Measuring political influence during elections using a deep learning approach

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ABSTRACT

This contribution introduces a methodology for measuring political influence on Twitter during the 2020 U.S. presidential election campaign. The approach employs deep knowledge scores, which are generated through sentiment analysis of Tweets from users responding to influential users, coupled with an assessment of the strength of their interactions. The deep knowledge scores enable the categorization of three types of Twitter's users engaging with influential users: influenced users, distrustful users, and connected users. Our approach, structured around a five-layer framework, effectively constructs networks of trust and distrust, and establishes the relationship between fluctuations in trust or distrust levels and the topics discussed by influential users.

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1. INTRODUCTION

Social media are transforming the political landscape, and all political events, such as elections, referendums, and related gatherings, are experiencing the widespread use of social media. Prior to that, the primary channels used by candidates to interact with the public consisted only of TV, radio, and newspapers, which broadcasted messages of general interest. In the mid-1990s, the internet was first utilized by political parties through emails and forums to exchange information and inform citizens. This period is known as the Politics 1.0 era. Since 2006 and up until now, political events and social media have been going hand in hand. As a result, parties and candidates are taking advantage of social media to stay in touch with the electorate and gauge public opinion by delivering carefully crafted messages that target specific audiences, such as ethnic groups (Afro-Americans, Latino community). Currently, in the realm of political communication, we refer to this as the Politics 2.0 era because new politics employ new media platforms to conduct their electoral campaigns and communicate with the electorate [1]. Table 1 summarizes the evolution of politics and media and their impact on the electoral campaigns.

Social media are like a microcosm of our societies with their demographic richness and variety. The users' behaviors and posts could be a reliable source of insights which will allow us to follow effectively the evolution of political events and therefore to measure the users' opinions in response to online and offline campaigns lead by parties and their nominee candidates. Experts in political communication argue that the opportunities offered by social media are not attainable in face-to-face conversations. They allow for the circumvention of the Hawthorne effect because social media users express spontaneously their opinions without being aware that their opinions could be utilized in political polls or surveys [2]. Social media could be considered as an alternative to the classical methods of polling, which delivered wrong predictions in two major political rendezvous, namely: The American Presidential Election of 2016 and the Brexit's Referendum.

In order to identify the public mood or opinion, numerous contributions have used data extracted from social media to measure sentiment analysis of users in one hand and in the other hand to predict the outcomes of elections or referendums [3]-[7]. These approaches could be strengthening by political and interpersonal communication theories which could support their predictive dimensions and deepen their analyses to achieve better results. The two-step flow theory as shown in Figure 1 is one of the most well-known communication theories which emphasize the significance of opinion leaders who act as intermediaries between mass media and followers [8]. According to this theory, individuals are more influenced by influential users or opinion leaders rather than mass media and were described as individuals to whom others turn for advice and information, or at least to obtain a reality check on information acquired from mass media [9].

Table 1. Evolution of politics and media

	Politics with old media	Politics with new media
Casting model	Broad casting	Narrow casting
Channel	Traditional media (TV, Radio, and press)	New media including social media
Message	General-interests news items	Carefully crafted
Era	From 1992 until 1994: new politics with old media. new politics with old media. From 1994 until 2006: politics 1.0	From 2006 until now: politics 2.0 New politics with new media

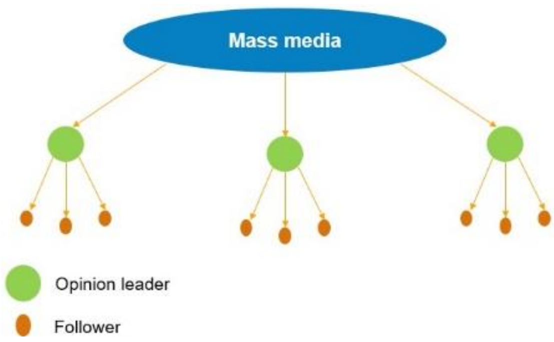

Figure 1. The two-step flow theory scheme

Several approaches have addressed the issue of influence in social media. Kim and Tran [10] proposed three metrics: knowledge score, jaccard coefficient, and matching coefficient, to measure the trust relationship between opinion leaders and users in a social network marketing campaign. In their study, they extracted data from the Epinions website, where users explicitly indicate whom they trust or distrust. The significance of this approach lies in its use of three distinct measures to identify opinion leaders: in-degree, out-degree, and a hybrid measure represented as α*in-degree + (1 - α) *out-degree. This allows for a comparison between opinion leaders with a substantial number of followers (high in-degree) and opinion leaders who follow a considerable number of users (high out-degree). This approach was based on three generations: Gen^0, composed of opinion leaders; Gen^1, composed of activated and connected users; and Gen^2, consisting of users who may be influenced by the activated users of Gen^1. According to this approach, an activated user is someone who is likely to purchase a product advertised by the social network marketing (SNM) campaign, while a connected user is someone who has been exposed to the SNM campaign but will not make the purchase. To distinguish between an activated user and a connected user, the researchers defined a threshold for each metric (KS, JC, or MC) that reflects the trust level between an opinion leader and another user.

