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An artificial intelligence analysis of climate-change influencers' marketing on Twitter

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Abstract

Designing marketing strategies with social media influencers are becoming increasingly relevant for setting political agendas. This study focuses on how two representative social influencers, Greta Thunberg and Bill Gates, engage in advising against climate change. The investigation uses 23,294 tweets posted by them or their followers citing them on climate change around the 25th edition of the United Nations Climate Change Conference. This study applies artificial intelligence and natural language processing to analyse the marketing mechanism of social influencers. We scrutinize the sentiment of the messages and then identify and analyse the different networks constructed around them to discern how pervasive a social influencer's message is. The results show that Thunberg and Gates follow different and unconnected strategies to deliver their messages to their followers.

KEYWORDS
artificial intelligence, natural language processing, sentiment analysis, social influencers, social networks, Twitter

1 | INTRODUCTION

Climate has always been of utmost public interest (Purcell et al., 2010), but it has recently become a major public concern because of the emerging scientific data on climate change (Corbett & Savarimuthu, 2022; Wei et al., 2021). The increasing concern regarding the negative effects of climate change is evidenced by the topic's popularity in Gallup's rankings, opinion polls in web search engines, and social media debates (Rosenthal, 2022). In the construction of a discourse on climate change, society prefers to receive its information from trustworthy sources.

The marketing literature shows that discussion on environmental topics focuses on few influential informants, based not only on their expertise, but also on trustworthiness and intentions: the "prestige newspapers," news aggregators or organisations, and opinion leaders, which also include celebrities (Lee et al., 2021) Managing climate change requires transnational decision-making and global debate. Under these circumstances, social networks are an ideal space for this discussion and have become a channel of public participation for scientists and policymakers (Cody et al., 2015; Nisbet et al., 2009).

Digital networks have become essential tools for marketers and activists, who value the engagement catalysed by including their messages on the influencer's narratives over time (Schouten et al., 2020). Considering the growing need for information on the climate crisis and the proliferation of information sources, traditional communication processes have been altered.

In the backdrop of criticism of political inactivity by governments and administrations, digital networks have facilitated an individual-led open endeavour to curb global warming (Gómez-García et al., 2019). There has been intense academic debate in the marketing and communication literature on how influencers attempt to mobilise individuals in social networks, how they react to their followers' messages, how they reach their audience, and the degree of homophily (Boutet et al., 2012; Brown & Hayes, 2008; Cha et al., 2010; Corbett & Savarimuthu, 2022; Kim & Kim, 2021; Lee et al., 2021; Lou & Yuan, 2019; Schouten et al., 2020; Shoenberger & Kim, 2022).

However, the analysis of the role, characteristics, and strategies of digital "environmental influencers" as a particular type of "digital activists" compared with other influencers has received scant attention in the literature. This study aims to address this gap by using the World Climate summit in Madrid in December 2019 (COP25) as a natural experiment to analyse the Twitter behaviour of two representative influencers: Greta Thunberg and Bill Gates. Twitter has become an essential tool for raising awareness about the environmental and climate crisis (Cody et al., 2015). However, few researchers have attempted to establish the impact and characteristics of environmental leaders in these networks. A broad application of the methods and technologies developed to quantify the power and effects of influencers (such as the number of times a post is retweeted or the number of followers) has not been implied. Extant literature has also overlooked the qualitative dimensions such as perceived trust, quality of the influencer's information, evidence of the impact on followers, or the feelings they arouse.

We seek to develop insights on the effectiveness of using influencer endorsements, opinions, and strategies in raising climate change awareness—which is not still well understood. Extrapolating from influencer marketing literature, we expect that the informative value of the content, trustworthiness, attractiveness, and identification with the influencer affects awareness (Lou & Yuan, 2019). As Shoenberger and Kim (2022) show, homophily and perceived authenticity, when understood as the perception of sharing values and uniqueness, drives following the influencer's recommendations. Furthermore Raimondo et al. (2022) find that social groups' belonging attracts individuals desiring to dissociate from relevant out-groups signalling goals towards social group, a strategy relevant in social media (Accenture, 2006).

The remainder of this document is structured as follows: Section 2 presents the literature review and the theoretical framework; Section 3 focuses on the data by describing how the tweets was gathered from Twitter and also the different methods used to analyse these tweets to achieve our research goals. These methods comprise sentiment analysis, word cloud analysis and segmentation, and social network analysis. Section 4 discusses the results. Finally, Section 5 presents the conclusions along with the limitations of our study that can guide future research.

2 | THEORETICAL FRAMEWORK

In digital marketing, influencers have become an increasingly important community of "stakeholders" who influence discourse and action (de Veirman et al., 2017; Schimmelpfennig & Hunt, 2020)). But to our knowledge, no study has measured the effectiveness of using influencer marketing strategies in raising awareness on climate change.

We define influencers as "individuals who disproportionately impact the spread of information or some related behaviour of interest" and "seed content"; they create a large part of their content" (Giachanou & Crestani, 2016). Based on Nisbet et al. (2009), we classify digital climate digital influencers as "agitators" (i.e., they spark discussions on and attention to climate change-related events) and others as "synthesisers" (i.e., they compile and put into plain language the news and strategies).

We apply this aprioristic classification to Thunberg and Gates, whose messages jointly reach more than 100 million people. These online leaders have set agendas and provoked or facilitated debate or dialogue on certain issues with specific and different approaches on the network that may even yield a polarisation of the debate (Dunlap et al., 2016).

