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PHOTOVOLTAICS - SENTIMENT ANALYSIS OF TWEETS PUBLISHED IN POLISH

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Purpose: Based on sentiment analysis of tweets, determining people's thoughts, feelings and opinions on photovoltaics.
Design/methodology/approach: Tweets posted in Polish that contained among others the word "photovoltaic" were downloaded automatically. The tweets' content has undergone preprocessing. All characters other than letters, URLs, hashtags, emojis, usernames, and phrases used to search for tweets were taken out of their text. The tweets' sentiment value was determined. To display the proportion of favourable, negative, and neutral tweets, visualisations were created. Word clouds were employed to display the tweets' most popular words.
Findings: For tweets related to photovoltaics, proportions of positive, negative and neutral tweets were determined.
Research limitations/implications: Only Polish-language tweets' content was examined. Without author oversight, sentiment analysis was carried out automatically by the "ccl emo" service. Only viewpoints expressed by Twitter users were analysed. It was assumed that if a tweet contains the word photovoltaic, its content is about photovoltaics.
Practical implications: Automatic assessment of people's opinion towards photovoltaics.
Originality/value: Opinions on photovoltaics were collected. Based on the growing number of tweets, it was found that interest in photovoltaics in Poland is steadily growing.

Keywords: sentiment analysis, Twitter, photovoltaics.

Category of the paper: research paper, case study.

1. Introduction

As the effects of global warming become more apparent, there is growing concerned about the harmful effects of the traditional energy sector on the environment. Societies are taking action to reduce greenhouse gas emissions (Peng, Lu, Yang, 2013; Pestana, Rodrigues, Morgado-Dias, 2018; Decuypere et al., 2022). Globally, the use of renewable energy is expanding to help reduce air pollution and carbon emissions (Dincer, Dincer, Ibrahim, 2000; Moriarty, Honnery, 2011). The benefits of green energy are acknowledged by many nations, which has led to changes in energy acquisition policies (Pellerin-Carlin et al., n.d.; Salim, Rafiq, 2012; Omri, Daly, Nguyen, 2015; Bórawski et al., 2019; Eyl-Mazzega, Mathieu, 2020). An important factor in the transition to a low-carbon energy system is public acceptance and support for renewable energy (Kim et al., 2021). Public sentiment and opinion on renewable energy have been studied in (Noblet et al., 2015; Stokes, Warshaw, 2017; Hamilton, Hartter, Bell, 2019; Qazi et al., 2019; Lee, 2022; Peñaloza et al., 2022).

The global renewable energy sources (RES) market is growing steadily (especially in the solar and wind sectors) and its growth has not even been slowed by the coronavirus pandemic (Bilgili, Ozturk, 2015; Bhuiyan et al., 2021; Eroğlu, 2021; Quitzow et al., 2021). Among renewable energy sources, photovoltaic technology has the greatest potential due to its low cost and simplicity of installation (Mota et al., 2020; Alves dos Santos et al., 2021; C.B. et al., 2021; Castilho et al., 2021). The photovoltaic sector in Poland is currently of a very dispersed nature and is based on micro installations. At the end of 2019, micro-installations accounted for over 70% of the total installed photovoltaic capacity in Poland. Residents were encouraged to invest in photovoltaics through solar support energy programs like the governmental program "My Electricity", and the long-term EU support based on the Regional Operational Programs (Grębosz-Krawczyk et al., 2021).

In recent times, households, industries and services in Poland have been facing increasingly higher bills for electricity consumption (Chomać-Pierzecka et al., 2022). The increase in electricity prices has led to even greater interest in photovoltaics, but choosing the right solution is not simple. This is influenced in Poland by the following factors, among others:

- the right size of installation (overproduction of electricity does not make economic sense) (Zrównoważonego et al., 2015),
- terms and conditions for accounting for electricity overproduction with distribution system operator (Zator, Lambert-Torres, 2021),
- deciding whether or not to purchase an electricity storage system (Zator, Lambert-Torres, 2021),
- relatively limited knowledge of the technical criteria for selecting the appropriate solution for energy needs; purchase decisions are mainly determined by the price of the installation, the lifetime of photovoltaic panels, the availability of solutions determining the time of investment implementation, and the aesthetics of the panels (Chomać-Pierzecka et al., 2022).

As the digital age progresses people frequently express their ideas and post them on social media. To examine people's thoughts, feelings and judgements, instead of surveys and interviews, a method known as sentiment analysis may be used. Sentiment analysis offers a method for automatically analysing sentiment, emotion, and opinion in written language (Xu, Chang, Jayne, 2022). It involves the process of analyzing, processing, generalizing from, and making sense of emotionally charged subjective texts, such as comments on people, events, things, etc., posted by users online (Deng et al., 2022).

