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Getting emotional or cognitive on social media? Analyzing renewable energy technologies in Instagram posts

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ABSTRACT

Renewable energy development is a widely and intensively discussed topic, though it is still unclear which exactly variables may influence people's evaluation of the phenomenon. There is a need to study the general public's knowledge, emotions, and cognitions linked to energy technologies especially in the context of advanced inventions. Social media is a powerful communication tool which has a huge impact on studying public opinions. This study aims to describe linguistic connections through an analysis of 1500 Instagram posts, assuming and interpreting emotional and/or cognitive words. Using a socio-cognitive approach, this research explores the salient words under a set of pre-specified renewable energy technology (RET) hashtags. Building on the appraisal theories of emotions, this research investigates the coexistence of several energy technologies (solar, wind, biomass, and geothermal) and powerlines. The results showed the highest linguistic interconnection between solar and wind energy posts. Furthermore, powerlines were not linguistically connected to the RETs, as they are not included in the schema or not salient when people write posts about renewable energy. Solar, wind, and geothermal posts evoked more emotional and positive emotions than the other RETs and powerlines. Instead, biomass posts had a high frequency of cognitive processes and causal words. Powerline posts were linked to the words of risk, body, health, and biological process showing a great concern for health and perceived threat. These differences in the words used can be a guide to understanding peoples' reactions and communication for each of the energy sources. This study, taking both emotions and cognitions into account, explains different types of considerations towards energy projects.

1. Introduction

Renewable energy technologies (RETs) increasingly penetrate people's daily lives and lead to emotions and cognitions that may eventually influence attitudes towards renewable energy [1]. Sustainable energy transition is not a purely technological endeavour, but it has a prominent social dimension and requires public support to be successfully achieved [2]. In light of research on dual-process models of information processing [3], recent models have proposed that behavior stems from emotional reactions or affective feelings about cognitive beliefs of a topic [4]. Affective and cognitive evaluations are interactive such that affective evaluations can precede cognitive evaluations and vice versa [5]. Emotions and cognition have played an important role in the study of energy transition analyzing the predictors to accept energy technologies [6] or the emotional and cognitive response to energy systems [7]. Other studies have assessed the cognitive aspects of acceptance for RETs in terms of political attitudes (e.g. [8]), process-related effects (e.g. [9]), and perceived side effects (e.g. [10]). Furthermore, if people experience certain emotions towards energy projects this may influence their cognitive evaluations of these projects, a phenomenon known since 2007 as Affect Heuristic [11]. These results emphasize the importance of including both affective and cognitive factors when studying the social consideration of energy technologies and energy-related behaviors (e.g. [12,13]). In fact, emotions and cognition-related variables have an explanatory power in relation to energy-related decisions [14]. Affective reactions to energy technologies influence the way people look for

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information, their energy technology preferences, and the behavioral responses to energy projects [15].

Social media are an arena for public emotions and cognitions and for this reason we have used a media platform as a source of information. Many existing studies rely on surveys and interviews to understand public perception of renewable energy [16]. Although surveys and interviews can provide targeted individual level data, they can be susceptible to selection and response biases [17]. Furthermore, social media platforms can offer several types of interactions and, consequently, different levels of analysis. For example, distinct communication channels permit users to build various explicit or implicit social relationships [18], as well as real or implicit information [19]. By posting on Instagram, people can share the complexity of their emotional words and concepts to a wider audience in an intuitive way [20]. Instead, Instagram can be a driver of the use of renewable energy, having a role not only in perceptions of various technologies but also influencing people's intentions to use renewable energy sources [21]. One of the technique used on social media for studying emotions is Sentiment Analysis natural language processing dealing with the detection and classification of sentiments in texts into several classes of emotions and cognitions [22]. Building on the appraisal theories of emotions [23] and with the help of the Linguistic Word Count (LIWC) software [24], this research evaluates the text of Instagram posts. The appraisal theories of emotion assume that emotions are elicited by a person's appraisal of events with regard to his or her concerns. Appraisal criteria involved in eliciting emotion include the novelty and pleasantness of events, their controllability and evaluation.

The paper presents a Socio-Cognitive Approach (SCA) to the language on the Instagram posts. The SCA is issue-oriented and able to investigate relevant social problems focusing on the relations between discourse and society in a critical approach of studying text and talk conversations [25]. SCA is based on the role of salience in language production. This means that when a person is faced with having to choose a word, a ranking of the available choices is obtained and the word is selected for utterance on the basis of maximum salience [26].

Research on energy transition often focuses on the study of the impact of one renewable energy source (e.g., [27]), or on the relationship between two energy technologies and their support/opposition (e.g., [28]). Instead, the following research proposes a combined approach in which RETs, powerlines, and their ties are the major factors of the study, considering a systemic picture of the coexistence of the technologies.

The remainder of this article is structured as follows: in Section 2, *Theoretical background*, we address some prevailing theories on the word associations with a socio-cognitive approach to the language used in Instagram posts. Furthermore, the appraisal theory of the emotions was discussed with the aim of emphasizing the relevance of emotional and cognitive connotations in the context of renewable transition. Then, studies on communication and social media platforms provided insight into the opportunities that social media platforms offer to examine the dynamics of social perceptions of energy issues. Section 3, *Method and procedures*, explains the methodology used from the data scraping of the Instagram posts to the analytical procedure of text analysis by keyword analysis (with the frequency observation) and sentiment analysis (with LIWC). Section 4, *Results*, shows the findings of the analyses on the dataset, explaining them by referring to the research hypotheses. Section 5, *Finding overview and discussion*, presents an overview of the results and their discussion also referring to scientific literature, as well as the limitations of the study and future research ideas.

2. Theoretical background

2.1. Appraisal theory

All forms of RETs have environmental impacts, and their potential impacts on wildlife as well as on the evaluation and reaction to RETs have been the subject of multiple studies (e.g., [29]). Scholars have analyzed the affective and cognitive side of decision-making regarding energy projects (e.g., [30]), especially when the context is complex and uncertain [11]. According to appraisal theory "*emotional components are caused and differentiated by an appraisal of the stimulus as mis/matching with goals and expectations, as easy/difficult to control, and as caused by others, themselves or impersonal circumstances*". [31]. This theory pointed out that different appraisals can elicit several types of emotions (e.g., [1]). However, the question remains which emotions are aroused from which energy technologies and if there are RETs that elicit more emotional aspects than cognitive ones (and vice versa). We propose that taking both emotions and cognitions into account can help explain different types of considerations towards energy projects.

The relevance of emotional and cognitive connotations in the context of renewable transition is given by the complexity of the topic of energy supply. The public attitudes towards RETs can additionally be influenced by affect [32], emotional connotations of the energy source and its infrastructure, such as the perception of risks and uncertainty [33]. Furthermore, the salience of emotional and cognitive aspects depend on 1) the direct (perceived) effect that a RET technology has on a person; 2) the idea of what that specific RET means for the self-well-being; 3) the potential coping perceived. Thus, people may perceive little or no control over the occurrence of energy projects and this can lead to negative emotions (e.g. fear, anger, etc.) [1] and 4) the perception of energy projects elicit morality-based emotions.

As highlighted in the SCA, the interrelations between emotions and language have achieved a significant scope and diversification [26]. Through a close attention to language, a schema can be reconstructed that systematically shows the relationships between concepts and experiences represented in written messages. It has been shown that there is a fundamental relationship between the structures of mental life and the production of written and/or verbal discourse [34]. The terms people use in their daily lives can provide important information about their beliefs, attitudes, and social relationships. Thus, mental associations imply proximity to other schema of words in the mind with cognitive, emotional, or neutral connotations. Mental representations are important and decisive because they reflect realities and perceptions which influence the decision for or against a specific energy supply solution and project [35]. Social media offers the manifestation, interpretation, and processing of emotions using natural conversations. Social media also cultivates massive public opinions through emotional and cognitive words. Online platforms, such as Instagram, allow free social interactions and provide a lens to investigate competing views on various energy-related public issues [17].