Cha *et al.* [11] compared three measures on Twitter: mention, retweet, and in-degree (number of followers). This study provides a deeper understanding of the various roles played by users in social media. The most followed users, who have a high number of followers, are considered popular but not necessarily influential. The most retweeted users who receive a high number of retweets, indicating the value of their tweet content. The most mentioned users, who are frequently mentioned by others, are often celebrities, and their names hold significant value. The researchers also analyzed the correlation between the three measures and found a strong correlation between retweets and mentions, while a weak correlation existed between in-degree and the other two measures. To enhance their analysis, they introduced a topical dimension, which helped determine if a user's influence extended across all topics or was limited to specific ones.

Weng *et al.* [12] developed a framework called TwitterRank to identify influential users on Twitter. This framework assesses the topical similarity between users as well as the link structure connecting them. The study reveals that the "Following" relationship is primarily a form of courtesy between users and does not necessarily indicate influence. This was demonstrated by the strong correlation observed between in-degree and out-degree measures. Furthermore, when user A follows user B, it indicates a case of homophily, suggesting that A and B share similar interests in terms of topics. To identify the topics that Twitter users are interested in, the researchers employed latent dirichlet allocation (LDA) [13]. They aggregated all the Tweets published by each user into a single large document, which was then transformed into a matrix DT' (Number of users * Number of topics). This matrix highlighted the main topics discussed by each user. Jenson-Shannon divergence was utilized to measure the topical difference between users. The influence of user j on user i was determined by considering the topical difference between i and j, as well as the number of Tweets posted by j compared to the total number of tweets posted by all of i's friends.

Anger and Kittl [14] proposed an approach to measure the social networking potential (SNP) of individual Twitter users. Three performance indicators were calculated to assess the users' influence. These indicators are as follows:

– Follower/Following ratio: This ratio measures the number of followers a user has in comparison to the number of users they follow.
– Interaction ratio: This ratio indicates the number of users who interacted with a user's posts by retweeting them, divided by the total number of their followers.
– Retweet and Mention ratio: This ratio calculates the number of Tweets that generate retweets or mentions in relation to the total number of Tweets posted by the user.

The last two ratios were combined to calculate the SNP of each user.

Yang [15] studied the impact of influential users on Twitter during the 2020 U.S. presidential election by constructing a Retweet network. In this network, Twitter users were represented as nodes, retweet interactions as edges, and the strength of relationships was reflected by the number of retweets between users. Using the label propagation algorithm on this network, Yang identified two main communities with weak connections, consisting of Twitter users leaning towards either the Democratic or Republican candidate. To pinpoint influential users, Yang employed in-degree (users who retweeted others' Tweets) and out-degree (users whose Tweets are retweeted by others). The analysis revealed that users with high in-degree and low out-degree had limited influence, while those with high out-degree, termed as hubs, exhibited greater influence by generating and disseminating information to other users. Additionally, Yang observed a substantial reciprocal rate (Trump community 51.3% and Biden community 48.1%) among the top 100 Twitter users of the retweet network, indicating that influential users predominantly engage with each other, emphasizing their central role within the network.

To effectively address the broad and complex concept of influence, it's necessary to narrow the scope by selecting a specific domain, such as politics, and focusing on related events like election or referendum campaigns. This approach is similar to how SNM managers conduct campaigns to boost product and brand awareness [16], [17]. This method can also be applied to electoral campaigns, where individuals with more in-depth political knowledge lead and influence the public opinion. The main goal of our study is to apply the Two-step flow theory to electoral campaigns and identify influential and influenced Twitter users. We chose the 2020 U.S. presidential election as a case study, where we analyze fluctuations in trust and distrust among Twitter users towards these political influencers. Our approach involves initially identifying a first generation of users based on their Twitter activities. Then, we use deep knowledge scores to identify a second generation of users who express trust or distrust towards the first generation. Finally, we examine whether these second-generation of users can become influential by spreading their trust or distrust to those who interact with them. The major constraints of such studies involve the representativeness of the analyzed data, as the Twitter API permits extraction of only 10% of Tweets, even when we have the IDS of all Tweets we intend to study. Additionally, the American electoral campaign spans several months, during which new political actors enter the race and others exit. Similarly, politically engaged users may not remain active throughout the entire electoral campaign.

2. METHOD

To measure influence among Twitter users during the 2020 U.S. presidential election, we created a five-layer framework, illustrated in Figure 2. The Tweets' extracting layer utilized the Tweets' IDS dataset, the Twarc command, and the Twitter API to extract the corresponding JSON files from Twitter and store them in our development environment, hosted in Google Colab. The second layer transforms each JSON file into three easily readable CSV files and cleans the Tweets' texts from newline characters, mentions/hashtags/RT symbols, hyperlinks, and emojis. By utilizing RoBERTa ("Robustly Optimized BERT Approach"), the third layer is designed to determine the sentiment (negative/neutral/positive) expressed by Twitter's users who interact with each other through textual communication. The influence measurements layer is the core of our approach because it employs various measures to calculate the deep knowledge scores. These scores enable us to construct respectively webs of trust and distrust between influential political figures and other Twitter's users. The final layer graphically presents our results, enabling us to visualize the evolution of trust and distrust during the studied period. It helps us establish a connection between the increase or decrease in trust or distrust and the topics discussed by influential users.

