Int. J. Production Economics 260 (2023) 108861

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Impact of extreme weather in production economics: Extracting evidence from user-generated content

Jose Ramon Saura [a,*], Samuel Ribeiro-Navarrete [b,e,f], Daniel Palacios-Marqués [c], Abbas Mardani [d]

[a] Rey Juan Carlos University, Madrid, Spain
[b] University of Valencia, Valencia, Spain
[c] Politechnic University of Valencia, Valencia, Spain
[d] Business School, Worcester Polytechnic Institute, Worcester, MA, United States
[e] ESIC University, Madrid, Spain
[f] University of Economics and Human Sciences, Warsaw, Poland

ARTICLE INFO

Keywords:
Extreme weather
Production economics
User-generated content
Data-driven method

ABSTRACT

The last decade has witnessed an increase in the number of extreme weather events globally. In addition, the economic output around the world is at all-time high in terms of production and profitability. However, global warming and extreme weather are modifying the natural ecosystem and the human social system, leading to the appearance of extreme climate events that have an adverse impact on the world economy. To address this challenge, the present study identifies the main impacts of extreme weather on production economics based on the analysis of user-generated content (UGC) on the social network Twitter. Methodologically, a sentiment analysis with machine learning is developed and applied to analyze a sample of 1.4 m tweets; in addition, computing experiments to calculate the accuracy with Support Vector Classifier, Multinomial Naïve Bayes, Logistic Regression, and Random Forest Classifier are conducted. Second, a topic modeling known as latent Dirichlet allocation is applied to divide sentiment-classified tweets into topics. To complement these approaches, we also use the technique of textual analysis. These approaches are used under the framework of computer-aided test analysis system and natural language processing. The results are discussed and linked to appraisal theory. A total of 7 topics are identified, including positive (Sustainable energies and Green Entrepreneurs), neutral (Climate economy, Producer's productivity and Stock market), and negative (Economy and policy and Climate emergence). Finally, the present study discusses how the recent trend of an increase in extreme weather conditions has significantly impacted international markets, leading companies to adapt their business models and production systems accordingly. The results show that the climate economy and policy, producers' productivity, and the stock market are all heavily influenced by extreme weather and can have significant effects on the global economy.

1. Introduction

In the last decade, an increasing number of adverse weather events have been recorded around the world (Cho et al., 2018). While the hottest temperatures ever observed on our planet are recorded, the economic activity around the world is also at all-time high in terms of output and profitability (Lee et al., 2014; Huang et al., 2018). However, as argued by Stott (2016), global warming and extreme weather modify both the natural ecosystem and the human social system (Chik and Xue, 2021). Thus, weather conditions have a direct impact on economic production (Minner, 2001). Overall, the adverse consequences of climate change include pollution, fires, earthquakes, the decline in the animal population, and the increase in massive logging (Keleş et al., 2018; Shafi and Mohammadi, 2020; UNDRR, 2020).

Global temperature changes cause heat waves, records of extreme hot days, intense storms or droughts, among other issues (Kovács, 2017). These consequences caused by global warming mean that economic production worldwide undergoes systematic changes and is vulnerable

* Corresponding author.
E-mail addresses: joseramon.saura@urjc.es (J.R. Saura), samuelribeironavarrete@gmail.com (S. Ribeiro-Navarrete), dapamar@doe.upv.es (D. Palacios-Marqués), amardani@wpi.edu (A. Mardani).

https://doi.org/10.1016/j.ijpe.2023.108861
Received 15 September 2022; Received in revised form 5 January 2023; Accepted 29 March 2023
Available online 30 March 2023

to extreme stimuli from nature (Choi et al., 2012). As noted by Jian-Bin et al. (2012), the massive emission of greenhouse gases retained in the atmosphere and on the earth's surface increase the planet's temperature, thereby causing an imbalance over time (Coumou and Rahmstorf, 2012; Tang and Rehme, 2017).

In parallel to these climate changes, the world population increases every year, leading to a reduction of reserves and natural resources (Lam et al., 2016). Accordingly, as indicated by Weilnhammer et al. (2021), the future of humanity is linked to the rationalization of natural sources, as well as the reduction of pollution and gases that cause global warming (Lam et al., 2016). In this context, the development of sustainable and environmentally friendly strategies can be an important incentive to create and boost economic value in companies (Zhu and Sarkis, 2004; MacCarthy and Jayarathne, 2012; Zhan et al., 2021).

To date, several studies have turned to the analysis of the data from social networks to better understand the consequences of climate change (Moernaut et al., 2022), natural disasters (Platania et al., 2022), and other events linked global warming (Lydiri et al., 2022). In this context, the data generated in social networks and on digital platforms are collectively referred to as user-generated content (UGC). Overall, UGC embraces user opinions, comments, content about user interests and user interact with companies (Ribeiro-Navarrete et al., 2021). In recent years, UGC has been widely used as a valid source of information to identify trends (Saura et al., 2022), make predictions (Kim, 2012), establish measurement indicators (Saura et al., 2021), identify variables for empirical models, as well as to better understand the influence of concepts and events (Smith et al., 2012).

However, despite the general growth of the literature extreme weather and its impact on various aspects of human life (e.g., (Moernaut et al., 2022), UGC-based studies on climate change, pollution or microplastics, as well as and their influence on economic development, remains scarce. In the present study, we aim to bridge this gap in the literature so as to better understand the impacts of extreme weather on economic production on local and global levels. The specific research question addressed in the present study is as follows: (RQ1) What are the main impacts of extreme weather on economic production according to the UGC in the social network Twitter? To answer this question, and following Chae (2015) and Majumdar and Bose (2019), we use a data-driven model to extract evidence from tweets. The specific research objectives of our study are as follows:

- To create knowledge about the relationship between extreme weather and production economics;
- To identify the main impacts of extreme weather on production economics according to the UGC on Twitter;
- To explore the main influences and causes of extreme weather on production economics;
- To formulate future research questions concerning the relationships and predictions linked to extreme weather and production economics using social media.

The originality of the present study lies in the methodological process used to analyze the data. Specifically, we apply two data-mining algorithms. First, we use sentiment analysis with Textblob, with which experiments are performed to calculate the accuracy with Support Vector Classifier (SVC), Multinomial Naïve Bayes (MNB), Logistic Regression (LR), and Random Forest Classifier technologies (RFC). Second, we use a topic modeling known as LDA (Latent Dirichlet allocation) for the division of sentiments into topics. Additionally, we also use the technique of content analysis/textual analysis. These approaches are developed using the theoretical frameworks of Computer-Aided Test Analysis System (CATA) and Natural Language Processing (NLP). Similarly, the sentiment analysis on extreme weather is linked to appraisal theory.

The remainder of this paper is structured as follows. After a short review of previous literature on the topic, we present the methodology used in the present study. This is followed by the presentation of the results, which are then discussed. The paper concludes with an overview of theoretical and practical implications of our results for further research on extreme weather conditions and their impact on economics.

2. Related works

In recent years, there has been growing research on climate change, weather, global warming, or extreme events linked to environment. In one relevant study, Jang and Hart (2015) used the keywords "climate change" and "global warming" to understand people's opinions about these phenomena around different US states. The authors applied Big Data analysis techniques to explore a UGC database extracted from Twitter in order to understand the influence of both terms on politics.

Similarly, the UGC was also used to understand user behavior in digital environments and user attitudes towards certain topics. For example, Qiao and Jiang (2021) analyzed Twitter data to understand the main attitudes towards global warming by performing a sentiment analysis of the Twitter dataset. The authors linked the results and their negative influence to appraisal theory, which is also used in the present study. Appraisal theory is a psychological theory that focuses on emotions extracted from the evaluation of events that cause reactions in society or individuals (Watson and Spence, 2007).

A large-scale analysis of the content published on social networks such as Twitter makes it possible to investigate the relationships between various topics. Accordingly, Al-Rawi et al. (2021) analyzed the discourses on Twitter applying an LDA on climate change and global warming. The authors identified politicized points of view in relation to the use of both terms, quotes linked to political figures, as well as different terminologies to refer to global warming and its consequences.

Furthermore, the influences of climate change can also be studied locally. For instance, in a study of local mass media, Kirilenko et al. (2015) compared the temperature of climate change and identified indicators in corresponding Twitter discussions. Based on the results, the authors concluded that temperature anomalies increase the number of tweets published by users in relation to climate change. Therefore, they compared tweets versus the information shared in the mass media. These types of events were also studied by Anderson and Huntington (2017) in order to understand how Twitter users use sarcasm and incivility in relation to climate change discussions.

Extreme weather was also analyzed in relation to extreme weather events such as tropical cyclones. In one such study, Takahashi et al. (2015) analyzed user communications through Twitter during Typhoon Haiyan in the Philippines. The authors tested different variables and indicators such as time of use, location, and type of user and, based on the results, concluded that retweet information, coordinate relief, and memorialize victims were the main uses. The results of this study highlighted the importance of Twitter as a tool to study extreme weather events. According to Ripple et al. (2022), in relation to extreme weather conditions such as heat waves, droughts, and floods, have been shown to have a significant impact on production economics. These events can disrupt supply chains, reduce crop yields, and lead to reduced productivity in various industries (Frame et al., 2020). Therefore, economic impacts can be significant with some estimates suggesting that the costs of extreme weather events are expected to increase in the coming years. As stated by Markkanen and Anger-Kraavi (2019), policymakers have a crucial role to play in addressing the challenges posed by climate change and extreme weather events, as they have the ability to implement policies and regulations that can shape the economic decisions of individuals and businesses.

