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Inclusive Measurement of Public Perception of Corporate Low-Carbon Ambitions: Analysis of Strategic Positioning for Sustainable Development Using Natural Language Processing

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ABSTRACT

Climate change remains one of the most important challenges of the 21st century, both for organizations as well as for society. While many corporates around the globe embed sustainability goals into their strategies, inclusive research on the public perceptions of the same is limited. Aiming to fill this gap, we apply an innovative natural language processing approach to determine the persuasiveness of corporate climate agendas. Based on public opinion data from various online platforms (n=5284), research is conducted to understand whether stakeholders structurally support or oppose the sustainability agendas. For this purpose, reactions and statements of users were mined, subjected to a sentiment analysis and have been examined concerning their polarity both platform-specific and cross-platform. While on the one hand the research helps company representatives to better understand the effectiveness of their proposed agenda and strategic positioning, our approach also challenges traditional ways of collecting data and measuring public opinion through interviews, questionnaires or surveys. Compared to other studies dealing with opinion research, our analysis sets new academic impulses by analyzing the very topical and demanded issue of evaluating sustainability campaigns. The study does not only provide evidence of an overall optimistic attitude towards corporate sustainability targets, but also sheds light on the polarity of public opinion and the share of perceptions. We were able to show that with an overarching average ratio of 4:1, sustainability ambitions are supported, whereby concerns on average can only be found in 1 of out 10 reactions, which contributes significant insights for steering transitioning companies as well as for the corresponding management by campaign leaders.

1. INTRODUCTION

Many different types of environmental change are accelerating worldwide and posing major challenges to humanity [1]. These include, for example, the increase in hunger and water crises (especially in developing countries), loss of biodiversity, health risks due to rising air temperatures and heat waves, or economic consequences due to the required elimination of climate-related damage. This results in a need for adaptation in numerous areas of human coexistence and in rethinking the use of resources (e.g., agriculture, forestry, energy industry, infrastructure & tourism).

Nonetheless, the engagement of governments, organizations, public figures, businesses and non-governmental organizations on climate change has only increased over time. Thereby, online platforms have been used to spread and initiate debates on climate change in the form of posts or tweets and various other textual statements. Typically, polls, questionnaires and surveys are used to gather public opinion, not only concerning sustainability issues, but on various topics. Also, in recent years, social networks have gained popularity among people all over the world. To provide an example: the use of social media by American adults has steadily increased since 2005, with 65% of American adults using social networks nowadays, compared to 7% in 2005 [2].

Public opinions about specific products, actions, policies, or news are already used to help organizations in many ways, e.g. to analyze their commercial offering, to understand business structures in depth or to ensure that customers are satisfied. Especially in business-related research, common methods of opinion research can lead to potential biases due to lack of purity or intentional manipulation if the survey is not random or driven by misinterpretation of data [3].

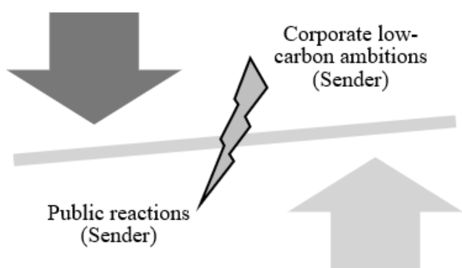

Figure 1. Presentation of the contextual field of conflict

To encounter this issue, non-parametric approaches emerged as suitable alternatives for the measurement of the proportions of non-random, textual data [4]. The advantages of the non-parametric approach initially stem from the nature of the underlying data. In the case of social media, unstructured data from the platforms serve as material to be analyzed. This enables the advantage that a large number of varying aspects can be included. The disadvantage of the parametric approach, that the same can only be applied to variables and not to attributes, thus gets compensated.

In this study, we draw on these insights and use sentiment analysis and data from online platforms to explore public perceptions of companies' ambitions to reduce their carbon emissions (see Figure 1).

