; Hao, Y.; Zhang, Y. Does public opinion affect air quality? Evidence based on the monthly data of 109 prefecture-level cities in China. *Energy Policy* **2018**, *116*, 299–311. [CrossRef]
34. Weller, K.; Bruns, A.; Burgess, J.; Mahrt, M.; Puschmann, C. *Twitter and Society*; Peter Lang: New York, NY, USA, 2014. [CrossRef]
35. Bentley, S.V.; Greenaway, K.H.; Haslam, S.A.; Cruwys, T.; Steffens, N.K.; Haslam, C.; Cull, B. Social identity mapping online. *J. Personal. Soc. Psychol.* **2020**, *118*, 213–241. [CrossRef]
36. Buntain, C.; McGrath, E.; Golbeck, J.; LaFree, G. Comparing social media and traditional surveys around the boston marathon bombing. *CEUR Workshop Proc.* **2016**, *1691*, 34–41.
37. Boulianne, S. Social media use and participation: A meta-analysis of current research. *Inf. Commun. Soc.* **2015**, *18*, 524–538. [CrossRef]
38. Fownes, J.R.; Yu, C.; Margolin, D.B. Twitter and climate change. *Sociol. Compass* **2018**, *12*, e12587. [CrossRef]
39. Pilař, L.; Kvasničková Stanislavská, L.; Pitrová, J.; Krejčí, I.; Tichá, I.; Chalupová, M. Twitter Analysis of Global Communication in the Field of Sustainability. *Sustainability* **2019**, *11*, 6958. [CrossRef]
40. Gokulakrishnan, B.; Priyanthan, P.; Ragavan, T.; Prasath, N.; Perera, A. Opinion mining and sentiment analysis on a Twitter data stream. In Proceedings of the International Conference on Advances in ICT for Emerging Regions (ICTer2012), Colombo, Sri Lanka, 2–3 December 2012; pp. 182–188. [CrossRef]

41. Hridoy, S.A.; Ekram, M.T.; Islam, M.S.; Ahmed, F.; Rahman, R.M. Localized twitter opinion mining using sentiment analysis. *Decis. Anal.* **2015**, *2*, 8. [CrossRef]
42. Liu, B.; Zhang, L. A Survey of Opinion Mining and Sentiment Analysis. In *Mining Text Data*; Springer: New York, NY, USA, 2012; pp. 415–463. [CrossRef]
43. Stets, J.E.; Burke, P.J. Identity Theory and Social Identity Theory. *Soc. Psychol. Q.* **2000**, *63*, 224. [CrossRef]
44. Tajfel, H. *Human Groups and Social Categories: Studies in Social Psychology*; Cambridge University Press: Cambridge, UK, 1981.
45. Turner, J.C.; Hogg, M.A.; Oakes, P.J.; Reicher, S.D.; Wetherell, M.S. *Rediscovering the Social Group: A Self-Categorization Theory*; Basil Blackwell: Oxford, UK, 1987.
46. Stryker, S. *Symbolic Interactionism: A Social Structural Version*; Benjamin-Cummings Publishing Company: San Francisco, CA, USA, 1980.
