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Stakeholder engagement in carbon reduction engineering: A perspective analysis of production optimization leveraging social-media interactions

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ABSTRACT

This study investigates the complex dynamics of stakeholder engagement on social media platforms within the context of carbon reduction engineering. To shed light on this underexplored phenomenon, we gather a unique dataset of 6,940 Facebook-verified page posts, and we employ advanced data mining techniques to analyze the factors influencing stakeholder engagement. The findings demonstrate the significant impact of post characteristics on stakeholder engagement rates. Factors such as post length, hashtags, vividness level, hyperlinks, and the inclusion of call-to-action (CTA) play essential roles in shaping engagement patterns. Specifically, we find that shorter posts without hashtags tend to have lower engagement, while posts with moderate character counts, low vividness, and no hyperlinks often generate higher engagement. Additionally, our topic modeling analysis identifies critical themes discussed in carbon reduction engineering, including collaborative efforts among stakeholders, the role of academic institutions, renewable energy adoption, AI technology, and climate change mitigation. This, in turn, highlights the diverse perspectives and concerns of stakeholders actively engaged in these discussions. Our results significantly expand the literature on stakeholder theory, social interaction management, and the application of data mining techniques in analyzing social media engagement.

1. Introduction

The need to address global climate change has increased attention toward carbon reduction engineering, a comprehensive term for engineering measures to achieve carbon neutrality (Wei et al., 2024). As countries strive to meet the goals outlined in the Paris Agreement at the United Nations (UN) 21st yearly session of the Climate Change Conference (COP) in 2015, the focus on carbon reduction engineering has intensified from practical and academic perspectives (Ourbak & Tubiana, 2017). The world leaders convened in Glasgow for the 2021 COP26[1] due to the increasing urgency pervading discussions surrounding the climate crisis. A climate emergency has been acknowledged in the declarations of campaigners, activists, and academics, underscoring the anticipated escalation of global temperatures and subsequent ramifications such as rising sea levels (Smith et al., 2022). These changes pose severe threats to biodiversity and human existence, thereby engendering catastrophic consequences impacting millions of lives. The event's organizers argued that COP26 is widely recognized as humankind's most vital opportunity to successfully confront and reduce the increasing difficulties of uncontrolled climate change. COP26 was an outlet for discussing climate challenges from the production processes requiring immediate attention (Bai et al., 2023).

The UN has delineated Sustainable Development Goal (SDG) 13 as *"Urgent action to combat climate change and its impacts."* In this context,

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[1] **COP26** – https://ukcop26.org/the-conference/how-is-cop26/.

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carbon reduction engineering includes a range of engineering approaches aimed at mitigating climate change and reaching a state of net-zero carbon emissions (Kong et al., 2023; Wei et al., 2024). This need has led to considerable focus and research initiatives from academics and professionals in production and supply chain management. Studies explore different approaches to carbon reduction. For instance, Cappelletti and Germani (2023) re-design industrial process scraps and off-specification pieces in primary materials. Li et al. (2024) optimize product grouping and sequencing for energy conservation concerns, implement low-carbon and sustainable supply chain operations, and develop carbon reduction modeling frameworks. Bag et al. (2024) and Zhu et al. (2024) respectively investigate the impact of government policies on critical Industry 4.0-enabled smart manufacturing assets and the influence of government regulations on recycling rates and carbon neutrality within the context of power batteries. However, as noted by both studies, a significant gap remains in investigating stakeholder engagement and social acceptance of achieving carbon neutrality. This gap in the literature should be addressed in light of ongoing concerns surrounding the UN SDG 13.

The engagement required to appropriately confront the magnitude of climate change has been utterly insufficient, not meeting the level of public concern and attention climate scientists' forecasts demand. However, attempts to minimize climate change have been greeted with severe *social inertia*, a complex interaction of cultural, organizational, and personal factors that limit early steps to meet this intense global crisis (Brulle & Norgaard, 2019). In this regard, the widespread inability to adequately tackle the facts of climate change is a recurring theme in social science studies. Still, scientific debate on the causes of social inertia differs widely among fields and stands fragmented without a unified and broad comprehension. In recent years, the importance of social interaction management in achieving carbon reduction engineering strategies has gained increasing interest. Social interaction management involves strategic planning and support of exchanges among varied stakeholders, such as authorities, industries, communities, charities, and people. Stakeholder engagement, efficient interaction, and collaboration among varied actors are the most critical factors impacting the public's acceptance and implementation of carbon reduction measures (Dhanda et al., 2022).

Social media is essential for organizations and companies in the rapidly growing digital environment. With its interactive, communal, and interpersonal qualities, social media has offered companies multiple ways to engage stakeholders and create durable connections (De Luca et al., 2022; Surucu-Balci et al., 2020). Many studies have investigated the role of social media in disseminating and influencing sustainability-related communication, originating from both political and corporate leaders (e.g., Grover et al., 2019; Grover et al., 2021; Jha & Verma, 2022). However, by examining the engagement rate relative to the discussion's content, assessed with metrics, such as the post type, it is possible to determine and assess the level of stakeholder engagement in carbon reduction engineering, which remains a relatively unexplored area of research.

Extending previous efforts in climate engineering, this paper seeks to improve our comprehension of stakeholders' engagement in influencing carbon reduction strategies. Also, this study draws upon Goffman (1974) seminal question, "What is it that is going on here?" to identify the underlying frames shaping discourse. As an empirical method, topic modeling facilitates the inductive uncovering of these latent frames, extending the theoretical boundaries of frame analysis (Hannigan et al., 2019). Taking this as a motivation, this work addresses the following research questions:

RQ1. *How do Facebook posts motivate and engage stakeholders with carbon reduction engineering?*
RQ2. *What themes are emerging in stakeholder discussions about carbon reduction engineering on Facebook?*

Inspired by stakeholder theory, this study re-examines this theory as a lens to view the motivation for operational choices that reflect concerns for various groups in the context of carbon reduction engineering (Samson & Swink, 2023). We depart from previous research endeavors by centering its social media investigation on exploring the nuances of carbon reduction engineering and examining unique data collected from 6940 Facebook posts of verified pages. This work aims to identify the groups of social media posts that result in very high stakeholder engagement rates. This paper offers various contributions to the literature on social interaction management in carbon reduction engineering. First, this work shows how the stakeholder engagement level is influenced by five social post attributes and how these characteristics may be used to categorize posts meaningfully. Second, the findings of this study make valuable contributions to the existing body of knowledge in stakeholder engagement, literature on social interaction management, and climate engineering.

Third, this study presents an innovative method for analyzing social media data and enhancing decision-making processes. This approach makes it simpler to evaluate production optimization in carbon reduction engineering management, allowing professionals in the field to inform decarbonization policymaking decisions successfully through Big Data analysis. Fourth, this study thoroughly examines stakeholders' perspectives on carbon reduction engineering by carefully reviewing large datasets, revealing trends and patterns, and providing a more in-depth grasp. Therefore, cutting-edge techniques that combine *CHAID decision tree analysis*, *non-negative matrix factorization (NMF) based Topic Modeling*, *t-distributed Stochastic Neighbor Embedding (t-SNE)*, and *Latent Dirichlet Allocation (LDA) clustering techniques* are efficient in examining the relationship between dependent and independent variables and offering comprehensive text analytics.