Therefore, the research questions investigated in this study aim to better understand:

(1) How might sentiment analysis help businesses to understand perceptions of their climate agendas?

(2) Will it be beneficial to apply sentiment analysis and natural language processing (NLP) techniques instead of conventional ways of analyzing public opinion concerning corporate climate agendas?

1.1 Climate change and public opinion

Many companies have expressed the intention to decarbonize their operations, recognizing compelling business opportunities, to retain their license to operate, or to develop new business models that are in line with future policy. Some of them have committed to ambitious targets for reducing their emissions, e.g. complying with the targets set by the Science-Based Targets Initiative [5].

Considering the case of greenhouse gas emissions, it can be argued that shareholders are interested in the disclosure of carbon emissions by companies with national and international investors being concerned about climate change related issues. Enterprise-level carbon and environmental footprint reduction can be evaluated as corporate reaction (Figure 2 shows examples of relevant interactions). Approaches of reducing internal carbon emissions e.g. through fuel substitution or through heat recovery in the plant can be seen as examples of the considerations from the literature [6].

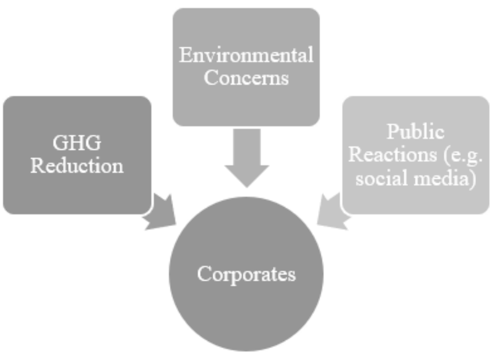

Figure 2. Excerpt of interactions in the thematic context

One-way communication via corporate publications or newspaper reports may lack proper debate, while at the same time scientific research may not be noticed or fully understood by the public. In contrast, social platforms allow people from various backgrounds to exchange opinions & experiences and might represent one of the purest forms of public opinion available [7].

Twitter, for example, has become a powerful platform to study public reaction concerning current events and news as media consumption has shifted from the past to modern media. Sentiment analysis, usually performed on text documents such as Twitter tweets, has already been used in numerous studies to assess public opinion on various topics related to climate change and environmental issues [8].

1.2 Sentiment analysis in the climate transition

Sentiment analysis and opinion mining are research areas that deal with the analysis of texts, which expresses people's emotions, feelings, beliefs, attitudes or moods. It is one of the most active research areas in natural language processing and is also studied in depth in the context of data mining, web mining and text mining (for a conceptual overview of mining techniques see Table 1).

Justified by its importance for the economy and society as a whole, this research has expanded into management and social sciences complementing the limited application outside computer science. Sentiment analysis itself has grown with the development of modern social media such as online rating forums, blogs, microblogs, platforms and social networks. Nowadays, as part of the rise of the digital age, big amounts of opinion data became available for analysis [9].

In the context of other business-related issues, sentiment analyses have been conducted using newspaper articles, magazine data and online forums, to examine what people think about specific issues and stakeholders' views concerning the plans and proposals of companies [10, 11].

Table 1. Overview of properties and concepts of mining

#	Data Mining	Web Mining	Text Mining
1	Data mining is a statistical technique of processing raw data in a structured form.	Web Mining is the process of data mining techniques to automatically discover and extract information from web documents.	Text mining is the part of data mining which involves processing of text from documents.
2	Statistical techniques are used to evaluate data.	Special tools for web mining are Scrapy, PageRank and Apache logs.	Computational linguistic principles are used to evaluate text.
3	Data is homogeneous and is easy to retrieve.	Data/ Information from structured, unstructured and semi-structured web pages.	Data is heterogeneous and difficult to retrieve.
4	Combines artificial intelligence, machine learning and statistics and applies on data	Includes data engineering with mathematical modules like statistics and probability.	Applies pattern recognizing and natural language processing to unstructured data.
	-	-	-

Notes: 1. The relevant properties and concepts for this comparison have been retrieved from geeksforgeeks.org and should be seen as a comparison besides an overview of the main properties and concepts.

