SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2022
ORGANIZATION AND MANAGEMENT SERIES NO. 167

SENTIMENT ANALYSIS CONCERNING HEAT PUMPS - ANALYSIS OF TWEETS PUBLISHED IN POLISH

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Purpose: Identifying thoughts, feelings and opinions on "heat pumps" based on the content of tweets.
Design/methodology/approach: Tweets written in Polish, containing all possible grammatical cases of the terms "heat pump" and "heat pumps", were automatically downloaded. The content of the tweets has been preprocessed. URLs, hashtags, emojis, usernames, all characters except letters, and phrases used to search for tweets were removed from their content. The sentiment value of the tweets was calculated. Visualisations were prepared to show the percentage of positive, negative and neutral tweets. The most frequently used words in tweets were shown with word clouds.
Findings: The number of tweets concerning heat pumps and the percentage of positive, negative and neutral tweets were determined.
Research limitations/implications: Only the content of tweets written in Polish was analysed. Sentiment analysis was performed automatically by the service "ccl_emo", without author supervision. Only the opinions of people who posted on Twitter were analysed.
Practical implications: Automatic monitoring of people's feelings about heat pumps.
Originality/value: Information on the attitudes of people from Poland towards heat pumps was obtained. It has been established, based on a growing number of tweets, that interest in heat pumps in Poland is growing all the time.

Keywords: sentiment analysis, Twitter, heat pump.

Category of the paper: research paper, case study.

1. Introduction

As global warming becomes more visible in the environment, society faces several climate-related challenges to significantly reduce greenhouse gas emissions from heating and cooling buildings (Decuypere, Robaeyst, Hudders, Baccarne, de Sompel, 2022). The heating and cooling of buildings cause one-tenth of anthropogenic greenhouse gas (Edenhofer, 2015). These emissions are likely to increase sharply in the coming decades (Ürge-Vorsatz, Cabeza, Serrano, Barreneche, Petrichenko, 2015). Heating systems need a rapid transition to low-carbon options to meet global climate goals (Martiskainen, Schot, Sovacool, 2021).

Thanks to technological advances, heat pumps now have the potential to reduce emissions from heating and cooling in many settings by half or more (Billimoria, Guccione, Henchen, Louis-Prescott, 2021). Heat pumps are diverse, using renewable energy from the air, water, ground or air exhausted from buildings to provide heating and cooling (Nowak, 2018). Two common types of heat pumps are air-source, which transfers heat to and from the outdoor air, and ground-source, which transfers heat to and from the ground (Kircher, Zhang, 2021). Heat pumps can be used for a variety of purposes, including providing heating and cooling for buildings, generating electricity and providing hot water (Soltani et al., 2019). Heat pump technology has developed significantly in recent years, both in terms of efficiency and heating performance at low temperatures (Chua, Chou, Yang, 2010). Despite their advantages, heat pumps face several obstacles to widespread adoption. Their lifetime costs are not always competitive with existing technologies such as natural gas furnaces (Billimoria et al., 2021). Even when the operating costs of heat pumps are competitive, the initial purchase and installation costs can be prohibitive (Bergman, 2013). Additional barriers to heat pump adoption include finding installers who are familiar with modern heat pumps, choosing the right models and sizes of heat pumps, and finding and applying for rebates, tax credits, and other incentives (Snape, Boait, Rylatt, 2015).

With the rise of the digital age, people often express their opinions and post them on social media. People's thoughts, feelings and judgements can be analysed using a technique called sentiment analysis. Sentiment analysis provides an automated method for analysing sentiment, emotion and opinion in written language (Xu, Chang, Jayne, 2022). It is the process of analyzing, processing, generalizing, and reasoning about subjective texts with emotional overtones, such as valuable commentary information about people, time, products, etc., posted by users on the Internet (Deng, Ergu, Liu, Cai, Ma, 2022).

One of the most popular places 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). They can share their instantaneous thoughts or information on a wide range of topics or interests through short messages (known as "tweets") (Das, Sun, Dutta, 2015). Users have established certain conventions to support more conversational features. They can republish someone else's tweets ("retweeting"), and also use the "@" symbol and/or the "#" symbol when posting tweets. (Boyd, Golder, Lotan, 2010; Panagiotopoulos, Sams, 2012). By using the "@" users can directly address or refer to other users in conversations (Akshay Java Xiaodan Song, Tseng, 2007; Honeycutt, Herring, 2009). Using hashtags marked with the "#" symbol, users can categorize posts about a specific topic or event (Bruns, 2012; Small, 2011).