We hypothesize that there are differences in the words used to describe energy technologies on Instagram posts because there are different emotions and experienced cognitions underlying each RET. Going more into details, we hypothesize that solar and wind energies are more linked to emotional words than the other RETs. A possible reason could be that people perceive wind energies as the most intrusive and this can rouse emotional reactions. Alternatively, solar energy is well-known and usually it is accompanied by high consensus and positive feelings. We hypothesize that powerlines, biomass, and geothermal evoke cognitive words, especially related to the physical aspect, biological process, and risk, assuming that people may include a greater concern of health thinking of biomass, geothermal, and powerlines.

2.2. Communication, social media platforms, and energy transitions

The formation of public opinion has been conceptualized as a multilayered process, involving not only interpersonal communication among individuals, but also mass communication over media platforms [36]. Studies on communication and change of attitude describe the switch of perception or opinion, in terms of cognitive, affective, and (or) behavioral towards the "*attitude object*" [37]. A high number of researchers on energy transitions have used different social media platforms as data sources. Social media provides an opportunity to examine the dynamics of social perception of energy issues (such as emerging technologies, energy conservation, and environmental impacts). Furthermore, social media contains temporal, spatial, relational and contextual information that may be leveraged to represent and examine the dynamics of social perception on energy topics [38]. Nuortimo and Härkönen [39] studied the opinion mining approach to media-image of energy production with implications to public acceptance and market deployment. The findings support the notion of social media having an increasing role in shaping public opinion, which may need to be acknowledged largely from all the institutions, public, and governments that could use this information appropriately. Kim et al. [16] proposed a word network model in social media services and conducted a network analysis for examining the public perceptions of renewable energy resources. The results showed that the network model in social networking services could obtain latent and usually social, industrial, economic, and environmental issues related to renewable energies.

Insights from social psychology indicate that familiarity with an object influences preference formation, which in turn influences choices [40]. Several researchers illustrate that familiarity with energy technology is correlated with the social acceptance of renewable energy. Attitudes follow a U-shaped curve, in which projects initially show high acceptance levels but drop in their local acceptance rates during the permitting and construction phase [41]. Research studies suggested that local newspapers play a significant role in the RET perception. (e.g., [42]). More generally, TV and social media platforms are the main source of information about renewable energy, and only sometimes people have personally seen or visited RET farms [43]. The way in which this information is shaped influences the people's perception and evaluation of RETs. Thus, this study using a social media platform, gives an overview of the description of different energy technologies.

2.2.1. Instagram

Instagram is the fifth most used social media platform worldwide with nearly 1.3 billion active users [44]. Instagram has a growing role in shaping public opinion and is a virtual place where people share their beliefs and emotions with others. The advantages of using Instagram for this research are: i) the number of words used in the caption is unlimited, contrary to other platform (e.g. Twitter) and this is an important advance for the purpose of this research based on the text analysis; ii) Instagram is known for the strong use of hashtags, both as a description of a picture/video and as a search term for particular topics [45]. The extensive use of hashtags allows us to study the set of words associated with RET descriptions; iii) Instagram as web source has never been used for the studying of RETs. Aware of the fact that Instagram is social media for sharing videos and pictures as well as text, we want to clarify that the analyses of this paper are focused on the analytical procedure of the text and not on the analyses of the images. A good understanding of the public's affective reactions and communication elicited by energy technologies is crucial to anticipate signs of public concern. The developer, for example, can communicate directly with consumers through blogs, online content, and videos with the keyword language used by consumers [46].

2.3. Word associations in a socio-cognitive approach

An assumption of theories of memory and association is that the meaning of a word can be represented by a vector which places a word as a point in a multidimensional semantic space [47]. It is common practice in linguistics (e.g. [48]) to classify words not only on the basis of their meanings but also on the basis of their co-occurrence considering the probability of observing "*x*" and "*y*" together.

This paper presents a SCA to the language used in Instagram posts by investigating the interconnection between the salient words referring to RET hashtags. In SCA, language production and interpretation are governed by the mechanism of salience. A sign can be interpreted as a measure of how well an element stands out from other entities, and how it influences the preference of the individual in selecting words and constructs in the process of communication, considering the degree of familiarity, frequency, and conventionality [26]. By socio-cognitive processes, we refer to those group-level factors known to moderate human decision making [49]. This study based on the word and sentiment associations between RETs and powerlines gives information such as opinions, attitudes, and feelings expressed in text (whether the semantic orientation in positive, negative or neutral classification words).

2.4. Aims and hypotheses

This work aims to study two main points: 1) the co-occurrence of words referring to RETs; 2) to what extent people express emotions and cognitions writing about RETs. The research questions that this study seeks to answer are[1]: Is there a repeated language association between some RETs and powerlines? Which are the emotions/cognitions associated with the language description of RETs and powerlines?

Starting from the idea that there is a complementary thinking of RETs and powerlines (mentally organized as a single mental block connected to each other), our first group of hypothesis is that solar and wind energies are more interconnected, belonging to the same category. These assumptions have been developed based on a review of the literature on RETs and power lines. We expect more interconnection between wind and solar energies and the reasons could be given by their greater visibility, familiarity, and knowledge than other RETs. Thus, more familiar a person is with the RET farms, the more positively they are likely to support the RET development [50]. On the other hand, there are different physical aspects of the technologies that create people's argumentations and opinions. For example, the impact on the landscape causes visual intrusions (e.g., [51]) and reduces the quality of the recreational area (e.g., [52]). The effects on wildlife have also been the reason for great criticism, as well as the construction on the local environment as on land use (e.g., [53]). These and many others are the critical components on the social acceptance of wind energy infrastructure. Instead, solar energy has a broad distribution, even though it is not conflict-related, as wind energy. We hypothesized that these two RETs evaluate bigger stimulus than the others and are mentally strong interconnected.

Hypothesis 1. Different RETs are often named with each other.

H 1.1. #windenergy Instagram posts have a higher frequency of words with reference to solar energy and vice versa than #powerlines, #biomass, and #geothermalenergy.

H 1.2. In the #renewableenergy posts, wind and solar energies and powerlines have higher frequency of words that refer to each other than #biomass and #geothermalenergy.

According to appraisal theory, the emotional components are caused by an appraisal of the stimulus, goals, expectations, control, and circumstances [31]. When confronted with a stimulus of renewable energy, people ask themselves questions such as: "Does this affect me directly?" "What does it mean for my well-being?" "Can I face the challenge?" The answers to these questions will shape the congruency with moral considerations and, consequently, the approach/evaluation/feeling towards RETs. The research hypotheses of this study are built on the statement that different RETs elicit different emotions and there are some energy technologies that evoke more emotional than cognitive aspects. We hypothesize that solar and wind energies are more related to emotional words than other RETs. One possible reason could be that people

[1] The following research has been pre-registered on https://aspredicted.org/create.php and made public on September 14th 2020. The .pdf is available from https://aspredicted.org/mz9ti.pdf.

perceive wind energy as the most intrusive (height, colour, noise, etc.), but also evaluate it with positive aspects (economic, environmental, etc.) and this may elicit emotional reactions. Alternatively, solar energy is well known and is usually accompanied by high acceptance and positive evaluations. The appraisal of powerlines, biomass, and geothermal evoke cognitive words, especially related to the physical aspect, biological process, and risk, assuming that people may include a greater concern of health. On the basis of the literature, the following hypotheses have been proposed.