47. Stryker, S.; Serpe, R.T. Identity Salience and Psychological Centrality: Equivalent, Overlapping, or Complementary Concepts? *Soc. Psychol. Q.* **1994**, *57*, 16. [CrossRef]
48. Beller, C.; Knowles, R.; Harman, C.; Bergsma, S.; Mitchell, M.; Van Durme, B. I'm a Belieber: Social Roles via Self-identification and Conceptual Attributes. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Baltimore, MD, USA, 22–27 June 2014; Volume 2, pp. 181–186. [CrossRef]
49. Semertzidis, K.; Pitoura, E.; Tsaparas, P. How people describe themselves on twitter. In Proceedings of the ACM SIGMOD Workshop on Databases and Social Networks, DBSocial 2013, New York, NY, USA, 25–30 June 2013. [CrossRef]
50. Gifford, R.; Nilsson, A. Personal and social factors that influence pro-environmental concern and behaviour: A review. *Int. J. Psychol.* **2014**, *49*, 141–157. [CrossRef]
51. Knez, I. Toward a Model of Work-Related Self: A Narrative Review. *Front. Psychol.* **2016**, *7*, 331. [CrossRef]
52. Wüstenhagen, R.; Wolsink, M.; Bürer, M.J. Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy* **2007**, *35*, 2683–2691. [CrossRef]
53. Rocque, M.; Posick, C.; Paternoster, R. Identities Through Time: An Exploration of Identity Change as a Cause of Desistance. *Justice Q.* **2016**, *33*, 45–72. [CrossRef]
54. Liu, K.; Xu, L.; Zhao, J. Co-Extracting Opinion Targets and Opinion Words from Online Reviews Based on the Word Alignment Model. *IEEE Trans. Knowl. Data Eng.* **2015**, *27*, 636–650. [CrossRef]
55. Van Holsteyn JJ, M.; Irwin, G.A. The Dutch Parliamentary elections of March 2021. *West Eur. Politics* **2022**, *45*, 1493–1505. [CrossRef]
56. Assenmacher, D.; Fröhling, L.; Wagner, C. You are a Bot!—Studying the Development of Bot Accusations on Twitter. *arXiv* **2023**, arXiv:2302.00546.
57. Llewellyn, C.; Cram, L.; Hill, R.L.; Favero, A. For Whom the Bell Trolls: Shifting Troll Behaviour in the Twitter Brexit Debate. *JCMS J. Common Mark. Stud.* **2019**, *57*, 1148–1164. [CrossRef]
58. Birnholtz, J.; Merola, N.A.R.; Paul, A. Is it Weird to Still Be a Virgin. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems 2015, Seoul, Republic of Korea, 18–23 April 2015; pp. 2613–2622. [CrossRef]
59. Perbawani, P.S.; Rahayu, R.; Anshari, I.N. Netizens Anonymity in Indonesia's Digital Democracy: Political Participation in Social Media According to the Online Disinhibition Effect Theory. *PCD J.* **2018**, *6*, 185. [CrossRef]
60. Rosenberry, J. Users Support Online Anonymity despite Increasing Negativity. *Newsp. Res. J.* **2011**, *32*, 6–19. [CrossRef]
61. Gond, V.K.; Dubey, A.; Rasool, A. A Survey of Machine Learning-Based Approaches for Missing Value Imputation. In Proceedings of the 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2–4 September 2021; pp. 1–8. [CrossRef]
62. Goyal, N.; Du, J.; Ott, M.; Anantharaman, G.; Conneau, A. Larger-Scale Transformers for Multilingual Masked Language Modeling. In Proceedings of the 6th Workshop on Representation Learning for NLP (RepL4NLP-2021), Online, 6 August 2021; pp. 29–33. [CrossRef]
63. Laconi, P. Buitenlandse Investeerders Gaan er Vandoor Met Miljoenensubsidies én Winst van Zonneparken. Het AD. 2021. Available online: https://www.ad.nl/economie/buitenlandse-investeerders-gaan-er-vandoor-metmiljoenensubsidies-en-winst-van-zonneparken~a3f41bf9/ (accessed on 25 January 2023).
64. Feinerer, I.; Hornik, K.; Meyer, D. Text Mining Infrastructure in R. *J. Stat. Softw.* **2008**, *25*, 1–54. [CrossRef]
65. Markard, J. The next phase of the energy transition and its implications for research and policy. *Nat. Energy* **2018**, *3*, 628–633. [CrossRef]
66. Scovell, M.D. Explaining hydrogen energy technology acceptance: A critical review. *Int. J. Hydrog. Energy* **2022**, *47*, 10441–10459. [CrossRef]
67. Hagemann, L.; Abramova, O. Sentiment, we-talk and engagement on social media: Insights from Twitter data mining on the US presidential elections 2020. *Internet Res.* 2023; *advance online publication*. [CrossRef]
68. Paletto, A.; Bernardi, S.; Pieratti, E.; Teston, F.; Romagnoli, M. Assessment of environmental impact of biomass power plants to increase the social acceptance of renewable energy technologies. *Heliyon* **2019**, *5*, e02070. [CrossRef]
69. Sociaal-Economische Raad SER. Biomassa in Balans: Een Duurzaamheidskader voor Hoogwaardige Inzet van Biogrondstoffen. 2020. Available online: https://www.ser.nl/-/media/ser/downloads/adviezen/2020/biomassa-inbalans.pdf?la=nl&hash=6E441F5E399C6398278A5B07D28E9146 (accessed on 10 January 2023).