One of the popular and well-known services where people can express themselves is Twitter (Chinnasamy et al., 2022). It is one of the most popular micro-blogging platforms. A user can follow a stream of messages (tweets) posted by another user (Panagiotopoulos, Sams, 2012). Through short messages (known as "tweets") users can instantly communicate their ideas or information on a variety of subjects or interests. (Das, Sun, Dutta, 2015). To support more conversational features, users have established certain conventions. They can republish other people's tweets ("retweeting"), and include the "@" and/or "#" symbols in their tweets (Boyd, Golder, Lotan, 2010; Panagiotopoulos, Sams, 2012). Users can refer to or directly address other users by using the "@" symbol (Akshay, Java, Xiaodan, Song, Tseng, 2007; Honeycutt, Herring, 2009). Using hashtags marked with the "#" symbol, allows users to group posts about a particular subject or event (Small, 2011; Bruns, 2012).

Twitter can be a source of big data. Various tools can be used to analyse downloaded data. Due to a large amount of data, techniques such as text mining, data mining, machine learning, topic modelling, sentiment analysis and similar approaches are used. Exploration of data collected on social media is a new field. It is becoming increasingly popular due to its affordability, accessibility and anonymity (Evans-Cowley, Griffin, 2012; Das, Sun, Dutta, 2015; Das et al., 2019). It is possible to predict how popular or current topics will develop by using sentiment analysis on data from social networks (Ağrali, Aydin, 2021). There are many studies in the literature about sentiment analysis on data extracted from the Internet (Pang, Lee, 2004, 2008; Read, 2005). Sentiment analysis of tweets is a topic covered in many studies (Go, Huang, Bhayani, 2009; Sarlan, Nadam, Basri, 2014; Zavattaro, French, Mohanty, 2015; Çoban, Tümüklü Özyer, 2018; Ayan, Kuyumcu, Ciylan, 2019; Das et al., 2019; Alqaraleh, 2020; Fadel, Cemil, 2020; Garcia, Berton, 2021; Antypas, Preece, Collados, 2022; Sunitha et al., 2022; Gabarron et al., 2022; Nezhad, Deihimi, 2022). The use of sentiment analysis of tweets to find out people's opinions on renewables was presented (Jain, Jain, 2019a, 2019b; Loureiro, Alló, 2020; Kim et al., 2021; Corbett, Savarimuthu, 2022; Ibar-Alonso, Quiroga-García, Arenas-Parra, 2022; Zarrabeitia-Bilbao et al., 2022).

2. Research Methodology

On January 9, 2023, from Twitter 119554 tweets were downloaded. This was accomplished using the Python snscrape library. This library contains several functions to gather tweets, user data, profile data, hashtags, and comments. It makes these elements accessible via a Twitter API-free interface. It offers useful flags that assist in filtering tweets based on criteria like the number of likes, responses, language, tweet ID number, etc. (Blair et al., 2021; Nkonde et al., 2021; Sarkar, Rajadhyaksha, 2021).

There were no retweets in downloaded tweets. Tweets had to include one or more of the following nouns, adjectives or phrases in Polish:

- nouns: “fotowoltaika”, “fotowoltaice”, “fotowoltaiką”, “fotowoltaikę”, “fotowoltaiki”, “fotowoltaiko”, “fotowoltaik”, “fotowoltaikach”, “fotowoltaikami”, “fotowoltaikom”,
- adjectives: “fotowoltaiczna”, “fotowoltaiczną”, “fotowoltaicznego”, “fotowoltaicznej”, “fotowoltaicznemu”, “fotowoltaiczni”, “fotowoltaicznych”, “fotowoltaicznym”, “fotowoltaicznymi”, “fotowoltaiczne”,
- phrases: “instalacja pv”, “instalacjach pv”, “instalacjami pv”, “instalacją pv”, “instalacje pv”, “instalację pv”, “instalacji pv”, “instalacjo pv”, “instalacjom pv”, “pv instalacja”, “pv instalacjach”, “pv instalacjami”, “pv instalacją”, “pv instalacje”, “pv instalację”, “pv instalacji”, “pv instalacjo”, “pv instalacjom”.

These nouns, adjectives and phrases are in all possible grammatical cases for the Polish language and are translations of the terms “photovoltaics”. Phrases are a bigram formed from the word “instalacja” – (eng. installation) and abbreviation of a word “photovoltaics“.

In the next step, the author removed:

- tweets were written in languages other than Polish,
- duplicate tweets (some tweets were retrieved multiple times because they contained more than one word or phrase used during the search, such as "fotowoltaiczna" and "fotowoltaicznej"),
- tweets whose content was the same as the content of other tweets (it was frequently an advertisement for a company's services, products, or jobs); the content was treated as a string of characters and compared using the comparison operator “==”.