Hypothesis 2. Different RETs are linked to distinct emotions and cognitions.

H 2.1. #windenergy Instagram posts contain more emotional than cognitive words.

H 2.2. #solarenergy and #windenergy Instagram posts contain more words of affective process and positive emotions than #powerlines, #biomass, and #geothermalenergy.

H 2.3. #powerlines Instagram posts contain more words of power, health, and risk than #windenergy, #solarenergy, #biomass, and #geothermalenergy.

H 2.4. #biomass Instagram posts contain more words of body and biological process than #windenergy, #solarenergy, #powerlines, and #geothermalenergy.

H 2.5. #geothermalenergy Instagram posts contain more words of cognitive process, insight, and causation than #windenergy, #solarenergy, #powerlines, and #biomass.

3. Method and procedures

This study provides an account of co-occurrence, emotional, and cognitive words elicited by wind, solar, geothermal energies, powerlines, and biomass on Instagram using the text available in published posts. The method used to collect and analyse the data followed a precise scheme shown in Fig. 1.

First, Instagram posts were scraped with R version 4.0.0, package Jsonlite version 1.6.1. The analytical procedure to analyse the text had two main steps: 1) the frequency method analysis with the keywords; and 2) the sentiment analysis by the LIWC2015 tool with the hashtag and caption text. The frequency was statistically investigated through the one-way within-subjects ANOVA and chi-test on JASP 0.12.2.0. The following paragraphs explain in detail all the phases of the method.

3.1. Data source: scraping data from Instagram posts

The 1500 posts (250 for each hashtag) used in this study were scraped from public Instagram accounts (without privacy restrictions) on 17th September 2020. We chose to sample 250 posts for each hashtag because we expected a small effect size (see for example [54]). An important clarification is that on Instagram the data can be scraped for free only selecting a specific number of posts, not following a day-frame. Furthermore, the data collection by time series was not possible considering that the number of posts published is very different depending on the day and this means that it would not be possible to have a comparison between the RETs. For having the same number of posts, the dataset was filtered on "recent"[2] not on "most popular" posts at the moment of scraping. We used the "*following the hashtag*" method for scraping data (instead of the "*following people*" method in which one or more public accounts are attained). In this way, all published posts containing the selected hashtags in the caption are obtained. Only posts written in English were taken in the analyses. To respect users' privacy, the public contents (in which there are no privacy restrictions) have been taken into consideration.

3.2. Sample description

The sample is composed of 1500 posts and 82,616 words (see Fig. 1 for more details on the number of words in each hashtag), 250 posts for each hashtag which are #windenergy, #solarenergy, #biomass, #geothermalenergy, #powerlines, #renewableenergy. In detail, the length of the 1500 posts is M = 63.72 and SD = 51.72. The length varies from M = 47.56 for the #powerlines posts to M = 73.26 for the #windenergy posts. In addition, we made another validation step, scraping the 30% of the posts, for a total of 450 posts. We evaluated them with regard to their length. In this case, the length of the posts is M = 67.8 and SD = 49.15. To provide a criterion for the assessing lexical richness, we calculated the type/token ratio (TTR) in the text for each selected hashtag. In detail, the TTR of the 1500 posts is TTR = 19.06. The TTR varies from TTR = 5.56 for #powerlines posts to TTR = 34.41 for #renewableenergy.

Posts that contained more than one hashtags among the chosen ones were scraped for all hashtags contained, if these posts were among the 250 most recent ones. We decided to use these specific RET hashtags (wind, biomass, geothermal) because they have a strong local penetration, becoming subjects with high consideration and discussion by the communities [55]. Solar was added due to its broad distribution even though it is not conflict related as the others. Powerlines are central for energy infrastructure and often contested, thus also included. To gain an overall overview, we integrated the hashtag #renewableenergy.

Fig. 2 shows an Instagram post as an example and it contains a picture, an ID name, a place in the geotag, and a caption.

3.3. Analytical procedure

3.3.1. Keyword analysis with the frequency analysis observation

The co-occurrence analysis aims to find similarities in meaning between and within word patterns, in order to discover latent structures of mental representation [56]. In this research, the frequency of keywords has been observed in the text of Instagram posts. The keywords are words that have been selected to analyse the frequency of times a renewable energy was named in the posts. The words inserted are the nouns used in reference to specific RET (see Fig. 1). The keywords were selected by analyzing Instagram posts and papers referring to the RETs. The goal was to identify the different words used for naming the RETs and a document was prepared with the frequency of times the keywords were named in the text. The authors discussed and chose the keywords following a specific schema: 1) selecting the keywords named in the text with the highest frequency of occurrence; 2) having for each hashtag the same number of keywords; 3) trying to use (when possible) for each hashtag similar words (for example, using the word power for each keyword). In the end, five keywords have been chosen for each hashtag. The frequency was statistically investigated through the one-way within-subjects ANOVA (H1.1) and chi-test (H1.2) on JASP 0.12.2.0. Appendix A shows the descriptive statistics of all the keywords of each hashtag.

3.3.2. Sentiment analyses with LIWC

Broadly, there exist two types of methods for sentiment analysis: machine-learning-based and lexical-based. While one advantage of learning-based methods is their ability to adapt and create trained models for specific purposes and contexts, their drawback is the availability of labeled data and hence the low applicability of the method on new data. Instead, lexical-based methods make use of a predefined list of words, where each word is associated with a specific sentiment. In this research, the LIWC software was used for analyzing the hashtag and caption texts of Instagram posts, version 2015 English dictionary. The LIWC is an example of a popular tool in the literature (e.g., cited and

[2] The 250 posts scraped of each hashtag have been posted on the same day. No hashtags had less than 250 posts on the day of the scraping.