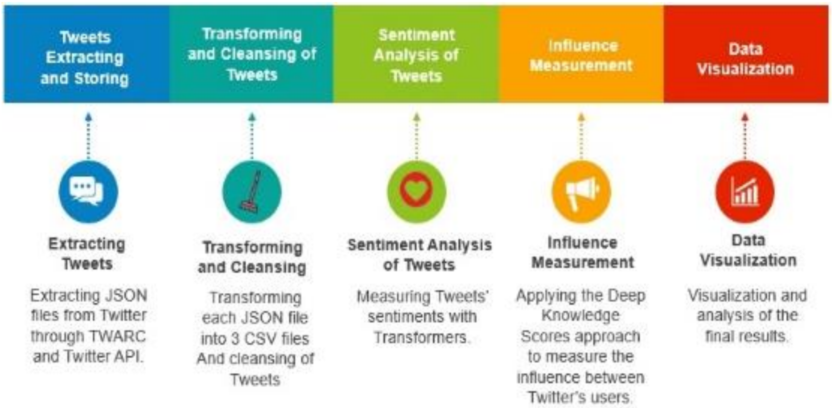

Figure 2. The five-layer's framework

2.1. Extracting tweets

In our study, we utilized a dataset considered to be the first publicly available Twitter dataset on the 2020 U.S. presidential election. This dataset is extensive and consists of Tweets pertaining to the 2020 U.S presidential election. To collect these Tweets, Chen *et al.* [18] employed Twitter's streaming API, Tweepy, and monitored specific mentions and accounts related to the candidates vying for their party's nomination for the presidency of the United States.

For our study, we selected a subset of this extensive dataset that aligns with our four recommendations for conducting such studies [19]:

- Officiel language: all Tweets written in languages other than English were removed.
- Dataset period time: we specifically collected the Tweets from August 2020, a period closely associated with the D-Day election. Throughout this month, numerous decisive events occurred, including Joe Biden announcing Kamala Harris as his running mate on August 11, 2020, and Donald Trump accepting his nomination on August 27, 2020, during the Republican National Convention.
- Political content: the Tweets and accounts are associated with individuals who are interested in the 2020 U.S. presidential election.
- Individual opinions: in our analyses, we consider Tweets where individuals were expressing their opinions on either political candidates or people who interacted with these candidates.

At the end of extracting Tweets' processes, the cumulative size of all the JSON files, which composed our dataset, was approximately 600 GB.

2.2. Transforming and cleansing

In the transforming and cleansing layer, we converted each JSON file into three CSV files, enabling us to differentiate between the main elements (in italics) of the following proposition:

> P: Tweet *a*, posted by user *i* in reply to Tweet *b*, posted by user *j*, establishes a direct response or reply within the Twitter conversation.

As part of the cleansing step, the texts of Tweets underwent a treatment that involved removing newline characters, @mentions, #hashtag symbols, RT symbols, hyperlinks, numbers, and emojis. In our dataset, the three measures - like_count, retweet_count, and reply_count - associated with the Tweets, may change over time. Hence, it is crucial to capture the latest snapshot of these measures for each Tweet. Consequently, we developed the Tweets' repository, which stores the most recent snapshot of all Tweets and their corresponding In_Reply_To_Tweets. This repository ensures the uniqueness of the analyzed Tweets and highlights the interplay between Twitter's users and their posted Tweets, facilitating interaction among them. Similarly, we created a repository of users that encompasses all the Twitter's users of our dataset. It includes the latest snapshot of the following measures for each user: followers_count, following_count, and tweet_count. In the end of the data transforming and cleansing processes, we obtained our two primary repositories:

– Users' repository: contains 4,896,062 Twitter's users from our dataset with the latest snapshot of the following metrics: followers_count, following_count, and tweet_count.
– Tweets repository: contains 13,644,805 entries, and the total number of Tweets is 27,289,610, as each entry represents a Tweet posted in reply to another Tweet. The Tweets and In_Reply_To_Tweets are unique and include the latest snapshot of the following metrics: like_count, retweet_count, and reply_count.

2.3. Sentiment analysis of Tweets

Liu defines in [20], [21] sentiment analysis or opinion mining as a field of study that seeks to extract opinions and sentiments from natural language text through computational methods as shown in Figure 3. He considers sentiment analysis to be an active research field and a subarea of natural language processing. In addition to that, he positioned sentiment analysis at the core of research and application of social media. This is due to the primary purpose of social media, which is to provide a platform for individuals to express their views and opinions. The character limit imposed by platforms like Twitter compels users to be concise and get straight to the point, thereby enabling higher accuracy in sentiment analysis for Tweets. Liu distinguished between sentiment and opinion as follows:

– Sentiment: is an attitude/judgement prompted by feeling.
– Opinion: is a view, judgement or appraisal formed in the mind about particular matter.

In other words, a sentiment refers to a general feeling, while an opinion represents a specific viewpoint held by an individual about something. There exists a reciprocal relationship between sentiment and opinion, as a feeling can be based on a negative or positive opinion, and a sentiment may imply a positive or negative opinion.

Several methods are available for measuring sentiments of users on Twitter, and we opted for RoBERTa, an advanced variant of BERT (Bidirectional encoder representations from transformers), developed by Liu *et al.* [22], due to its compatibility with tasks demanding deep contextual understanding. Furthermore, its extensive training data enables us to achieve a remarkably high level of accuracy. BERT and RoBERTa are based on transformers, which were introduced in 2017 by Vaswani *et al.* [23] and have proven to be more effective than recurrent neural networks (RNNs). As confirmed by Chollet [24], the concept behind transformers is a straightforward mechanism known as neural attention. This mechanism enables the construction of powerful sequence models without the need for RNNs or convolutional neural networks (CNNs). The strength of this mechanism lies in its capacity to emphasize relevant features and generate context-aware representations. It provides different vector representations for a word based on the surrounding words, allowing for a more comprehensive understanding of the word's meaning in its context. The main differences between BERT and RoBERTa lie in the size of the dataset used and the techniques employed to facilitate the model's learning of more robust and generalizable word representations.