Then the tweets' content was pre-processed. All characters other than letters, URLs, hashtags, emojis and user names were removed from the tweets. Additionally, the terms used to search for tweets have been also removed. Next, the number of words in the cleaned content of each tweet was checked. Less than two-word tweets were deleted. After these operations, the number of tweets was 70307.

The ***ccl_emo***[1] service, created by CLARIN-PL[2], was used in the next step. In Polish, this service is also known as “Wydźwięk” and “Sentiment” (in English). It is a service for statistically analysing texts' overtones and emotions (Janz et al., n.d.; Grubljesic, Coelho, Jaklic, 2019). It can be used using Python language[3]. In addition to this service, other CLARIN-PL’s services were used. These were:

- Any2txt - a service that transforms text files (e.g. doc, docx, xlsx) into text.
- Speller2 - a service that verifies the text's spelling. It uses a tool called Autocorrect[4] for this.
- Wcrft2 - is a basic morpho-syntactic tagger for Polish.

[1] https://wiki.clarin-pl.eu/pl/nlpws/services/ccl_emo; https://clarin-pl.eu/index.php/wydzwiek/.
[2] CLARIN-PL is a Polish scientific consortium, part of the European Research Infrastructure CLARIN (Common Language Resources and Technology Infrastructure)(*CLARIN-PL*, n.d.).
[3] This service is also available as a web application at http://ws.clarin-pl.eu/sentyment.shtml.
[4] https://languagetool.org/pl/.

– WSD - a service for word sense disambiguation, which works for Polish texts. As a source of possible senses, it uses plWordNet, which consists of lexical units grouped into synsets which are linked by lexico-semantic relations. A lexical unit represents a lexical meaning and is a triple: lemma, part of speech and sense identifier (Janz et al., n.d.).

For the selected lexical units stored in plWordNet emotive annotation was added. Lexical units were described by (Janz et al., n.d.):

– sentiment polarity – it is expressed on the 5 grade scales: strong & weak vs negative & positive, plus neutral.
– basic emotions - gladness, trust, enjoying something expected, sadness, anger, fear, disgust, surprise with something unpredictable - these emotions are created based on the 8 basic emotions mentioned by Plutchik and his Wheel of Emotions (Plutchik, 1980; Wierzbicka, 1992a, 1992b).
– fundamental human values – utility, good of another man, truth, knowledge, beauty, happiness, uselessness, harm, ignorance, error, ugliness, unhappiness - the fundamental human values indicated by (Puzynina, 1992) were used.

Table 1.
Example of calculating the sentiment of a tweet

Sample tweet	Prawda o fotowoltaice jest ***smutna*** [-1]: za pieniądze podatnika wciskane są ludziom instalacje, które bardziej obciążają różnymi kosztami system ***energetyczny*** [1] niż produkują prąd. Ktoś za te ***straty*** [-1] musi zapłacić - płacą podatnicy. A w nocy i zimą, gdy potrzeba dużo prądu, fw nie działa.
Sentiment calculation	***straty*** [1] = 1 ***smutna*** [-1] + ***straty*** [-1] = -2
	The number of positive words (1) < The number of negative words (2)
	The sentiment of the tweet = negative

Sources: original research.

At this stage, each tweet's cleaned content was saved to a separate text file and sequentially processed by Any2txt, Speller2, Wcrft2, WSD and ccl_emo services. Among others, spelling checks and word sense disambiguation were done. For words, emotive information like polarity (positive, negative, neutral or ambiguous), 8 basic emotions and 12 fundamental human values were retrieved. This information was saved to separate text files (each tweet to one file). Then the sentiment for each tweet was calculated using information from these files. Table 1 shows how the sentiment of a tweet was calculated. In square brackets, there is information about the polarity of the words before them for one of the downloaded tweets. Words with negative polarity have a value of -1, and those with positive polarity have a value of 1. A tweet has a negative sentiment if there are more negative words than positive ones. Positive sentiment is if there are fewer negative words than positive ones. A neutral sentiment if the ratio of positive to negative words is equal.

In the next step, for each tweet, it was counted how many words, with annotated basic emotions and fundamental human values, it contained. From Table 2, it can be read that the example tweet contained 3 words with the emotion “gladness”, 2 words with the emotion “anger”, and 1 word with the emotion “sadness”.

Table 2.
The number of words with annotated basic emotions - sample tweet

TweetId	gladness	enjoying something expected	trust	disgust	fear	anger	surprise with something unpredictable	sadness
1611753205972570113	3	0	0	0	0	2	0	1

Sources: original research.

3. Results

Using a ribbon chart figure 1 shows how many of the analyzed tweets were published in individual years and months. It can be seen from it that only 27 tweets were published in 2010, 42 tweets in 2011 and 15456 tweets in 2021. In 2022 it was 28753 tweets with the most in September and the least in April. Similarly, figure 2 shows how many users published the analyzed tweets in particular years and months. It can be read from it that in 2021, 10681 users published the tweets and the most users published in December.