In 2021, People magazine commented that Greta Thunberg's digital activism "has taken on a life of its own" (DeSantis, 2021). Ever since her isolated battle against the Swedish Parliament began in August 2018, with a "school strike against climate change," she has become an international leader in the fight against political inactivity. Greta Thunberg has become a social celebrity and gained the nickname "the voice of the planet," for her influence on millions of people on and off social media, creating a long-lasting impact on younger generations (Lawson, 2019).

Thunberg's message, panned as simplistic by some and justified by others (Caldwell, 2019; Kühne, 2019), focuses on four major issues: (1) There is a crisis in all levels due to climate change; (2) The existing population is responsible for climate change; (3) The youngsters will be the ones paying the highest price and nobody seems to care about it; and (4) Politicians and decision-makers should listen to scientists. Thunberg urges individuals to pressure private companies and public authorities to take action on those issues that have long been neglected, as summarised in the title of her book: *No One Is Too Small to Make a Difference* (Thunberg, 2019).

Bill Gates, on the other hand, has a different profile. As the founder of Microsoft and being among the world's wealthiest individuals, Gates is one of the more recognisable faces on earth. He has vowed to leverage on his popularity to impact climate change awareness through his network of relationships (van Noorden, 2014). Unlike Thunberg, Gates wants policy solutions to primarily help vulnerable populations, emphasising the promotion of innovation and progress in the places that need it most. Gates has been critical of some environmental activists, such as Ecologists in Action, because he believes that they are wasting their time pressuring investors to abandon fossil fuels. Instead, he argues that it is more useful to promote innovative companies to prevent climate change (Uzzi & Dunlap, 2005).

2.1 | Twitter's communicative environment for climate change activism

The willingness of both to position the problem at the top of the public and political agenda does not dilute their differences in terms of solutions and strategies. The recommendations range from a call to citizens to adopt habits for sustainability and guidance to governments, to the toughest pressure on companies to make decisions that preserve the environment. In this context, activists use new technologies to transmit personalised content to generate public reactions and reshape political priorities, hierarchies, and processes (Martín-Llaguno et al., 2022; Saura et al., 2017).

Nejad et al. (2015) and, more recently, Bu et al. (2022) have observed a high degree of homophily, defined as "contact between similar people [which] occurs at a higher rate than among dissimilar people" on social networks (McPherson et al., 2001). This is true across generations and affects aspects as consumer behaviour (Casalegno et al., 2022) and social networks' building (Ballestar et al., 2016). Notably, in the general polarisation between activists and deniers, Twitter provides an "echo chamber" in which individuals interact with like-minded people, creating communities dominated by a single approach. The more sceptical or convinced an activist is, the more polarised they become, generating negative feelings as a result of the polarisation (Williams et al., 2015). In environmentalism, Twitter has seldom presented itself as an open forum with mixed communities that lead to less split attitudes, working as an instrument of polarisation (Dunlap et al., 2016).

2.2 | Hypotheses

The 25th edition of the United Nations Climate Change Conference (COP25) in Madrid in December 2019 provides the setting for this natural experiment on the climate debate. Its political failure to discuss issues such as carbon emissions, the centrality of science, and the use of oceans has allowed the analysis of the messages, labels, and reactions of different audiences to climate opinion leaders.

Our study analyses, for the first time, the messages issued during COP25 by Greta Thunberg and Bill Gates. As we stated before, our aim is to evaluate how social influencers market their messages to diffuse their ideas. To achieve this goal, we propose the following three hypotheses:

H.1. Twitter "climate influencers" display pattern profiles and behaviours similar to other social network climate influencers.

Greta Thunberg is a "celeb agitator" versus Bill Gates who is an opinion "synthesiser," as we defined earlier (Nisbet et al., 2009), try to convince their own crowds (Delbaere et al., 2021; Santori et al., 2021).

H.2. Twitter is a marketing tool for "climate influencers."

Greta Thunberg and Bill Gates use new technologies to convey personalised content and labels to reshape political priorities, hierarchies, and processes.

The profiles and strategies of activists and climate influencers are diverse; their results may be contradictory, exacerbating the response of climate change deniers, as they are in another area (Rice et al., 2012; Shoenberger & Kim, 2022; Torres et al., 2019). This leaves room to the existence of multiple strategies with focus on different subgroups within the same network (Ballestar et al., 2016).

H:3. Twitter "climate influencer" audiences and their reactions are not homogeneous.

Twitter is an echo chamber only for the "equals." Homophily is reproduced among the audiences of different opinion leaders, and despite the pursuit of a common purpose, Twitter is not a forum for discussions among diverse communities (Delbaere et al., 2021; Schouten et al., 2020).

3 | METHODS

Thunberg and Gates are undoubtedly social influencers, with 5 million and 54 million followers, respectively. This provides us with both the opportunity to test social methods and understand the dynamics behind current social discussions like climate change and how to address it.

This framework allows us to perform intense data analysis using opinion mining and sentiment analysis on Twitter, thereby producing relevant insights into the underlying processes and dynamics of their goals and behaviour and an analysis of the negative responses to their messages.

Giachanou and Crestani (2016) note that 'mining opinions and sentiment from social media is very challenging due to the vast amount of data generated'. Machine learning facilitates the discovery of hidden patterns and successfully mine opinionated information within the millions of records available. In this situation, the appropriate technique choice is a relevant issue, as highlighted by Athey and Imbens (2019) and Yue et al. (2019). Our approach, depicted in Figure 1, represents an evolution of the traditional Cross Industry Standard Process for Data Mining (CRISP-DM) as recommended by Ballestar and Sainz (2020).