This paper is structured as follows. After the introduction, section 2 discusses related works to this study. Next, section 3 presents the methodology. Section 4 illustrates the results of the data analysis. In the following section, the study reviews and discusses the data analysis findings. Section 6 presents the theoretical contributions and practical implications. Lastly, this study is finalized with a conclusion and limitations section.

2. Related works

2.1. Production optimization in carbon reduction engineering

Carbon reduction engineering, globally known as climate engineering, includes a variety of engineering solutions aimed at reducing climate change and achieving carbon neutrality goals. The procedure of decarbonization inside industrial systems is critical to the efficient operation of carbon reduction engineering. As a result, production activity optimization has become a central focal point of consideration in production and supply chain management. Practical strategies for carbon reduction engineering depend on the features of production processes, which determine the form of greenhouse gas (GHG) emissions inside individual companies. Firms that emit burning emissions, mainly in the energy and manufacturing industries, frequently emphasize initiatives to reduce fossil fuel consumption (Cadez et al., 2019). On the other hand, process emissions are typical in industries such as cement, steel, lime, glass, ceramics, pulp, and paper that involve nonfossil carbon-based substances (e.g., limestone, iron ore). In these circumstances, initiatives often aim to lower nonfossil carbon-based material usage (Cadez & Czerny, 2016; Cadez & Guilding, 2017).

Initially, firms may choose to improve the efficiency of their GHG emissions by applying actions such as replacing input elements or improving their products and production processes. These initiatives are targeted at effectively contributing to carbon reduction engineering and have been studied previously (e.g., Du et al., 2016; Xiang et al., 2022). An alternative way to climate engineering is by decreasing the manufacturing and sale of GHG-emitting products. Unlike the first suggestion, this solution focuses on reducing the total quantity of such products rather than changing the product, manufacturing process, or technology. It is important to note that stakeholder pressures rarely lead companies to stop producing these products suddenly. Instead, they tend to enhance a gradual transition from emission-intensive products to those with lower emissions, aligning with evolving market demands and sustainability considerations (Sprengel & Busch, 2010).

2.2. Stakeholder theory in climate engineering

Stakeholder theory, an influential management theory, has received much attention and generated extensive debate in sustainable business. The notion of stakeholders and their primary role in developing organizational strategies is central to this approach (Daddi et al., 2018; Hosseini & Brenner, 1992). Based on the stakeholder theory, involving stakeholders in decision-making is not just a proper attitude but is also acknowledged as a tactical component for achieving competitive benefits (Cennamo et al., 2009; Plaza-Úbeda et al., 2010). According to Freeman (2010)'s influential study, Strategic Management: a Stakeholder Approach, it provided a seminal definition of stakeholders as individuals or groups who possess the capacity to influence or be influenced by the activities and outcomes of an organization.

The adoption of stakeholder theory in the context of climate change has been widely used. Several scholars have used this notion to investigate and explain business practices relating to carbon emissions. For example, Comyns (2016) adopted stakeholder theory by evaluating the extent and caliber of greenhouse gas records in the gas and oil industry. The researcher conducted a comprehensive analysis of 232 records provided by 45 firms between 1998 and 2010, employing the content analysis research method. Similarly, Cadez et al. (2019) aimed to improve the comprehension of climate change reduction options in organizations with high GHG emissions. Based on stakeholder theory, the study explored the impact of market pressures for climate change reduction, notable regulatory ambiguity about GHG emissions, and enterprises' focus on environmental measures to minimize GHG emissions from industrial procedures. Furthermore, the study investigated the influence of GHG reduction techniques in moderating overall GHG performance.

Furthermore, various existing research on environmental management includes many stakeholders, including but not limited to clients, providers, contestants, stockholders, workers, economic institutes, non-governmental administrations, the broadcasting, regional and state governments, and the general community (e.g., Chatrchyan et al., 2017; Wellstead & Biesbroek, 2022). While all stakeholders have the potential to impact firm performance, their influence is not evenly distributed. Stakeholders can demonstrate their engagement and impact the standards of an institute across straight stress or by providing relevant data (Henriques & Sadorsky, 1999). Among them, the prominent stakeholders often potentially put pressure on highly polluting upstream and downstream companies.

2.3. Stakeholder engagement indicators

Social media platforms have revolutionized stakeholder engagement (Viglia et al., 2018), enabling rapid communication and promoting various organizational activities (Lee et al., 2013). However, effective engagement on these platforms is complex, depending on various post attributes such as media type, content, timing, and length, all impacting metrics like likes, shares, and comments (De Luca et al., 2022). One such attribute is the inclusion of external hyperlinks. While some studies suggest that hyperlinks increase interactive engagement, others note that they may lead to less engagement with the original content due to diversion to external sources Bandy and Diakopoulos (2021). Call-to-action (CTA) prompts are another factor to consider. Research in business-to-consumer (B2C) suggests that strategically placed CTAs can increase engagement, especially when integrated with existing platforms (Bhattacharyya & Bose, 2020; Jung et al., 2020).

The vividness of a post, determined by the inclusion of multimedia elements like images, GIFs, or videos, also plays a role. While some research indicates that visual content drives higher engagement, other studies suggest that video or GIF-based posts lead to more significant interaction. Finally, message fluency, influenced by factors like message length and hashtag usage, can impact engagement. While hashtags often enhance visibility, they may also decrease clarity, leading to lower engagement (McShane et al., 2019; Surucu-Balci et al., 2020).

3. Methodology

Data mining, a process of extracting valuable insights from datasets, enhances informed decision-making by identifying relevant information. Classification, an essential data mining technique, often employs the supervised decision tree algorithm with CHAID to categorize data and support decision-making (Higueras-Castillo et al., 2023; Muñoz-Rodríguez et al., 2023). Here, we leverage this technique to group and categorize social media posts based on several independent and dependent variables. This section of the work thoroughly describes the sampling process and data collection methodology used in this study. The study provides a complete description of this approach, clarifying its application and usefulness in the present study and a list of the specific variables taken into account in the analysis.

3.1. Selection process and data collection

Facebook has emerged as a powerful and widespread online social network influencing billions of users' daily lives globally. It promotes cross-border relationships, communication, and information exchange while supporting a variety of social interactions (Kosinski et al., 2015). There is an expanding amount of research in the academic community investigating how Facebook impacts people and societies (Yang & Lin, 2014; Shiau et al., 2018). This social media network allows organizations to engage effectively with diverse stakeholders and establish meaningful connections (Viglia et al., 2018). This study adopted a data collection approach inspired by Surucu-Balci et al. (2020) but on a different social media platform, Facebook. The current research work utilized *CrowdTangle* (CrowdTangle Team, 2023), a publicly accessible insights service operated by Meta, to obtain access to data from the Facebook platform. CrowdTangle provides publicly accessible data, allowing for enhanced accessibility to metrics such as engagement rate, encompassing factors like the count of likes, shares, comments, and views (Théro & Vincent, 2022; Yang et al., 2021). This study focused on Facebook pages having verified status using the following search query *[("Carbon reduction" OR "Carbon emission" OR "Climate change" OR "Climate") AND "Engineering"]*. Then, it selected a data sample of 6957 posts in the English language with 1,461,445 interactions from the 1st of January 2017 to the 30th of April 2023, focusing on carbon reduction engineering (refer to Fig. 1). However, the extracted data file from CrowdTangle resulted in 6940 posts.