Twitter can be a source of big data. Downloaded data can be analyzed using various tools. Due to a large amount of data, text mining, data mining, machine learning, topic modelling, sentiment analysis and similar approaches are used. Social media data mining is an emerging field. It is gaining popularity due to its cost-effectiveness, accessibility, and anonymity (Das, Dutta, Medina, Minjares-Kyle, Elgart, 2019; Das et al., 2015; Evans-Cowley, Griffin, 2012). There are many studies in the literature on sentiment analysis based on data obtained from the Internet (Pang, Lee, 2004, 2008; Read, 2005). Many studies deal also with sentiment analysis of tweets (ALQARALEH, 2020; Antypas, Preece, Collados, 2022; Ayan, Kuyumcu, Ciylan, 2019; Çoban, Tümüklü Özyer, 2018; Das et al., 2019; FADEL, Cemil, 2020; Gabarron, Dechsling, Skafle, Nordahl-Hansen et al., 2022; Garcia, Berton, 2021; Go, Huang, Bhayani, 2009; Nezhad, Deihimi, 2022; Sarlan, Nadam, Basri, 2014; Sunitha, Patra, Babu, Suresh, Gupta, 2022; Zavattaro, French, Mohanty, 2015). By examining current or popular topics with sentiment analysis over social network data it is possible to have an idea about the future of these topics (Ağrali, AYDIN, 2021).

2. Research methodology

On 11.05.2022. 20298 tweets were retrieved from Twitter. The snscrape library for Python was used for this. This library contains various functions to collect tweets, user information, profile information, hashtags and comments. It makes these elements available through a Twitter API-free interface. It provides helpful flags that help filter tweets based on conditions such as the number of likes, the number of replies, language, identification number of tweet 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 phrases in Polish: “pomp ciepła”, “pompa ciepła”, “pompach ciepła”, “pompami ciepła”, “pompą ciepła”, “pompę ciepła”, “pompie ciepła”, “pompo ciepła”, “pompom ciepła”, “pompy ciepła”. These phrases are in all possible grammatical cases for the Polish language and are translations of the terms: "heat pump" and "heat pumps".

In the next step author removed:

- tweets, which were written in languages other than Polish,
- duplicated tweets (some tweets were retrieved several times because they contained more than one phrase used during the search e.g. “pompę ciepła” and “pompy ciepła”),
- tweets whose content was identical to the content of other tweets (it was often 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 “==”

In the next step, the content of the tweets was pre-processed. URLs, hashtags, emojis, users' names and all characters except letters were removed from the content of the tweets. The phrases used to search for tweets have also been removed so that they do not take part in the calculation of a tweet's sentiment value. Next, the number of words in the cleaned content of each tweet was checked, not including words considered unhelpful (such as stop words, conjunctions or prepositions). Tweets that had less than 2 words were removed. After these actions, the number of tweets was 11830. These tweets formed the corpus named Corpus_1. This number of tweets was published by 3731 users.

In the next step, the **ccl_emo** (https://wiki.clarin-pl.eu/…; https://clarin-pl.eu/…) service (developed by CLARIN-PL[1]) was used. This service also has the names "Wydźwięk" (in Polish) and "Sentiment" (in English). It is a service for statistical analysis of the overtone and emotions in texts (Grubljesic, Coelho, Jaklic, 2019; Janz, Kocoń, Piasecki, Zaśko-Zielińska, n.d.). It can be used in the Python language[2]. In addition to this service, other CLARIN-PL's services were used. These were:

- Any2txt - service that converts a file containing text (e.g. doc, docx, xlsx) into text.
- Speller2 – a service for checking the spelling of the text. It uses the Autocorrect (https://languagetool.org/pl/) tool to correct text.
- Wcrft2 - is a simple morpho-syntactic tagger for Polish.
- WSD - a service for word sense disambiguation. It works for Polish texts and as a source of possible senses using plWordNet (plWordNet 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.).