From a different perspective, Gupta et al. (2021) focused on the understanding of reactions to the COVID-19 pandemic to identify user perceptions in relation to their organization and understanding of the global situation. However, UGC can also be used to make predictions and weather forecasting using machine learning, as was done by Purwandari et al. (2021). Overall, a review of previous research suggests that Twitter and UGC can be applied to study any type of social media events, both to improve the supply chain (Chae, 2015) and to explore value creation in manufacturing firms (Majumdar and Bose, 2019), as well as to investigate social media crisis management (Lachlan et al., 2016) or indicators for the creation of open innovation (Saura et al., 2022a). The possibility of studying extreme events through UGC on social networks was also demonstrated by Lin et al. (2016) who explored the online chatting after several extreme events and compared the results of user actions and behaviors when creating UGC.

3. Methodology

In this study, we developed a methodology focused on the analysis of data from social networks, specifically Twitter. This approach is based on Chae (2015), Majumdar and Bose (2019) and Saura et al. (2021), who used UGC collected on Twitter to extract insights, identify valuable indicators that can explain an event, or create theories through their analysis.

In the present study, we specifically used the theoretical frameworks known as CATA (Belderbos et al., 2017) and NLP (Hirschberg and Manning, 2015). The objective of the present study was not to empirically test hypotheses, but rather to identify exploratory future constructors or variables that could create statistical and empirical models to further investigate extreme weather and economic production (Du and Jiang, 2015). In order to implement different applications linked to computed processes, following previous studies focused on CATA, we intended to create knowledge and theory by using a model that would work with data mining and machine learning for the training of the algorithms used in the present study. Likewise, we also used the textual analysis/content analysis, which is commonly used to analyze large-scale data obtained from social networks to identify insights and establish coherent relationships in the results (Liu et al., 2016).

In this way, we first applied a sentiment analysis using Textblob. Textblob is a text analysis algorithm that can be trained to classify pieces of text into different sentiments (Aljedaani et al., 2022). In addition, this technological approach can be used through technologies such as Support Vector Machines (SVM), Vector Classifiers (SVC), Multinomias Naïve Bayes (MNB), Logistic Regression (LR) and Random Forest Classifier (RFC). Our objective was to develop experiments to improve the accuracy of the results of the sentiment analysis algorithm, a standard procedure in methodologies that work with the training of algorithms and machine learning (Balaji et al., 2021).

Second, we also used an algorithm known as LDA to identify relevant topics in our data (Zhao et al., 2011). This topic modeling algorithm divides a text sample into different topics based on mathematical variables that explain the relationship between the texts within a sample. This algorithm has been frequently used in previous studies on discourse analysis and mutual information (e.g., Wu and Su, 1993; Enarsson and Lindgren, 2019). The overarching aim of using algorithm is to create knowledge and propose models of the relationship between sentiments and topics that can be analyzed in future research. To increase the robustness of the model, NLP-focused algorithms are combined using CATA. Finally, in order to establish associations needed to identify useful variables and indicators, we also used an analysis developed in Python. Specifically, we used this technique to identify specific keywords and, based on their weight, to produce relationships based on groups of words known as nodes (Anand et al., 2020). The three approaches presented above discussed in further detail below. The data-driven model developed in the present study is shown in Fig. 1.

3.1. Data sampling

In order to collect a correct sample to develop the analysis outlined above, a total of 1.4 m tweets were extracted from Twitter (De Choudhury et al., 2010; Brummette and Sisco, 2015). The queries used on Twitter to get the results were #ExtremeWeather, #ClimateEconomics, #ClimateChange and #GlobalWarming. To optimize the selection of terms for searching and collecting tweets, it is essential to adhere to guidelines for collecting data from social media platforms such as Twitter (See De Choudhury et al., 2010; Culotta, 2014; Wartberg et al., 2020; Faelens et al., 2021). This ensures that the collected data is relevant and aligned with the research objectives. Careful consideration should be given to the choice of terms used, avoiding any indirect or inappropriate associations with similar terms or topics not linked to the study objectives (Saura et al., 2023). Additionally, it is crucial to ensure that there are no global events related to the subject of the study directly or indirectly (for example, the World Environment Day or the World Climate Summit) occurring during the data collection process, as these could potentially alter the results (Grover, 2019). By following these steps, researchers can ensure that the collected data is reliable and relevant to the study being conducted based on UGC analysis, NPL, CATA and appraisal theory (Wolfe et al., 2021; Lin et al., 2022).

Likewise, the queries were made from June 18 to August 30, 2022, using Python. For the development of data sampling, the so-called non-probability sampling frame (Lehdonvirta and Oksanen, 2021) was followed, which was previous used in studies on UGC collected from social networks and digital platforms. Overall, a non-probability sampling, also known as simple judgment, is an approach where the sample is constructed and elaborated (Gerlitz and Rieder, 2013). In order to create knowledge and structure the study sample, we followed Lehdonvirta and

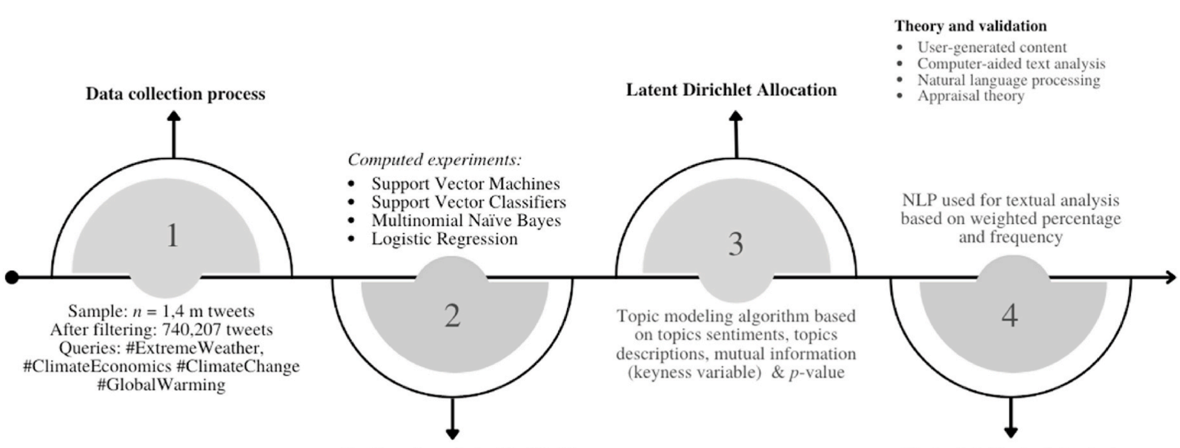

Fig. 1. Data-driven model of the present study.
Source: The authors

Oksanen (2021) to establish an adequate non-probabilistic variable process. As verified in the studies of Sloan (2017) and Chakraborty et al. (2020), the sample size in studies that work with social networks is determined by the case applied and linked directly to the research objectives. The total number of text pieces analyzed should be sufficient to extract insights and create knowledge in relation to knowledge discovery and big data approaches (Safhi et al., 2019). As previously mentioned, (i)protocols for selecting search terms have been applied to avoid bias in data collection, (ii)filters have been applied to ensure the quality of the sample, and its validity has been verified in light of the (iii) non-probabilistic nature of the chosen sample.

The data collection process was carried out as follows. First, we connected to Twitter's public Application Programming Interface (API), taking into account that it has the limit of 7 days in the past to collect tweets. Queries were made and deposited in the database without debugging. Once the database was complete, the filtering process started. Our methodological approach was focused on understanding the text, but not the audiovisual, graphic or other format content. Python and Pandas libraries (Lamsal, 2021) were used for debugging the database (Barbosa et al., 2023).

The 43 queries that were made in the analyzed time horizon allowed us to collect a total of 1,391,729 tweets generated by a total of 1,104,434 Twitter users. The total number of collected retweets amounted to 1,026,351. In order to properly filter and purge the final database of tweets, the URLs containing the tweets were removed. Only the tweets published in English were included in the dataset. Special characters and symbols, as well as emoticons, were removed (Chae, 2015; Saura et al., 2022a). This was done to avoid incorrect analysis of the sample. Similarly, retweets were taken into account as independent tweets and were not removed from the database. The tweets published by the same user more than once were not considered (Majumdar and Bose, 2019). Finally, the tweets with less than 80 characters were removed as invalid. After these filtering stages, the number of tweets in the final sample amounted to $n = 740{,}207$ (Saura et al., 2021).

3.2. Sentiment analysis using textblob

Overall, in order to identify sentiments in text samples, different sentiment analysis methods and approaches are used in the literature (Yadav and Vishwakarma, 2020). As mentioned above, in the present study, we categorized the content using the Textblob Python algorithm. This algorithm works with machine learning (Ain et al., 2017). Since a UGC sample was used, Textblob was deemed to be a relevant algorithm, as it is a robust and efficient sentiment analysis algorithm commonly used in the scientific literature in studies using CATA and NLP (Arslan et al., 2022). Textblob is built on NLTK and patterns. However, a limitation of this algorithm, which is shared with other sentiment analysis algorithms, is that it cannot identify sarcasm, irony, or connotations in the analyzed tweets. However, and following the instructions of Yadav and Vishwakarma (2020), the algorithm was trained to optimize the results to surpass this challenge.

To get a sufficiently high accuracy, the Textblob algorithm was trained a total of 845 times. In doing so, we followed the indications of Saura et al. (2021, 2022). The training results showed a polarity score measured and classified in relation to the subjectivity of the pieces of text. In this way, the polarity was defined in ranges between −1 and 1, and the subjectivity was established between 0.0 and 1.0. The training of the algorithm was performed manually; to this end, the tweets were classified to determine the polarity based on the keywords (Iyengar et al., 2012). These types of classifications are focused on discourse analysis and linguistics and are standard procedures carried out in exploratory studies using NLP and CATA (Sarkar et al., 2019). The determination and use of a machine learning algorithm means that, once an algorithm has been trained, it learns by itself to classify the rest of the tweets based on the in-puts offered by the researchers. Accordingly, we determined the relevance and follow-up of the tweet classification protocol in the training of the algorithm.