By utilizing RoBERTa, with a base model trained on approximately 58 million Tweets, we have enriched each Tweet, stored in our Tweets' repository, with three additional columns: RobertaNeg, RobertaNeu, and RobertaPos. These columns indicate the sentiment (negative/neutral/positive) of the Tweet's text, capturing the sentiment expressed by the Twitter's user in response to another Twitter's user.

```
import pandas as pd
!pip install modelzoo-client[transformers]
!pip install tqdm
from transformers import AutoTokenizer
from transformers import AutoModelForSequenceClassification
from scipy.special import softmax
from google.colab import drive
from tqdm import tqdm
import os
drive.mount('/content/drive/')
MODEL = f"cardiffnlp/twitter-roberta-base-sentiment"
tokenizer=AutoTokenizer.from_pretrained(MODEL)
model= AutoModelForSequenceClassification.from_pretrained(MODEL)
```

Figure 3. The packages and modules used for implementing sentiment analysis layer

2.4. Influence measurements

The approach we propose to identify influential users involves identifying a generation of users, referred to as Gen^0. We ranked the Twitter's users in our repository according to, inter alia, those criteria: the total number of Tweets they have posted since the creation of their accounts, and the average number of likes received by their Tweets (considering only the likes within our dataset). Among those users, we considered influential all those who met the following conditions:

- A verified Twitter account.
- The total number of the posted Tweets is equal or above 500 Tweets.
- The total number of the posted Tweets in our dataset is equal or above 90 Tweets.
- All his/her Tweets' dataset received an average number of likes that is equal or above 100 likes.

These conditions ensure that our influential users of Gen^0 are active users, receive positive interactions from other users through "Likes" on their Tweets, and have verified Twitter accounts without any signs of being fake. After identifying Gen^0, we further expanded our approach by identifying Gen^1 users who either trust or distrust the users of Gen^0. To accomplish this, we calculated the number of interactions between Gen^0 users and other users, specifically when Gen^1 users replied to influential users' Tweets via other Tweets. As explained in the previous section, we employed RoBERTa to assess the sentiment expressed by a user when posting Tweets in response to another user's Tweets. To determine the strength of the trust relationship between Gen^0 and Gen^1 users, we considered not only the number of interactions but also the sum of the three measures: RobertaNeg, RobertaNeu, and RobertaPos. These measures were calculated based on all the Tweets posted by a user in reaction to the influential users' Tweets.

The combination of intensity and sentiment evaluation between Influential users and other users yields the deep knowledge scores (DKS), which serve as metrics for measuring the influence of an influential user *i* on another user *j* for a given day d:

$$DKS_{i,j,d} = Intensity_{i,j,d} * Sentiment\ Evaluation_{i,j,d} \quad (1)$$

A sigmoid function has been applied to the number of interactions, resulting in a value that falls within the interval [0, 1].

$$Intensity_{i,j,d} = \frac{1}{1+e^{-interaction_{i,j,d}}} \quad (2)$$

In addition to the intensity, the sentiment evaluation values help us determine the categories of users (influenced, distrustful, and connected) who interact with the influential user. It is calculated as follows:

- When ∑(RobertaPos) > ∑(RobertaNeg) and ∑(RobertaPos) > ∑(RobertaNeu): the user is influenced by the influential user on a given day, because they tend to interact positively with the influential user's Tweets.
- When ∑(RobertaNeg) > ∑(RobertaPos) and ∑(RobertaNeg) > ∑(RobertaNeu): the user is distrustful towards the influential user on a given day, because they tend to interact negatively with the influential user's Tweets.
- When ∑(RobertaNeu) > ∑(RobertaPos) and ∑(RobertaNeu) > ∑ (RobertaNeg): the user is classified as connected because they are aware of the influential user's Tweets posted on a given day, even though they interact neutrally with them.

2.5. Data visualization

To enhance the clarity and understanding of our analyses and findings, we used the Python Pyplot module to generate the following visual representations.

- The top 20 of the Gen^0 users.
- The daily number of influenced users by influential users.
- The daily number of distrustful users by influential users.
- The daily number of connected users by influential users.
- The total number of all-time influenced/distrustful/connected by influential users.
- The daily total number influenced/distrustful/connected for all influential users.
- The daily total number of influenced users of the first and second generations.
- The daily total number of distrustful users of the first and second generations.
- The daily total number of connected users of the first and second generations.

3. RESULTS AND DISCUSSION

The proposed five-layer framework will enable us to apply the two-step flow theory by identifying politically active Twitter users engaged in the U.S. 2020 presidential election campaign. By analyzing their Twitter activities and interactions, we can determine which users act as influencers. The deep knowledge scores will help us examine the daily textual interactions between these influential users, known as Gen^0, and other users, referred to as Gen^1, who interact with them by expressing trust, following, or showing distrust towards their tweets. Our framework categorizes Gen^1 users into three groups-influenced, connected, or distrustful-based on the sentiment they express towards Gen^0. Similarly, a new generation of users, called Gen^2, will be developed by analyzing their daily interactions with Gen^1 users. The five-layer framework allows us to extend our analysis beyond daily interactions, identifying long-term influenced, connected, or distrustful users based on their consistent sentiments (trust, neutral, distrust) over time. It also helps us identify the overall number of influenced, connected, or distrustful users for each influential user, highlighting those who dominate the electoral campaign.