Sample tweet	Winą nie są domy jednorodzinne, a ***wysoka*** [1] cena gazu i pomp ciepła (często też ***brak*** [-1] ***dostępu*** [1] do sieci gazowej), dopuszczenie na rynek ***kiepskiej*** [-1] jakości węgla, ***śmiesznie*** [1] ***niskie*** [-1] kary za palenie śmieciami, ***słaba*** [-1] egzekucja prawa. Bloki też bywają opalane węglem (i byle czym)...
Sentiment calculation	***wysoka*** [1] + ***dostępu*** [1] + ***śmiesznie*** [1] = 3 ***brak*** [-1] + ***kiepskiej*** [-1] + ***niskie*** [-1] + ***słaba*** [-1] = -4
	The number of positive words (3) < The number of negative words (4)
	Sentiment of tweet = negative

Figure 1. Example of calculating sentiment of a tweet.

Sources: original research.

At this stage, the cleaned content of each tweet was saved to a separate text file and processed sequentially by Any2txt, Speller2, Wcrft2, WSD and ccl_emo services. Among others, checking the spelling and word sense disambiguation was performed. For words sense the emotive information (polarity - positive, negative, neutral or ambiguous) was retrieved. This information was saved to separate text files - each tweet to one file. Based on the data from

[1] CLARIN-PL is a Polish scientific consortium, part of the European Research Infrastructure CLARIN (Common Language Resources and Technology Infrastructure) (CLARIN-PL, n.d.).

[2] This service is also available as a web application at http://ws.clarin-pl.eu/sentyment.shtml.

these files, the sentiment for each tweet was calculated. The calculation of the sentiment of a tweet is shown in figure 1. The figure shows one of the tweets downloaded. The square brackets contain information about the polarity of the words in front of them. Words with negative polarity have a value of -1. Words with positive polarity have a value of 1.

If the number of negative words is greater than the number of positive words, the tweet has a negative sentiment. If the number of negative words is less than the number of positive words, the tweet has a positive sentiment. If the number of positive words is equal to the number of negative words tweet has a neutral sentiment.

Table 1.
Number of tweets and users in Corpus_2

Number of		Total number of tweets	Percentage of tweets in Corpus_1
tweets	users		
1	2467	2467	20,9%
2	513	1026	8,7%
3	243	729	6,2%
4	114	456	3,9%
5	95	475	4,0%
6	50	300	2,5%
7	31	217	1,8%
8	26	208	1,8%
Total	**3539**	**5878**	**49,7%**

Source: original research.

Table 2.
Number of tweets and users in Corpus_3

Number of		Total number of tweets	Percentage of tweets in Corpus_1
tweets	users		
606	1	606	5,1%
408	1	408	3,4%
259	1	259	2,2%
218	1	218	1,8%
194	1	194	1,6%
128	1	128	1,1%
115	1	115	1,0%
Total	**7**	**1928**	**16,3%**

Source: original research.

During the analysis, it was noted that there are differences in the number of tweets published by users. Therefore, the author decided to analyse two additional corpora (Corpus_2 and Corpus_3) which were subsets from Corpus_1. Tweets of users who posted between 1 and 8 tweets formed Corpus_2. Table 1 provides information about this corpus. It can be read from it that, 2467 users published one tweet (2467 tweets in total, which is 20.9% of the tweets in Corpus_1), 513 users published 2 tweets (1026 tweets in total, which is 8.7% of the tweets in Corpus_1). Corpus_2 included 49.7% of tweets from Corpus_1. This corpus was formed by the tweets published by 3539 users.

Tweets of users who posted between 115 and 606 tweets formed Corpus_3. Table 2 provides information about this corpus. It can be read from it that, each of the seven users published 606, 406, 259, 218, 194, 128, and 115 tweets respectively. The percentage of tweets from Corpus_3 in Corpus_1 was 16,3%.

3. Results

Figure 2 shows how many tweets from Corpus_1, Corpus_2 and Corpus_3 were published each year. Tweets from Corpus_3 have been published since 2015 and from Corpus_1 and Corpus_2 from 2009. The number of tweets has been increasing since 2016. The number of tweets for 2022 is lower than for 2021, but this is because for 2022 figure only shows tweets published between 01.01.2022 and 11.05.2022. When we compare the number of tweets published in January, February March, and April for 2021 and 2022 we can assume that the number of tweets in 2022 will be higher than in 2021.