In this way, each tweet was classified based on its sentiment (positive, negative or neutral), and the general database was therefore divided into three subsets. However, for the validation of the results, we followed Hiremath and Patil (2022) and used a 5-step validation scale. For the validation scale, we used the technologies of SVC (Saura et al., 2021), MNB (Abbas et al., 2019), LG (Saura et al., 2021), and RFC (Karoui et al., 2017). For the validation of the results, we also computed the variables of precision, recall, f1-score, and support. Finally, the global results were presented in terms of macro average and weighted average.

3.3. Topic modeling using LDA

In the next step of the presented model, a thematic modeling algorithm commonly known as LDA (Yang and Zhang, 2018) was developed and applied. In general, LDA is used in research on documents and texts. This mathematical algorithm is applied in Python to develop a probabilistic assumption that determines the relationship of words to each other to identify topics. In the present study, the LDA algorithm was developed in Python LDA 1.0.5 using Gibbs sampling (MAC version). Although the LDA model cannot determine sentiments, we used three databases of tweets previously classified into sentiments, in order to obtain positive, negative or neutral topics applied to LDA (Liu et al., 2017).

The LDA algorithm was applied to a database and returned the results in the form of repeated words according to their relevance in the database. From this list of words, the first twenty classified words were considered. Taking into account the words, as well as the objectives of the study, we then determined a title that should make sense when combining the obtained words (Saura et al., 2022a), which is a standard approach when LDA is used in studies that work with CATA and NLP. This enabled us to link the results of the algorithm to a topic, as well as its description.

In general, the topic modeling algorithm aims to understand the inputs (normally documents containing text) in terms of frequency and positioning in the database. In the present study, the text inputs were included not in documents, but in tweets classified in three different databases. Accordingly, we took advantage of the power of this algorithm to directly identify topics from the tweet databases. According to the positioning and frequency of the words, topics classified with a name were obtained (Al-Sultany and Aleqabie, 2019). First, in the application of the model in LDA, the frequency and distribution of the topics in the sample were identified. Second, the topics were automatically grouped in the form of keywords in relation to the number of times these were repeated in the database (Zhou et al., 2021). The equation applied in Python is shown in Eq. (1).

$$\rho(\beta_{1:k},\theta_{1:D},Z_{1:D},\omega_{1:D}) = \prod_{i=1}^{K}\rho(\beta_i\Big)(\beta_1)\times\prod_{d=1}^{D}\rho(\theta_d)$$
$$\times\sum_{n=1}^{N}\rho\left(Z_{d,n}\middle|\theta_d\right)\,\rho\left(W_{d,n}\middle|\beta 1_{:K,}{}^{Z}{}_{d,n}\right) \tag{1}$$

βi Distribution of word in topic i, altogether K topics

θd Proportions of topics in document d, altogether D documents

Z_d Topic assignment in document d

$Z_{d,n}$ Topic assignment for the nth word in document d, altogether N words

W_d Observed words for document d

$W_{d,n}$ The nth word for document d.

Next, the words were automatically divided into each of the identified topics. Eq. (2) shows how the different keywords that make up each topic were computed. From here, we translated their meaning to make sense of the identified topics.

$$\rho(\beta_{1:k},\theta_{1:D},Z_{1:D}|\omega_{1:D}) = \frac{\rho(\beta_{1:K},\theta_{1:D},z_{1:D}\omega_{1:D})}{p(w1:D)} \tag{2}$$

3.4. Textual and content analysis

In the third step of the data-driven model, we applied textual and content analysis to understand the weight and relevance of the keywords within the identified topics (Garten et al., 2018). Specifically, we applied textual analysis with Python to calculate the weighted percentages of each keyword with respect to the total of the database. This and similar approaches were previously used with other software or applications such as VBPro, CATPAC, Concordance, DICTION, General Inquirer, LIWC, NVivo, ATLAS or MECA considered suitable for working with CATA and NLP (Saura et al., 2021).

Specifically, the individual weights of the keywords within the topics divided into sentiments were computed. These sets of words were grouped into nodes, which were equal to the identified topics. In this way, the global weight percentages of each of the topics were calculated. Similarly, based on these percentages, we were able to grasp the global weight of each topic over another and make comparisons (Carley, 1993) so as to shape theory and create insights related to our research objective. The frequency of keywords, as well as their weight and repetition, were identified and measured (Hardy et al., 2004).

4. Results

4.1. Results of sentiment analysis with textblob

For the Textblob computation with SVC, MNB, LG, and RFC, the accuracy was measured as the variables that determine the quality of the results. Overall, the accuracy defines the number of times that the algorithm has successfully determined results (Purwandari et al., 2021). To increase the quality of the results, only the result of the classification method that has obtained the highest accuracy is taken into account. Accuracy is the standard measure in machine learning models to determine success. The results of the model are summarized in Table 1.

The result with a greater precision was the one corresponding to LSV Sl. No. 3 with a total of 0.871081. The subsequent sentiment analysis was based on the results of this process. In relation to the rest of the experiments, the largest values obtained were in the following order: LG Sl. No. 2 with 0.829012, MNB Sl. No. 2 0.699,370 and finally, RFC Sl. No. 4 with 0.584008. Likewise, in relation to the results of the feelings obtained, Table 2 summarizes the results related to recall value, fl-score, and support values.

Table 1
Results of sentiment analysis.

Sl. No.	Classification model name by number of experiments	Fold_idx	Final Accuracy Textblob
0	RandomForestClassifier	0	0.574081
1	RandomForestClassifier	1	0.540247
2	RandomForestClassifier	2	0.542170
3	RandomForestClassifier	3	0.560321
4	RandomForestClassifier	4	0.584008
5	LinearSVC	0	0.840431
6	LinearSVC	1	0.839155
7	LinearSVC	2	0.870230
8	LinearSVC	**3**	**0.871081**
9	LinearSVC	4	0.822510
10	Multinomial Naïve Bayes	0	0.699370
11	Multinomial Naïve Bayes	1	0.680003
12	Multinomial Naïve Bayes	2	0.693691
13	Multinomial Naïve Bayes	3	0.687120
14	Multinomial Naïve Bayes	4	0.687447
15	LogisticRegression	0	0.807925
16	LogisticRegression	1	0.814041
17	LogisticRegression	2	0.829012
18	LogisticRegression	3	0.814993
19	LogisticRegression	4	0.827405

Source: The authors

Table 2
Sentiment classification report.

Sl. No.	Parameters	Vader			
		precision	recall	f1-score	support
1	Negative	0.76	0.80	0.73	20.510
2	Positive	0.82	0.76	0.79	2300
3	Neutral	0.88	0.92	0.91	20.491
4	Accuracy	–	–	0.84	43.641
5	Macro avg	0.78	0.76	0.72	43.641
6	Weighted avg	0.78	0.81	0.85	43.641

Source: The authors

According to Deshwal and Sharma (2016), accuracy is a metric that measures the quality of the machine learning model. It determines not only the quality of the model, but also that of the tasks related to the qualification of the inputs. As defined by Saif et al. (2012), recall measures the necessary amount of machine learning used in the model in terms of the amount of technology employed. As concerns the f1-score variable, Zimbra et al. (2018) indicated that it is used to combine the metrics and their precision and recall scores represented in a single variable that summarizes their results. In this way, as argued by Deshwal and Sharma (2016), its practical nature makes results comparable in terms of accuracy.

The support component, according to Saura et al. (2022a), is the necessary support that the model needs for the use of machine learning. On the other hand, the macro average variables measure terms similar to the model mean, as well as their weight in relation to the weighted average. In our results, the highest precision and recall were obtained for neutral feeling (0.88 and 0.92, respectively). The negative sentiment obtained a precision of 0.76, and a recall of 0.80. Finally, the positive sentiment obtained a precision of 0.82 and a recall of 0.76. In relation to f1-score, it was 0.91 for neutral sentiment, 0.73 negative sentiment, and 0.79 positive sentiment.

Fig. 2 summarizes the results and visually increases their rigidity by providing a summary of the precision results obtained. In the figure, the X-axis represents a maximum value of 0.99, and the Y-axis shows the results obtained for each LSVC experiment performed, including RFC, LG, and MNB with a total of 20 points.

In Fig. 2, the X axis shows the highest accuracy value with a limit of 0.90, while the Y axis shows the total number of experiments performed. The shaded horizontal lines show the areas of the results obtained by each classification experiment. There is a black highlighted line for each variable where the accuracy number is displayed. These are the highest

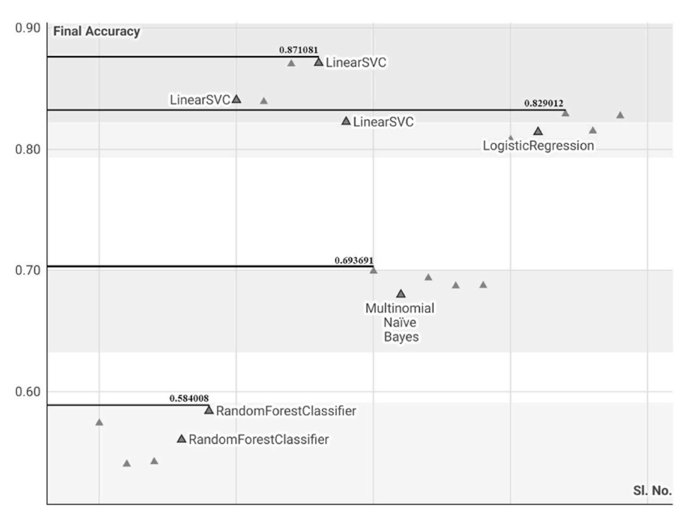

Fig. 2. Accuracy results.
Source: The authors

values obtained for each of the classification technologies performed in the sentiment analysis. Of the total 740,207 tweets, 329,281 were classified as neutral, 186,201 were positive, and 224,725 were negative.