With the help of professional text analyses, a large number of textual data can be evaluated and allow for conclusions about opinions of the targeted group. Within the scope of the work, an application benefit such as the investor relations team or the management of companies can be identified. After application, they can potentially better understand how their agenda is being received and develop steering options or intervene.

In comparison, the integration of typical market research via surveys or other means proves to be comparatively sluggish and slow, which is detrimental to rapid responsiveness in decision-making. The advantages are enabled not only by increase in speed, but also by the relatively simple and uncomplicated application. However, online datasets usually cover a long period of time and their content is potentially richer compared to other data sources, especially because such datasets are usually cross-cutting. Several topics may be addressed in the context of a single question on climate change. Thus, it may be necessary to understand the focus of a particular opinion, e.g., what aspect of climate change the opinion is covering [12].

Recent studies show that growing awareness of climate change is not only leading to behavioral changes among individual consumers, but that politicians are also promoting systemic changes that they believe are necessary. To investigate the extent to which climate change leads to greater political engagement among citizens compared to other issues, previous studies have analyzed a large number of tweets using social media data analysis tools [13].

Such analyses aim to identify views on climate change, global pollution and corporate behavior. Finally, this is important for several reasons:

a) To develop campaigns and strategies, organizations need to better understand how the public will react.

b) Automated opinion analysis can help to holistically understand public opinion on important issues and events in time.

c) Opinion research is also useful to determine how opinions of demographic users are distributed, how they evolve, who the opinion leaders are and what impact and influence they have [14].

After the introduction, the methodology as well as the data are presented in the following in chapter 2. Besides the division into data, extraction & processing, a subdivision into the essential elements of NLP in an application-oriented context is made. In the third chapter we present the results of our application and analysis, which is divided into two views. First, the individual platforms are considered, followed by the cross-platform perspective, which is discussed both individually and in context. Finally, our conclusions are presented in chapter 4, where we also discuss the value of our research and its usefulness for practice.

2. METHODOLOGY AND DATA

This section examines different approaches and methods for analysing sentiment. The most appropriate approach for our study and its theoretical basis is explained. In the first section, we discussed how social media data has been used to analyze public opinion on specific issues from different angles and in different application areas. Over time, various methods have evolved to gain insights about public perception and understanding people's opinions, such as opinion mining, NLP, artificial intelligence and machine learning. In this context, sentiment analysis is the simplest and perhaps most valuable form of gaining such insights, even considering the level of complexity of analyzing unstructured text data. Sentiment is associated with feelings, thoughts, emotions and opinions that are not factual but subjective in nature. Sentiment analysis generally aims to define, capture or characterise the context of a given text using NLP or statistical machine learning methods [15]. The impression, semantic orientation or polarity of a given text is typically represented as binary opposition, e.g.:

a) Good/Bad
b) Negative/Positive
c) Like/Dislike
d) For/Against

News can be classified as either facts or opinions. While facts are objective and represent factual statements, opinions represent perceptions, judgements and emotions concerning a given topic. Several studies focus on developing methods for evaluating factual information. However, the recent trend in text analysis is mainly focused on developing applications for opinion data [16].

The programming language Python is used to collect and analyze data from the respective Internet sources, whereby the libraries of Tweepy, Pandas, Textblob, Matplotblib and Selenemium have been used for this purpose.

2.1 Application of NLP in opinion mining

Opinion mining is used to analyze social network data for various purposes, including predicting events and analyzing public opinion on specific social topics. It can support the prediction of events or the identification of new customer groups and their needs. To understand the viewpoints or opinions expressed in the material at hand, a review of sentiments, i.e. sentiment analysis, is required. Textual sentiment analysis uses computers to analyze the emotions of a text. The study of textual knowledge and the value of textual material is a natural language technique [17].