Figure 3 shows the percentage of positive, negative and neutral tweets. For all tweets analysed (Corpus_1) 37% had a positive sentiment., 15% negative sentiment and 48% were neutral. Corpus_2 had similar values of 35% positive, 16% negative, 49% neutral respectively. Corps_3 had fewer negative (12%) and neutral tweets (44%) and more positive tweets (44%) than Corps_2 and Corps_1. All corpuses had more positive than negative tweets.

Figure 4 shows the percentage of positive, negative and neutral tweets by year. As we can see, there were no tweets with negative sentiment in Corps_1 and Corps_2 in 2009. Analysing the results, it can be seen that the percentage of negative tweets has increased since 2009 (for Corpus_1, for example, it was 0% in 2009, 5% in 2010, 11% in 2018 and 21% in 2021). At the same time, the share of tweets with a neutral sentiment has decreased. The decreasing share of tweets with a neutral sentiment can be seen especially in Corpus_3. The percentage of tweets with a positive sentiment from 2018 to 2022 ranged between 37% - 41% for corpus_1 and 33% - 42% for corpus_2. From 2018 to 2021, the percentage of negative tweets tended to increase and the percentage of neutral tweets trended downwards.

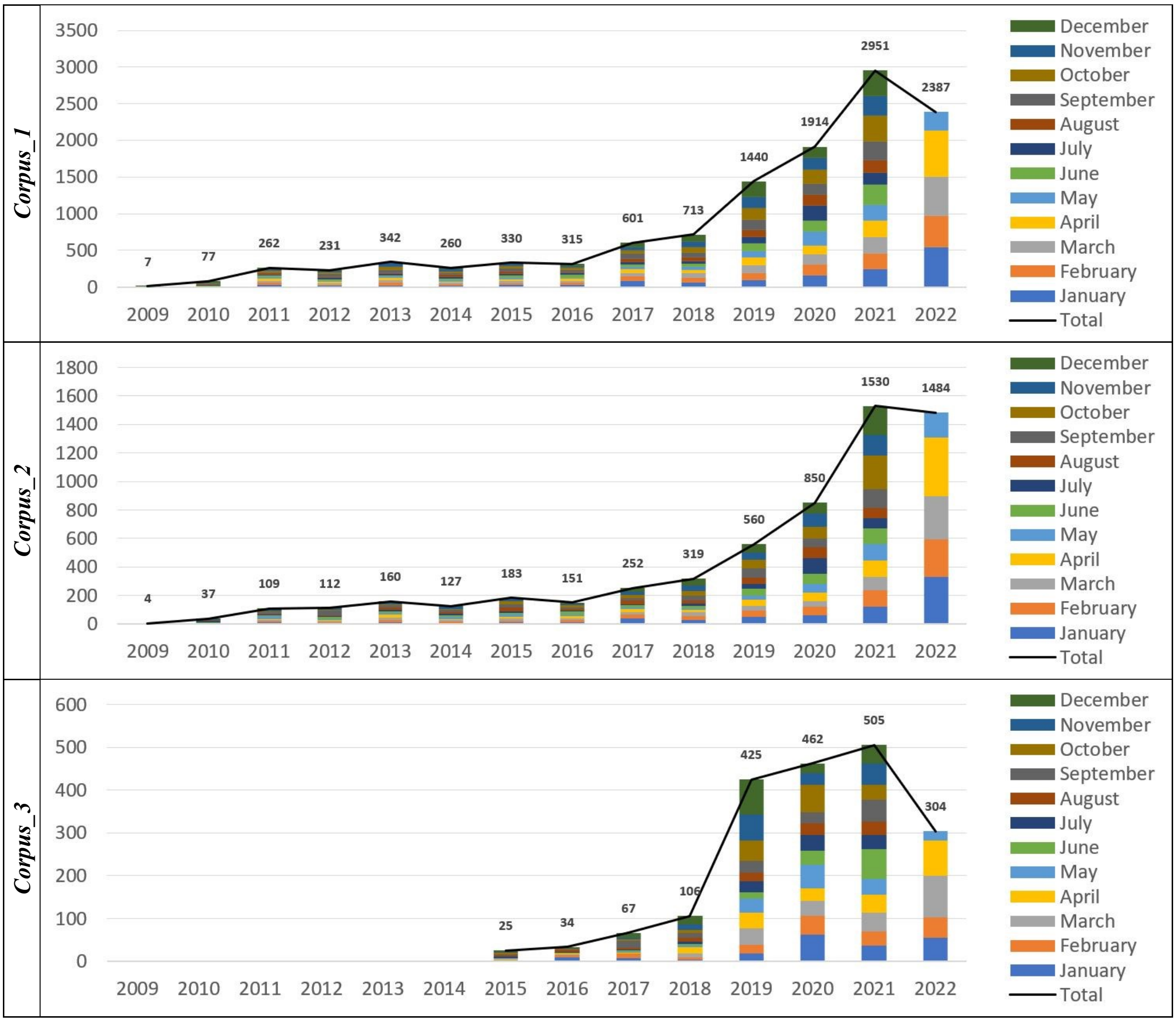


Figure 2. The number of tweets by year.

Sources: original research.

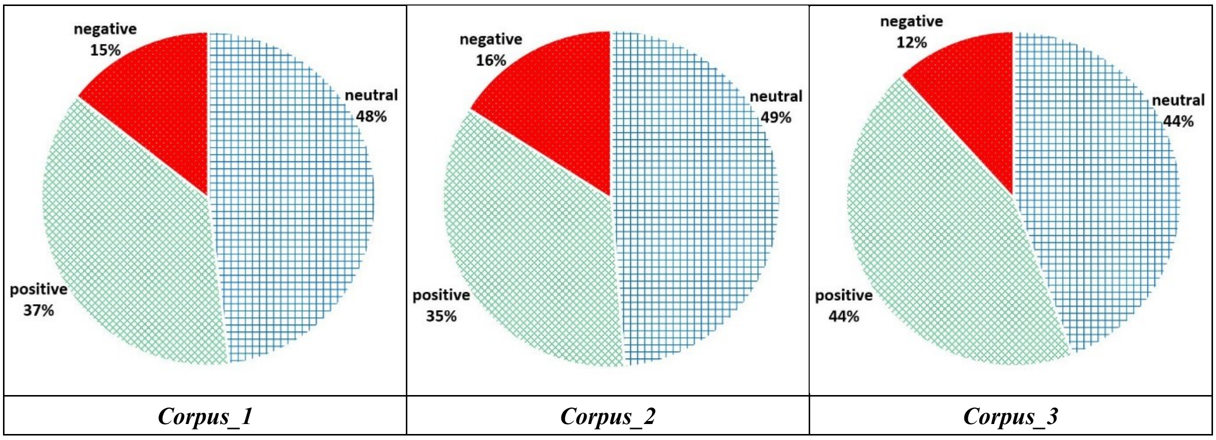


Figure 3. Percentage of positive, negative and neutral tweets.

Sources: original research.