3.1 | Data collection

Our research has a dual aim. First is an analysis of our chosen influencers' messages and who talks about them on Twitter. We collected 23,294 tweets written in English, between 1 and 24 December 2019, around the time when COP25 was held in Madrid: 11,910 (51.12%) tweets contained the keyword "BillGates"; and 11,384 (48.8%), "GretaThunberg." We carefully verified that this sample fulfilled the criteria we used in this study, including the language.

Second, we examined the network of accounts that interact with or mention their content, thereby becoming a referrer for their social network and followers. Thereafter, we delineated the structure and hierarchy of the networks of their followers—where and how they distribute their information and ideas.

To extract the data, we completed a python script using our approved Twitter Developer account, which provided a rolling 30 days of Twitter posts. The script also allowed for different

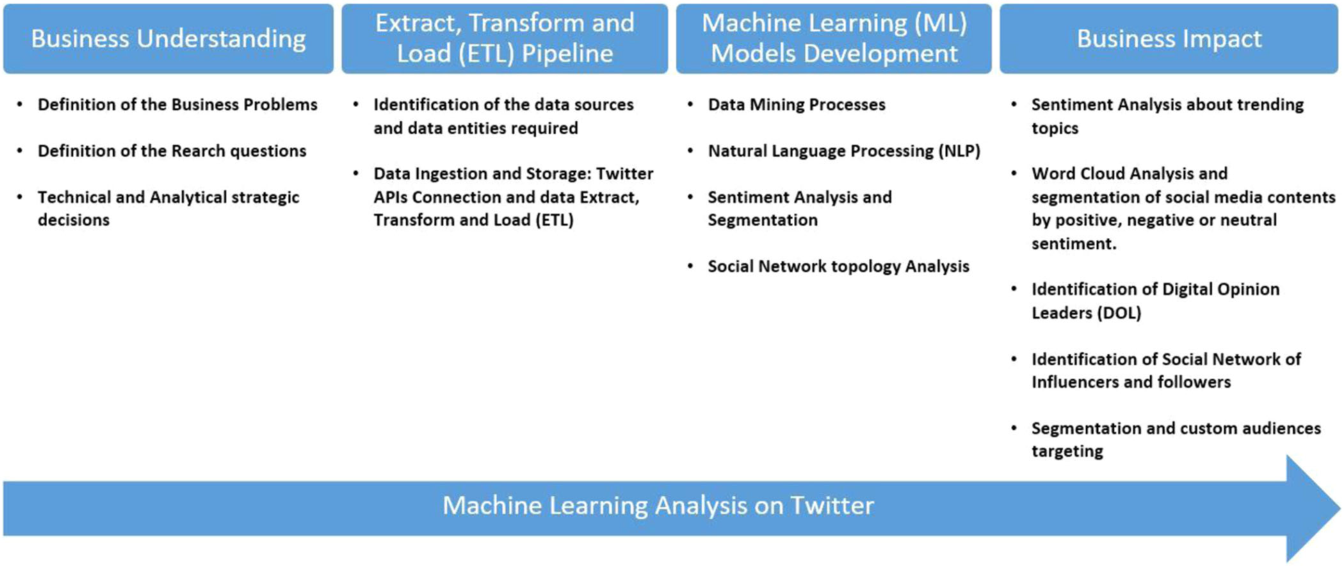


FIGURE 1 Waterfall process of Twitter data analysis using machine learning methods

screeners, but we only filtered by the keywords and the language of the tweets which was English. This 30-day full-archive provides low-latency, full-fidelity data, and query-based access to the tweet archive. The information was then stored and processed in a JSON file and treated by using standardized natural language processing (NLP) libraries for sentiment analysis and word cloud construction. We applied Gephi, an open-source software used for network analysis and visualisation, to identify communities and relationships among users that generate and interact with posts concerning both influencers. All data were treated using Twitter's rules for data analysis for research under our developer's licence.

3.2 | Sentiment analysis

Ahuja and Shakeel (2017) propose the use of lexicon-based sentiment analysis and classification for measuring the popularity of sentiment in a collection of documents. Following their recommendation, we performed sentiment analysis and word cloud visualisations by applying the Valence Aware Dictionary for Sentiment Reasoning (VADER), which enabled us to estimate a metric score for the sentiment of the tweet.

This initial score was adjusted according to five rules based on syntactic and grammatical conventions. VADER is a robust and simple dictionary, described as a "rule-based model that manages a variety of content generated in social media and can compute with high precision its sentiment polarity," and evaluates all the lexical features composing a tweet written in English (Ballestar & Sainz, 2020). It also minimises the bias and false positive and negative errors in the classification process (Dahal et al., 2019). We performed the same scoring and classification process for the extracted 23,294 tweets and then evaluated whether the conversations are associated with a positive, neutral, or negative conversation in the community.

3.3 | Word cloud analysis and segmentation

Ahuja and Shakeel (2017) describe a word cloud as a pictorial depiction of the words in a text based on the absolute frequency of each word or word-phrase that appears in a data corpus. These methods are being increasingly used because they are highly efficient in visualising large amounts of data, such as tweets from Twitter, and represent the ideas behind a textual discourse. In our case, we use it to recognize the most relevant topics and concepts linked to both influencers and to validate whether there is some degree of coincidence among them in the conversations on social media.

Additionally, we apply a clustering method based on the sentiment score of the compiled tweets, which is a two-step machine learning method that conjugates the word cloud analysis with the previously conducted sentiment analysis (Martín-Llaguno et al., 2022; Ballestar et al., 2020). We developed this analysis individually for Gates and Thunberg. The output comprised two word clouds that acknowledge the main issues that have raised feelings among the contributors, be they positive or negative (Katre, 2019).