In our case, the experimental data, likewise extracted from the online platforms has been retrieved as raw data, whereby cleansing activities have been performed in preprocessing stage. By cleaning up language specific characters, special characters and other non-compatible languages, the data was converted into a format that could be analyzed.

The field of NLP has been growing for several decades. It relies heavily on information from the internet, which was originally limited to processing data from a small selection of digital datasets with information in a variety of programming languages [18]. Procedurally the NLP approach initially takes the following discrete steps [19]:

a) Text pre-processing/tokenization
b) Lexical analysis
c) Syntactical analysis
d) Semantic analysis

The classification devices of the Natural Language Toolkit (NLTK) network, such as Naïve Bayes, multinomial Naïve Bayes classification and support vector machine (SVM), besides the various types of SVM from the Scikit library (NLP classifiers used in sentiment analysis) should be mentioned in that context.

Naïve Bayes is one of the most frequently chosen and efficient methods of classification in NLTK. During preparation, the classifier searches through all text documents and determines the probability of the terms being good, negative and neutral, and then assigns them to tweet labels, which in this case are emotions. This is based on Bayes' principle, where all variables are assumed to be independent. Each attribute to be defined is independent of the other features in the text and relates to the conceptual framework. Furthermore, the classifier is suitable for the classification of very large data sets. The naïve Bayes classifier is also suitable for real-time classification and for classifying multiple classes. The Naïve Bayes classifier is well suited for opinion analysis with data from social networks such as Twitter [20].

Moreover, the Naïve Bayes classifier is a simple machine-learning classifier and therefor fits best with textual content [21]. Because of its feasibility, it is chosen in this paper for the sentiment analysis of public reactions to corporate low carbon agendas. The cross-institutional classification method is based on the probability of the class given in a text whereby each feature is considered as self-conditioning [22].

2.2 Data, extraction & processing

When non-numerical information is being examined, a qualitative approach is useful and is therefore used for studies based on descriptive information [23, 24]. The approach increases the accuracy of the results, but also reduces the informative value of the report, as no numerical data and/or statistical analyses are available [25]. In order to confirm such results, a quantitative method can be applied on top, collecting numerical data that can be used to analyze the research questions and allow verification with statistical tools [26].

Although the use of numerical data is useful, a purely quantitative method is not suitable for all studies, as in some cases both numerical and non-numerical data are needed. In such cases, qualitative and quantitative data are examined using a mixed methods approach. The latter is comparatively time-consuming but can improve the reliability and validity of the research [27].

The dataset we use in this study to analyze public opinion comes from the online platforms Twitter, LinkedIn and YouTube. In order to get an overview of the actions and plans of different companies regarding carbon emissions, additional data from different companies is analyzed using big data scraping methods. The articulated initiatives are subsequently matched with the official websites of the companies.

Data scraping: Web mining is a method of collecting large amounts of internet data. The data is collected and stored in a tabular format (spreadsheet), as a local computer file or in a database.

The data from a website can usually be accessed through a single internet browser. Web mining software does not provide the ability to store a copy of all data that is individually identifiable. Nevertheless, a copy/paste function for the raw data is providing a solution. Depending on the size of the data set, the process can take several hours up to days. Web scraping is an automated process, so manual copying of data is not required. Thus, it offers a solution to the problem of processing and farming large data sets. In this study, the web scraping tool Selenium is predominantly used.

Data collection: Primary and secondary data sources are commonly used when processing data. Primary data refers to data collected through primary instruments such as questionnaires, surveys, interviews, focus group discussions and observation, with participants and/or respondents. On the other hand, secondary data sources refer to earlier records of analyses which are not gathered for the immediate study at hand [28].