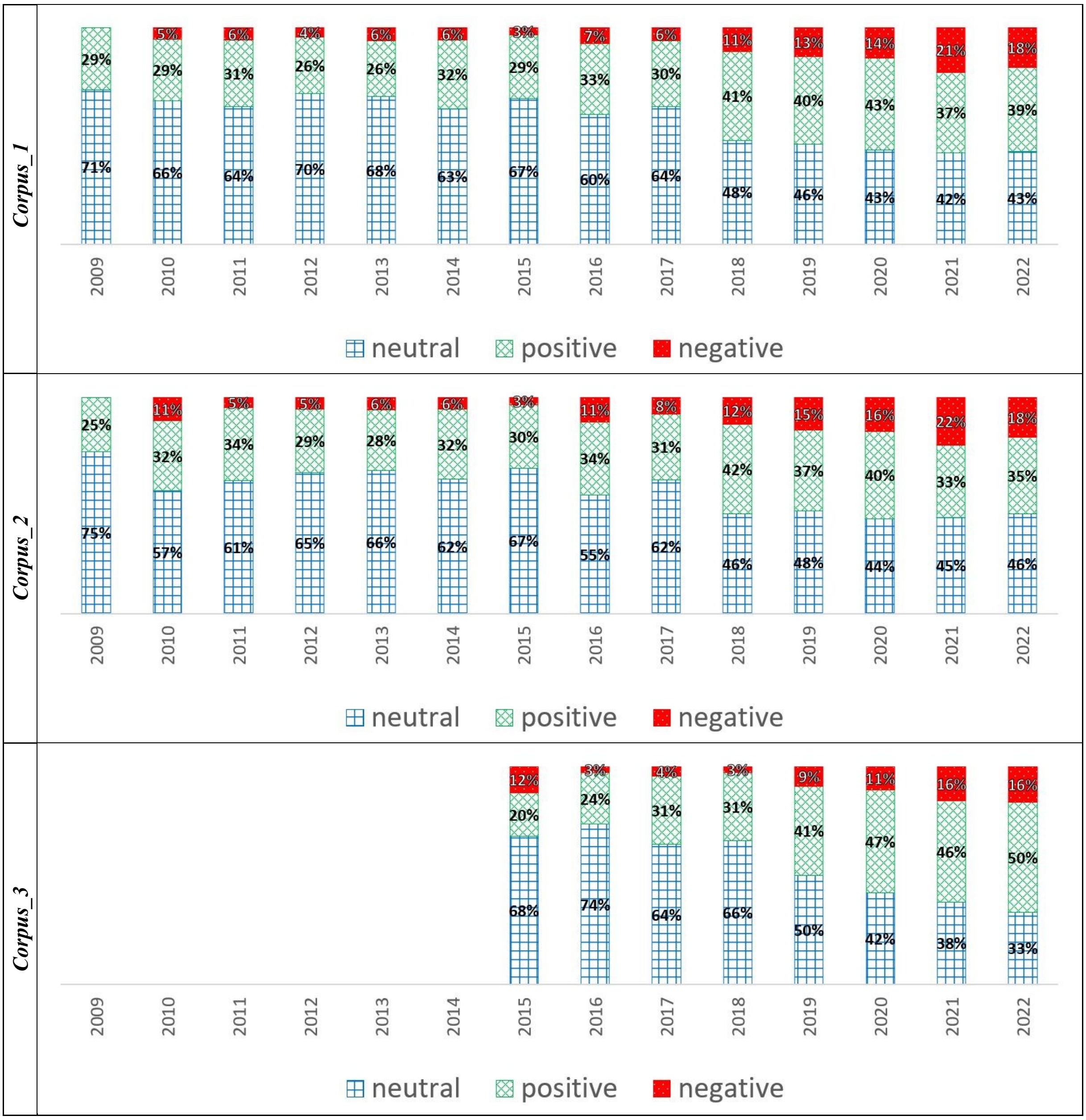