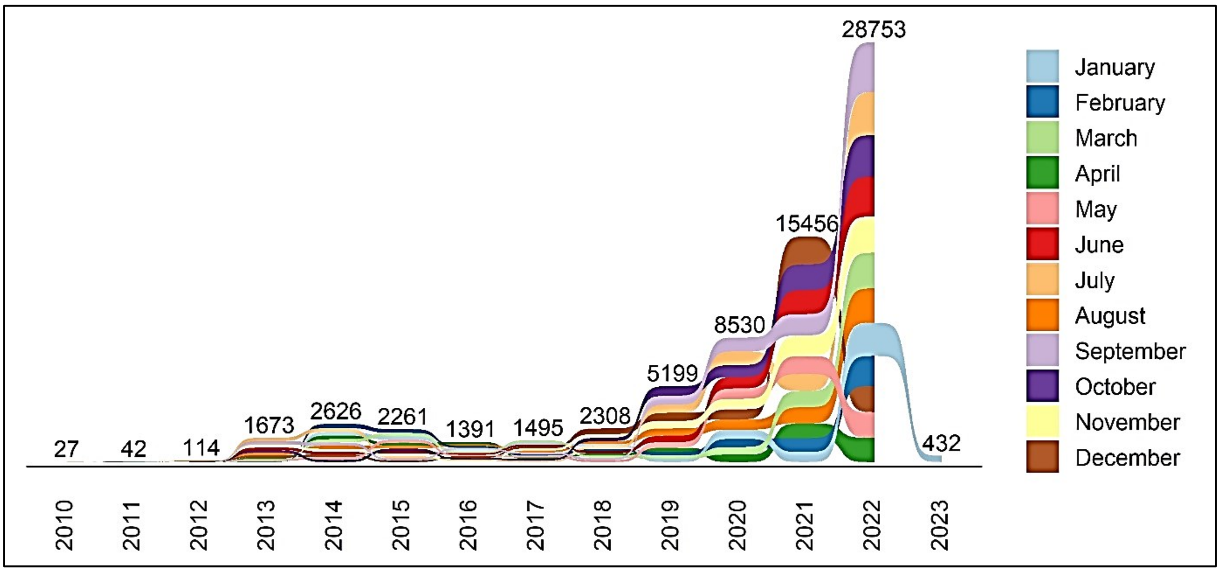

Figure 1. Number of tweets by year.

Sources: original research.

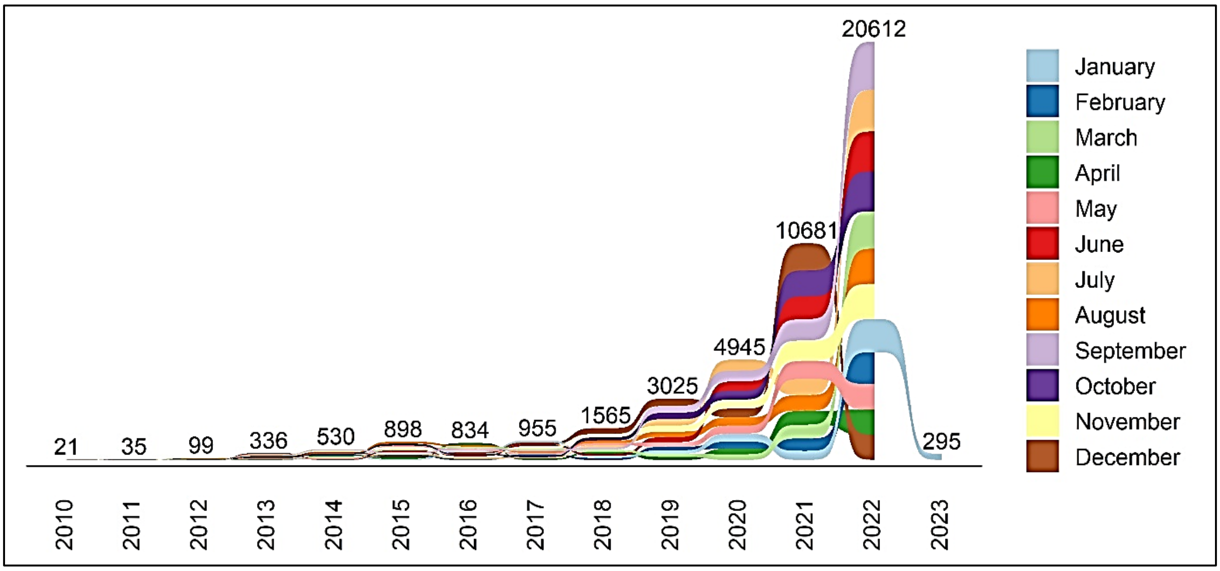

Figure 2. Number of the user by year.