Twitter is a social media website well known for its tweets, corresponding to short messages with very limited characters. To collect tweets, we use Twitter API. The Twitter API, used to collect tweets that are streamed on Twitter can also store tweets along with associated information such as date and time. 'T. Creating Streaming Link()' is a method to create a request message to the Twitter API to display the search results as a stream [29]. The data is collected in textual form and is partly analyzed with the help of Selenium, the tool for automating browsing that also supports data scraping [30]. Like Twitter, YouTube is a social media platform, with content providing a much richer environment that is multi-functional, socially visual and includes conversations between individuals. Approximately 2,500 comments related to carbon emissions and corporate agendas to reduce carbon emissions were collected (irrelevant comments were removed manually). On LinkedIn, people can also publish their views and share posts that help them in their job search. LinkedIn is one of the fastest ways for companies and individuals to share their goals and plans with a relevant audience of professionals in the public domain. Around 200 comments and posts on the low-carbon agenda have been collected on LinkedIn.

3. RESULTS AND DISCUSSION

Given the complexity and mostly invisible application of the NLP and sentiment analysis approach, we aim to present the results as visually as possible based on the data collected for this study. We present the comprehensive and cross-sectional results of the different platforms and a comparison of the themes. The descriptive presentation is followed by a compelling interpretation of the results.

The collected data is divided into positive, negative and neutral comments. The comments reflect public opinion on low-carbon strategies. The reactions to YouTube videos, tweets from Twitter (which have a maximum length of 280 characters) and comments from LinkedIn together form a very diverse spectrum of data.

3.1 Platform specific results

3.1.1 Results from Twitter data

The data collected on Twitter includes 2,858 tweets from various users, all of which address stakeholder responses and views on low-carbon agendas for different parts of the business.

Table 2. Classified data from Twitter

	Polarity	Quantity	Proportion
	Positive	1,160	0.41
	Neutral	1,286	0.45
	Negative	412	0.14
	Total	**2,858**	**1**

The data collected by Twitter shows that less people react negatively to companies' suggestions regarding their low-carbon agenda. However, it must be emphasized that only about 41% of all comments are classified as positive by the algorithm. The data can be considered pure as each tweet is unique and has not been altered in any way. A complete overview of the results of the analysis of the Twitter data can be found in Table 2. In conclusion, we can infer from the Twitter data that the largest group of people are not unconditionally negative towards corporate carbon reduction announcements or initiatives, as cumulatively 86% of comments are classified as neutral or positive, indicating that these people are in favor, neutral, or at least not clearly pessimistic.

3.1.2 Results from YouTube data

The data collected from YouTube includes 2,212 comments, which are again divided into three categories: positive, negative and neutral comments. YouTube is the second largest source of the sample data, contributing over 43% of the data collected. Based on the classifications, there are 0.4 negative reactions for every positive reaction. The ratio of negative over neutral comments is 0.72:1. Overall, about every second reaction is classified as positive (see Table 3).

Table 3. Classified data from YouTube

Polarity	Quantity	Proportion
Positive	1,128	0.51
Neutral	631	0.29
Negative	453	0.20
Total	**2,212**	**1**

Less than a quarter of comments are negative, and the ratio of positive over negative comments is greater than 2:1. Based on our dataset, the majority of people are in favor or supportive towards companies' ambitions to reduce carbon emissions, followed by people considering the ambitions neutral, but do not send clearly negative signals. Word clouds were used to identify the following words that appear most frequently in the data: "CO_2, plant, problem, carbon, people and solutions".

3.1.3 Results from LinkedIn data

The data collected from LinkedIn consists of 214 posts related to companies' low-carbon agendas. This data makes up the smallest portion of the total sample, representing only 4% of the overall data. For every neutral response, there are 3 positive responses. The ratio of positive to negative responses is even higher, 12.7:1. The ratio of negative over neutral comments is 0.23:1. About 7 out of 10 responses are classified as positive by the algorithm (see Table 4).