3.2. Data coding

The data coding followed the guidelines set by de Vries et al. (2012), Luarn et al. (2015), and Surucu-Balci et al. (2020). Two authors actively carried out the coding process and contributed to this work. Following a thorough training session on the coding processes that lasted approximately one hour, the two coders individually coded stakeholder posts between the 1st of January 2017 and the 30th of April 2023. Following the coding procedure, the authors thoroughly compared their respective findings. The coders rechecked the doubtful posts in cases where disagreements arose regarding the coding of particular posts or when one author noticed a stakeholder post not having any references to reach a consensus and ensure consistency with the final coding decisions. The Perreault and Leigh (1989) approach was used to evaluate inter-coder reliability. This method states that coding results are accurate when

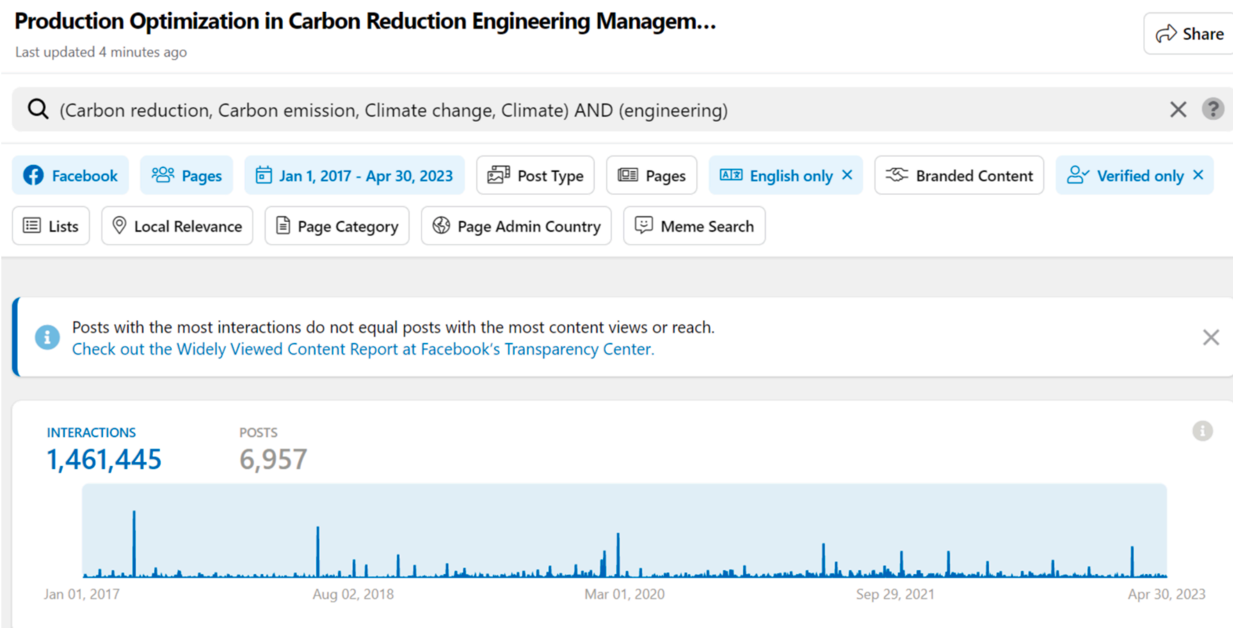

Fig. 1. Data collection using CrowdTangle.

they fall between 0.8 and 1. This study's computed inter-coder reliability obtained a result of 0.88, which complies with the coding reliability standards. This study's analysis used one dependent variable and five independent variables.

3.2.1. Independent variables

This work selected five independent variables based on Facebook posts' characteristics and parameters that have already been studied and discussed by academic researchers in the past (e.g., Bhattacharyya & Bose, 2020; Liu et al., 2017; Tariq, 2022). The existence of hashtags and the message length were used as independent factors to assess message fluency. First, based on the number of characters in a Facebook post, *message length* is the independent variable measured by the study. The maximum number of characters that can be used in a post on Facebook is 63,206. Second, the presence or absence of *hashtags* is considered a separate independent variable for each post, with a Yes/No response being given during data coding. Third, three operational levels—*low, medium, and high*—were assigned to the *vividness level*. Low-vivid posts are primarily made up of links or texts without pictures. An image or several images are used in posts with a medium level of vividness.

Furthermore, GIF or a video component inclusion indicates highly vivid posts. Fourth, a hyperlink's existence within a post can be binaurally categorized as present or missing. Posts with an external hyperlink are labeled "yes," indicating the presence of a link, whereas those without a hyperlink in the message are labeled "no," showing the absence of a link. Fifth, CTA existence could be examined by searching for specific words, such as "Watch the video," "Sign up," "Learn more," "Subscribe," "Follow us," "Register now," or "Call now." CTA's existence in Facebook posts is divided into "Yes" or "No" (refer to Table 1).

Table 1
Dependent variables' measures and description.

Independent variables	Measures	Description
clarity and coherence of messages	Message length	Number of characters used in a Facebook post
	Hashtags	Yes or No
Hyperlink existence	External link in the Facebook post	Yes or No
CTA existence	Call-to-action prompts	Yes or No
Vivideness level	Text or links without a picture	Low
	Existence of pictures	Medium
	Existence of a GIF or a video	High

Source: Adopted from Bonsón and Ratkai (2013) and Surucu-Balci et al. (2020)

3.2.2. Dependent variable

In line with Surucu-Balci et al. (2020) and De Luca et al. (2022) findings, this study used the *CHAID* approach to analyze the stakeholder participation level as a dependent variable. The stakeholder engagement level was calculated similarly using the method created by Bonsón and Ratkai (2013), as this formula applies to both Facebook and Twitter postings. Their formulae were utilized to calculate the engagement rate, and it was necessary to consider the volume of interactions, such as likes, comments, and shares, as detailed in Table 2. Therefore, the coders used Python libraries to compile the comments, likes, and shares counts for all the data points. Mean volumes of reactions (Likes, Love, Wow, Haha, Sad, Angry, and Care) per post (Popularity), mean volumes of comments per post (Commitment), and mean volumes of shares per post (Virality) were estimated by aggregating the respective counts. Popularity was

Table 2
Dependent variable measures and formulas.

Dependent variable	Measures	Formula	Description
Stakeholder Engagement Level	Popularity (P2)	Total reactions / total posts	Average number of reactions per Facebook post
	Popularity (P3)	(P2 / total followers) * 1000	Average number of reactions per 1000 followers
	Commitment (C2)	Total comments / total posts	Average number of comments per Facebook post
	Commitment (C3)	(C2 / total followers) * 1000	Average number of comments per 1000 followers
	Virality (V2)	Total shares / total posts	Average number of shares per Facebook post
	Virality (V3)	(V2 / total followers) * 1000	Average number of shares per 1000 followers

derived by dividing the overall volume of reactions by the total number of posts. The same formula was applied to calculate Commitment and Virality using comments and shares. Additionally, mean volumes of reactions for every 1,000 followers (P3), mean volumes of comments for every 1,000 followers (C3), and mean volumes of shares for every 1,000 followers (V3) were computed by dividing the respective metrics (Popularity, Commitment, and Virality) by the total number of followers and multiplying by 1,000. The stakeholder engagement rate was obtained by totaling P3, C3, and V3.