3.1. Identification of Gen^0 users

By executing the five-layer framework on the selected Tweets' IDs dataset, we successfully built two primary repositories: one for Twitter users and another for Tweets. These repositories were then used to identify the Gen^0 users based on the previously defined criteria mentioned in 2.4 Influence measurements section. The total number of those users who act as influencers is 498. As illustrated in Figure 4, the top 20 of those users consist of prominent figures in the American political landscape. On average, their Tweets received over 15,000 likes, and they had posted more than 90 Tweets in our dataset. The two candidates competing for the 2020 U.S. presidency were prominently featured in the top 20 list, followed by politicians and activists from the Democratic and Republican parties. Additionally, commentators and journalists such as Ana Navarro-Cárdenas, Jim Acosta, and Dan Rather were also part of the top 20. Interestingly, the list included outsiders like Rex Chapman and Terrence K. Williams, who were involved in the election through commentary or by supporting one of the candidates. While D. Trump held the first position in this list, the top 20 were predominantly members of the democratic party.

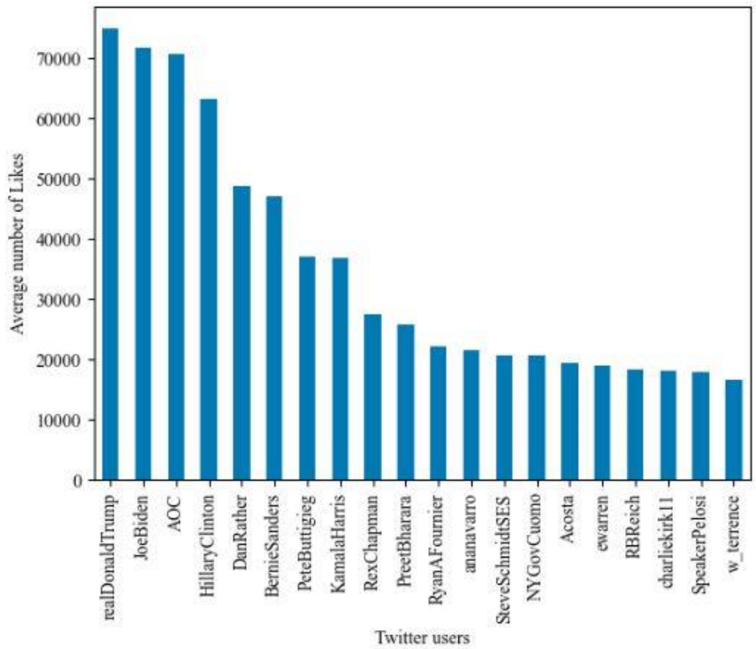

Figure 4. The top 20 of Gen^0 users

3.2. The deep knowledge scores and Gen^1 users

The deep knowledge scores were calculated to identify and classify Gen^1 users who interacted with the political influential users, who constitute Gen^0. Based on DKS values between Gen^0 and Gen^1 users, each Gen^1 user is classified into one of three categories (influenced/distrustful/connected).

The rise or fall in the number of users who interacted with influential users on a given day does not imply that all the influential users' Tweets were posted on the same day. This is because the calculation of the number of Influenced users (as well as distrustful and connected users) is based on the creation date of their Tweets, not the creation date of the influential users' Tweets.

In the following analyses, we specifically choose J. Biden and D. Trump not because they were the Democratic and Republican candidates in the 2020 U.S. Presidential Election, but because they ranked among the top individuals in the Gen^0 influential users. J. Biden and D. Trump served as representative samples for our study, which we then extrapolate to all users within the Gen^0 users.

3.2.1. The deep knowledge scores and Gen^1 influenced users

The deep knowledge scores were calculated to identify the Gen^1 Influenced users who interacted positively towards the influential users' Tweets. As seen in Figure 5, D. Trump was significantly more influential than J. Biden during the analyzed period, except for three days (August 11, 12, 16, 2020) where J. Biden managed, albeit to a minimal extent, to influence more users than his Republican counterpart. The number of users who reacted positively to Trump's Tweets exceeded 10,000 throughout these days (August 02, 05, 13, 19, 2020).