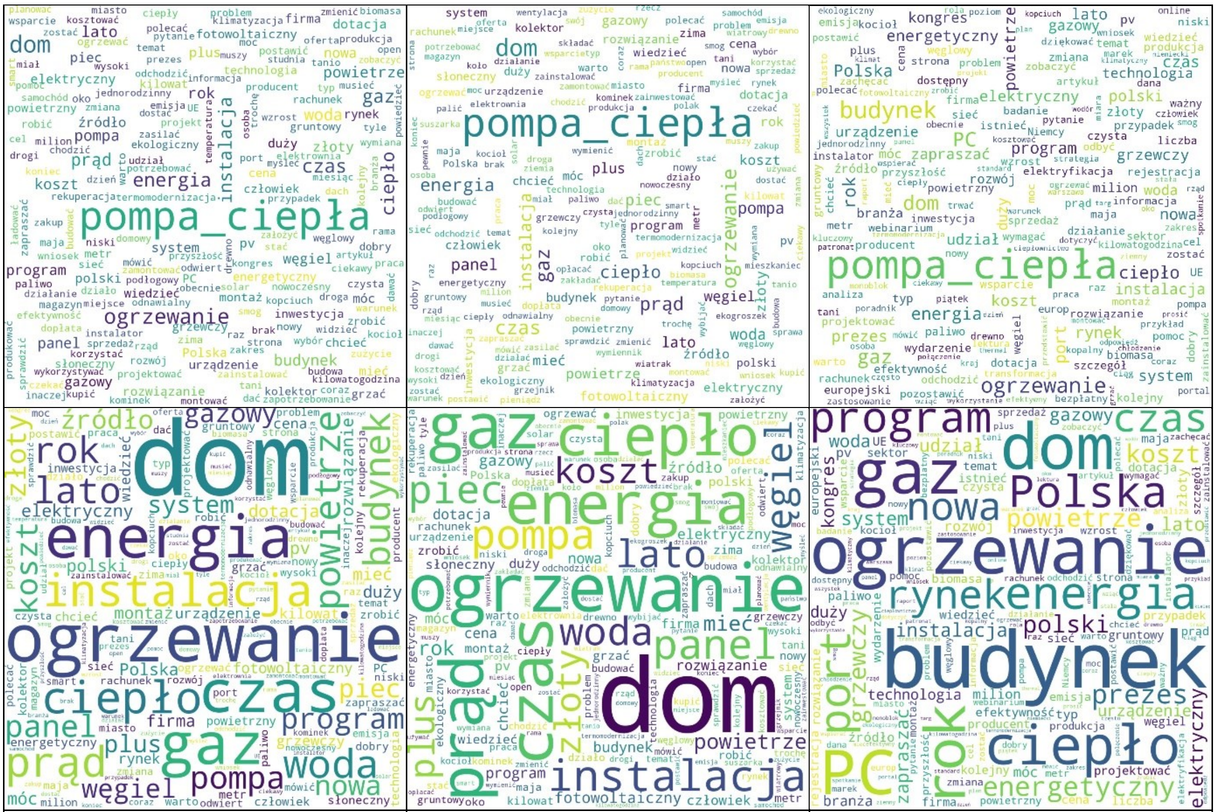