Table 4. Classified data from LinkedIn

Polarity	Quantity	Proportion
Positive	152	0.71
Neutral	50	0.23
Negative	12	0.06
Total	**214**	**1**

Utilizing world cloud analysis, several company brands including "Unilever" and "Nestle" are directly embedded in most of the comments. Furthermore, words such as "thanks" or "congratulations" appear most frequently in the top ten words used in LinkedIn comments.

3.2 Cross-platform results and discussion

The results presented above support, that the trend of tweets, comments or posts about low-carbon emissions or corporate initiatives to avoid carbon impacts are gaining momentum. A growing number of organizations are stepping up to mitigate their impacts on the environment, with government intensifying policies and claiming actions.

The entire data set (n=5,284) from the three sources analyzed above shows that, on average, about half of the reactions to the announcement of low-carbon statements are classified as positive. Negative reactions account for only 13% on average. Given the differences and diversity of comments on the different platforms, it should be noted that these figures are based on the unweighted data from the sources and it could be argued that a weighted analysis should be carried out to account for the different sample sizes of the platforms. This should be evaluated in light of the fact that the non-parametric research design does not intend to influence the data set and the responses should be analyzed unfiltered. Furthermore, the presentation of the individual results allows for a plausibility check and validation.

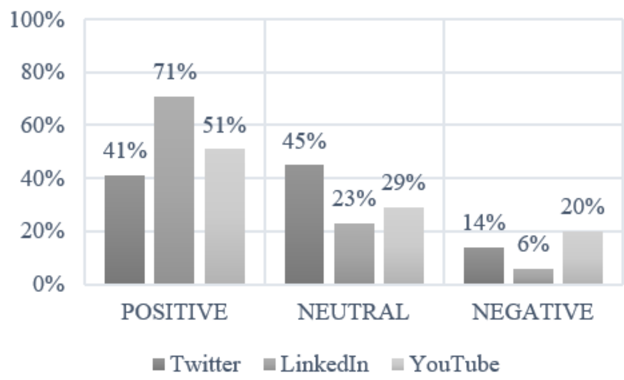

Figure 3. Cross-platform comparison of sentiment analysis

Figure 3 shows a comparison of the platforms in terms of opinion classification. The figure illustrates that even the largest share for the negative segment is smaller than all shares for positive or neutral segments. The highest positive value of 71% and the lowest negative value of 5.6% both come from LinkedIn data. Consequently, the largest difference between positive and negative opinions is also found in this data, namely 65.4%. The smallest gap between positive and negative shares is found in the Twitter data.

This leads researchers to speculate about the reasons for the discrepancies between the figures of the platforms. One can assume that LinkedIn is stronger pronounced, since people try to present themselves well to potential employers. The finding that companies are mentioned in many comments could be seen as an indicator of this. The approach of understanding which social media platforms most accurately reflect people's true feelings and attitudes could be an interesting topic for future research under the umbrella of the thematic field.

In terms of the respective categories, positive shares range from 40.6% to 71.2%, which corresponds to a range of 30.4%. Neutral comments have a range of 16.5%, ranging from 28.5% to 45%. Negative comments range from 5.6% to 20.5%. As an observation, the researchers derive from the size of each platform's dataset that there is a negative correlation between the proportion of comments and the number of observations when the polarity is positive. Thus, the proportion of positive comments decreases as the size of the platform's dataset increases. However, this logic is not observed consistently for negative and neutral reactions.

In terms of limitations, this study focuses on data collected from three different online platforms in relation to this research. Further research can be conducted with larger datasets. In this study, it became clear that opinion classification requires advanced methods of text data analysis, while human interaction remains essential. In fact, sarcasm, colloquialisms or the continuation of certain interactions are still better recognized by humans than by most basic algorithms.

For example, a person may reappear in an online debate after a period of absence. A human can understand emotions much more deeply and accurately than a machine. Nevertheless, a number of different approaches can be useful to achieve accurate analysis and synthesis and to strengthen the interpretation of people's thoughts and ideas. In particular, to gain a deeper understanding of the emotional attitudes of a population, large amounts of data need to be collected, which contributes to accuracy. With the goal of better understanding text data, many other strategies such as deep learning and advanced machine training could be considered in further research.