Sources: original research.

Table 3 shows how many tweets were published by users and how many users there were in total. The number of total users during the analysis period was 20433. It can be read from this table that 12278 users published one tweet. 535 users posted 5 tweets each, bringing the total to 2675 tweets. 7 users published between 401 and 3000 tweets each. Together they published 6861 tweets.

Table 4 shows how many hashtags each tweet had. It can be read from it that 59974 tweets, which are 85.3% of the tweets analysed, had no hashtags. 3743 tweets had 1 hashtag each. 88 tweets had 10 hashtags.

Table 3.
The number of tweets published by users

The number of published tweets by the user	The number of users	The total number of published tweets
1	12278 (60,089%)	12278 (17,463%)
2	3332 (16,307%)	6664 (9,478%)
3	1497 (7,326%)	4491 (6,388%)
4	810 (3,964%)	3240 (4,608%)
5	535 (2,618%)	2675 (3,805%)
6	398 (1,948%)	2388 (3,397%)
7	260 (1,272%)	1820 (2,589%)
8	205 (1,003%)	1640 (2,333%)
9	143 (0,7%)	1287 (1,831%)
10	124 (0,607%)	1240 (1,764%)
11-20	505 (2,471%)	7124 (10,133%)
21-50	234 (1,145%)	7122 (10,13%)
51-100	65 (0,318%)	4540 (6,457%)
101-400	40 (0,196%)	6937 (9,867%)
401-3000	7 (0,034%)	6861 (9,759%)
Total	**20433 (100%)**	**70307 (100%)**

Source: original research.

Table 4.
Number of hashtags in tweets

Number of the hashtag in one tweet	Number of tweets
0	59974 (85,303%)
1	3743 (5,324%)
2	2452 (3,488%)
3	1600 (2,276%)
4	943 (1,341%)
5	660 (0,939%)
6	313 (0,445%)
7	198 (0,282%)
8	119 (0,169%)
9	93 (0,132%)
10	88 (0,125%)
from 11 to 20	124 (0,176%)
Total	**70307(100%)**

Source: original research.

Figure 3 shows the percentage of positive, negative and neutral tweets by year. We can see from it that in the year 2022 23.8% of tweets had negative, 46.1% neutral and 30.1% positive sentiment.

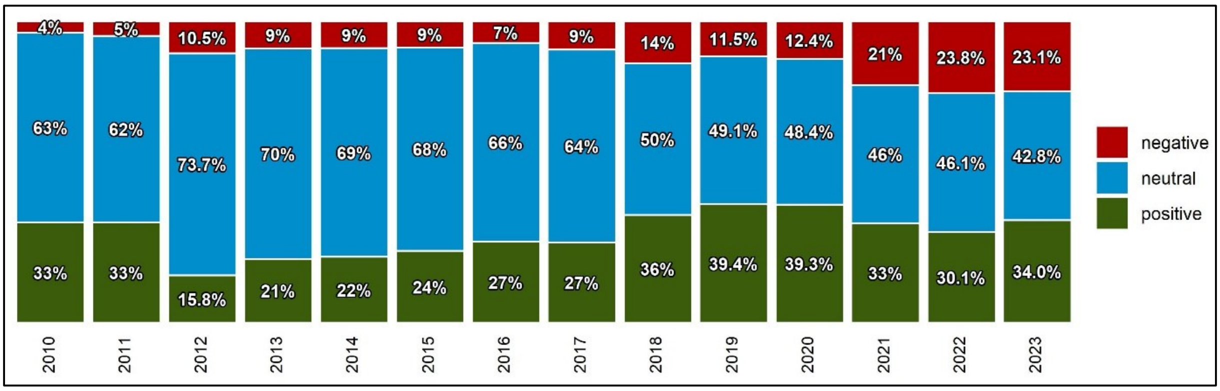

Figure 3. Percentage of positive, negative and neutral tweets.

Sources: original research.

Figure 4 shows the percentage of words with annotated basic emotions by year. Positive emotions are marked in green (gladness, enjoying something expected, trust). Negative emotions are marked in red (disgust, fear, anger, surprise with something unpredictable, sadness). We can see from it, that words with positive emotions had the following percentages in 2022 - gladness 23.9%, enjoying something expected 8.5% and trust 12.4%.

Figure 5 shows the percentage of words with annotated fundamental human values. The positive human values are marked in green (beauty, happiness, good of another man, utility, knowledge). Among the positive human values, not once did the “truth” occur. The negative human values are marked in red (unhappiness, error, harm, ignorance, uselessness, ugliness).