4.2. LDA results

The development and application of the LDA model identified a total of 7 topics directly linked to extreme weather and production economies in relation to the three sentiments studied. In order to identify a sufficient number of topics, the first 20 words related to each of the identified topics were studied. Then, based on the results, the topics were named and described, as well as linked to their sentiment.

At the time of classification and naming of each topic, we took into account the use of the most frequent words, as well as their number of alterations. This allowed us to extract insights related to the relationship of our topics with the subject of study and the corresponding feelings. In this way, the research question of the study, as well as the research objectives, can be addressed based on the identification of the themes and the insights and knowledge created after the described process.

Similarly, in order to measure the relevance of topics identified by the data-driven model, we computed the keyness indicator. This indicator shows the robustness of the linking of the words that make up a theme. Statistically, keyness represents the log-likelihood score values (Rayson and Garside, 2000). In the present study, keyness was calculated to understand the relevance of the identified topic. This approach has been widely used in linguistics to understand speech and word organization, making it possible to link several keywords with a theme. Since our topics were composed of keywords, MI could be computed and its relation could be understood in terms of keyness and *p*-value. Therefore, log-likelihood of >3.8 was statistically significant when *p*-value <0.05. Therefore, in our results, a statistically significant relationship was obtained for the topics indicated below. Table 3 provides a summary of the indicators and variables.

Amon the identified topics, positive topics were Sustainable energies and Green Entrepreneurs, neutral ones were Climate economy, Producer's productivity, and Stock market, and negative ones were Economy and policy and Climate emergence. Fig. 3 shows the topics according to their sentiment and the number of classified tweets.

Table 3
LDA topics results.

R	Topics	Description	Keyness	*p*-value
1	Climate economy	The economic impulses that develop around climate change, global warming and extreme weather events	800.23	0.044
2	Economy and policy	The economic and political messages of the policymakers in relation to the actions to solve the environmental problem	761.62	0.040
3	Producers' productivity	Detriment of production due to the global consequences of extreme weather events	641.13	0.035
4	Stock market	Linking the influences caused by extreme weather with the stock market worldwide	560.31	0.029
5	Sustainable energies	Promotion of sustainable and renewable energies to fight the problems of extreme weather.	473.94	0.021
6	Climate emergence	Global climate emergency, causes, consequences, and political inaction	414.52	0.017
7	Green entrepreneurs	Green initiatives that create sustainable projects to promote green production	394.00	0.016

Source: The authors

4.3. Results of textual and content analysis

Based on the results of the textual and content analysis, the topics were separated into nodes. Next, the weighted percentage (WP) of these keywords was computed against the global database (Loughran and McDonald, 2016). In this way, the weight of the keywords was represented based on their importance in the total database. This approach was applied using the NLP framework with Pandas GroupBy in Python. The number of times the words were repeated, as well as their average total weight, was represented by their frequency (f). Table 4 summarizes these values.

5. Discussion

A recent trend of an increase in extreme weather conditions has modified international markets, causing companies to flexibly adapt their business models and production systems to adverse extreme events (Ingirige et al., 2008). In the present study, a total of seven topics directly linked to extreme weather and economic production were identified.

In the first place, we identified the topic of climate economy (keyness 800.23 and *p*-value 0.044), which includes the economic impulses developed around climate change, events linked to global warming, as well as situations caused by extreme weather events, droughts, heat waves, or floods (Vandewege, 2021). Around these actions, a new economy emerged to which companies should adapt their economic and production systems (see Dell et al., 2014; Felbermayr et al., 2022). This new climate economy influences the decision-making processes of policymakers (Shao et al., 2014). As confirmed by Ingirige et al. (2008) and Feng et al. (2021) policymakers play a crucial role in addressing the challenges posed by climate change, as they have the opportunity to implement policies and regulations that can shape the economic decisions of individuals and businesses. Effective climate policy requires a holistic approach that considers both the economic and environmental consequences of different actions (Abdul Karim et al., 2022).

This is directly linked to the second topic we identified in the results that was the economy and politics (keyness 761.62 and *p*-value 0.040), which groups the economic and political messages shared by public figures and policymakers. This topic summarizes strategies to solve the environmental problem worldwide from their messages. Although these strategies are focused on boosting the economy and promoting public policies that respect the environment (Sandhani et al., 2022), the negative sentiment associated with this topic indicates the discontent of society about these initiatives, as well as their insufficiency to combat extreme weather events and climate change. Similar evaluations of this topic were also pointed out by Cai et al. (2021) and Felbermayr et al. (2022). As highlighted before, it is essential that public agents take into account the long-term impacts of their decisions on the economy, as well as the well-being of present and future generations. The transition to a low-carbon economy can bring significant economic benefits, such as the creation of new jobs and the development of new technologies, but it also requires a proactive approach to address potential challenges and ensure a just transition for all stakeholders (Ying et al., 2022).

The third topic that emerged in our results was producers' productivity (keyness 641.13 and *p*-value 0.035), which encompasses the detriment and the evolution that producers have undergone to address the effects and consequences of extreme weather events on a global level. Indeed, producers are directly affected by extreme weather—for example, to produce cereals or wheat, it is necessary that the climate conditions do not entail droughts or floods, which can lead to no production or harvests. However, as indicated by Gogokhia and Berulava (2021), various industries depend on the natural landscape to develop their raw materials, and the consequences of the events produced by extreme weather influence productivity and the economy.

The fourth topic was the stock market (keyness 560.31 and *p*-value 0.029), which captures a link between economic production and the

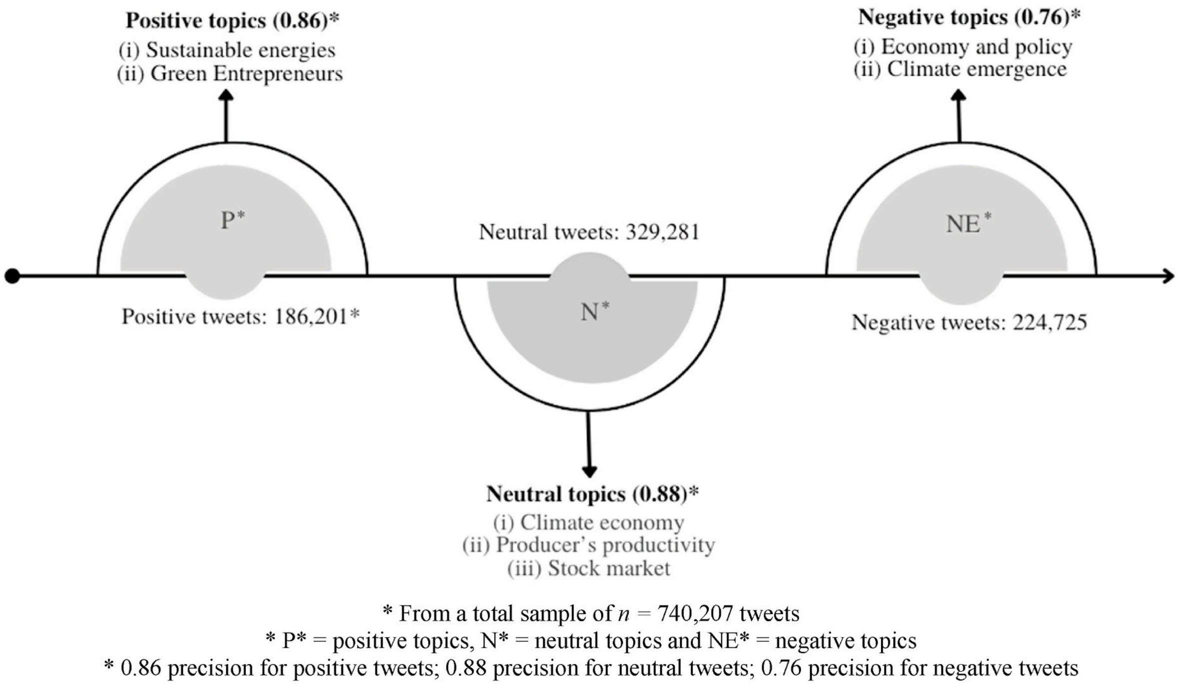

Fig. 3. Topics by sentiment
* From a total sample of n = 740,207 tweets
* P* = positive topics, N* = neutral topics and NE* = negative topics
* 0.86 precision for positive tweets; 0.88 precision for neutral tweets; 0.76 precision for negative tweets.
Source: The authors

Table 4
Grouped keywords, count, and weighted percentage.

R	Topics	Keywords in topic	f *	WP*
1	Climate economy	economy and climate, economic growth, climate industry, new economy, etc.	250,202	17.21
2	Economy and policy	economic policy, economy policies, climate action, policy options, economic perspectives, etc.	190,485	14.86
3	Producers' productivity	production issues, food productions, agricultural production, primary productivity, lower productivity, etc.	104,291	11,02
4	Stock market	stock prices, price fluctuations, climate change risks, climate change stocks, etc.	90,687	9,97
5	Sustainable energies	renewable power, sustainable energy, renewable energy, energy efficiency, sustainability, green energy, among others.	59,533	7,06
6	Climate emergence	over-producing, extreme weather, heat waves, emergency declarations, world climate declaration, etc.	58,005	6,01
7	Green entrepreneurs	eco-friendly projects, recycling businesses, green industry, green business, green opportunities, etc.	25,531	4,94

*f = Frequency.
*WP = Weighted percentage.
Source: The authors

influences caused by extreme weather on the stock market worldwide. Many companies develop their businesses using raw materials necessary for the viability of their projects. However, climate change is putting many global supply chains at risk, causing investments to have unprecedented levels of uncertainty and volatility (Symeonidis et al., 2010). As identified in this study, extreme weather conditions can have a significant impact on the stock market, as they can lead to disruptions in supply chains, damage to infrastructure, and loss of life and property. These impacts can lead to economic losses for businesses and investors, which can in turn affect stock prices. For example, natural disasters such as hurricanes, earthquakes, and wildfires can disrupt production and distribution processes, leading to decreased profits and negative performance on the stock market (Abdul Karim et al., 2022).