Figure 4. Percentage of positive, negative and neutral tweets by year.

Sources: original research.

Figure 5 shows as a words cloud the most common words in tweets for Corpus_1, Corpus_2 and Corpus_3. These words have been reduced to their base form. The upper part of the figure shows word clouds with the 2-gram "pompca_ciepła" (Eng. heat pump). This 2-gram occurred often enough that the other words are much smaller. The lower part of the figure shows word clouds without this 2-gram. By analysing words from this figure is possible to determine what the tweets were about. Words such as "dom" (Eng. house), "budynek" (Eng. building), "ogrzewanie" (Eng. heating), "instalacja" (Eng. installation), "ciepło" (Eng. heat), "pompa" (Eng. pump), "piec" (Eng. heating oven), "woda" (Eng. water), "powietrze" (Eng. air) show that the content related to heating systems for houses and buildings. System for heating water and air. The word "powietrze" (Eng. air) can also indicate the type of heat pump used, and air quality considerations. Words like "rekuperacja" (Eng. recuperation), "termomodernizacja" (Eng. thermomodernization), "emisja" (Eng. emissions), "ekologiczny" (Eng. ecological) suggest a desire or need for a greener heating solution. The content of tweets also covered the energy carriers like "prąd" (Eng. electricity), "gaz" (Eng. gas), "węgiel" (Eng. coal), "paliwo" (Eng. fuel), "biomasa" (Eng. biomass). Some words may indicate systems for producing electricity from solar energy, words like "energia" (Eng. energy), "fotowoltaiczny" (Eng. photovoltaic), "panel" (Eng. panel), "lato" (Eng. summer). The words "program" (Eng. programme), "dotacja" (Eng. grant), and "zapraszać" (Eng. Invite) may indicate the provision of information on solutions encouraging the replacement of non-ecological heat sources with ecological ones, e.g. heat pumps.



Corpus_1	*Corpus_2*	*Corpus_3*

Figure 5. Most frequently used words.

Sources: original research.

4. Conclusion

Analysis of tweets, containing one or more of the following phrases in Polish "pomp ciepła", "pompa ciepła", "pompach ciepła", "pompami ciepła", "pompą ciepła", "pompę ciepła", "pompie ciepła", "pompo ciepła", "pompom ciepła", "pompy ciepła" which are translations of the terms: “heat pump” and ”heat pumps” allowed to established the following conclusions:

- an increasing number of tweets show that interest in heat pumps is growing all the time, especially after the year 2016,
- for analysed tweets 37% had a positive sentiment., 15% negative sentiment and 48% were neutral,
- the percentage of negative tweets has increased since 2009 (it was 0% in 2009, 5% in 2010, 11% in 2018 and 21% in 2021),
- analysing the most frequently used words can determine that tweets did not only concern heat pump but also in general:
  - heating systems for houses and buildings, using different equipment and energy carriers,
  - system for heating water and air,
  - the type of heat pump,
  - the air quality,
  - systems for producing electricity from solar energy,
  - the information about solutions encouraging the replacement of non-ecological heat sources with ecological ones.

Research has confirmed that Twitter can be a source of big data. This data can be used for sentiment analysis to find out people's thoughts, feelings and opinions regarding “heat pumps”. This study identified only the opinions of those posting on Twitter in Polish.

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