The word clouds developed for each influencer show the top 400 recurrent words and word-phrases in our sample of messages. We also generated six word clouds for the two clusters of positive and negative sentiment tweets. This strategy adds richness to the current applications of word cloud segmentation (Shahid et al., 2017). In these depictions, the larger the size of the terms or group of terms the higher the frequency. Meanwhile, the colours facilitate visualisation and better comprehension of the results.

3.4 | Social network analysis

There are different types of social networks depending on several factors such as the agents involved, the relationships reanalysed, and whether the network is directed or undirected (Golbeck, 2013). In this study, we analyse the social network topology of the sample and its dynamics with Gephi software and its ForceAtlas2 algorithm. ForceAtlas2 is a continuous graph layout algorithm available in Gephi, which simulates a physical system to spatialise a network and facilitate data interpretation (Jacomy et al., 2014). We analysed the dynamics of the accounts that, during the period of observation, contributed tweets on Gates and Thunberg or the topic of sustainability or those that interacted with such content, thereby acting as prescribers of these tweets in the form of retweets.

4 | RESULTS AND DISCUSSION

4.1 | Sentiment analysis

We analysed their strategies based on general sentiment (Figure 2). Almost 12,000 tweets (11,910) including the keyword "Bill Gates" were extracted, of which those with neutral-positive sentiment were 79.06%. The conversations regarding Gates are often more positive and optimistic than those including the keyword "Greta Thunberg"; 40.92% of the tweets with her name (11,384 tweets) were classified as negative (Martín-Llaguno et al., 2022; Ballestar et al., 2020). According to Figure 2, the average sentiment of tweets containing "BillGates" is +0.22 (standard deviation = 0.51), while that of tweets containing "GretaThunberg" is −0.10 (standard deviation = 0.48). A two-sample Z-test was conducted to confirm significant differences between the average sentiment of the tweets of both influencers. The Z-test confirmed that the average sentiment of the tweets differs depending on the influencer ($|Z| = 50.79 > Z_c = 1.96$, $p = 0.00$ [$\alpha = 0.05$]).

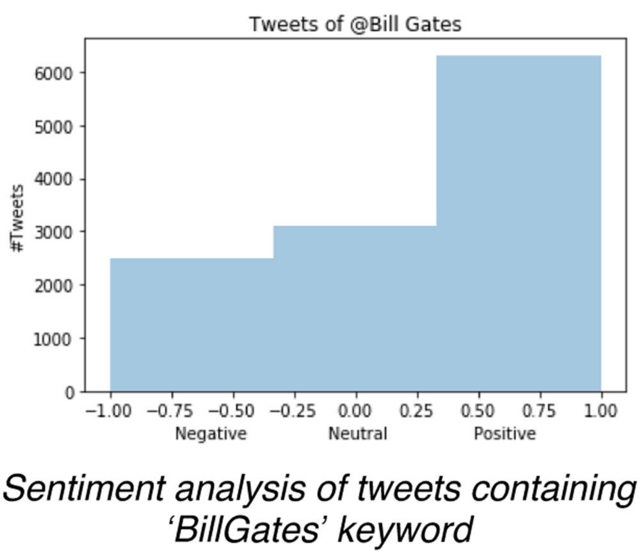
Hence, our results confirm H1: "climate influencers" have been essential in positioning climate change on the public agenda, but in varying degrees and directions, as we expected based on Delbaere et al. (2021) and Santori et al. (2021).

Greta Thunberg is classified as an "agitator" because her conversations and topics are related to the expected harmful effects of climate change and address public administrations and firms to radical action against associated behaviour. Moreover, such messages generated a strong opposition in Twitter among reactionary groups. Bill Gates is classified as a "synthesiser" because he is raising awareness and searching for political support for his foundation's projects. Gates' tweets are more positive, focusing on a constructive perspective, which receive fewer rebuttals from third parties, unlike Thunberg's tweets, which garner a negative sentiment (Martín-Llaguno et al., 2022; Ballestar et al., 2020).

4.2 | Word cloud analysis

The word cloud analysis clearly represents the dynamics of Gates and Thunberg—who listened to them and to which messages (Figure 3). For both, "climate change" is a major topic of discussion. In the word cloud for Gates, this topic is one of the many topics associated with his activism. In the word cloud for Thunberg, there are words in favour of or against the "climate crisis". These findings demonstrate that the activism of Greta Thunberg is based on one topic, namely the climate change crisis. We observe that this specialisation seems to have a double effect: while all the references focus on it, there is strong rebuttal to her communication, which in turn hampers the transmission of her ideas (Nejad et al., 2015; Rice et al., 2012).

Each word cloud is a visual representation of the absolute frequency in which specific words and word-phrases appear in the tweets, segmented by its sentiment—positive, negative, or neutral (Martín-Llaguno et al., 2022; Ballestar et al., 2020).



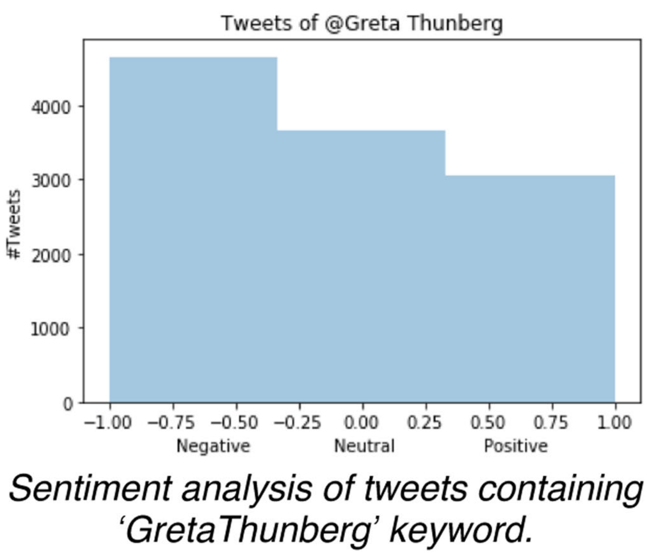


FIGURE 2 Sentiment analysis for Bill Gates and Greta Thunberg on Twitter. Distribution of tweets by their sentiment score.