The fifth topic we identified in the results was sustainable energies (keyness 473.94 and p-value 0.021), which reveals the impetus for world economic production not to stagnate due to extreme weather events. Sustainable energies are generally seen as the positive future with respect to the environment (Kelle et al., 2019). However, at present, they are being applied inefficiently, largely due to the increase in policies and limitations in production and infrastructure systems (Ingirige et al., 2008). However, sustainable energies are jointly positioned as the greatest boost to economic production in the medium and long term for an industry that is adapting and must be flexible to an uncertain future where climate change and extreme weather events can cause irreparable losses (cf. Shao et al., 2014; Xie and Zhu, 2021).

The sixth topic that emerged in our data analysis was that of climate emergency (keyness 414.52 and p-value 0.017). This topic refers to the fight against the causes and consequences of political inaction worldwide. A greater and more concerted action is expected from public institutions in the face of the development of policies that force companies to produce sustainably. In economic terms, production should match the existing demand; however, with the growing the climate emergency and problems with extreme weather, economic production may be jeopardized. These indications were also mentioned by Henseler and Schumacher (2019). At present, there is substantial evidence of the existing climate emergency, and the consequences of political inaction may prevent this situation from being reversed. Additionally, through the development and promotion of sustainable agriculture and land management practices by governments and public institution it can help to mitigate the effects of droughts, floods, and other extreme weather events on food production and availability (Andati et al., 2022). By fostering the growth and success of social projects and green entrepreneurs for example, policymakers can help to create a more sustainable and resilient economy that is better equipped to withstand the impacts of extreme weather (Zinecker et al., 2022).

Finally, the seventh topic we identified in the data was that of green entrepreneurs (keyness 394.00 and p-value 0.016). This topic brings together sustainable projects to promote green production, actions and initiatives that use renewable energy production sources, that promote recycling, or the use of sustainable materials for the economic development of current business models. This topic was found to be associated with positive sentiment, as green entrepreneurs are engaged in implementing changes in the reproductive system in the long term on the global level (cf. Karimi et al., 2019). Green entrepreneurs often aim to reduce greenhouse gas emissions, conserve natural resources, and minimize waste in order to create a more sustainable and resilient economy. By doing so, green entrepreneurs can contribute to the prevention of extreme weather events and the reduction of their negative impacts on society and the environment (Ying et al., 2022). For example, through the use of renewable energy sources and the implementation of energy-efficient technologies, green entrepreneurs can help to reduce the reliance on fossil fuels, which are a major contributor to climate change and extreme weather events (Štreimikienė et al., 2022).

In recent years, UGC has been widely used to identify the opinions of the society, the future interests of the society, as well as various types of information to be used, for instance, by public institutions to adapt their communication policies and sustainable strategies (Saura et al., 2022a). As posited by the appraisal theory, essential in this context are the feelings extracted from individually estimated evaluations (Ross and Caldwell, 2020). These evaluations are directly linked to people's reactions to an event with a specific cause. Extreme weather events of the recent years, such as droughts, floods, extreme heat, or very cold winters, are directly linked to people's perceptions of these events. Therefore, the appraisal theory can be linked to UGC as a source of interpretations and explanations that users make under different circumstances and in different parts of the world (Loughran and McDonald, 2016). A clear example of such circumstances is the increase in the planet's temperature as a result of global warming, which is a leading cause of extreme weather conditions around the world.

In this way, applying the appraisal theory to study UGC, we can observe that climate emergency is associated with strongly negative perceptions among people. At the same time, these circumstances help to create a positive perception in relation to sustainable energies, since such technologies are perceived as being capable of solving the biggest problems that human beings have faced throughout history. Similarly, the perceived positive sentiment for green entrepreneurs is linked to long-term sustainable economic output. However, the economy and politics are among the biggest concerns of users in relation to the actions and strategies developed by public institutions to fight against the climate emergency and extreme weather (Felbermayr et al., 2022).

Based on the topics identified in the present study, we can formulate a series of research questions on extreme weather conditions and production economics that should be addressed in further research. These questions are summarized in Table 5.

Based on the future research questions presented above, it is important to note that extreme weather events can have significant impacts on economic production, and it is relevant for companies to have strategies and tactics in place to adapt to these changes. The role of policymakers and companies in shaping the transition to a low-carbon economy and the influence of extreme weather on the stock market and sustainable energy sources are also crucial considerations that should be kipped in mind. Likewise, the perception of climate emergency among the general population and the implications for green business models and entrepreneurship in the face of a changing climate are important factors to consider for the future of the global economy. Overall, it is essential for businesses, policymakers, and the general public to understand the impacts of extreme weather events on the economy and take proactive measures to address these challenges and transition towards a more sustainable future.

Table 5
Future research questions on extreme weather and production economics.

Topics	Future research questions
Climate economy	- What are the main characteristics of an economy based on climate change? - How can the economic production of a company adapt to sudden changes in the ecosystem and extreme weather events? - What strategies should companies follow to maintain their levels of economic production in an economy characterized by uncertainty arising from extreme weather events?
Economy and policy	- How should the economic system adapt global business models beyond the reduction of pollution and the use of renewable energies? - What are the environmental respect monitoring protocols that public institutions should apply in the future of a sustainable economy?
Producers' productivity	- How do extreme weather events influence producers' productivity? - What are the future extreme weather events that will most influence the economic output of companies? - What tools and systems will allow companies to adapt their activities to extreme weather events?
Stock market	- What is the influence of extreme weather on the stock market in the face of emerging climate problems? - How is it possible to predict economic production with stock market analysis when extreme weather causes losses in the production and supply chain?
Sustainable energies	- What are the risks associated with sustainable energies when extreme weather events occur? - Is it possible to take advantage of extreme weather events to promote sustainable energy?
Climate emergence	- Will extreme weather events increase the perception of climate emergency in the population? - What are the main problems caused by extreme weather perceived by the population in relation to climate emergency?
Green entrepreneurs	- How should green business models be adapted to the consequences of extreme weather events? - How should a green entrepreneurial project adapt to a climate economy in the context of high uncertainty? - What are the most profitable entrepreneurial projects in terms of economic production, from the perspective of future climate change?

Source: The authors

6. Conclusions

In the present study, we developed a data-driven model to identify the main impacts of extreme weather on economic production using the UGC from Twitter as a source of information. In order to understand these impacts, we conducted different types of analyses to identify a total of seven topics associated with three sentiments, including positive (Sustainable energies, Green Entrepreneurs), neutral (Climate economy, Producer's productivity, Stock market), and negative (Economy and policy, Climate emergence). Based on the results, we formulated a total of 17 future research questions to understand the main characteristics of extreme weather events on economic production.

With regard to our main research question (RQ1: *What are the main impacts of extreme weather on economic production according to the UGC in the social network Twitter*?), we identified the main impacts of extreme weather events on economic output. These impacts were then discussed around the seven identified topics. The main consequences and characteristics were revealed, as was the future influence of extreme weather on economic production. In relation to the secondary objectives, we accumulated knowledge on the relationships between climate change and economic production and tested the applicability of the appraisal theory to analyze UGC from Twitter. Finally, we also identified the main influences of extreme weather on economic production. Based on the results, the following conclusions can be drawn.

Extreme weather conditions and meteorological uncertainty of recent years have had a considerable adverse impact on economic output and the business system. In this paradigm, there emerged a new climate economy characterized by different economic impulses developed around the actions that aim to counteract climate change, global warming, or the damage caused by extreme weather events. This new climate economy is directly linked to economic and political decision-making driven by public institutions. However, these strategic actions remain insufficient and the society in general negatively perceived the policies implemented thus far to solve meteorological problems.

Likewise, in this paradigm where the climate economy and extreme weather events influence economic production, a detriment in the economic production of companies worldwide is identified, since extreme weather events and global warming produce adverse situations for the development and economic production in supply chains, logistics, or production. All these factors make the stock market volatile and lead to high uncertainty, which harms a stable economy.

In this context, renewable energies continue to be the hope of the society, and sustainability continues to be perceived as the main actor to fight against extreme weather events. Green entrepreneurs are perceived as the future of the business where economic production linked to sustainable actions may be the best option for the development of the industry and economy adapted and flexible to the climate emergencies around the world.

6.1. Theoretical implications

As discussed previously, the present study is exploratory and aimed to qualitatively identify research questions and future variables to be later studied in empirical research. Based on the results, we identified a total of seven topics that can be used in further research that would aim to better understand the relationship between extreme weather and economic production.

The theoretical implications of the research are directly linked to the identified topics and to the discussion on their relationship with extreme weather conditions and economic production. In future studies, researchers can focus on the 18 proposed research questions as a better understanding of the main characteristics of an economy based on climate change can help inform the development of strategies for companies to adapt to sudden changes in the ecosystem and maintain their levels of economic production in the face of uncertainty.