3.3. Decision tree analysis

This study endeavors to categorize social media stakeholders' postings on Facebook about carbon reduction engineering according to their engagement levels, allowing scholars to identify post categories associated with higher engagement levels. The CHAID decision tree is used to do this, which leverages a decision tree approach for categorization and forecasting. Decision trees do extensive statistical analysis as data-mining tools while delivering graphically comprehensible results to aid understanding. Non-binary trees are generated by dividing the data into harmonized subcategories depending on the relationship between the independent and the dependent variables (Kass, 1980). Additionally, this technique partitions the data into separate subcategories following the dependent variable without assuming a normal distribution (Chen, 2003; Díaz-Pérez & Bethencourt-Cejas, 2016).

As defined by Ozgulbas and Serhan Koyuncugil (2006), this approach divides the dataset using chi-square statistics for nominal dependent variables and F-tests for continuous or metric dependent variables. The significance rate for the node splitting criterion is set at 0.05 for splitting nodes and merging categories. There are three sorts of nodes: *root, parent, and child* nodes. The root node on the top contains the whole sample, whereas parent nodes are partitioned nodes that can be split further, and child nodes are groups that do not. The parent/child node ratio was modified to a smaller ratio of 30/15 to guarantee enhanced tree growth (McCormick et al., 2017). The parent node was configured to have at least 30 instances, while a child node was configured to have at least 15 instances. The tree was constrained to 7 layers to permit a more robust representation, ensuring that additional splitting stops after seven layers. The analysis was performed in SPSS version 29.

3.4. Topic modeling through the non-negative matrix factorization approach

The Non-negative Matrix Factorization (NMF) method, closely related to the widely-used K-means clustering approach, has been adapted for analyzing networked text data to incorporate additional information (Lee & Seung, 1999; Yu et al., 2024). Unlike Latent Dirichlet Allocation (LDA), which relies on a bag-of-words model and term frequency without feature weighting, NMF involves preprocessing data and assigning weights to each feature. This is often achieved through the term frequency-inverse document frequency (TF-IDF) scheme, commonly employed in text mining to quantify the significance of a term within a document corpus. Similar to Principal Component Analysis (PCA), the number of topics (k) needs to be predetermined in NMF. The ultimate goal of NMF is to factorize the original matrix (A) into two non-negative matrices (W and H), minimizing the distance between A and their product (W × H), typically measured using the Frobenius norm (Sajjadiani et al., 2024).

4. Data analysis

4.1. Descriptive findings

According to the descriptive statistics of binary independent variables in Table 3, nearly 69 % of the shared Facebook posts include an

Table 3
Binary independent variables descriptive statistics.

	Existence of hyperlink		Existence of a hashtag		Existence of a CTA	
	Number	Percent	Number	Percent	Number	Percent
Yes	4780	68.88 %	2250	32.42 %	493	7.1 %
No	2160	31.12 %	4690	67.58 %	6447	92.9 %
Total	6940	100 %	6940	100 %	6940	100 %

external hyperlink, allowing users to get more details by opening and accessing the hyperlink provided. Furthermore, about 32 % of the shared posts contain at least one hashtag. Further, just 7 % of the shared posts include CTA prompts.

Table 4 shows that nearly half of the Facebook posts, approximately 45.72 %, are characterized by low vividness, as evidenced by posting text without pictures. A closer percentage of postings, particularly 44.74 %, represent medium vividness, as evidenced by including pictures. In contrast, 9.54 % of the messages are highly vivid due to the inclusion of GIFs or videos.

4.2. Decision tree findings

The CHAID decision tree (see Table 5) explored factors influencing stakeholder engagement with Facebook posts related to carbon reduction engineering, considering five independent variables: vividness, hashtag existence, hyperlink existence, number of characters, and CTA existence. The analysis produced substantial results visually shown in Figs. 2–4.[2,3] We employed different techniques to mitigate the risk of overfitting, such as cross-validation and parameter tuning (e.g., tree depth, minimum node size), ensuring that the resulting decision tree is generalizable to unseen data. The resulting decision tree (see Fig. 2) identified 17 nodes comprising the root, six parent, and ten child nodes. The analysis revealed that post vividness significantly influences stakeholder engagement, with medium and high vividness levels (Node 2, mean = 14.523) leading to higher engagement than low vividness (Node 1, mean = 9.490) (Table 6).

Within low-vividness posts, the number of characters played a crucial role in differentiating engagement levels (see Fig. 3). Posts with 254–1245 characters showed the highest engagement (Node 4, mean = 11.738), followed by those with more than 1950 characters (Node 6, mean = 10.668), while posts with fewer than 254 characters had the lowest engagement (Node 3, mean = 5.941). The presence of hyperlinks further differentiated engagement within this subgroup, with posts lacking hyperlinks (Node 9, mean = 59.735) garnering significantly higher engagement than those with hyperlinks (Node 10, mean = 11.171). Notably, Node 9 emerged as a high-influencing node, representing only 0.2 % of the population (16 posts).

For posts with medium to high vividness, hashtags did not significantly impact overall engagement (see Fig. 4). However, hashtag presence differentiated engagement within specific subgroups, particularly among posts with extended character counts. For instance, posts with over 1950 characters and hashtags (Node 11, mean = 45.885) had

Table 4
Descriptive statistics of vividness level.

Vividness level	Number	Percent
High	662	9.54 %
Medium	3105	44.74 %
Low	3173	45.72 %
Total	6940	100 %

[2] Due to the large size of the decision tree, it has been divided into three separate figures called Part 1 (Fig. 2), Part 2 (Fig. 3), and Part 3 (Fig. 4).

[3] Icons by Flaticon (https://www.flaticon.com/)

Table 5
CHAID decision tree model summary.

Model Summary		
Specifications	Growing Method	CHAID
	Dependent Variable	Engagement
	Independent Variables	vividness, has_hashtag, has_link, no_of_characters, has_cta
	Validation	None
	Maximum Tree Depth	7
	Maximum Cases in Parent Node	30
	Maximum Cases in Child Node	15
Results	Independent Variables Included	vividness, has_hashtag, has_link, no_of_characters
	Number of Nodes	17
	Number of Terminal Nodes	10
	Depth	3

higher engagement than similar posts without hashtags (Node 14, mean = 8.676).

4.3. Topic modeling

Given the massive amount of information that exceeds human cognitive capacity, topic modeling proves highly advantageous (Vayansky & Kumar, 2020). This study employed the Python programming language to implement NMF-based topic modeling on a corpus of 6940 Facebook posts. The objective was to extract and identify the top five significant topics in carbon reduction engineering discussed by stakeholders. In Fig. 5, the outcomes of the topic modeling analysis conducted in this study unveil the predominant themes and frequently employed vocabulary within stakeholders' discussions on the Facebook platform. Following a series of brainstorming sessions among the experts in sustainable operations management, the labels were assigned to each topic to reflect the predominant themes in the associated keywords and posts. Topic 1 concerns *community development and engineering solutions*, containing terms such as business, government, development, engineering, project, and change. Topic 2 refers to *scientific research, environmental studies, and technology*, containing many keywords like college, research, technology, environment, and climate. Topic 3 focuses on *renewable energy transition and pollution reduction*. Based on trendy terms: electricity, emission, solar, clean, renewable energy, and pollution. Topic 4 explores the relationship between *artificial intelligence (AI), hackathons, and social impact*, as AI, hackathons, creativity, and social are primary keywords in this topic. Finally, Topic 5 concerns the *role of engineering in addressing climate change*, as it contains terms such as engineering, climate change, technology, and carbon.