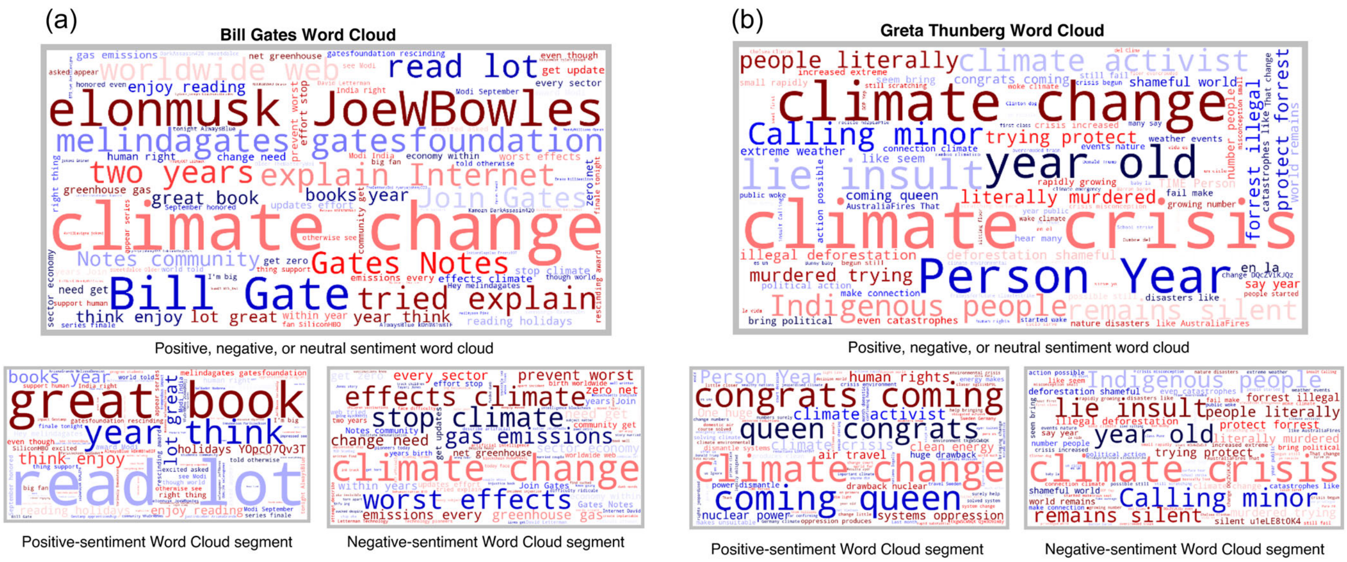


FIGURE 3 Word cloud of the 400 most frequently used words and word-phrases where (a) "BillGates" and (b) "GretaThunberg" are mentioned.