The findings include the need to adapt global business models beyond the reduction of pollution and the use of renewable energies, as well as the implementation of environmental respect monitoring protocols by public institutions in the pursuit of a sustainable economy. In addition, new theoretical research is needed to examine the impacts of extreme weather events on producers' productivity and the stock market, as well as the risks and potential opportunities associated with sustainable energy sources. The perception of climate emergency among the general population and the implications for green business models and entrepreneurship should also be explored in the future. By addressing these research objectives, it will be possible to gain a deeper understanding of the challenges and opportunities facing economic production in the face of extreme weather events and a changing climate theoretically. While the present study explored the link between climate economics and efficient production in times of climate uncertainty, future studies can take the proposed research questions as the main objective of their investigation, along with replicating and improving the data-driven process used.

6.2. Practical implications

The practical implications of the present study are linked to perspectives from policymakers, entrepreneurs, and public institutions specialized in the environment. These actors can use the insights derived from our analysis of UGC on Twitter to improve decision-making in their institutions as well as the activities they develop in this thematic area. In addition, our results can serve as a guide for practitioners in relation to the understanding of the main impacts that climate change and extreme weather have on economic production. Additionally, as mention before, the findings of this study can provide valuable insights for policymakers, business leaders, entrepreneurs and other public agents related to production economics. By understanding the impacts of extreme weather on economic production they can create more effective strategies to mitigate the negative consequences of these events. Similarly, business leaders can use these insights to develop more resilient and adaptable business models that can better navigate the challenges posed by extreme weather. In today's increasingly interconnected and globalized economy, it is essential that companies and public institutions are prepared for the disruptions caused by extreme weather events in order to ensure their long-term viability and success.

This will made it possible to identify the main consequences or strategies that should be adapted in today's practices. For instance, green entrepreneurs can use research to adapt their business models and plan projects using sustainable energy so that their economic productivity is not diminished in response to extreme weather events. Also, companies can use the present research to develop strategies for adapting their supply chain management to mitigate the negative impacts of extreme weather events on their production levels. For example, a company producing agricultural goods may consider implementing contingency plans for sourcing raw materials from alternative suppliers in the event that their primary supplier experiences crop failures due to extreme weather conditions. As highlighted before, policymakers can also use research to inform the development of policies and regulations that support the transition to a low-carbon economy, such as incentivizing the use of renewable energy sources and implementing carbon pricing mechanisms. Overall, the identification of research questions and the gathering of exploratory evidence can help to better understand the complex relationship between extreme weather events and economic production, and inform the development of effective responses to these challenges.

6.3. Limitations and future research

The limitations of the present are linked to two fundamental facts. First, the sample obtained from UGC on Twitter may be expanded in the future. The samples of UGC extracted from Twitter can be increased exponentially in the future by collecting data over longer time horizons and including more tweets. The second limitation is linked to the fact that the present study was exploratory. Future studies can take these two limitations into account to improve the research design and conduct a more exhaustive empirical investigation.

Data availability

Data will be made available on request.

References

Abbas, M., Memon, K.A., Jamali, A.A., Memon, S., Ahmed, A., 2019. Multinomial Naive Bayes classification model for sentiment analysis.*IJCSNS Int. J. Comput. Sci. Netw. Security* 19 (3), 62.

Abdul Karim, Z., Muhamad Fahmi, F.S.R., Abdul Karim, B., Shokr, M.A., 2022. Market sentiments and firm-level equity returns: panel evidence of Malaysia. Economic Research-Ekonomska Istraživanja 1–20. https://doi.org/10.1080/1331677X.2021.2025126.

Ain, Q.T., Ali, M., Riaz, A., Noureen, A., Kamran, M., Hayat, B., Rehman, A., 2017. Sentiment analysis using deep learning techniques: a review. Int. J. Adv. Comput. Sci. Appl. 8 (6).

Al-Rawi, A., Kane, O., Bizimana, A.J., 2021. Topic modelling of public Twitter discourses, part bot, part active human user, on climate change and global warming. Journal of Environmental Media 2 (1), 31–53. https://doi.org/10.1386/jem_00039_1.

Al-Sultany, G.A., Aleqabie, H.J., 2019. Events tagging in twitter using twitter latent Dirichlet allocation. Int. J. Eng. Technol. 8 (1.5), 503–508.

Aljedaani, W., Rustam, F., Mkaouer, M.W., Ghallab, A., Rupapara, V., Washington, P.B., Ashraf, I., 2022. Sentiment analysis on Twitter data integrating TextBlob and deep