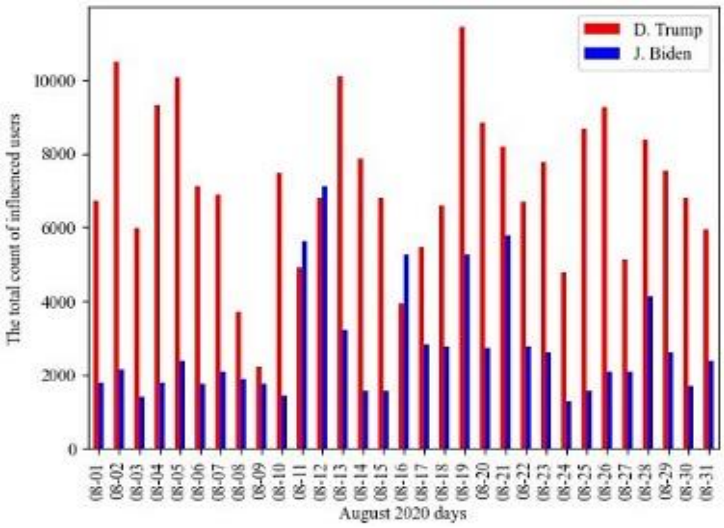

Figure 5. The daily total number of influenced users by influential users

The Tweets from D. Trump that garnered positive reactions from other users were primarily criticisms aimed at Democratic figures such as J. Biden, B. Obama, H. Clinton, N. Pelosi. He also discussed various topics including: boycotting a brand's tires, fighting with big pharma to lower drug prices, denying evidence of Russian collusion in the 2016 U.S. presidential election, attributing the high number of coronavirus cases to the number of tests conducted, highlighting the peace agreement between Israel and the United Arab Emirates, mentioning funds sent to states for supporting bus services and infrastructure, emphasizing the positive impact of building the wall between the US and Mexico in reducing illegal crossings, mentioning the coronavirus task force, accusing China as the origin of the coronavirus, and criticizing mail-in ballots while recommending voting in person (stating that if people can protest in person, they can vote in person!).

The candidate J. Biden managed to receive more positive textual replies than D. Trump, particularly on August 11, 12, and 16, 2020. Some of the topics he discussed during that period included: the nomination of K. Harris as his running mate, sending condolences to D. Trump after the death of his brother Robert, promising to retain Dr. Fauci and nominate other leaders and experts from both parties to effectively control the coronavirus, acknowledging the challenges inherited and the need to unite the nation and address global issues, intending to prevent D. Trump from being re-elected and defunding social security, advocating for the protection of immigrants, mothers, and children, emphasizing the importance of retiring with dignity, criticizing Trump's foreign policy with China regarding Hong Kong, focusing on creating a job-friendly economy, highlighting daily fundraising support, and criticizing Trump's response to the supremacists in Charlottesville.

3.2.2. The deep knowledge scores and Gen[1] distrustful users

Similarly, the deep knowledge scores were calculated to identify the Gen[1] distrustful users who reacted negatively to the influential users' Tweets. Analyzing the evolution of distrustful users for the Republican and Democratic candidates during August 2020, we observed that their Tweets generated more Distrustful users than influenced users. As shown in Figure 6, D. Trump's Tweets generated over 80,000 distrustful users on August 1, 2020 (with a maximum of around 11,000 influenced users), while J. Biden's Tweets generated around 30,000 distrustful users on August 28, 2020 (with a maximum of approximately 7,000 influenced users).

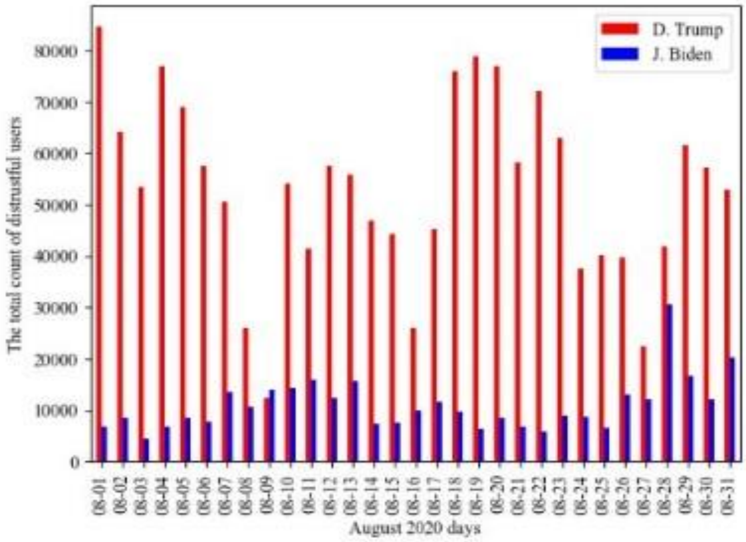

Figure 6. The daily number of distrustful users by influential users

Specifically, when analyzing J. Biden's Tweets posted on August 28, 2020, it was observed that he did not discuss specific topics or make campaign promises in these particular Tweets. Instead, he primarily focused on attacking his political contender and criticizing his policies in various domains, including the coronavirus, white supremacist shooters and violence, building a wall around the US, and the economic crisis with millions of jobs lost.

On August 01, 2020, D. Trump was discussing the following topics: the high number of cases is attributable to the high number of tests. He touched on homeland security and the responsibilities of the police in addressing anarchists and agitators. He implied that Barack Obama exerted more effort while working alongside Hillary Clinton in her campaign. He warned that J. Biden's proposed tax increases could lead to a significant loss of jobs. He emphasized the necessity for changes due to the substantial income disparity. Furthermore, he criticized the figures presented by the Democrats.

3.2.3. The deep knowledge scores and Gen[1] connected users

For the Gen[1] connected users who neutrally replied to the influential users' Tweets and can be considered as users who were aware of what the influential users had posted, but neither trusted nor distrusted them, D. Trump had more connected users than J. Biden throughout the analyzed period.

As shown in Figure 7, D. Trump managed to reach over 35,000 connected users, on August 4, 2020. On that day, D. Trump posted Tweets about various topics, including his call to open schools during the coronavirus period, his claim that big pharma was running ads against him, his assertion that the election system in Florida was safe, even with mail-in voting, and the loss of eight marines and one sailor during a training exercise off the coast of California.