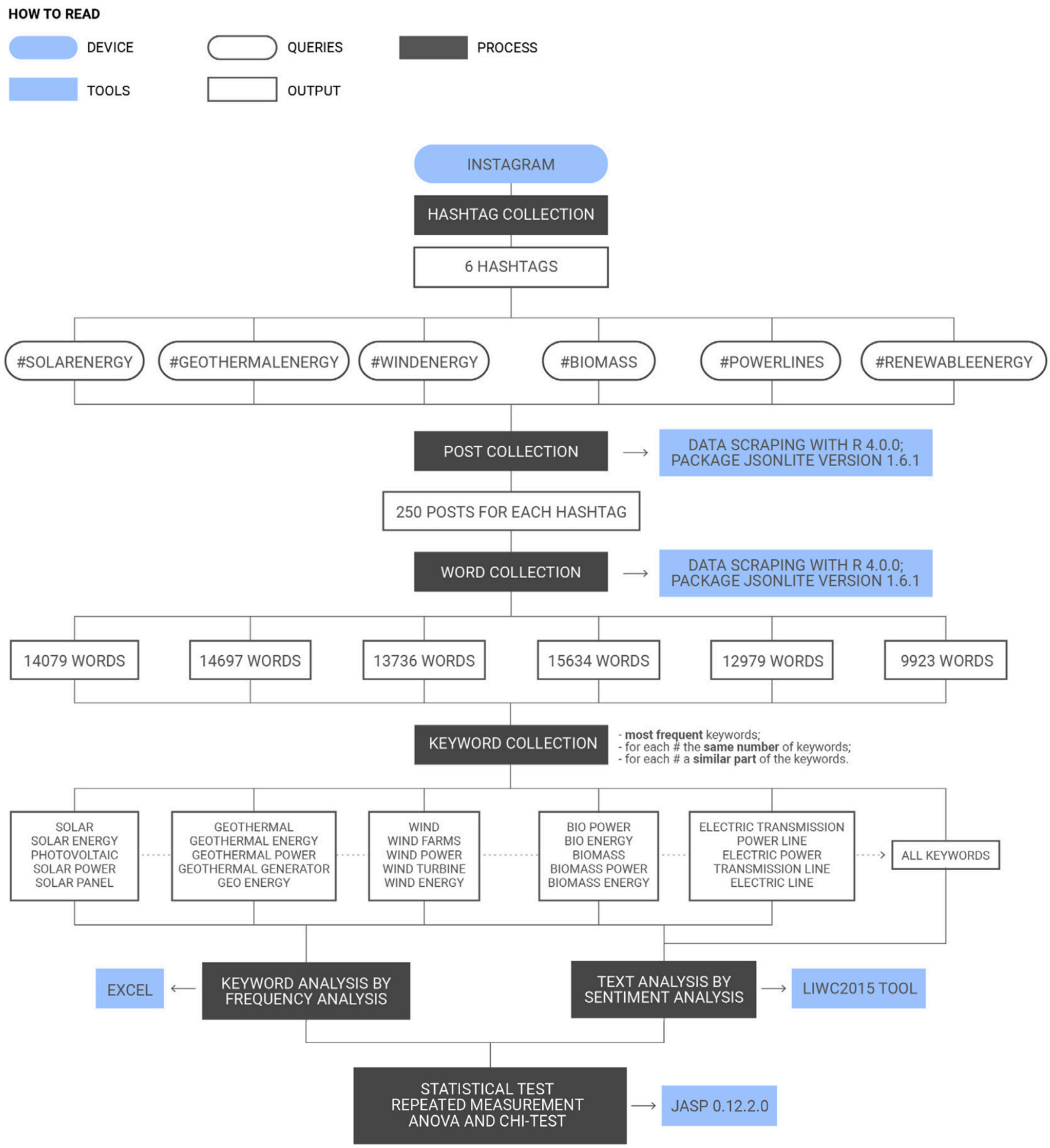

Fig. 1. Method process: from the data collection to the data analysis.

used) lexical method with the most percentage of agreement with other methods such as PANAS-t, SASA, SentiWordNet, etc. [57]. The latest version of LIWC software captures over 86% of the words people use in writing and speech. Each word in a given text file is compared with the dictionary file and calculate the percentage of each LIWC category selected. The dictionaries allow the user to read "internet slang" language that is common in Twitter, Instagram, and Facebook posts. The authors of the program analyzed the degree to which language varies across settings and since 1986 they have been collecting text samples from a variety of studies. The analyses include comments from over 80,000 writers or speakers totaling over 231 million words.

Table 1 illustrates the emotional and cognitive processes taking for the analyses of different hypotheses. The output of the software is the percentages of total words within a text. The LIWC2015 output was statistically investigated through the one-way within-subjects ANOVA on JASP 0.12.2.0. Appendix B shows the descriptive statistics of LIWC2015 output.

4. Results

4.1. Different RETs are often named with each other. Wind and solar energies have a high frequency of words with reference to each other in all the hashtags

Part of the analyses was focused on the frequency observation in all the hashtags (see Fig. 3). As general founding, different RETs are named in the hashtags, with exception of #powerlines. The highest frequency is given by solar words. In some hashtags there are specific places named, such as Africa (#biomass), India (#solarenergy), and Iceland (#geothermalenergy), underlining a place-RET word association. In all the

Fig. 2. An example of an Instagram post.

Table 1
Output variable information from LIWC2015 development manual.

		Hypotheses
Emotional processes	Affective processes	H2.1–H2.2
	Positive emotion	H2.2
	Negative emotion	H2.2
Cognitive processes	Cognitive processes	H2.1–H2.5
	Insight	H2.5
	Causation	H2.5
	Biological processes	H2.4
	Body	H2.4
	Health	H2.3
	Power	H2.3
	Risk	H2.3

posts, there is a high mental association between RETs, nature, and "green" words (such as landscape, environment, sky, clean, future, etc.).

Other analyses were focused on the frequency analysis observation (see Table 2) of the keywords (kw in the table). As an overall founding, the solar energy keywords have the highest frequency in all (with exception of powerlines) the hashtags compared to the other keywords. The highest value is in the #renewableenergy, as for the wind energy keywords, showing that solar and wind energies are both salient in the general broad of renewable energy topic. High percentage of solar keywords is in #windenergy, confirming the statement of the hypothesis. Looking at #solarenergy there are low general frequencies of RET keywords, with the highest value for the wind energy. It manifests that the solar energy keywords have high frequency in all the posts, but in the #solarenergy there is not the same elevated frequency of the RET keywords. From these results we can consider that thinking of wind energy has strong mental association with solar energy, but the association is not so strong thinking of solar energy. The powerlines hashtag has only few words referring to the other renewable energies, with the highest frequency of wind energy keywords. At the same time, the powerline keywords are the less present in the other posts, with the highest frequency in the #biomass.

The frequency of keywords was statistically verified. In details, for each hashtag, we conducted a repeated measures analysis of variance with one within subjects' factor with four levels, five for #renewableenergy. With Bonferroni adjusted post hoc tests we analyzed pairwise which keywords differed from each other significantly. In cases where the sphericity condition was not met (Mauchly's test for sphericity became significant), the Greenhouse-Geiser correction procedure was used.

In the #windenergy posts only the frequency values of solar energy is significantly higher than all other levels, $p < .001$. In the #biomass posts the frequency values of solar energy is significantly higher than wind energy $p < .05$ as well as geothermal and powerlines (both $p < .001$). The frequency value of wind energy keywords was significantly higher than geothermal energy ($p < .01$) and powerlines ($p < .001$). The values of geothermal energy and powerlines keywords did not differ significantly from each other ($p > .05$). In the #geothermal posts the frequency values of solar energy keywords is significantly higher than biomass ($p < .05$) and powerlines ($p < .001$), and did not differ significantly from wind ($p > .05$). The frequency value of wind energy keywords did not differ significantly from biomass ($p > .05$), but the value was significantly higher than powerlines ($p < .001$). The values of biomass energy were significantly higher than powerlines keywords ($p < .01$). In the #powerlines posts the frequency values of wind energy keywords is higher than all other levels ($p < .001$). The biomass and geothermal keywords did not differ significantly from each other ($p > .05$); the value of solar energy keywords is significantly lower than wind energy ($p < .05$). In the #solarenergy posts only the frequency values of wind energy is significantly higher than all other levels ($p < .001$). In the #renewableenergy posts only the frequency values of solar energy is significantly higher than all other levels ($p < .001$).

In the #renewableenergy posts were counted the frequency of times the RET keywords were mentioned together. The highest interconnection of words were between solar and wind (13 times), followed by biomass-solar (3 times), biomass-wind (3 times), geothermal-wind (2 times), geothermal-solar (2 times), and geothermal-biomass (2 times). Contrary to what we expected, the words referring to the powerlines were 0. In this case, as in the previous analyses, the words referring to powerlines are low if not completely absent showed a missing of the connection with all the RETs. The frequency value between the RETs named together in the posts was statistically verified by a Chi-squared test, resulting in $\chi^2 = 133.33$, df $= 1$, $p < .001$.

4.2. Different RETs are linked to different emotion and cognition words

A sentiment analysis has done on the words of 250 #windenergy posts for the Section 4.2.1, and on 1250 posts for the other hypotheses of this section. We have excluded the #renewableenergy posts from this analysis because these hypotheses were focused on the emotional and cognitive words used in describing specific RETs. The #renewableenergy was integrated to gain an overall overview of the topic, for this reason we have used that dataset in the previous analysis.