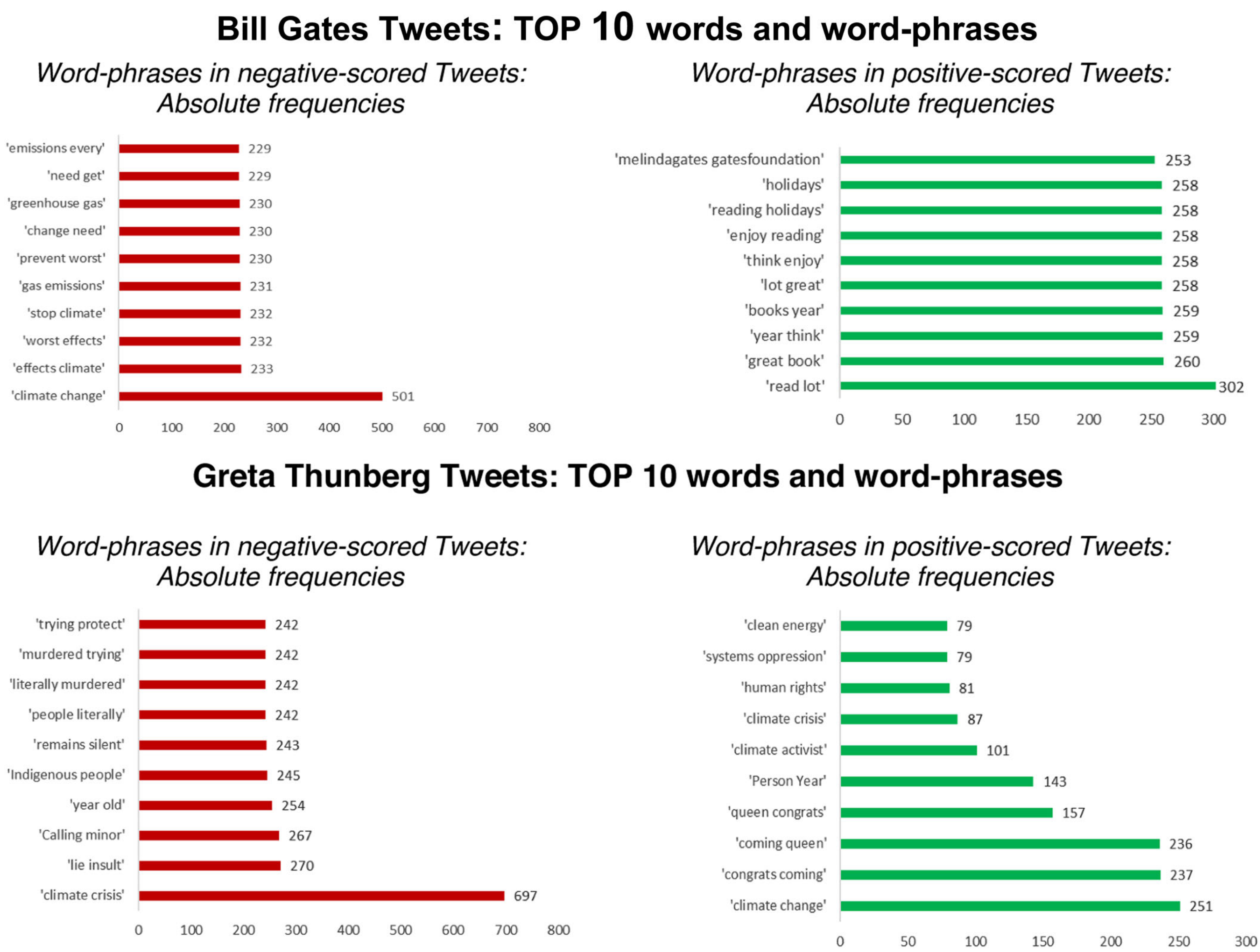


FIGURE 4 Absolute frequencies of top 10 word-phrases in positive-scored and negative-scored tweets

Complementary to the word cloud analysis, the bar diagrams in Figure 4 quantitatively represent the top 10 word and word-phrases in terms of the absolute frequencies for both positive and negative word clouds of Bill Gates and Greta Thunberg.

Based on these statistics (Figure 4), we observe that in the case of Gates, the terms or word-phrases with the highest absolute frequencies in the positive sentiment word cloud are "read lot" (302), "great book" (260), "year think," and "books year" (259). Thus, the positive sentiment conversation is based on culture and books. The highest absolute frequencies in the negative sentiment word cloud were observed for "climate change" (501), "effects climate" (233), "worst effects" (232), "stop climate" (232), and "gas emissions" (231), all of which focus on climate change and its consequences. Only the last word-phrase, in the fifth place, is an essential term in the discussions at the COP25 climate summit.

In the Thunberg community, the frequently occurring positive terms and word-phrases are "climate change" (251), "congrats coming" (237), "coming queen" (236), "queen congrats" (157), "person year" (143), and "climate activist" (101); the positive sentiment surrounding these conversations is mostly related to climate change, but also depict her as a leading activist and influencer. The highest absolute frequencies in the negative sentiment word cloud were observed for "climate crisis" (697), "lie insult" (270), "Calling minor" (267), "year old" (254), "Indigenous people" (245), and "remains silent" (243). In the case of Greta Thunberg, the first reference to the central themes of COP25 Madrid is "Ignoring Science," which appears in the negative sentiment word cloud in the 167th position. They are less engaged in the political discussions than Gates' network, even though Greta Thunberg was one of the keynote speakers.

Gates sends many other messages, but "climate change" has a special urgency, which can also be seen in his latest book (Gates, 2021). This is different from Thunberg's social network, where this word-phase is used in the most positive-scored tweets. With regard to tweets created by Gates or those that mention him, the "climate change" word-phrase appears among the negative-scored tweets because it is used for warning about the need to reduce greenhouse gas emissions to avoid the effects of climate change.

The meta-information contained in social content helps evaluate the information (Martín-Llaguno et al., 2022). The context is derived from the prior references to the value of the influencer and his or her behaviour and intersection on the issue, a theory derived from the early seminal work of Katz, (1957). Social influencers are stars, and the difference between these two categories is who retweets whom, which provides evidence on how information travels on Twitter. There are substantial differences between Greta Thunberg and Bill Gates. The latter wants to produce positive images of altruism regarding the topic, while the former reflects an image of social activism. As Satell (2014) notes: "…if you want things to spread, forget about special people with 'rare qualities'"; thus, influencers motivate those who they want to motivate.

As proposed in H2, climate opinion leaders are using new technologies to generate custom content and dialogue to reshape political priorities, hierarchies, and processes. Our results show that the strategies of activists and climate influencers are diverse, depending on the influencer's characteristics and profile. Gates prefers positive activism, pays little attention to himself, and is fully focused on his foundation's proposals and projects (especially education and innovation). Thunberg prefers a more critical version of environmental activism that, compared with that of Gates, is more focused on herself and her celebrity status than on the activism. She demands radical changes from governments and companies while addressing an audience younger (even with specific labels) than that of Gates, whereas Gates promotes his specific projects or initiatives that he hopes will contribute to making this change a reality (Delbaere et al., 2021).

4.3 | Social network analysis

What are the drivers of this difference? The answer is again based on who retweets whom. A naïve analysis may present Bill Gates and Greta Thunberg as sharing audiences and followers who may be willing to interact with either one.

In Figure 5, we try to validate that climate influencers' audiences and their reactions and interactions on the Twitter social network are not homogeneous, even when pursuing the same objective (H3). The network representation (Figure 5) shows that the communication across both is similar, but their respective communities have limited interaction. This shows that their characteristics and profiles differ, as does the attitudes and communications of their messages, affecting the type of audiences, followers, and referrers they have. These findings are also statistically supported by the social network topology measures described in Table 2.