In addition, changes in events and underlying data should be taken into account. It must be considered, that the amount of information available on the internet has increased exponentially in recent years, partly due to the growth of social media. Platform operators tend to delete this data from time to time in order to save costs for data storage and processing. It is therefore typical for databases to be purged in a timely manner. This may have an impact on data collection on social media websites, as relevant data may be deleted before extraction. This impact can be seen as a limitation of existing studies and may be important for future research. For example, future research could focus on identifying trends over time, including how to handle and analyze data that is deleted from platforms. Regarding further deficiencies and limitations, it should be emphasized that studies should always be meaningful for the population. Due to the user profile of the platforms, especially older and very young people (as non-heavy users) are not necessarily represented. This contrasts with the fact that users who are actively engaging in social networks are increasingly represented in all age groups. Furthermore, the permanence of the data must be viewed critically, as it became apparent in the course of the study that comments and statements can also be deleted by users of platforms. Nevertheless, snapshots, as they were used in the study, offer the possibility of freezing data and data points in time and thus keeping them available, assumed they are stored appropriately.

With regard to the further development of technology, it can be assumed that the use of quickly available opinion analysis will become increasingly important. Thus, decisions of the management or departments of companies can be evaluated to an even greater extent in time proximity to the execution of campaigns, whereby decisions can be made in real time, which cannot be delivered by classical means of opinion research or alternatively with great delay. The online medium is the central enabler. In addition, the ongoing automation of the technology can be seen as further accelerator of the technology.

4. CONCLUSION

For a company to be successful, it needs to know its customers and their views on the various success rates of the company's business. Sentiment analysis is an unbiased, time-efficient and large-scale method of data analysis for businesses. With the help of sentiment analysis, companies can gain an understanding of their stakeholders and the public's reaction to a particular venture. In this study, we focus on low-carbon agendas. Analyzing public opinion on this issue based on big data is important, but difficult to implement applying traditional methods. Using information from social media, whilst utilizing sentiment analysis, we can solve this problem. In today's world, companies can use data processing technologies to analyze the opinions of their customers, consumers and stakeholders using sentiment analysis to derive actions and targets.

Based on the research conducted, we show that sentiment analysis is a suitable method for analyzing information from social media. Sentiment ratings can be considered as objective method for measuring the emotions of users, customers and the general public. Similar to other computer tools, sentiment analysis ensures that uncertainty and information overload are minimized, and that marketing departments, managers and others involved in the decision-making process get the information and data relevant to their decisions.

The significance of the results can be noted as an interface solution. In the context of sustainable finance, important conclusions can be conceptionally drawn concerning the perception of private and institutional investors. Both the top management of companies and the investor relations departments may be interested in these results. After the publication of a campaign, but also when new information is published for capital market participants, shareholders and stakeholders, reactions are essential in order to initiate timely measures.

Furthermore, the implementation is also suitable for problems in which the reaction to the publication of low carbon ambitions is to be tested first. With an increasing focus on sustainability by politics, society, but also by the capital markets, companies are sensitized to react. The main challenge is to find the right and appropriate paths. Our results and proposed measurement methods offer a modern approach to generate meaningful information in a short time. NLP uses statistical and linguistic methods to classify textual information as negative, positive, neutral. Text data analysis can be particularly useful in market research, as it allows companies to learn more about public opinion and find out which actions can be beneficial or should be avoided. We show that sentiment analysis and NLP make it possible to transform, analyze and convert even unstructured data into actionable insights.

The sentiment analysis approach to studying public opinion can be viable when immediate and unbiased feedback is needed. Companies can eventually benefit from efficiencies as less effort is required to gather feedback in this way, alongside scalability as the boundaries, which social media platforms previously faced become redundant in the digital century.

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