The LIWC2015 output for each post was statistically verified. We conducted a repeated measures analysis of variance with one within subjects' factor two level (affect and cognition) for the Section 4.2.1 and five levels (#biomass, #geothermal, #powerlines, #solarenergy, and #windenergy) for all the other hypotheses. With Bonferroni adjusted post hoc tests we analyzed pairwise which values differed from each other significantly (see Appendix C). In cases where the sphericity condition was not met (Mauchly's test for sphericity became significant), the Greenhouse-Geiser correction procedure was used.

Fig. 4 shows the percentage of LIWC category on the emotional and cognitive processes. The following sections explain in detail the results.

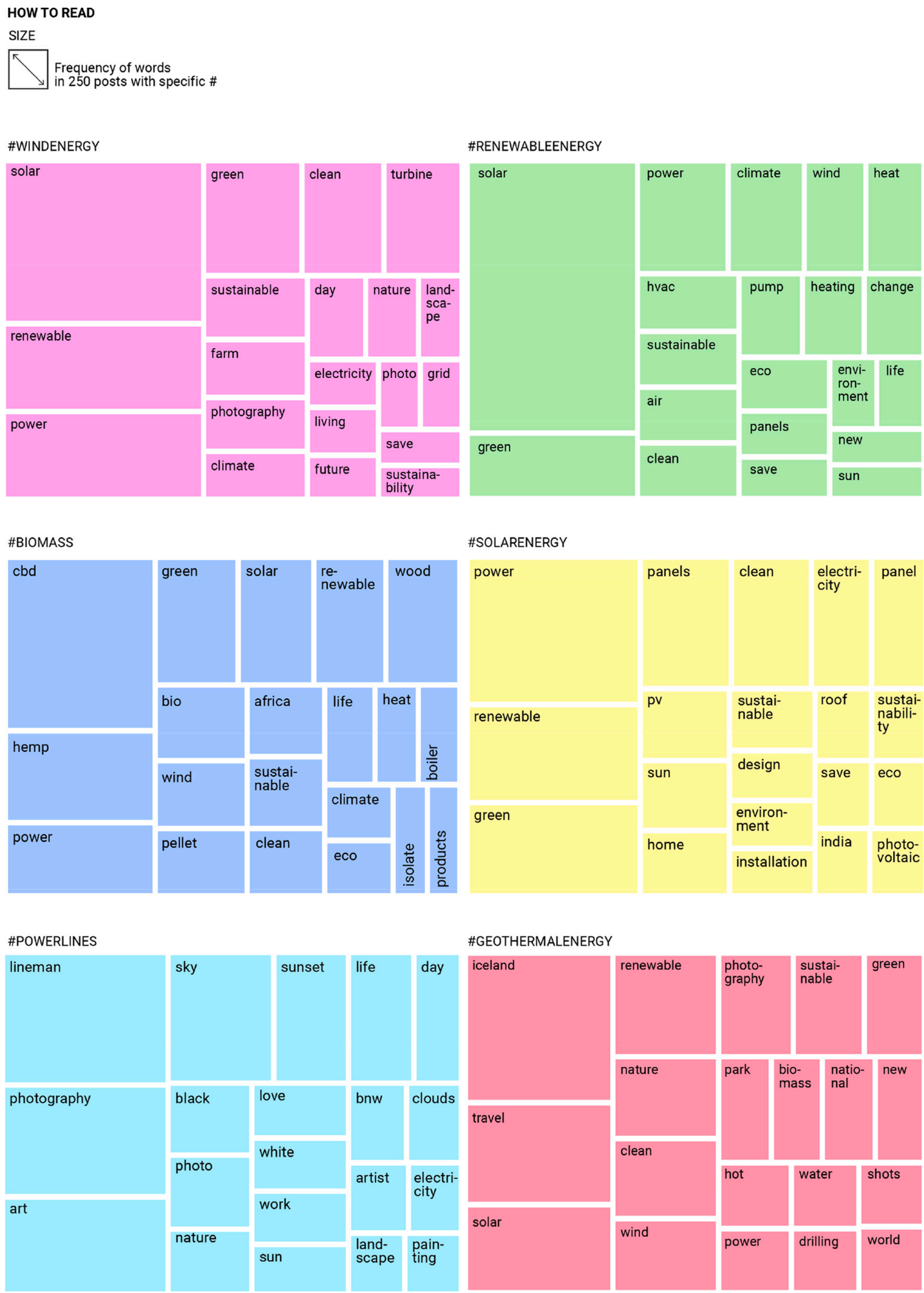

Fig. 3. Frequency of words in the hashtags.

4.2.1. #windenergy contains more emotional than cognitive words

The analysis revealed a significant overall effect (F = 195.58, df = 1, $p < .001$) meaning that there are significant differences in the frequencies between cognition and emotional words used. We found that the percentage values of affect are significantly higher than the cognitive processes $p < .001$. Our hypothesis was confirmed, stressed that the words used with #windenergy are more emotional than cognitive.

4.2.2. #solarenergy and #windenergy contain affective process and positive emotions words

The analysis of affect values revealed a significant overall effect (F = 49.07, df = 4, $p < .001$). We found that the affect LIWC2015 category of

Table 2
Frequency of keywords in the posts and comparison by ANOVA.

Hashtags	Keywords					ANOVA		
	Wind	Solar	Biomass	Geothermal	Powerlines	F	DF	P
#windenergy		471	17	11	2	44.26	3	<.001
#solarenergy	25		6	7	0	9.46		<.001
#biomass	102	159		35	5	25.18		<.001
#geothermal	60	96	53		1	16.16		<.001
#powerlines	15	3	0	0		6.96		<.001
#renewablenergy	175	913	7	2	4	66.71	4	<.001

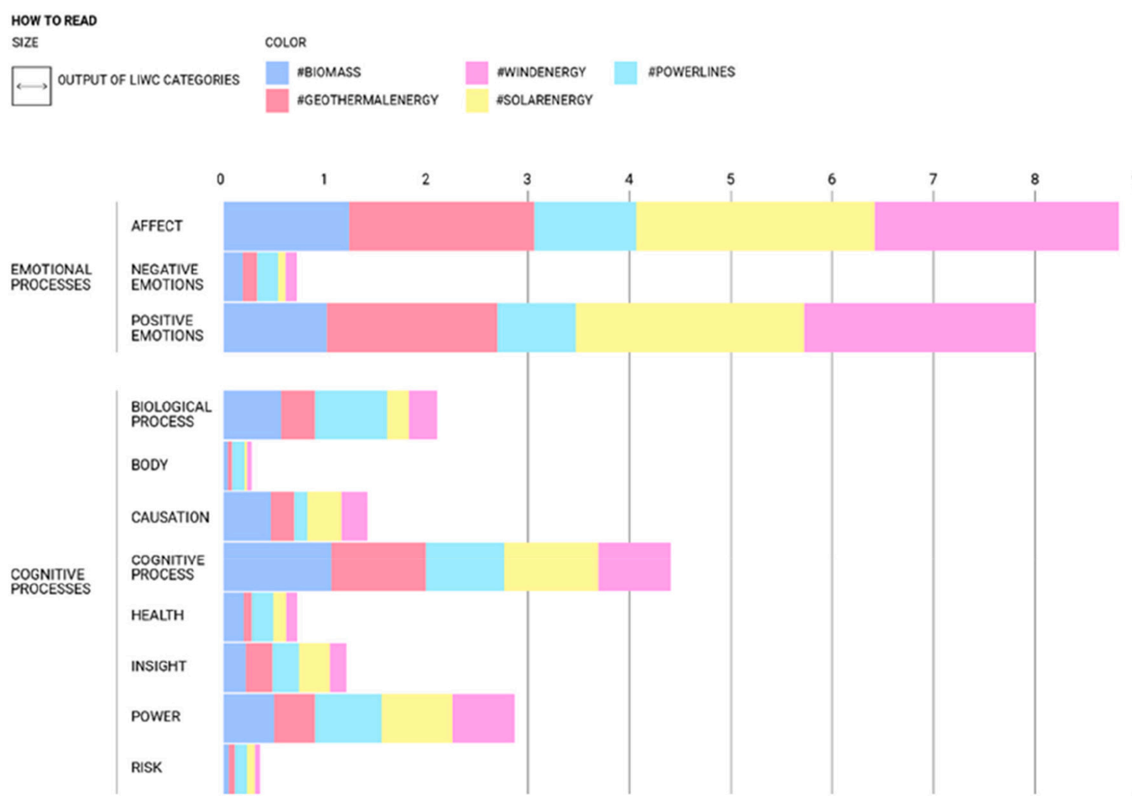

Fig. 4. Output (percentage) of LIWC categories emotional vs cognitive processes.