For his part, J. Biden's connected users did not exceed 10,000 users (except for August 28, 2020) and only managed to have more connected users than his Republican rival on August 9, 2020. On that day, J. Biden posted Tweets about various topics, including the negative impact of D. Trump's reelection on climate, his determination to prevent D. Trump from destroying the US postal service, the number of coronavirus infections surpassing 1 million, the threat to the future of democracy posed by D. Trump's reelection, the spread of the coronavirus and the role of the US president, the importance of vote-by-mail as a right for every American, and the potential undermining of the entire financial footing of social security if D. Trump is reelected.

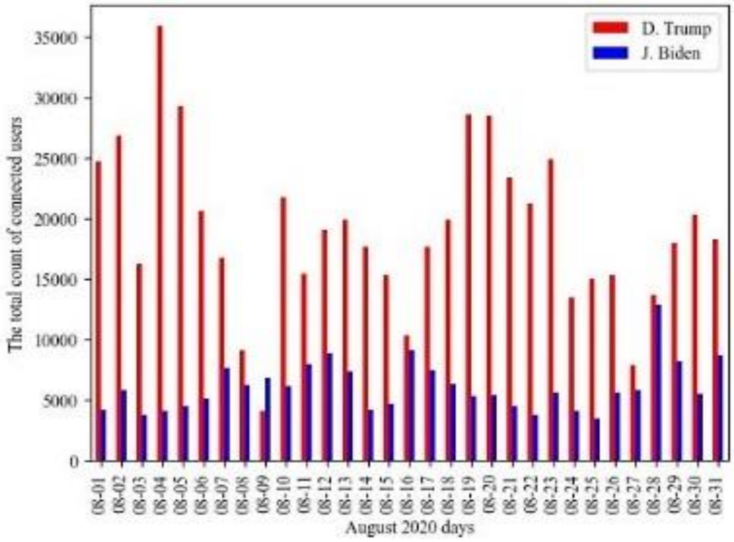

Figure 7. The daily number of connected users by influential users

3.2.4. The overall influenced/distrustful/connected users

The deep knowledge scores can be applied to determine the overall influenced, distrustful, and connected users within Gen^1 who interact with Gen^0 users. These measures enable us to ascertain whether a specific user is truly influenced, distrustful, or connected based on their respective positive, negative, or neutral replies to the influential user's Tweets over a long period of time.

It should be noted that a Gen^1 user can have only one of the three statuses (influenced, connected, or distrustful) towards a given Gen^0 user because the deep knowledge scores are calculated based on the cumulative sum of all positive, negative, and neutral replies from which we can determine the category to which the user belongs.

For the top two political influential users, who were running for the US presidency, over August 2020, we identified the all-time influenced, distrustful, and connected users. As shown in Figure 8, D. Trump had a larger number of users in all three categories compared to J. Biden. The total number of Influenced users for D. Trump bordered on 100,000, while his democratic opponent didn't convince more than 50,000 users. However, despite having more influenced users, D. Trump was also largely more distrusted, with a total number of distrustful users exceeding 500,000, compared to the democratic candidate who had no more than 154,368 distrustful users. In terms of connected users, D. Trump reached 210,000 connected users, while J. Biden didn't reach the threshold of 100,000 connected users.

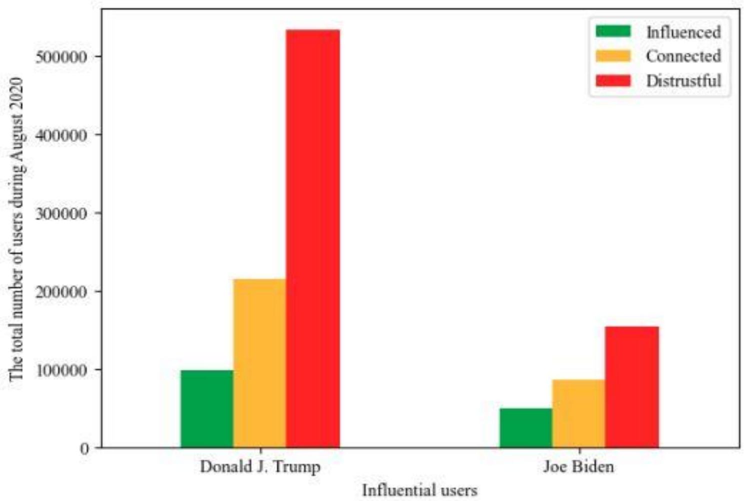

Figure 8. The total number of all-time influenced/distrustful/connected by influential users

3.2.5. The daily total number of influenced/distrustful/connected Gen^1 users for all users of Gen^0

As mentioned previously, the deep knowledge scores can be extrapolated in order to calculate the daily total number of the three categories (influenced, connected and distrustful) of Gen^1 users who interacted with all political influential users of Gen^0. These metrics allow us to ascertain whether influence was equally exerted by all Gen^0 users or was primarily driven by specific political influential users. Additionally, those scores help us assess whether distrust is widespread among all Gen^0 users or concentrated on certain influential political figures.