Natural language analysis provides inherent barriers due to its complexities and large datasets (Kim et al., 2017; Liu et al., 2018). This study analyzed 6940 Facebook posts about carbon reduction engineering, generating many dimensions. To further study the topic modeling outcomes, *t-SNE*, a machine learning technique, was used to graphically portray the results in a two- or three-dimensional map (Fang et al., 2020; van der Maaten & Hinton, 2008). By leveraging t-SNE, a lower-dimensional space was generated, capturing the maximum variation in the data by calculating characteristic vectors from the covariance matrix.

Fig. 6 illustrates the transformation of many high-dimensional data inputs into a two-dimensional map by leveraging the algorithm's nonlinearity and conformity to the original data. The multivariate data points correspond to the five indicated topics, giving reliability to the modeled topics. Fig. 6 illustrates that Topic 1, "*Community development and engineering solutions*" (orange color), Topic 2 "*Scientific research, environmental studies, and technology*" (blue color), and Topic 3, "*Renewable energy transition and pollution reduction*" (red color), have a higher prominence. In contrast, Topic 4, "*Artificial intelligence (AI), hackathons, and social impact*" (purple color), and Topic 5, "*Role of engineering in addressing climate change*" (green color), have a lower occurrence.

In order to acquire complete insights and understanding of the interrelationship between the generated topics, this work used the *pyLDAvis* Python library, a powerful tool for visualizing interactive topic models, to generate an inter-topic distance map (Mustak et al., 2021). Fig. 7 illustrates the significance of the modeled topics by varying circles' sizes, while the distances between the circles indicate the connectivity and relationships in different subject areas. The bar chart displays the 30

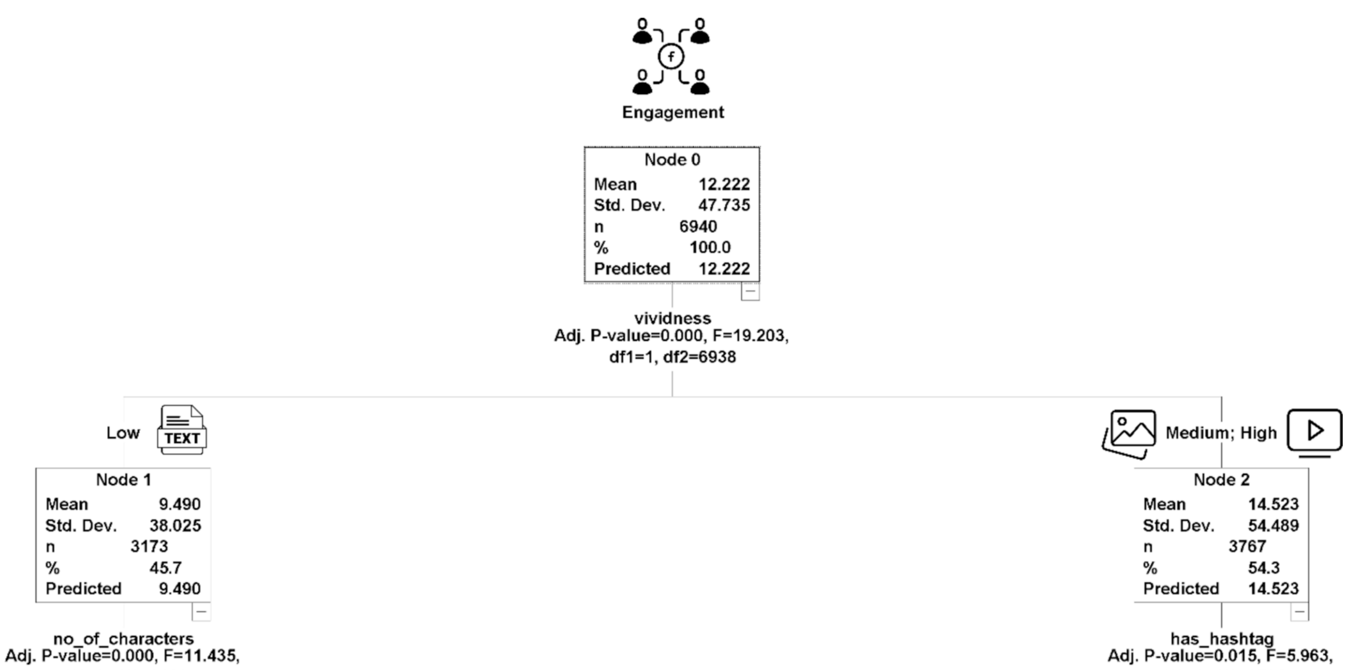

Fig. 2. CHAID decision tree result (Part 1).

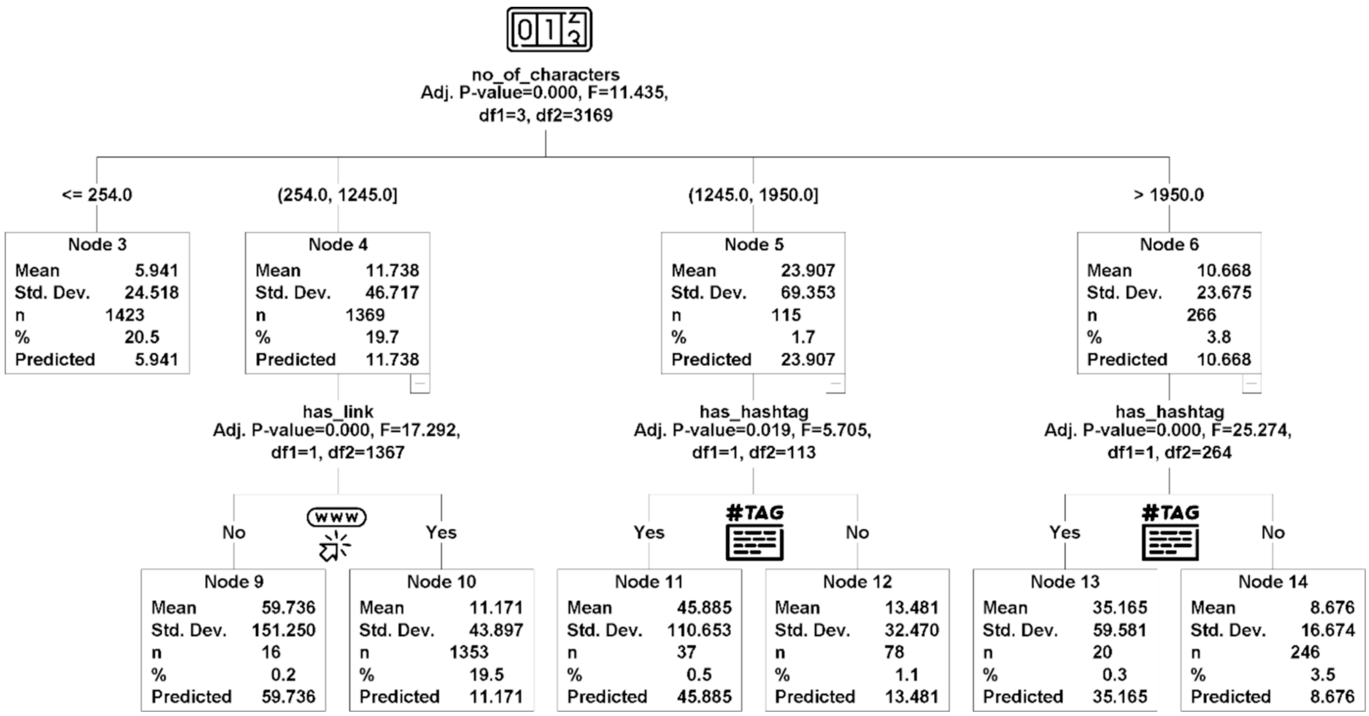

Fig. 3. CHAID decision tree result (Part 2).