Figure 6 and 7 shows the most frequent words and hashtags in tweets. They are presented in the form of a word cloud. By analysing these words, it is possible to determine what the tweets were about.

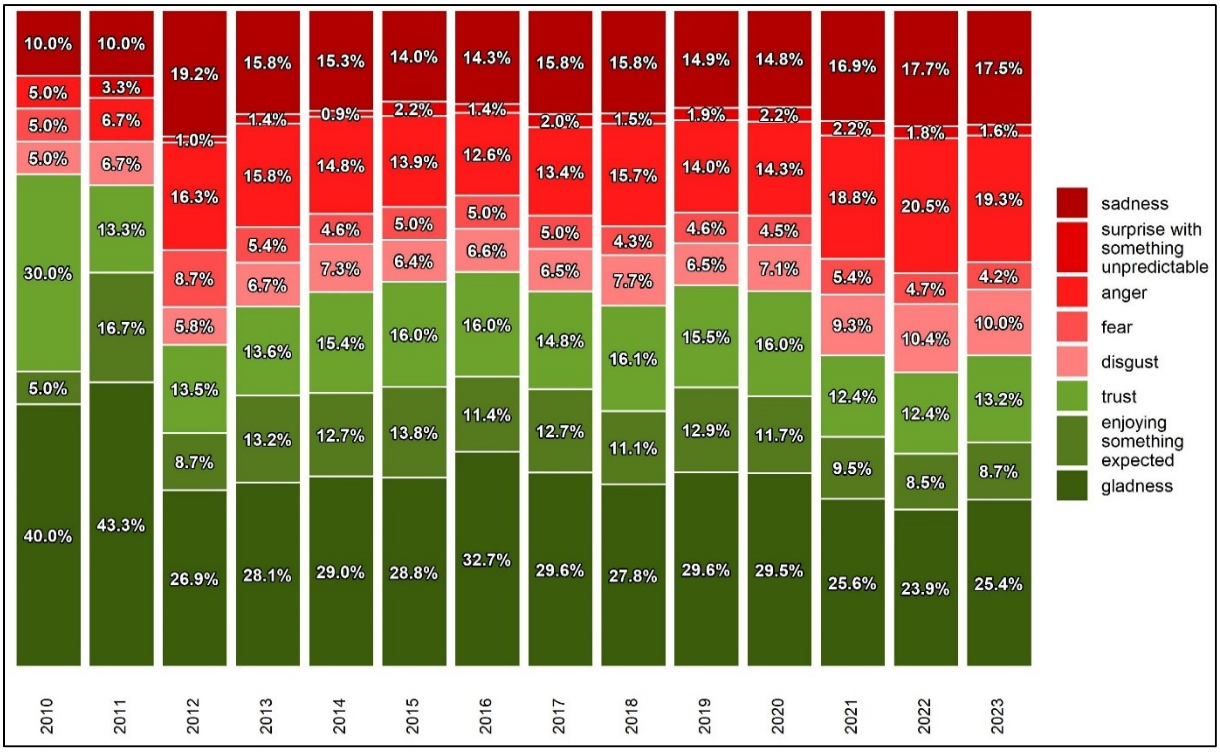

Figure 4. Percentage of words with annotated basic emotions by year.

Sources: original research.