#windenergy words were significantly higher than the powerlines, geothermal, and biomass factors ($p < .001$), and did not different significantly from the solar factor ($p > .05$). The affect #solarenergy values were significantly higher than the powerlines, geothermal, and biomass factors ($p < .001$). The #powerlines affect values were, instead, significantly lower than geothermal values ($p < .001$) and did not differ significantly from biomass ($p > .05$). The #geothermal affect words were significantly higher than biomass ($p < .001$).

The analysis of positive emotion values revealed a significant overall effect (F = 61.11, df = 4, $p < .001$). We found that the positive emotion category of #windenergy words were significantly higher than the powerlines, geothermal, and biomass factors ($p < .001$), and did not differ significantly from the solar factor ($p > .05$). The affect #solarenergy values were significantly higher than powerlines, geothermal and biomass factors ($p < .001$). The #powerlines affect values were, instead, significantly lower than geothermal values ($p < .001$) and did not differ significantly from biomass ($p > .05$). The #geothermal affect words were significantly higher than biomass ($p < .001$).

The analysis of the negative emotion values revealed a significant overall effect (F = 45.65, df = 4, $p < .001$). We found that for the negative emotion category only the #powerlines words were significantly higher than the solar factors ($p < .01$).

As expected, both #windenergy and #solarenergy posts evoke more affective process and positive emotions than #biomass, #geothermalenergy, and #powerlines. A result that we want to underline is the high value of affective process and positive emotion words found in the #geothermalenergy posts. This result should be explored in further studies.

4.2.3. *#powerlines contains power, health, and risk words*

The analysis of health values revealed a significant overall effect (F = 7.65, df = 4, $p < .001$) meaning that there are significant differences in the frequencies between the factors. We found that the health LIWC2015 category values of #powerlines were significantly higher than the geothermal ($p < .001$), wind ($p < .01$), and solar levels ($p = .01$), and did not differ significantly from biomass ($p > .05$). The geothermal values are significantly lower than biomass ($p = .01$) and did not differ significantly from the other factor level (solar and wind); $p > .05$. The wind energy values are significant lower than biomass ($p = .05$).

For the power output, the analysis revealed a significant overall effect (F = 6.16, df = 4, $p < .001$). We found that the power category of #powerlines values were significantly higher than geothermal ($p < .01$) and the other levels (solar, wind, and biomass) did not differ significantly ($p > .05$). The geothermal values were significantly lower than solar energy ($p < .001$) and wind energy ($p < .01$). The solar energy values were higher than biomass ($p = .5$).

For the risk output the analysis revealed a significant overall effect ($F = 4.19$, $df = 4$, $p < .01$). We found that only the risk category of #powerlines values were significantly higher than geothermal, wind energy and biomass ($p < .01$).

Summarizing, the #powerlines posts evoke more health and risk words than the other hashtags. Contrary to what we expected, the power words are higher in the #solarenergy, following by #powerlines and #windenergy. Concluding, in our sample people described the solar posts with both emotional and cognitive words. The powerlines, instead, are perceived as the most risky technology.

4.2.4. #biomass contains body and biological process words

The analysis of the biological process output revealed a significant overall effect ($F = 20.48$, $df = 4$, $p < .001$) meaning that there are significant differences in the values between the factors. We found that the biological process LIWC2015 category values of #biomass were significantly higher than solar and wind energies (both $p < .001$), and geothermal ($p < .01$). The geothermal values were significantly lower than powerlines ($p < .001$). The powerlines values were significantly higher than solar and wind energies ($p < .001$).

For the body process output, the analysis revealed a small significant effect ($F = 3.07$, $df = 4$, $p < .05$). We found that only the body process category values of #biomass were higher than solar energy ($p < .05$).

Contrary to what we expected, the body and biological process words were higher in the #powerlines posts, following by #windenergy for the power category and biomass for the biological process words. Powerlines posts had a high value related to the physical aspect of the people.

4.2.5. #geothermalenergy contains cognitive process, insight, and causation words

The analysis of the cognitive process output revealed a significant small effect ($F = 4.54$, $df = 4$, $p < .01$) meaning that there are small significant differences in the values between the factors. We found that only the cognitive process category values of #biomass were significantly higher than powerlines ($p < .05$) and wind energy ($p < .01$).

For the insight output, the analysis revealed a significant small effect ($F = 3.67$, $df = 4$, $p < .01$). We found that only the insight category values of #solarenergy were significantly higher than wind energy ($p < .01$).

For the causal output, the analysis revealed a significant effect ($F = 16.11$, $df = 4$, $p < .001$). We found that the causal category values of #geothermal were significantly lower than biomass ($p < .001$). The biomass values were significantly higher than powerlines and wind (both $p < .001$), and solar ($p < .05$). The powerlines values were significantly lower than solar ($p < .001$) and wind ($p < .05$).

Summarizing, the cognitive and causal processes were higher in #biomass posts and the insight values in #solarenergy. As we showed on the previous results, the #geothermalenergy posts have higher emotional than cognitive words.

5. Finding overview and discussion

Building on appraisal theory we studied the emotion and cognitive words used under the Instagram posts. With a SCA to the language we investigated the interconnection between the salient words referring to RET hashtags. We hypothesized that each RET was linked to specific emotional and/or cognitive words. Several discussions arise from our analysis on the interaction between RETs, cognitive, and affective components.

First, all the RETs are linguistically connected on our Instagram sample, both in the dataset of different hashtags and in the #renewableenergy. As we expected, the linguistic interconnection is higher between solar and wind energies. Furthermore, the solar energy keywords are the most interconnected to all the RETs with the highest number of words mentioned in the posts. This aspect underlines that solar energy plays a key role in the relation between people and energy transition, considering also that it is one of the fastest growing RET. Opinion polls also indicate that solar energy enjoys a high level of sociopolitical acceptance and it is preferred to other renewables [58]. These reasons could influence the salience of the topic for Instagram users. In addition, it is also important to consider that the co-occurrence of words in the Instagram posts can also depend on overall discourses and repertoires that provide the shared background in which the analyzed are embedded. For example, one or more energy technologies can be part of a figurative nucleus of a shared social representation (e.g., [59,60]) which is also replicated in individual mental representations. Future studies could include these considerations into account.