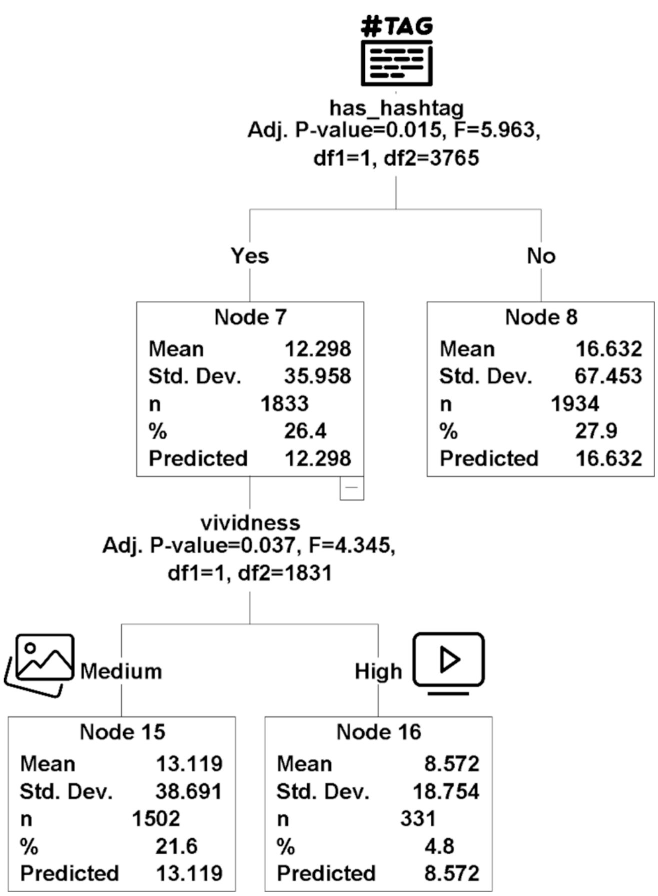

Fig. 4. CHAID decision tree result (Part 3).

Table 6
Gain summary for nodes.

Child node	Population	Percent	Mean
9	16	0.2 %	59.736
11	37	0.5 %	45.885
13	20	0.3 %	35.165
8	1934	27.9 %	16.632
12	78	1.1 %	13.481
15	1502	21.6 %	13.119
10	1353	19.5 %	11.170
14	246	3.5 %	8.676
16	331	4.8 %	8.572
3	1423	20.5 %	5.940

highest-scoring terms in the chosen topic (Topic 1 is selected as an example), emphasizing their importance.

Fig. 7 presents the inter-topic distance map, which explains the varied levels of significance given to the key research topics. Mainly, Topic 1, which includes community development and engineering solutions, arises as one of the essential topics in this research area, with a close connection to Topic 2, which covers scientific research, environmental studies, and technology, in addition to Topic 3, that focuses on renewable energy transition and pollution reduction. While Topic 5, which addresses the role of engineering in confronting climate change, is closely linked to this research subject, it is considerably more distant from the other topics under consideration. Lastly, Topic 4, which focuses on AI, hackathons, and social impact, stands independently without significant connections to the other topics.

5. Findings and discussion

We found upon analysis of the Facebook page categories that the most engaging categories in carbon reduction engineering discussions are universities, government organizations, non-profit organizations, media, news companies, groups passionate about engineering science, environmental conservation organizations, community groups, and Non-governmental organizations (NGOs). This, in turn, provides

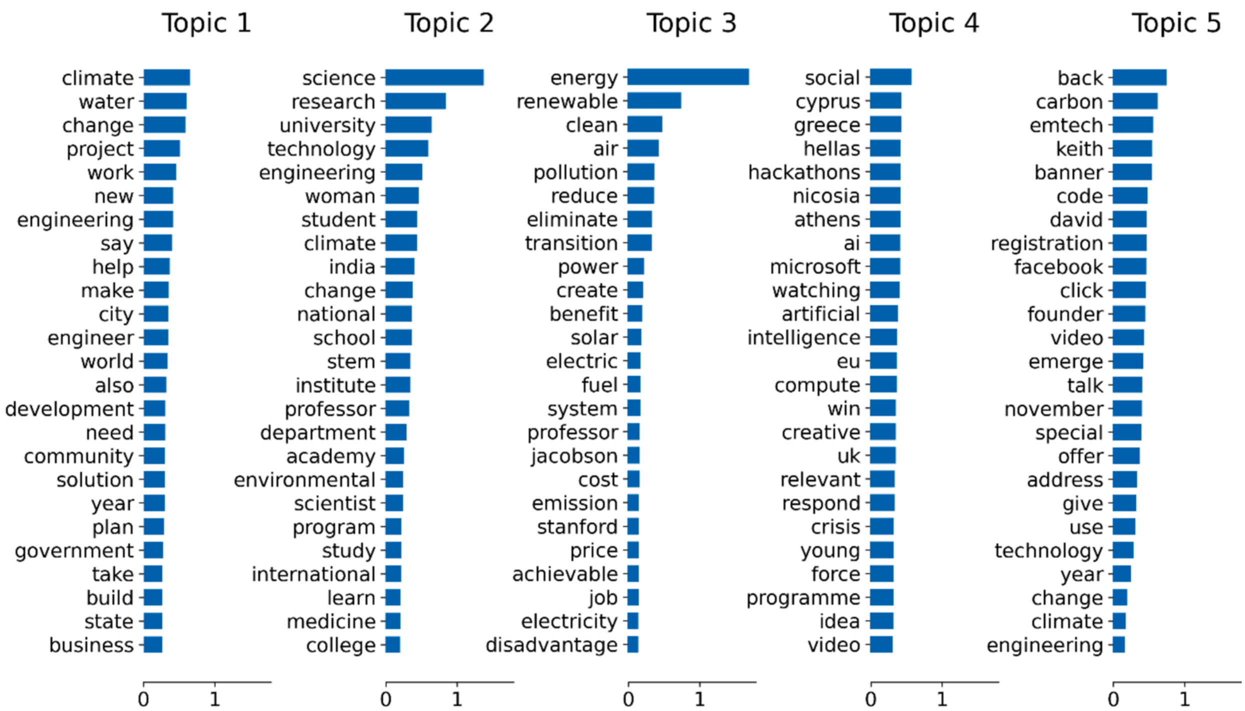

Fig. 5. Top five carbon reduction engineering NMF-based topics.

valuable insights into the diverse range of stakeholders actively engaging in these discussions on social media. This diversity aligns with stakeholder theory's emphasis on considering multiple perspectives in addressing complex issues like climate change (Freeman, 2010). However, the engagement patterns of these stakeholders vary considerably depending on the characteristics of the shared posts.