4.3.1 | Social network topology: Network structure and measures

Our network comprised the Twitter accounts of Bill Gates and Greta Thunberg, the accounts that refer to them, and the accounts which act as prescribers by retweeting their content (Figure 5). The spreading of the message is conditioned to the topology of the network; this finding shows that despite the strong social network of big communities, they are not closely connected, and that there is a high prevalence of many isolated micro-communities. We have used centrality measures to describe how this network operates (Golbeck, 2013). The network structure and its measures are conditioned by the topic of the research, that is, the social network of prescribers who retweet content related to Bill and Greta.

The topology of the network measures (Tables 1 and 2) shows that the number of nodes was 21,013 and the number of edges was 13,864. Nodes refer to both accounts that create the tweets and accounts that interacted with these tweets, acting as referrers and spreading the message in the form of a retweet. This means that the average degree of the network, measures the connectivity among the accounts and is calculated as the average number of edges per node.

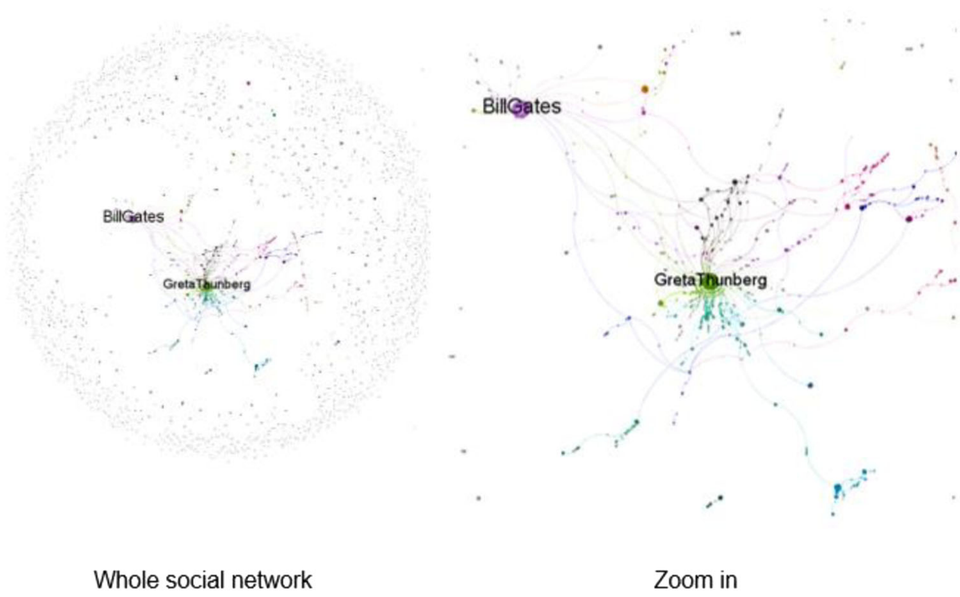


FIGURE 5 Social network analysis for Bill Gates and Greta Thunberg

In this case, we obtained a figure of 0.660. This result proves that there are no relevant interconnections among the two influencers and their respective audiences that retweet their content. In the peripheries of the network, coloured in grey, there are a large group of tiny communities talking about them and climate change, in a result that is similar to that observed for NGOs by Vu et al. (2020).

The average clustering coefficient for the single nodes is low, 0.002, which together with almost zero graph density authenticates our hypothesis (H3). Both are very low because our study uses a large social network where the interactions among users consist of retweets and are characterised by the existence of many small communities, apart from the two most popular ones led by Gates and Thunberg. The topology of the network is compatible with our hypothesis. Thus, two of the main measures, the average path length of the edges that connect the nodes and the network diameter are 1.038 and 4, respectively. These results imply that the dissemination of messages by both Thunberg and Gates does not reach much further than their followers given that the shortest distance between the most distant accounts in the network is the same as the maximum eccentricity among the nodes.

Continuing with the analysis of the network topology, we analyse its modularity (Figure 5). As proposed by Blondel et al. (2008), it measures the density between edges inside the communities and edges outside the community, and it has a value of ±1. Our estimation shows a modularity of 0.954, which indicates that the main points of the community (Gates and Thunberg), have a robust community network connected to them. This is reinforced by the fact that there is no relation among their respective communities, and the values of the out-degree centrality measure are 1901 and 1476 for Gates and Thunberg, respectively.

The size of the nodes is represented by their out-degree centrality, which is the number of links with other accounts that retweeted content that contained the keywords under investigation. As seen in Figure 5, Bill Gates has the highest out-degree with 1901 links, while that of Greta Thunberg is 1527 links, followed at a distance by the next accounts (Table 1). In this network, the out-degree centrality measure for each node is the same as the degree centrality measure because the network represents the interactions by retweeting content generated by other accounts.

Therefore, Bill Gates has only 24.49% more links to accounts on Twitter than Greta Thunberg does in the period of observation, even though Bill Gates has +1132%) more followers than Greta Thunberg. This finding indicates that Thunberg is capable of generating and spreading messages on Twitter; while the number of followers of Thunberg are considerably smaller than that of Bill Gates, her followers are heavily motivated to amplify Thunberg's messages. The in-degree measure represents the number of edges coming into the nodes. Hence, in this network, the accounts with the highest in-degree are those that interact the most by retweeting content related to Bill Gates or Greta Thunberg. The maximum in-degrees in the network are related to Bill Gates's activity, and the top two values are 40 and 23. The third largest number reaches a value of 18 and is related to Greta Thunberg's activity.

Brandes (2001) proposes a method to calculate the betweenness and closeness centrality and eccentricity for a given node defined in terms of the proportion of the shortest paths that go through it. It also shows the number of connections of a node shared by others. It addresses the question of who initiates threads, topics, and proposals in the network of interest; Table 1 shows that the maximum value is 224.