In our data, the powerlines are not linguistically connected to the RETs. It seems that they are not mentally included when people write about RETs, as if they belonged to another group of proximity between words. Powerlines are closely connected to the functioning of the renewable energies, and physically they have an important environmental impact. Studies showed that powerlines are associated with more positive feelings, higher perceived benefit, lower perceived risk, and higher general and local acceptance when they are linked to the energy transition (e.g. [61]). Although previous studies have confirmed the importance of connecting powerlines to the energy transition, our results showed that on Instagram this step has not yet taken place. This means that a future phase could be to build a stronger mental association between powerlines and RETs for increasing a more general acceptance of powerlines. For these reasons, we encourage future studies and social initiatives in this direction.

Concerning the words named in the hashtags, there are specific places such as Africa (#biomass), India (#solarenergy), and Iceland (#geothermalenergy), underlining a place-RET word association. African countries, in fact, are gifted with a huge bioenergy potential, with wood supply from surplus forest estimated at 520 GWh/year [62]; Iceland has a big geothermal potential based on the location of the country on the Mid-Atlantic Ridge [63]; solar is a significant energy source in India in which there are about 250–300 sunshine days yearly with regular solar radiation of 200 MW/km^2 [64]. An aspect that we want to underline is that the places named are all on large scale (continents and countries). The major salience of RET-place word associations in our dataset is given by global scale of place (including the “world” and “national” words used in #geothermalenergy). Existing studies of place attachments and place identities have taken a “local” vs “global” focus. The ‘psychological distance’ [65] is an important aspect of the ‘localist’ perspective, which argues that things of value to individuals must be close rather than distant. For example, climate change is a psychologically distant event, and for that reason, people mentally construe climate change in terms of high-level, abstract, and stable characteristics [66]. However, some research shows that 80% of people label themselves as ‘global citizens’, underlining the importance of the interplay between global and national attachments [67]. Future studies should consider the multiple scales of people-place bonds, in order to study their dynamics on social media platforms.

Second, solar and wind energies evoke more emotional and positive emotions than the other RETs and powerlines. The solar posts did not only have high values of emotional words, but also high values in few cognitive categories (insight and power), underlining that both, cognitive and emotional categories, were present significantly in our #solarenergy sample. The wind energy posts, instead, have more emotional than cognitive words. This is in line with a body of research that underlines that there is a rich diversity of emotional perspectives on what influences individual attitudes towards wind energy projects, which can be grouped into three key themes: personal attributes; perception of the fairness of procedural justice; and perceived impacts of the project, including site location proximity, and project characteristic [68]. Some researchers have attributed the strongest response to wind energy projects arising from the changes to local landscapes and fears of the resulting visual disruption (e.g. [69]). This suggests that an individual's reaction to a proposed project may primarily be one of '*place-protection*', stimulated as an emotional response to what they see is a disruption of places they have developed a close affinity to. This is a potentially expansive area, considering that if the project developers had the capability to predict sentiments and emotions early in the development of the project, that interventions could be introduced to manage the community's emotions and behaviors, hopefully increase the likelihood of the project's acceptance [68].

Geothermal posts also had a higher frequency of emotional than cognitive words. Researchers are still studying the affective responses elicited by geothermal energy. As a general point, people are confused about the difference between surface and deep geothermal energy projects, as well as for geothermal energy in general [13,70]. These reasons led us to think that this RET was addressed more at a cognitive level, with the aim of people to create a psychological distance. Indeed, the confusion may arise resistance, risk perception, and strong emotional response. Thus, following the appraisal theory, perceived risks are predictors of a wide range of negative emotions towards perceived externally controlled in the energy projects [1]. Incorporating affect and emotions into research may help to better understand drivers of public acceptance of geothermal projects, in turn helping policymakers and project developers in crafting new strategies for managing various elements of public acceptance.

Biomass posts have a high frequency of cognitive processes and causal words. Literature underlines that biomass is viewed as one of the critical renewable energies and despite the share of bioenergy in the overall energy supply has increased over the last decade, its social acceptance is fragile, mainly due to concerns about negative sustainability impacts [71]. For these reasons we were willing to hypothesize that biomass energy was linked to the body and biological process words assuming a great concern for health. Future studies in this direction are needed for a deeper understanding of this renewable energy and its relationship with emotions and cognitions.

Powerline posts are linked to the words of risk, body, health, and biological process showing a great concern for health and perceived threat. The literature confirms this statement having a dense corpus of papers studying the association between powerlines and possible health and body problems (e.g. [72]). Conflicting results have been established creating a public health concern to individuals. Furthermore, public response to powerline projects is mainly influenced by people's perceptions of risk and benefit [73]. According to the affect heuristic and the appraisal theory, negative feelings towards a given technology can lead to lower perceived benefit, higher perceived risk, and consequently, lower public acceptance. One strategy is to reduce the perceived risks of energy projects as much as possible and increase trust in responsible parties. It important to be clear in communicating risks and benefits linked to projects. Increasing trust and reducing morality-based emotions and feelings of powerlessness might be critical for stakeholders to have a social license to operate, because such emotions can particularly lead to resistance [1].

To the best of our knowledge, this study is the first to carry out an analysis of people's words concerning RETs on Instagram posts. Further, our results show that significant differences exist between emotion and cognition words used for describing RET, signaling that each technology should be approached in a different way when trying to manage processes of social acceptance. Communication strategies should thus be targeted based on specific words and the linkage between infrastructures. The results reveal that emotions and cognitions are not related only to the energy source per se, but rather to the specific energy infrastructure and powerlines.

5.1. Limitations and future research

While this study has its merits, we identify four limitations that can be the starting point for further research. First, the results must consider the Instagram users and its variables, such as age, use possibility, needs, etc. In fact, the data can have a strong bias of a specific age (younger populations between 18 and 34 years old) [44]. Second, the demographic factors, user personality, and cultural differences are some information that we cannot know with the data scraped. Third, the LIWC2015 software and the word count techniques are a coarse measure of language, devoid of context, and unable to interpret subtleties like irony or sarcasm. Furthermore, while we crawled for English hashtags, some posts used multiple languages. Since the English dictionary of the LIWC, we were only able to analyse the English text of captions and hashtags. Fourth, the day used for scraping data was a random day. Therefore, one concern could be that the data (and consequently the results) can be influenced by a "significant day" (elections, events, etc.). Further research could expand on how the data scraping date can be controlled to show the significance of Instagram as a tool for expressing opinions about energy issues. Furthermore, it would be appropriate to do a replication study. This research could be also adapted to other social media, such as Facebook and Twitter, to compare data across multiple platforms. Considering that this study was focused on the analytical procedure of the text, future works may consider adding pictures and video to the analyses. In addition, in the analysis of solar energy in the Instagram posts we have not made a distinction between distributed (e.g., rooftop) and more land-intensive installations. This distinction would help understanding the degree to which emotional and cognitive words are used at different solar facilities, so that conclusions that are more precise can be reached. We suggest more studies in this direction.

As with any data source, social media analysis presents both opportunities and challenges. One major critique of social media data is that the data are not generalizable outside of the platforms from which the data originate [74]. However, scholars (e.g., [75]) argue that while social media data have empirical limitations, the data retain integrity if they are strongly linked to theoretical concepts. Thus, research that starts with clear theoretical assumptions and concepts can create relevant information about social processes regardless of the degree to which the data are representative of a larger population. In our research, we used the analyses of studies *with* social media, in which the goal was to use digitally derived data to analyse general social topics. On one hand we agree that, in most cases, social media data are not generalizable to 'society' at large. On the other hand, social media are in everyday life and thus integral to larger social processes [74]. We agree with other authors [75] in claiming that "*researchers can maintain the full potential of social media data to inform a multitude of social phenomena, while maintaining the integrity of theory-data through theoretical generalisability in the tradition of formal theory*". With this in mind, we underline that the study of emotions and cognitions towards RETs is a guide to understanding peoples' reactions and social media data can help, for example, in developing communication strategies. However, we have to consider that it is not possible to isolate the study of energy from its socio-ecological contexts [76] because energy and society are strongly interlinked.