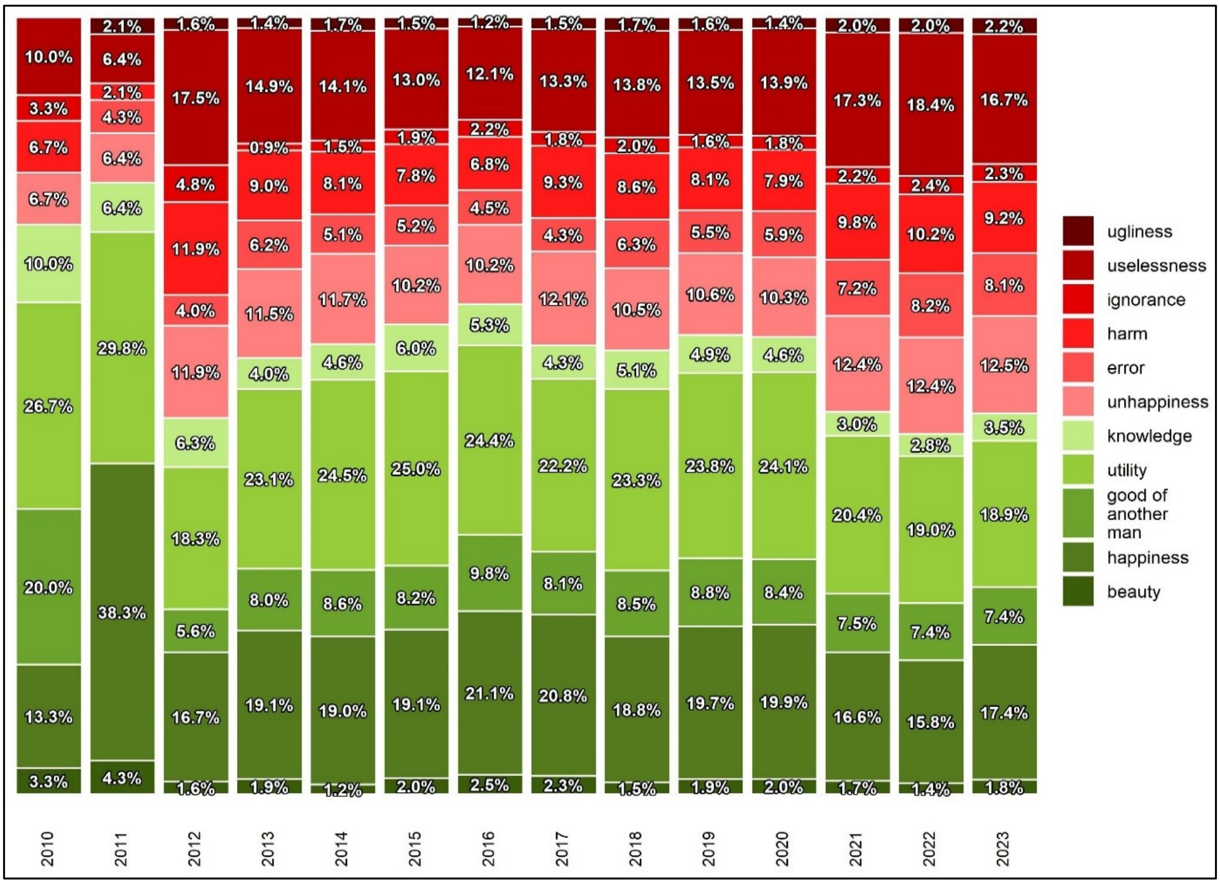

Figure 5. Percentage of words with annotated fundamental human values by year.

Sources: original research.

Figure 6. Most frequently used words.

Sources: original research.

Figure 7. Most frequently used hashtags.

Sources: original research.

4. Conclusion

Analysis of tweets allowed to establish the following conclusions:

- an increasing number of tweets show that interest in photovoltaics is growing all the time, especially after the year 2017,
- there is variation in the number of tweets published by users. Most often, users published only 1 tweet. Such users accounted for 60.089% of all users. The smallest group were users who published between 401 and 3.000 tweets each.
- in recent years, the number of tweets with positive and negative sentiment has been increasing, while the number of tweets with neutral sentiment has been decreasing,
  - the percentage of negative tweets has trended upward since 2010; in 2010 the percentage of negative tweets was 4% and in 2022 it was 23.8 %.
  - from 2012 onwards, the number of tweets with neutral sentiment decreased from 73.7% to 42.8%,
  - tweets with positive sentiment were highest in 2019 and 2020 at 39.4% and 39.3% respectively,
  - the number of tweets with neutral sentiment was the lowest in 2023.
- in 2012, 2021, 2022 and 2023 the percentage of words with annotated negative basic emotions was greater than that with positive ones. They were about 50.96%, 52.59%, 55.18% and 52.58% respectively,
- in 2012, 2021, 2022 and 2023 the percentage of words with annotated negative fundamental human values was greater than with positive ones. They were about 51.58%, 50.8%, 53.61%, and 50.99% respectively,
- analysing the most frequently used words, it can be assumed that tweets addressed the following issues related to photovoltaics:
  - households as the main users of photovoltaics – words: “dom” (eng. house), “domowy” (eng. domestic), “budynek” (eng. building), “gospodarstwo” (eng. household), “mikroinstalacja” (eng. micro installation), “prosument” (eng. prosumer), “własny” (eng. own), “właściciel” (eng. owner),
  - the main components of a photovoltaic installation – words: “słoneczny” (eng. solar), “ogniwo” (eng. cell), “panel”, “falownik” (eng. inverter), “moduł” (eng. module), “akumulator” (eng. battery), “bateria” (eng. battery), “magazyn” (eng. storage),
  - amount of energy produced by the photovoltaic installation over a given period – words and abbreviations like: “mwh” (MWh, eng. megawatt hour), “kilowatogdzina” (eng. kilowatt-hour), “produkować” (eng. to produce), “wytwarzać” (eng. to generate), “produkcja” (eng. production), prąd (eng.