70. Kieft, A.; Harmsen, R.; Hekkert, M.P. Heat pumps in the existing Dutch housing stock: An assessment of its Technological Innovation System. *Sustain. Energy Technol. Assess.* **2021**, *44*, 101064. [CrossRef]
71. Beauchampet, I.; Walsh, B. Energy citizenship in the Netherlands: The complexities of public engagement in a large-scale energy transition. *Energy Res. Soc. Sci.* **2021**, *76*, 102056. [CrossRef]
72. Sovacool, B.K.; Brossmann, B. Fantastic Futures and Three American Energy Transitions. *Sci. Cult.* **2013**, *22*, 204–212. [CrossRef]
73. Sütterlin, B.; Siegrist, M. Public acceptance of renewable energy technologies from an abstract versus concrete perspective and the positive imagery of solar power. *Energy Policy* **2017**, *106*, 356–366. [CrossRef]
74. Ulfsdotter Eriksson, Y.; Linde, M. "Being" or "Doing" a Profession: Work as a Matter of Social Identity. *Int. J. Interdiscip. Cult. Stud.* **2014**, *8*, 33–43. [CrossRef]
75. Blank, G. The Digital Divide Among Twitter Users and Its Implications for Social Research. *Soc. Sci. Comput. Rev.* **2017**, *35*, 679–697. [CrossRef]
76. Della Giusta, M.; Jaworska, S.; Vukadinović Greetham, D. Expert communication on Twitter: Comparing economists' and scientists' social networks, topics and communicative styles. *Public Underst. Sci.* **2021**, *30*, 75–90. [CrossRef]
77. Sluss, D.M.; Ashforth, B.E. Relational Identity and Identification: Defining Ourselves Through Work Relationships. *Acad. Manag. Rev.* **2007**, *32*, 9–32. [CrossRef]
78. Cooper, C.R.; Grotevant, H.D.; Condon, S.M. Individuality and connectedness in the family as a context for adolescent identity formation and role-taking skill. *New Dir. Child Adolesc. Dev.* **1983**, *22*, 43–59. [CrossRef]
79. Hagerty, B.M.; Williams, R.A.; Oe, H. Childhood antecedents of adult sense of belonging. *J. Clin. Psychol.* **2002**, *58*, 793–801. [CrossRef]
80. Wellman, B. The Place of Kinfolk in Personal Community Networks. *Marriage Fam. Rev.* **1990**, *15*, 195–228. [CrossRef]
81. Reekum, R. As nation, people and public collide: Enacting Dutchness in public discourse. *Nations Natl.* **2012**, *18*, 583–602. [CrossRef]
82. Aschbach, M.; Lüddeckens, D. Religion on Twitter Communalization in Event-Based Hashtag Discourses. *Heidelb. J. Relig. Internet* **2019**, *14*, 108–130.