Our study addressed an important question: *How do Facebook posts motivate and engage stakeholders with carbon reduction engineering?* In addressing this question via a social media study, we identify using the CHAID decision tree that posts with medium and high vividness levels generally lead to higher stakeholder engagement in carbon reduction engineering than low vividness. This finding corroborates previous research by Viglia et al. (2018), who found that visual content generates more interaction on Facebook. However, our study further reveals that other factors, such as post length and the presence of hyperlinks, can moderate the impact of vividness. For instance, we find that among posts with low vividness, those with moderate character counts (254–1245) and no hyperlinks receive the highest engagement. This, in turn, suggests that message fluency and conciseness may be essential when visual content is lacking.

Our findings also shed light on the role of different institutional pressures in driving engagement with carbon reduction engineering content. While Dhanda et al. (2022) focused on the impact of coercive, normative, and mimetic pressures on the organizational adoption of mitigation strategies, our research suggests that these pressures may also influence stakeholder engagement on social media. For example, the prominence of government organizations and NGOs in our dataset could indicate the influence of normative pressures. At the same time, the engagement of media outlets might reflect the role of mimetic pressures in amplifying particular messages.

According to the topic modeling findings, Topic 1 focuses on developing engineering solutions and planning to address diverse community concerns. This issue emphasizes the necessity of collaboration among stakeholders, such as corporations, governments, and engineers, in developing sustainable solutions, such as production optimization in climate engineering, that benefit the community and the environment (Cappelletti & Germani, 2023). Topic 2 emphasizes the importance of academic institutions, such as universities and research institutes, in performing climate change and environmental studies. The topic highlights the engagement of scientists, professors, and students in researching and understanding the environmental impact of technology and engineering. It highlights the significance of research and teaching in promoting sustainable behaviors and furthering environmental science (e.g., AbdulRafiu et al., 2022; Nussey et al., 2022).

Topic 3 emphasizes switching from fossil fuels to renewable energy sources to reduce pollution and emissions (e.g., York & Bell 2019; Zhang et al., 2019). This topic aligns with the findings of Jha and Verma (2022), who highlighted the importance of firms communicating their sustainability initiatives on social media. However, our study extends this research by identifying specific themes and keywords that resonate most strongly with stakeholders within the context of carbon reduction engineering. Topic 4 proposes addressing social concerns and crises using AI technology, such as machine learning. The mention of hackathons implies the engagement of youthful brains in developing innovative solutions (e.g., Kaack et al., 2022; Leal Filho et al., 2022). This topic demonstrates the involvement of companies like Microsoft and the importance of AI-related efforts in countries like Cyprus and Greece. Lastly, Topic 5 underlines the significance of addressing climate change and the role of engineering in finding solutions (e.g., Accorsi et al., 2022). It implies that engineering may provide specialized knowledge and technology to reduce the harmful effects of climate change. References to seminars and videos imply that knowledge is being disseminated and awareness regarding engineering's role in climate change mitigation is being raised.

6. Implications

This study contributes to the literature on stakeholder theory and social interaction management by providing valuable insights into how stakeholders perceive and engage with carbon reduction engineering strategies on social media. Our findings have significant implications for both academics and practitioners in this field. First, this work addresses a gap in the existing literature by exploring the specific characteristics of social media posts that influence stakeholder engagement. This, in turn, can inspire further research investigations into climate engineering strategies and potential collaborations with universities, government

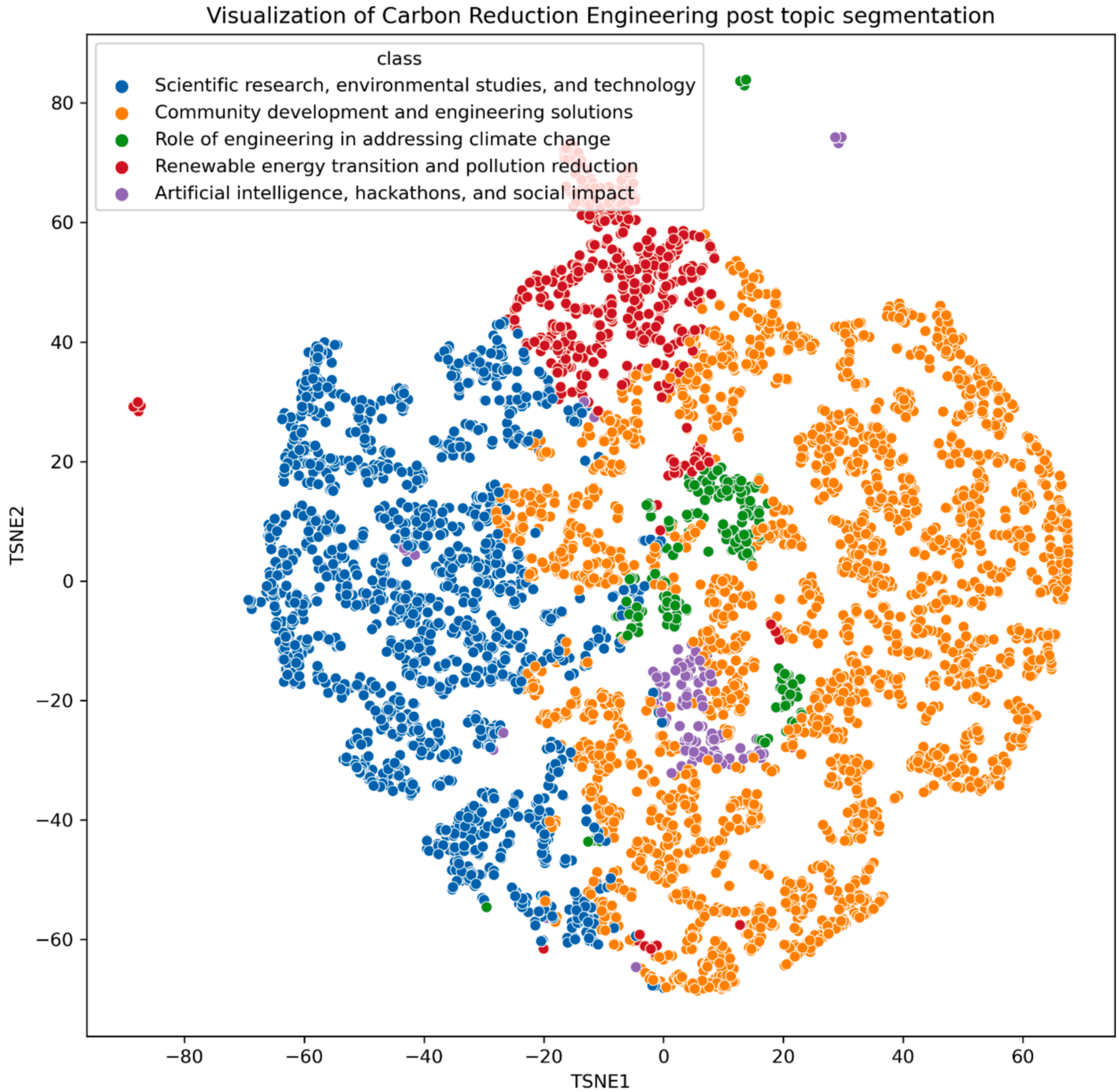

Fig. 6. Visualization of modeled topics using t-SNE.

organizations, NGOs, and media outlets to reach a wider audience. Second, this study demonstrates the effectiveness of using the CHAID decision tree and other data mining techniques to analyze stakeholder engagement and identify the predominant themes on social media platforms. Third, the existing body of literature in the field of production optimization in carbon reduction management has not yet explored the management of social media posts at the tactical or operational level. Our study tackles this lack of managerial understanding so practitioners can use our findings to optimize their social media strategies for carbon neutrality by creating posts with high levels of vividness, moderate character counts, and no hyperlinks to maximize engagement. Fourth, this work identifies different themes engaging various stakeholders to achieve carbon neutrality. Practitioners can leverage the identified themes to develop targeted content that resonates with specific stakeholder groups and addresses their concerns. Finally, this study is particularly relevant for business-to-business (B2B) service providers in climate engineering, as effective stakeholder engagement is essential for success in this sector.