Following Brandes (2001), we analysed the speed at which the information moves from one user to another. This is also referred to as closeness centrality, which is defined as the average distance from one node to all other nodes which belong to the network, showing

TABLE 1 Description of top five accounts

(a) *By out degree*		
Accounts	**Out-degree**	**Account's description**
@BillGates	1.901	Entrepreneur and philanthropist
@GretaThunberg	1.527	Environmental activist
@msrlble	233	Greta's sympathiser
@ValaAfshar	226	Chief Digital Evangelist
@arjunsethi81	212	Human Rights Activist
(b) *By betweenness centrality*		
Accounts	**Betweenness centrality**	**Account's description**
@ValaAfshar	224	Chief Digital Evangelist
@impulsivewoman	23	Social influencer
@Cheryl_Smith1	16	Science teacher
@ezralevant	14	Canadian media personality
@leoniehaimson	11	Director of class size matters

TABLE 2 Social network topology measures.

Closeness centrality	0	85.98%
	0–1	0.44%
	1	13.58%
Network	Average degree	0.660
	Network diameter	4
	Maximum eccentricity among nodes	4
	Modularity	0.954
	Connected components	7,489
	Maximum network's degree centrality	1,901
	Maximum network's out-degree	1,901
	Maximum network's in-degree	40
	Maximum betweenness centrality	224
	Closeness centrality equals to 1	0.136
	Graph density	0.00
Nodes	Number of nodes	21,013
	Average clustering coefficient	0.002
Edges	Number of edges	13,864
	Average path length of the edges	1.038

how long it takes to reach all the members within a network. Our results show that the number of accounts that realise maximum efficiency in the transmission of messages is 13.58%, but 85.98% of nodes in the network were unable to connect with the rest with a closeness centrality of 0; the remaining 0.44% have values greater than 0 but less than 1 (Table 2).

Again, the results show that our network was made of two separate communities characterised by the closeness of nodes within each but separated from each other's. It also showed that there was a low level of eccentricity (4), that is, any tweet did not reach very far from the point of origin; the listeners were not big prescribers themselves, and thus, the information did not travel very far from the community.

Eigenvector centrality, also called the prestige score, measures the importance of the nodes by considering the importance of their neighbours in the network. Thus, nodes with popular neighbours will present higher eigenvector centrality measures than those with less popular neighbours.

The topology of this social network reinforces H3 and confirms the existing homophily among the two major audiences of the social network, even though we predicted that their common interest in environmental issues would be a good reason to follow influencers as different as Bill Gates or Greta Thunberg. Table 2 presents a summary of the most relevant network statistics reviewed in this section.

According to H3, Twitter is a sounding board for "equals" at the first level of the agenda and at the second level (the framing and solutions to the problem). Homophily has been reproduced among the audiences of different opinion leaders despite the pursuit of a common goal; consequently, Twitter is not a forum for discussion among diverse communities as the literature in consumer marketing forecasted (Bu et al., 2022; McPherson et al., 2001; Nejad et al., 2015; Shoenberger & Kim, 2022).

5 | CONCLUSIONS

The title of Bill Gates, 2021 book *How to Avoid a Climate Disaster* easily represents his commitment to climate change, as does Greta Thunberg's work over the last 3–4 years. They are clearly climate change influencers in the sense that they are among the most representative pursuers of the fight against climate change and they recognize their activism toward impacting governmental policies that favour public intervention on such issues (Gates, 2021; Thunberg, 2019). While books are relevant, they are not the eco-chamber they used to be. Nowadays, social networks provide a platform for the exchange and diffusion of opinions, ideas, and discussions, gradually becoming the agora of the 21st century (Ballestar & Sainz, 2020; Martín-Llaguno et al., 2022).

Users searching for information rely on the authenticity, trustworthiness, attractiveness, and uniqueness of the influencers of their choice, with whom they share values (Delbaere et al., 2021; Lou & Yuan, 2019; Shoenberger & Kim, 2022). In this study, we show how Thunberg and Gates, although having the same final goal, use different network strategies to reach their audience. They employ different strategies to create awareness about climate change and their calls focus on their committed followers, and there is no interaction between both groups. We reach this conclusion by analysing how both addressed the discussions around the COP25 in Madrid in December 2019, with the focus on the need to stop greenhouse gas emissions to the atmosphere and the difficulty of trespassing a no-return point for our planet, in a result that reinforces the existence of homophily in social networks (Bu et al., 2022; McPherson et al., 2001; Nejad et al., 2015).

Using a combination of analytical methods such as NLP for sentiment analysis, word cloud analysis, segmentation, and social network topology analysis we have demonstrated that Gates has a clear commitment with regard to climate change, as well as with education or vaccination. His position as a world-renowned philanthropist allows him to combine different methods in social networks, but also employing traditional lobbying, or even the 'old-fashioned' way of writing a book on the issue to reach a wide audience. But his calls for change do not present on itself a revolution but are calls for action in an ordered manner, planning based on a top-bottom global strategy.

Greta Thunberg has the same focus, but her calls for action are more urgent. Her focus goes within a community of activists attracted by her commitment to the cause in a strategy that also has detractors that generate aggressive discussions on the network. The use of different social network topology measures empirically validate the separation between both influencers (Blondel et al., 2008; Brandes, 2001; Golbeck, 2013).

These results show the universality of the methods used. However, this study has limitations that can inspire further research. For example, to advance this topic, researchers should gather more information on shared networks and achieve a deeper understanding of the dynamics of the model. It also shows that sentiment analysis can provide advice and recommendations to all kinds of influencers on the effect of the different messages and on how to deliver them.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Twitter. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://twitter.com/home with the permission of Twitter.

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