83. Lin, M.-C.; Haridakis, P.M. The Impact of Political Identity and Outgroup Partisan Media Contact on Intergroup Bias and Unwillingness to Compromise with the Opposing Party: An Intergroup Threat Approach. *Mass Commun. Soc.* **2022**, *25*, 698–720. [CrossRef]
84. Mason, L.; Wronski, J. One Tribe to Bind Them All: How Our Social Group Attachments Strengthen Partisanship. *Political Psychol.* **2018**, *39*, 257–277. [CrossRef]
85. Jaidka, K.; Zhou, A.; Lelkes, Y. Brevity is the Soul of Twitter: The Constraint Affordance and Political Discussion. *J. Commun.* **2019**, *69*, 345–372. [CrossRef]
86. Afshari, L.; Young, S.; Gibson, P.; Karimi, L. Organizational commitment: Exploring the role of identity. *Pers. Rev.* **2020**, *49*, 774–790. [CrossRef]
87. Jiang, Y.; Zhan, L.; Rucker, D.D. Power and Action Orientation: Power as a Catalyst for Consumer Switching Behavior. *J. Consum. Res.* **2014**, *41*, 183–196. [CrossRef]
88. Wiebes, E.D. Kamerbrief Moties Dik-Faber over Zonneladder als Nationaal Afwegingskader bij Inpassing van Zonne-Energie. 2019. Available online: https://www.rijksoverheid.nl/onderwerpen/duurzameenergie/documenten/kamerstukken/2019/08/23/beantwoording-moties-dik-faber-over-een-zonneladder-als-nationaal-afwegingskader-bijinpassing-van-zonne-energie (accessed on 10 January 2023).
89. Moraitis, P.; Kausika, B.; Nortier, N.; van Sark, W. Urban Environment and Solar PV Performance: The Case of the Netherlands. *Energies* **2018**, *11*, 1333. [CrossRef]
90. Devine-Wright, P.; Howes, Y. Disruption to place attachment and the protection of restorative environments: A wind energy case study. *J. Environ. Psychol.* **2010**, *30*, 271–280. [CrossRef]
91. Kleespies, M.W.; Dierkes, P.W. Exploring the Construct of Relational Values: An Empirical Approach. *Front. Psychol.* **2020**, *11*, 209. [CrossRef]
92. Xia, D.; Li, Y.; He, Y.; Zhang, T.; Wang, Y.; Gu, J. Exploring the role of cultural individualism and collectivism on public acceptance of nuclear energy. *Energy Policy* **2019**, *132*, 208–215. [CrossRef]
93. CBS. Steeds Meer Warmtepompen Bij Woningen. 2022. Available online: https://www.cbs.nl/nlnl/nieuws/2022/40/steeds-meer-warmtepompen-bij-woningen (accessed on 23 January 2023).
94. Van Putten, M.; Zeelenberg, M.; Van Dijk, E. Dealing with missed opportunities: Action vs. state orientation moderates inaction inertia. *J. Exp. Soc. Psychol.* **2009**, *45*, 808–815. [CrossRef]
95. Knudsen, M.S.; Christensen, H.S. Future Orientation and Political Participation: The Moderating Role of Political Trust. *Front. Political Sci.* **2021**, *3*, 791467. [CrossRef]
96. Ministerie van Algemene Zaken; Ministerie van Economische Zaken en Klimaat. Stimulering Gebruik van Waterstof. Available online: https://www.rijksoverheid.nl/onderwerpen/duurzame-energie/overheid-stimuleert-de-inzet-vanmeer-waterstof (accessed on 13 June 2023).
97. Stokel-Walker, C. Why is Twitter becoming X? *New Sci.* **2003**, *259*, 9. [CrossRef]
98. Jenkins KE, H. Energy Justice, Energy Democracy, and Sustainability: Normative Approaches to the Consumer Ownership of Renewables. In *Energy Transition*; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 79–97. [CrossRef]

99. Caiafa, C.F.; Solé-Casals, J.; Marti-Puig, P.; Zhe, S.; Tanaka, T. Decomposition Methods for Machine Learning with Small, Incomplete or Noisy Datasets. *Appl. Sci.* **2020**, *10*, 8481. [CrossRef]
100. Sulis, E.; Irazú Hernández Farías, D.; Rosso, P.; Patti, V.; Ruffo, G. Figurative messages and affect in Twitter: Differences between #irony, #sarcasm and #not. *Knowl. Based Syst.* **2016**, *108*, 132–143. [CrossRef]