“electricity”), “energia (eng. energy), “elektryczny” (eng. electric), “rocznie” (eng. annually), “roczny” (eng. annual), “miesiąc” (eng. month), “wynik” (“result”),
  - photovoltaic installation capacity and the factors affecting it - words: “moc” (eng. power), “mw” (eng. MW), “kilowatt” (eng. kilowatt), “k” (eng. kilo), “dach” (eng. roof), “kierunek” (eng. direction), “metr” (eng. metre), “powierzchnia” (eng. area), “łączna” (eng. total),
  - considering the purchase of an electric or plug-in hybrid car – words: “auto” (eng. car), “samochód” (eng. car), ładować (eng. to charge),
  - complaints about intensive persuasion to buy photovoltaic – words: “dzwonić” (eng. to call), “oferować” (eng. to offer), “zadzwonić” (eng. to call), “telefon” (eng. phone), “sprzedać” (eng. to sell), “sprzedawca” (eng. salesman), “sprzedaż” (eng. sales), “proponować” (eng. to propose), “promować” (eng. to promot), “bot”[5],
  - financial support for the purchase of photovoltaic – words: „dopłata” (eng. subsidy), “dotacja” (eng. subvention), “dostać” (eng. to get), “wsparcie” (eng. support), “wspierać” (eng. to support), “gmina” (eng. district), “rząd” (eng. government), “przepis” (eng. law), “ustawa” (eng. law),
  - the profitability of investment in photovoltaics – words: “koszt” (eng. cost), “kosztować” (eng. to cost), “opłacalny” (eng. worthwhile), “zwrot” (eng. return on investment), “zwrócić” (eng. return on investment), “kredyt” (eng. credit),
- analysing the most frequently used words can determine that tweets did not only concern photovoltaic but also in general:
  - electricity and heat production from varoius energy sources – “atom”, “atomowy” (eng. atomic), “biogazownia” (eng. biogas plant), “elektrownia” (eng. power plant), “eneriga” (eng. energy), “gaz” (eng. gas), “gazowy” (eng. gas), “jądrowy” (eng. nuclear), “odnawialny” (eng. renewable), „prąd” (eng. electricity), “farma” (eng. farm) “turbina” (eng. turbine), “węgiel” (eng. coal), “węglowy” (eng. coal), “wiatrak” (eng. wind turbine), “wiatr” (eng. wind), “wiatrowy” (eng. wind), “woda” (eng. water), “wodór” (eng. hydrogen), “źródło” (eng. source), “grzać” (eng. to heat), “ciepło” (eng. heat), “pompa” (eng. pomp),
  - green power generation and the air quality – “czysta” (eng. clean), “ekologia” (eng. ecology), “ekologiczny” (eng. ecological), “środowisko” (eng. environment), “emisja” (eng. emission), “zielone” (eng. green), “zielony” (eng. green),
- analysing the most frequently used hastags, it can be assumed that tweets addressed the following issues:
  - photovoltaic – words / concatenations of words / abbreviation: “fotowoltaika” (eng. photovoltaics), “pv” (eng. photovoltaics), “instalacjefotowoltaiczne” (eng. photovoltaics systems), “prosument” (eng. prosumer), ,“prosumenci” (eng.

[5] Telephone bot - make sales calls to potential customers.

prosumers), "mójprąd"[6] (eng. my electricity), "panelefotowoltaiczne" (eng. photovoltaics panels), "panele" (eng. panels), "magazynenergii" (eng. energy storage), "magazynyenergii" (eng. energy storages), "twójprąd" (eng. your electricity),

- ecology, clean electricity generation – words / concatenations of words / abbreviation: "oze" (eng. renewables), "czystepowietrze" (eng. clean air), "solar", "energiasłoneczna" (eng. solar energy), "czystaenergia" (eng. clean energy), "zielonaenergia" (eng. green energy), "renewables", "energiaodnawialna" (eng. renewables), "środowisko" (eng. environment), "smog", "stopsmog", "solarenergy", "greenenergy", "eko" (eng. eco), "eco",
- heating – words / concatenations of words: "pompaciepła" (eng. heat pump), "pompyciepła" (eng. heat pumps), "pompyciepla" (eng. heat pumps), "ogrzewanie" (eng. heat),
- companies related to electricity generation, photovoltaic or/and renewable energy – words: "askoelectric", "columbus", "columbusenergy", "copernic", "enea", "energa", "pgfpolskagrupafotowoltaicznasa", "zielonyzwrottaurona", "pge", "pgnig",
- energy carriers – words: "wodór" (eng. hydrogen), "węgiel" (eng. coal), "biogas", "atom",
- financial support for the purchase of photovoltaic – words: "dotacje" (eng. subventions), "dofinansowanie" (eng. subsidy), "funduszeue" (eng. EU funds).

The conducted research confirms that Twitter can be a source of big data. Twitter data can be used for sentiment analysis to find out people's thoughts, feelings and opinions on "photovoltaics". Only the opinions of Polish speakers who posted on Twitter were identified in this study.

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