learning models: the case of US airline industry. Knowl. Base Syst. 109780 https://doi.org/10.1016/j.knosys.2022.109780.
Anand, V., Bochkay, K., Chychyla, R., Leone, A., 2020. Using Python for text analysis in accounting research. Foundations and Trends® in Accounting 14 (3–4), 128–359. https://doi.org/10.1561/1400000062.
Andati, P., Majiwa, E., Ngigi, M., Mbeche, R., Ateka, J., 2022. Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: does entrepreneurial orientation play a role? Sustainable Technology and Entrepreneurship 1 (2), 100017. https://doi.org/10.1016/j.stae.2022.100017.
Anderson, A.A., Huntington, H.E., 2017. Social media, science, and attack discourse: how Twitter discussions of climate change use sarcasm and incivility. Sci. Commun. 39 (5), 598–620.
Arslan, O., Xing, W., Inan, F.A., Du, H., 2022. Understanding topic duration in Twitter learning communities using data mining. J. Comput. Assist. Learn. 38 (2), 513–525. https://doi.org/10.1111/jcal.12633.
Balaji, T.K., Annavarapu, C.S.R., Bablani, A., 2021. Machine learning algorithms for social media analysis: a survey. Computer Science Review 40, 100395. https://doi.org/10.1016/j.cosrev.2021.100395.
Barbosa, B., Saura, J.R., Zekan, S.B., Ribeiro-Soriano, D., 2023. Defining content marketing and its influence on online user behavior: a data-driven prescriptive analytics method. Annals of Operations Research 1-26. https://doi.org/10.1007/s10479-023-05261-1.
Belderbos, R., Grabowska, M., Leten, B., Kelchtermans, S., Ugur, N., 2017. On the use of computer-aided text analysis in international business research. Global Strategy Journal 7 (3), 312–331. https://doi.org/10.1002/gsj.1162.
Brummette, J., Sisco, H.F., 2015. Using Twitter as a means of coping with emotions and uncontrollable crises. Publ. Relat. Rev. 41 (1), 89–96. https://doi.org/10.1016/j.langcom.2019.09.003.
Cai, Y., Xu, J., Ahmad, P., Anwar, A., 2021. What drives carbon emissions in the long-run? The role of renewable energy and agriculture in achieving the sustainable development goals. Economic Research-Ekonomska Istraživanja 1–22. https://doi.org/10.1080/1331677X.2021.2015613.
Carley, K., 1993. Coding choices for textual analysis: a comparison of content analysis and map analysis. Socio. Methodol. 75–126. https://doi.org/10.2307/271007.
Chae, B.K., 2015. Insights from hashtag# supplychain and Twitter Analytics: considering Twitter and Twitter data for supply chain practice and research. Int. J. Prod. Econ. 165, 247–259. https://doi.org/10.1016/j.ijpe.2014.12.037.
Chakraborty, K., Bhatia, S., Bhattacharyya, S., Platos, J., Bag, R., Hassanien, A.E., 2020. Sentiment Analysis of COVID-19 tweets by Deep Learning Classifiers—a study to show how popularity is affecting accuracy in social media. Appl. Soft Comput. 97, 106754 https://doi.org/10.1016/j.asoc.2020.106754.
Chik, H., Xue, M., 2021. China floods: how Zhengzhou's 'once in a thousand years' rainfall compares. South China Morning Post. https://www.scmp.com/news/china/science/article/3142157/china-floods-how-zhengzhous-once-thousand-years-rainfall.
Cho, J., Lim, G.J., Kim, S.J., Biobaku, T., 2018. Liquefied natural gas inventory routing problem under uncertain weather conditions. Int. J. Prod. Econ. 204, 18–29.
Choi, T.M., Lo, C.K., Wong, C.W., Yee, R.W., 2012. Green manufacturing and distribution in the fashion and apparel industries. Int. J. Prod. Econ. 135, 531.
De Choudhury, M., Lin, Y.R., Sundaram, H., Candan, K.S., Xie, L., Kelliher, A., 2010, May. How does the data sampling strategy impact the discovery of information diffusion in social media? 4 (1), 34–41. https://doi.org/10.1609/icwsm.v4i1.14024.
Coumou, D., Rahmstorf, S., 2012. A decade of weather extremes. Nat. Clim. Change 2 (7), 491–496.
Culotta, A., 2014. Reducing sampling bias in social media data for county health inference. InJoint Statistical Meetings Proceedings 1–12 (Citeseer).
Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798.
Deshwal, A., Sharma, S.K., 2016. Twitter Sentiment Analysis Using Various Classification Algorithms. In: In*2016 5th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*. IEEE, pp. 251–257. https://doi.org/10.1109/ICRITO.
Du, H., Jiang, W., 2015. Do social media matter? Initial empirical evidence. J. Inf. Syst. 29 (2), 51–70. https://doi.org/10.2308/isys-50995.
Enarsson, T., Lindgren, S., 2019. Free speech or hate speech? A legal analysis of the discourse about Roma on Twitter. Inf. Commun. Technol. Law 28 (1), 1–18. https://doi.org/10.1080/13600834.2018.1494415.
Faelens, L., Hoorelbeke, K., Soenens, B., Van Gaeveren, K., De Marez, L., De Raedt, R., Koster, E.H., 2021. Social media use and well-being: a prospective experience-sampling study. Comput. Hum. Behav. 114, 106510 https://doi.org/10.1016/j.chb.2020.106510.
Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V., Steinwachs, T., 2022. The economic impact of weather anomalies. World Dev. 151, 105745 https://doi.org/10.1016/j.worlddev.2021.105745.
Feng, Y., Akram, R., Hieu, V.M., Tien, N.H., 2021. The impact of corporate social responsibility on the sustainable financial performance of Italian firms: mediating role of firm reputation. Economic Research-Ekonomska Istraživanja 1–19. https://doi.org/10.1080/1331677X.2021.2017318.
Frame, D.J., Rosier, S.M., Noy, I., Harrington, L.J., Carey-Smith, T., Sparrow, S.N., Dean, S.M., 2020. Climate change attribution and the economic costs of extreme weather events: a study on damages from extreme rainfall and drought. Climatic Change 162 (2), 781–797. https://doi.org/10.1007/s10584-020-02729-y.
Garten, J., Hoover, J., Johnson, K.M., Boghrati, R., Iskiwitch, C., Dehghani, M., 2018. Dictionaries and distributions: combining expert knowledge and large scale textual data content analysis. Behav. Res. Methods 50 (1), 344–361. https://doi.org/10.3758/s13428-017-0875-9.
Gerlitz, C., Rieder, B., 2013. Mining one percent of Twitter: collections, baselines, sampling.*M/C Journal, 16*(2). https://doi.org/10.5204/mcj.620.
Gogokhia, T., Berulava, G., 2021. Business environment reforms, innovation and firm productivity in transition economies. Eurasian Business Review 11 (2), 221–245. https://doi.org/10.1007/s40821-020-00167-5.
Grover, Purva, 2019. Arpan kumar kar, yogesh K. Dwivedi, marijn janssen, polarization and acculturation in US election 2016 outcomes – can twitter analytics predict changes in voting preferences, technol. Forecast. Soc. Change 145, 438–460. https://doi.org/10.1016/j.techfore.
Gupta, M., Bansal, A., Jain, B., Rochelle, J., Oak, A., Jalali, M.S., 2021. Whether the weather will help us weather the COVID-19 pandemic: using machine learning to measure twitter users' perceptions. Int. J. Med. Inf. 145, 104340 https://doi.org/10.1016/j.ijmedinf.2020.104340.
Hardy, C., Harley, B., Phillips, N., 2004. Discourse analysis and content analysis: two solitudes. Qualitative methods 2 (1), 19–22.
Henseler, M., Schumacher, I., 2019. The impact of weather on economic growth and its production factors. Climatic Change 154 (3), 417–433. https://doi.org/10.1007/s10584-019-02441-6.
Hiremath, B.N., Patil, M.M., 2022. Enhancing optimized personalized therapy in clinical decision support system using natural language processing. J. King Saud Univ.-Computer and Information Sci. 34 (6), 2840–2848. https://doi.org/10.1016/j.jksuci.2020.03.006.
Hirschberg, J., Manning, C.D., 2015. Advances in natural language processing. Science 349 (6245), 261–266. https://doi.org/10.1126/science.aaa8685.
Huang, H.H., Kerstein, J., Wang, C., 2018. The impact of climate risk on firm performance and financing choices: an international comparison. J. Int. Bus. Stud. 49 (5), 633–656.
Ingirige, M.J.B., Jones, K., Proverbs, D., 2008. Investigating SME resilience and their adaptive capacities to extreme weather events: a literature review and synthesis. Retrieved from. http://www.irbnet.de/daten/iconda/CIB11642.pdf on 11 September 2022.
Iyengar, S., Sood, G., Lelkes, Y., 2012. Affect, not ideologya social identity perspective on polarization, Public Opin. Q. 76 (3) 405–431. https://doi.org/10.1093/poq/nfs038.
Jang, S.M., Hart, P.S., 2015. Polarized frames on "climate change" and "global warming" across countries and states: evidence from Twitter big data. Global Environ. Change 32, 11–17. https://doi.org/10.1016/j.gloenvcha.2015.02.010.
Jian-Bin, H., Shao-Wu, W., Yong, L., Zong-Ci, Z., Xin-Yu, W., 2012. Debates on the causes of global warming. Adv. Clim. Change Res. 3 (1), 38–44. 1248.2012.00038, 10.3724/SP.J.
Karimi, R.F., Nabavi Chashmi, S.A., 2019. Designing green entrepreneurship model in sustainable development consistent with the performance of Tehran Industrial Towns. J. Bus. Bus. Market. 26 (1), 95–102. https://doi.org/10.1080/1051712X.2019.1565143.
Karoui, J., Zitoune, F.B., Moriceau, V., 2017. Soukhria: Towards an irony detection system for Arabic in social media, Procedia Comput. Sci. 117, 161–168. https://doi.org/10.1016/j.procs.2017.10.105.
Keleş, B., Gómez-Acevedo, P., Shaikh, N.I., 2018. The impact of systematic changes in weather on the supply and demand of beverages. Int. J. Prod. Econ. 195, 186–197.
Kelle, P., Song, J., Jin, M., Schneider, H., Claypool, C., 2019. Evaluation of operational and environmental sustainability tradeoffs in multimodal freight transportation planning. Int. J. Prod. Econ. 209, 411–420.
Kim, J., 2012. The institutionalization of YouTube: from user-generated content to professionally generated content. Media Cult. Soc. 34 (1), 53–67. https://doi.org/10.1177/0163443711427199.
Kirilenko, A.P., Molodtsova, T., Stepchenkova, S.O., 2015. People as sensors: mass media and local temperature influence climate change discussion on Twitter. Global Environ. Change 30, 92–100. https://doi.org/10.1016/j.gloenvcha.2014.11.003.
Kovács, B., 2017. Too hot to reject: the effect of weather variations on the patent examination process at the United States Patent and Trademark Office. Res. Pol. 46 (10), 1824–1835.
Lachlan, K.A., Spence, P.R., Lin, X., Najarian, K., Del Greco, M., 2016. Social media and crisis management: CERC, search strategies, and Twitter content. Comput. Hum. Behav. 54, 647–652. https://doi.org/10.1016/j.chb.2015.05.027.
Lam, H.K.S., Yeung, A.C.L., Cheng, T.C.E., Humphreys, P.K., 2016. Corporate environmental initiatives in the Chinese context: performance implications and contextual factors. Int. J. Prod. Econ. 180, 48–56.
Lamsal, R., 2021. Design and analysis of a large-scale COVID-19 tweets dataset. Appl. Intell. 51 (5), 2790–2804. https://doi.org/10.1007/s10489-020-02029-z.
Lee, J.J., Gino, F., Staats, B.R., 2014. Rainmakers: why bad weather means good productivity. J. Appl. Psychol. 99 (3), 504–513.
Lehdonvirta, V., Oksanen, A., R ̈as ̈anen, P., Blank, G, 2021. Social media, web, and panel surveys: using non-probability samples in social and policy research. Pol. Internet 13 (1), 134–155. https://doi.org/10.1002/poi3.238.
Lin, X., Lachlan, K.A., Spence, P.R., 2016. Exploring extreme events on social media: a comparison of user reposting/retweeting behaviors on Twitter and Weibo. Comput. Hum. Behav. 65, 576–581. https://doi.org/10.1016/j.chb.2016.04.032.
Liu, H., Morstatter, F., Tang, J., Zafarani, R., 2016. The good, the bad, and the ugly: uncovering novel research opportunities in social media mining. International Journal of Data Science and Analytics 1 (3), 137–143. https://doi.org/10.1007/s41060-016-0023-0.
Lin, H., Lin, J., Wang, F., 2022. An innovative machine learning model for supply chain management. Journal of Innovation & Knowledge, 7 (4), 100276. October - December 2022. https://10.1016/j.jik.2022.100276. October - December 2022.
Liu, X., Burns, A.C., Hou, Y., 2017. An investigation of brand-related user-generated content on Twitter. J. Advert. 46 (2), 236–247. https://doi.org/10.1080/00913367.2017.1297273.

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: a survey. J. Account. Res. 54 (4), 1187–1230. https://doi.org/10.1016/j.pubrev.2014.10.009.

Lydiri, M., El Habouz, Y., Zougagh, H., 2022. Sentiment analysis decision system for tracking climate change opinion in twitter. In: International Conference on Business Intelligence. Springer, Cham, pp. 188–196. https://doi.org/10.1007/978-3-031-06458-6_15.

MacCarthy, B.L., Jayarathne, P.G.S.A., Sustainable collaborative supply networks in the international clothing industry: a comparative analysis of two retailers, 2012. Prod. Plann. Control 23 (4), 252–268.

Majumdar, Adrija, Bose, Indranil, 2019. Do tweets create value? A multi-period analysis of Twitter use and content of tweets for manufacturing firms. Int. J. Prod. Econ. https://doi.org/10.1016/j.ijpe.2019.04.008. S0925527319301318.

Markkanen, S., Anger-Kraavi, A., 2019. Social impacts of climate change mitigation policies and their implications for inequality. Clim. Pol. 19 (7), 827–844. https://doi.org/10.1080/14693062.2019.1596873.

Minner, S., 2001. Strategic safety stocks in reverse logistics supply chains. Int. J. Prod. Econ. 71 (1–3), 417–428.

Moernaut, R., Mast, J., Temmerman, M., Broersma, M., 2022. Hot weather, hot topic. Polarization and sceptical framing in the climate debate on Twitter.*Information, Communication & Society* 25 (8), 1047–1066. https://doi.org/10.1080/1369118X.2020.1834600.

Platania, F., Hernandez, C.T., Arreola, F., 2022. Social media communication during natural disasters and the impact on the agricultural market. Technol. Forecast. Soc. Change 179, 121594. https://doi.org/10.1016/j.techfore.2022.121594.