7. Conclusion, limitations, and future scope

This study examined how Facebook posts engage stakeholders, with a particular focus on finding the Facebook post attributes that led to better levels of stakeholder participation. The use of CHAID analysis revealed that five post factors influence the rate of stakeholder interaction. The sum of characters in a message, the presence of hashtags, the existence of a hyperlink, the level of vividness, and the existence of CTA are all examples of these characteristics. This study provides valuable insights for practitioners to engage stakeholders effectively on social media platforms like Facebook. Organizations can tailor their communication strategies to maximize reach and impact by understanding the impact of post attributes and content themes. For instance, incorporating visual elements and crafting concise, fluent messages can significantly enhance stakeholder engagement. The findings emphasize the significance of post characteristics, including message fluency, hashtags, and message length, in determining stakeholder engagement.

Furthermore, the study used novel tools to analyze massive data sets and better understand stakeholders' engagement in carbon reduction engineering. The findings reveal that posts with a more significant character count and no hashtags have lower engagement rates,

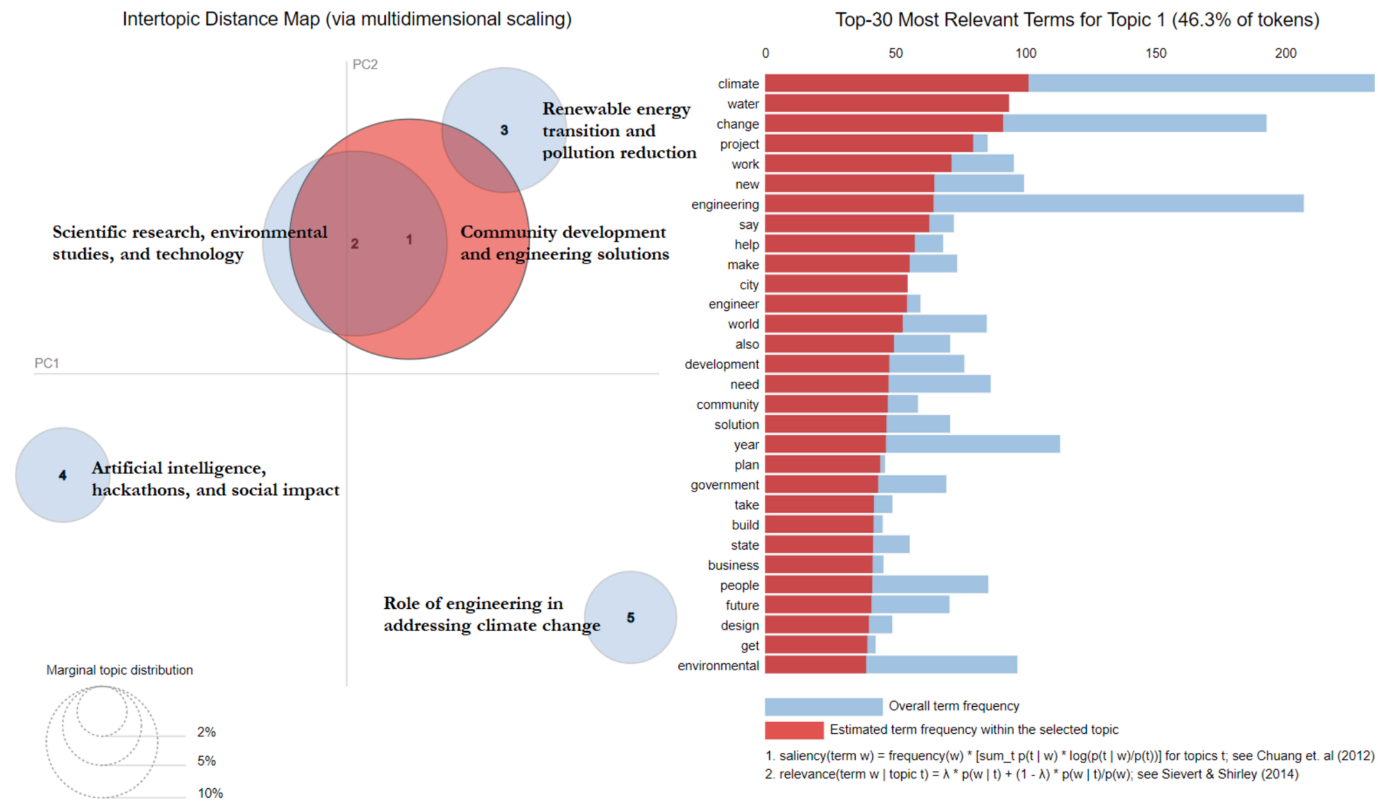

Fig. 7. The inter-topic distance map of modeled topics.

negatively impacting stakeholder engagement. Posts with specified characteristics, such as characters between 254 and 1245, a low vividness level, and the absence of hyperlinks, indicate higher levels of stakeholder engagement. Furthermore, the topic modeling sheds light on the primary topics and concerns influencing stakeholders' engagement. These topics include engineering solutions, the role of academic institutions, renewable energy adoption, the use of AI technology, and the significance of solving climate change through engineering.

This study has a few limitations that represent additional opportunities for future research. First, our study does not include additional variables such as content themes, sentiment analysis, and posting time. In this regard, there is room to investigate thoughts and emotions toward carbon neutrality strategies. Second, the findings are specific to the carbon reduction engineering field and may not necessarily be replicable or applicable in other fields. Third, the study relied only on the Facebook platform, limiting the results' generalizability. There is also room to introduce further new variables from different social media platforms, such as Reddit, Instagram, X, and Threads. These platforms have different user demographics, content formats, and algorithms, which could influence the types of conversations and the level of stakeholder engagement. So, future studies could leverage multiple platforms and compare the factors engaging stakeholders. Fourth, the results could have been more profound and insightful if some variables proposed by Surucu-Balci et al. (2020) (e.g., tangibility of resources, content type, and mentioning of a company) had been added to the analysis as independent variables. Unfortunately, the large dataset made it challenging. Finally, future research should explore how social media engagement impacts stakeholders' strategies in real-world scenarios.

CRediT authorship contribution statement

Zakaria El Hathat: Writing – original draft, Validation, Resources, Methodology, Conceptualization. **V.G. Venkatesh:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **V. Raja Sreedharan:** Writing – review & editing, Validation, Methodology, Investigation. **Tarik Zouadi:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Yangyan Shi:** Writing – review & editing, Writing – original draft, Supervision. **Manimuthu Arunmozhi:** Writing – review & editing, Validation.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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