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Declaration of competing interest

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

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Appendix A. Descriptive statistics of all the keywords (KW) of each hashtag

	Solar KW	Wind KW	Geothermal KW	Powerlines KW	Biomass KW
#biomass					
Mean	0,64	0,41	0,14	0,02	
Std. deviation	1,64	1,23	0,59	0,26	
#geothermalenergy					
Mean	0,38	0,24		4,00e−3	0,21
Std. deviation	1,20	0,76		0,06	0,73
#powerlines					
Mean	0,01	0,06	0		0
Std. deviation	0,14	0,31	0		0
#renewableenergy					
Mean	3,65	0,70	8.00e−3	0,02	0,03
Std. deviation	6,24	2,66	0,09	0,25	0,17
#solarenergy					
Mean		0,13	0,03	0	0,02
Std. deviation		0,61	0,27	0	0,22
#windenergy					
Mean	1,88		0,04	8,00e−3	0,07
Std. deviation	4,38		0,34	0,09	0,37

Appendix B. Descriptive statistics (standard deviation and means) of LIWC2015 output

Hashtags	Descriptive analyses of LIWC2015 output										
	Affect	Cognitive process	Positive emotions	Negative emotions	Heath	Power	Risk	Biological process	Body	Insight	Causal
Standard deviation											
#windenergy	6,45	3,36	6,37	2,26	1,09	2,8	0,6	2,43	1,62	1,27	1,51
#biomass	4,98	4,54	4,72	2,04	1,53	3,36	0,72	3,24	0,57	1,56	2,76
#geothermal	5,85	4,05	5,81	1,43	0,91	2,29	0,71	2,45	0,73	1,81	1,86
#powerlines	4,4	4,07	3,9	2,29	1,77	4,11	1,6	4,19	2,33	2,21	1,38
#solarenergy	6,64	3,85	6,69	0,81	1,18	2,94	0,95	1,88	0,53	2,1	1,94
Means											
#windenergy	9,62	2,86	9,14	0,43	0,44	2,47	0,21	1,11	0,18	0,64	1,02
#biomass	4,95	4,23	4,07	0,73	0,77	1,99	0,21	2,27	0,17	0,88	1,86
#geothermal	7,3	3,71	6,69	0,59	0,33	1,59	0,22	1,32	0,16	1,05	0,91
#powerlines	4,01	3,11	3,1	0,82	0,87	2,64	0,51	2,86	0,48	1,04	0,53
#solarenergy	9,39	3,71	8,99	0,29	0,48	2,78	0,29	0,86	0,11	1,21	1,34

Appendix C. ANOVA post hoc comparisons of the most relevant outputs with Bonferroni correction

Post hoc comparisons						
		Mean difference	SE	t	p_{bonf}	
Affect_Wind	Affect_Solar	0.2300	0.5128	0.4484	1.0000	
	Affect_Powerlines	5.6092	0.5128	10.9380	2.2395e−25	***
	Affect_Geothermal	2.3217	0.5128	4.5273	6.6947e−5	***
	Affect_Biomass	4.6752	0.5128	9.1167	4.1685e−18	***
Affect_Solar	Affect_Powerlines	5.3792	0.5128	10.4896	1.7257e−23	***
	Affect_Geothermal	2.0917	0.5128	4.0789	0.0005	***
	Affect_Biomass	4.4452	0.5128	8.6683	1.7543e−16	***
Affect_Powerlines	Affect_Geothermal	−3.2875	0.5128	−6.4107	2.2331e−9	***

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(continued)

Post hoc comparisons

		Mean difference	SE	t	p_{bonf}	
	Affect_Biomass	−0.9340	0.5128	−1.8213	0.6886	
Affect_Geothermal	Affect_Biomass	2.3535	0.5128	4.5893	5.0137e−5	***
Positive Emotion (Posemo)_Wind	Posemo_Solar	0.1426	0.5003	0.2850	1.0000	
	Posemo_Powerlines	6.0337	0.5003	12.0613	2.3009e−30	***
	Posemo_Geothermal	2.4488	0.5003	4.8951	1.1458e−5	***
	Posemo_Biomass	5.0634	0.5003	10.1218	5.4709e−22	***
Posemo_Solar	Posemo_Powerlines	5.8911	0.5003	11.7763	4.5901e−29	***
	Posemo_Geothermal	2.3062	0.5003	4.6101	4.5479e−5	***
	Posemo_Biomass	4.9209	0.5003	9.8368	7.4454e−21	***
Posemo_Powerlines	Posemo_Geothermal	−3.5849	0.5003	−7.1663	1.4988e−11	***
	Posemo_Biomass	−0.9702	0.5003	−1.9395	0.5272	
Posemo_Geothermal	Posemo_Biomass	2.6147	0.5003	5.2267	2.1015e−6	***
Health_Powerlines	Health_Geothermal	0.5422	0.1186	4.5716	5.4493e−5	***
	Health_Solar	0.3881	0.1186	3.2727	0.0110	*
	Health_Wind	0.4316	0.1186	3.6393	0.0029	**
	Health_Biomass	0.0958	0.1186	0.8075	1.0000	
Health_Geothermal	Health_Solar	−0.1540	0.1186	−1.2989	1.0000	
	Health_Wind	−0.1106	0.1186	−0.9323	1.0000	
	Health_Biomass	−0.4464	0.1186	−3.7641	0.0018	**
Health_Solar	Health_Wind	0.0435	0.1186	0.3666	1.0000	
	Health_Biomass	−0.2924	0.1186	−2.4652	0.1386	
Health_Wind	Health_Biomass	−0.3358	0.1186	−2.8318	0.0472	*
Biological Process (Biopro) Biomass	Biopro_Geothermal	0.9494	0.2642	3.5940	0.0034	**
	Biopro_Powerlines	−0.5918	0.2642	−2.2402	0.2530	
	Biopro_Solar	1.4077	0.2642	5.3292	1.2200e−6	***
	Biopro_Wind	1.1523	0.2642	4.3622	0.0001	***
Biopro_Geothermal	Biopro_Powerlines	−1.5411	0.2642	−5.8342	7.3015e−8	***
	Biopro_Solar	0.4584	0.2642	1.7352	0.8301	
	Biopro_Wind	0.2029	0.2642	0.7682	1.0000	
Biopro_Powerlines	Biopro_Solar	1.9995	0.2642	7.5694	8.5227e−13	***
	Wind	1.7440	0.2642	6.6024	6.5676e−10	***
Biopro_Solar	Wind	−0.2554	0.2642	−0.9670	1.0000	
Causal_Geothermal	Causal_Biomass	−0.9477	0.1759	−5.3871	8.9347e−7	***
	Causal_Powerlines	0.3845	0.1759	2.1858	0.2906	
	Causal_Solar	−0.4239	0.1759	−2.4096	0.1615	
	Causal_Wind	−0.1105	0.1759	−0.6280	1.0000	
Causal_Biomass	Causal_Powerlines	1.3322	0.1759	7.5730	8.3080e−13	***
	Causal_Solar	0.5238	0.1759	2.9776	0.0298	*
	Causal_Wind	0.8372	0.1759	4.7591	2.2321e−5	***
Causal_Powerlines	Causal_Solar	−0.8084	0.1759	−4.5954	4.8735e−5	***
	Causal_Wind	−0.4950	0.1759	−2.8139	0.0499	*
Causal_Solar	Causal_Wind	0.3134	0.1759	1.7815	0.7513	

*** $p < .001$.
** $p < .01$.
* $p < .05$.

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