Purwandari, K., Sigalingging, J.W., Cenggoro, T.W., Pardamean, B., 2021. Multi-class weather forecasting from twitter using machine learning aprroaches. Procedia Comput. Sci. 179, 47–54. https://doi.org/10.1016/j.procs.2020.12.006.

Qiao, F., Jiang, K., 2021. Attitudes towards global warming on twitter: a hedonometer-appraisal analysis. J. Global Inf. Manag. 30 (7), 1–20. https://doi.org/10.4018/JGIM.296708.

Rayson, P., Garside, R., 2000. Comparing corpora using frequency profiling. Proceedings of the workshop on Comparing corpora 1–6, 9.

Ribeiro-Navarrete, S., Saura, J.R., Palacios-Marqués, D., 2021. Towards a new era of mass data collection: assessing pandemic surveillance technologies to preserve user privacy. Technol. Forecast. Soc. Change 167, 120681. https://doi.org/10.1016/j.techfore.2021.120681.

Ripple, W.J., Wolf, C., Gregg, J.W., Levin, K., Rockström, J., Newsome, T.M., Lenton, T. M., 2022. World scientists' warning of a climate emergency 2022. https://doi.org/10.1093/biosci/biac083.

Ross, A.S., Caldwell, D., 2020. 'Going negative': an appraisal analysis of the rhetoric of Donald Trump on Twitter. Lang. Commun. 70, 13–27.

Safhi, H.M., Frikh, B., Ouhbi, B., 2019. Assessing reliability of big data knowledge discovery process. Proc. Comput. Sci. 148, 30–36. https://doi.org/10.1016/j.procs.2019.01.005.

Saif, H., He, Y., Alani, H., 2012. International Semantic Web Conference. In: Semantic Sentiment Analysis of Twitter. Springer, Berlin, pp. 508–524.

Sandhani, M., Pattanayak, A., Kavi Kumar, K.S., 2022. Weather shocks and economic growth in India. Journal of Environmental Economics and Policy 1–27. https://doi.org/10.1080/21606544.2022.2087745.

Sarkar, D., Markovski, S., Gusev, M., Tomp, D., Muravyov, S., Filchenkov, A., Parundekar, A., Elias, S., Ashok, A., Sujitparapitaya, S., Shirani, A., Roldan, M., Bonta, V., Kumaresh, N., Janardhan, N., Mishra, S., Pappu, A., Bhamidipati, N., He, L., Zheng, K., Bandi, A., Fellah, A., 2019. Inferring advertiser sentiment in online articles using Wikipedia footnotes, Adv. Intell. Syst. Comput 2, 1224–1231. https://doi.org/10.29007/kzk1.

Saura, J.R., Ribeiro-Soriano, D., Palacios-Marqués, D., 2021. Using data mining techniques to explore security issues in smart living environments in Twitter. Comput. Commun. 179, 285–295. https://doi.org/10.1016/j.comcom.2021.08.021.

Saura, J.R., Ribeiro-Soriano, D., Iturricha-Fernández, A., 2022. Exploring the challenges of remote work on Twitter users' sentiments: from digital technology development to a post-pandemic era, Journal of Business Research, 142. Mar 2022, 242–254. https://doi.org/10.1016/j.jbusres.2021.12.052.

Saura, J.R., Palacios-Marqués, D., Ribeiro-Soriano, D., 2023. Exploring the boundaries of Open Innovation: evidence from social media mining. Technovation, 119 2023, 102447. https://doi.org/10.1016/j.technovation.2021.102447.

Shafi, K., Mohammadi, A., 2020. Too gloomy to invest: weather-induced mood and crowdfunding. J. Corp. Finance 65, 101761.

Shao, W., Keim, B.D., Garand, J.C., Hamilton, L.C., 2014. Weather, climate, and the economy: explaining risk perceptions of global warming, 2001–10.Weather. Climate, and Society 6 (1), 119–134. https://doi.org/10.1175/WCAS-D-13-00029.1.

Sloan, L., 2017. Who tweets in the United Kingdom? Profiling the Twitter population using the British social attitudes survey 2015. Social Media+ Society *3* (1). https://doi.org/10.1177/2056305117698981, 2056305117698981.

Smith, A.N., Fischer, E., Yongjian, C., 2012. How does brand-related user-generated content differ across YouTube, Facebook, and Twitter? J. Interact. Market. 26 (2), 102–113. https://doi.org/10.1016/j.intmar.2012.01.002.

Stott, P., 2016. How climate change affects extreme weather events. Science 352 (6293), 1517–1518.

Štreimikienė, D., Baležentis, T., Volkov, A., Ribašauskienė, E., Morkūnas, M., Žičkienė, A., 2022. Negative effects of covid-19 pandemic on agriculture: systematic literature review in the frameworks of vulnerability, resilience and risks involved. Economic Research-Ekonomska Istraživanja 35 (1), 529–545. https://doi.org/10.1080/1331677X.2021.1919542.

Symeonidis, L., Daskalakis, G., Markellos, R.N., 2010. Does the weather affect stock market volatility? Finance Res. Lett. 7 (4), 214–223. https://doi.org/10.1016/j.frl.2010.05.004.

Takahashi, B., Tandoc Jr., E.C., Carmichael, C., 2015. Communicating on twitter during a disaster: an analysis of tweets during Typhoon haiyan in the Philippines. Comput. Hum. Behav. 50, 392–398. https://doi.org/10.1016/j.chb.2015.04.020.

Tang, O., Rehme, J., 2017. An investigation of renewable certificates policy in Swedish electricity industry using an integrated system dynamics model. Int. J. Prod. Econ. 194, 200–213.

Undrr, 2020. Human Cost of Disasters: an Overview of the Last 20 Years 2000-2019. United Nations Office for Disaster Risk Reduction. Switzerland, Geneva.

Vandewege, R., 2021. Bad weather – another concern for a stressed global supply Chain. *Forbes*. https://www.forbes.com/sites/rennyvandewege/2021/06/29/bad-weather-another-concern-for-a-stressed-global-supply-chain.

Wartberg, L., Kriston, L., Thomasius, R., 2020. Internet gaming disorder and problematic social media use in a representative sample of German adolescents: prevalence estimates, comorbid depressive symptoms and related psychosocial aspects. Comput. Hum. Behav. 103, 31–36. https://doi.org/10.1016/j.chb.2019.09.014.

Watson, L., Spence, M.T., 2007. Causes and consequences of emotions on consumer behaviour: a review and integrative cognitive appraisal theory. Eur. J. Market. 41, 487–511. https://doi.org/10.1108/03090560710737570. No. 5/6.

Weilnhammer, V., Schmid, J., Mittermeier, I., Schreiber, F., Jiang, L., Pastuhovic, V., Heinze, S., 2021. Extreme weather events in Europe and their health consequences–A systematic review. Int. J. Hyg Environ. Health 233, 113688.

Wolfe, M.T., Patel, P.C., Manikas, A.S., 2021. Shock and awe: loudness and unpredictability in Twitter messages and crowdfunding campaign success. Journal of Innovation & Knowledge 6 (4), 246–256. https://doi.org/10.1016/j.jik.2021.06.002.

Wu, M.W., Su, K.Y., 1993. Corpus-based automatic compound extraction with mutual information and relative frequency count. Proceedings of Rocling VI Computational Linguistics Conference VI 1993, 207–216.

Xie, J., Zhu, M., 2021. What are the economic concerns on environment? Mapping the research trends and frontiers on air pollution and health. Economic Research-Ekonomska Istraživanja 1–27. https://doi.org/10.1080/1331677X.2021.2021434.

Yadav, A., Vishwakarma, D.K., 2020. Sentiment analysis using deep learning architectures: a review. Artif. Intell. Rev. 53 (6), 4335–4385. https://doi.org/10.1007/s10462-019-09794-5.

Yang, S., Zhang, H., 2018. Text mining of Twitter data using a latent Dirichlet allocation topic model and sentiment analysis. International Journal of Computer and Information Engineering 12 (7), 525–529.

Ying, J., Zhang, X., Zhang, Y., Bilan, S., 2022. Green infrastructure: systematic literature review. Economic Research-Ekonomska Istraživanja 35 (1), 343–366. https://doi.org/10.1080/1331677X.2021.1893202.

Zhan, Y., Chung, L., Lim, M.K., Ye, F., Kumar, A., Tan, K.H., 2021. The impact of sustainability on supplier selection: a behavioural study. Int. J. Prod. Econ. 236, 108118.

Zhao, W.X., Jiang, J., Weng, J., He, J., Lim, E.P., Yan, H., Li, X., 2011. Comparing twitter and traditional media using topic models. InEuropean conference on information retrieval 338–349. https://doi.org/10.1007/978-3-642-20161-5_34. Springer, Berlin, Heidelberg.

Zhou, S., Kan, P., Huang, Q., Silbernagel, J., 2021. A guided latent Dirichlet allocation approach to investigate real-time latent topics of Twitter data during Hurricane Laura. J. Inf. Sci. 1655515211007724 https://doi.org/10.1177/01655515211007724.

Zhu, Q., Sarkis, J., 2004. Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. J. Oper. Manag. 22 (3), 265–289.

Zimbra, D., Abbasi, A., Zeng, D., Chen, H., 2018. The state-of-the-art in Twitter sentiment analysis: a review and benchmark evaluation. ACM Transactions on Management Information Systems (TMIS) 9 (2), 1–29. https://doi.org/10.1145/3185045.

Zinecker, M., Skalicka, M., Balcerzak, A.P., Pietrzak, M.B., 2022. Identifying the impact of external environment on business angel activity. Economic Research-Ekonomska Istraživanja 35 (1), 83–105. https://doi.org/10.1080/1331677X.2021.1888140.