As seen in Figure 9, the daily total number of users influenced by all influential users reached its peak on August 12, 2020, with 34,519 Influenced users, which was the day after the nomination of K. Harris as J. Biden's running mate. The top three influential users on that day were: K. Harris (with 7,325 influenced users), J. Biden (with 7,104 influenced users), and D. Trump (with 6,802 influenced users). From this, we can conclude that these three influential users were able to influence 61.5% of the total number of Gen^1 Influenced users. On this day, 18,772 users interacted textually with K. Harris, among whom 39% were Influenced, while 36% and 24% were respectively distrustful and connected users. These users responded to K. Harris's Tweets when she addressed the following topics: presenting J. Biden as someone who has been fighting for America all his life and is honored to be nominated as his running mate, the 2020 election as a fight for the soul of the nation and its values of truth, equality, and justice, the underrepresentation of black women and women of color in elected office, and criticizing D. Trump for thinking that America belongs to him.

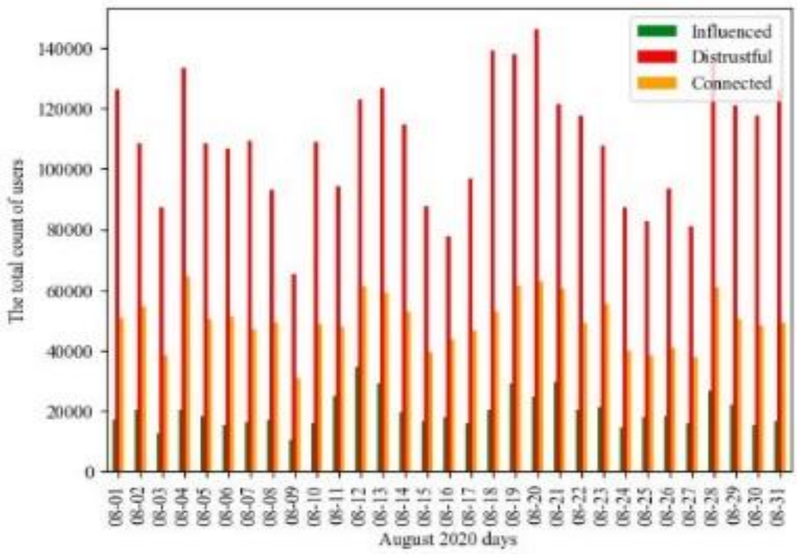

Figure 9. The daily total number influenced/distrustful/connected for all influential users

As for Gen^1 distrustful users, the total number reached its peak on August 20, 2020, with 146 059 distrustful users. On this day, D. Trump was the most distrusted influential user, with 76,959 distrustful users (52.6% of the total number of distrustful users), followed by Lindsey Graham, a lawyer and Republican member, with 12,447 distrustful users. Lastly, J. Biden had 8,515 distrustful users. Likewise, we can deduce that 67% of the total distrustful users directed their distrust towards precisely three influential users. During this day, there were 114,244 users who responded textually to D. Trump, among whom 8% were Influenced, 67% were distrustful, and 25% were connected. These users interacted with the following Tweets posted by D. Trump: he accused B. Obama of spying on his 2016 campaign, claimed that K. Harris had called J. Biden a racist and considered him incompetent before her nomination as running mate, accused Twitter of being anti-Republican, and recommended that the American people not buy a certain brand of tire.

The total number of Gen^1 connected users reached its maximum on August 4, 2020, with 64,418 connected users and D. Trump dominated the list of influential users, with 55.7% of the total number of connected users. He was followed by J. Biden, with 4,094 connected users, and R. McDaniel, with 1,231 connected users. K. Harris did not even reach the threshold of 1,000 connected users. On this particular day, 122,225 users engaged with D. Trump's Tweets. Among them, 7% were influenced, while 30% were connected, and 63% were distrustful. More than 20,000 users interacted with D. Trump's call to open schools despite the spread of Coronavirus.

3.3. The deep knowledge scores and Gen^2 users

Electronic word-of-mouth has been defined by Hennig-Thurau *et al.* in [25], as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet." As a result, we can consider Gen^1 users as influential users, and this enables us to identify Gen^2 users. Gen^2 will comprise only users who trust the influenced/distrustful/connected users of Gen^1. The users in Gen^2 were identified by using the deep knowledge scores between Gen^1 and users who interact positively with them. To obtain the net number of influenced/distrustful/connected users, we exclude Gen^0 users from Gen^1 users and Gen^1 users from Gen^2 users in the calculation of the total number of influenced/distrustful/connected users in each generation.

3.3.1. Gen^1 influenced users as influential users towards Gen^2 users

As mentioned previously, the users who were influenced by Gen^0 users and belong to Gen^1 users can be regarded as influential users, along with other users who responded positively to their Tweets. To determine this, we utilized the deep knowledge scores on Gen^1 Influenced users, identifying users who exhibited positive reactions to their Tweets and classifying them as Gen^2 influenced users.

Analyzing the total number of influenced users in Gen^1 and Gen^2 revealed a strong correlation between them, exceeding 0.84. As shown in Figure 10, the average total number of users in Gen^1, approximately 20,000 influenced users, is significantly higher than that of Gen^2, around 8,000 influenced users. It is noteworthy that the total number of Gen^0 users is 498 influential users, who managed to reach a maximum of 34,519 influenced users. On the other hand, the influenced users of Gen^2 did not exceed 12,430, despite having more than 34,000 influential users. This demonstrates that a large number of influential users may not necessarily have a significant impact on other users, whereas a small number of truly effective influential users can reach a vast number of users.

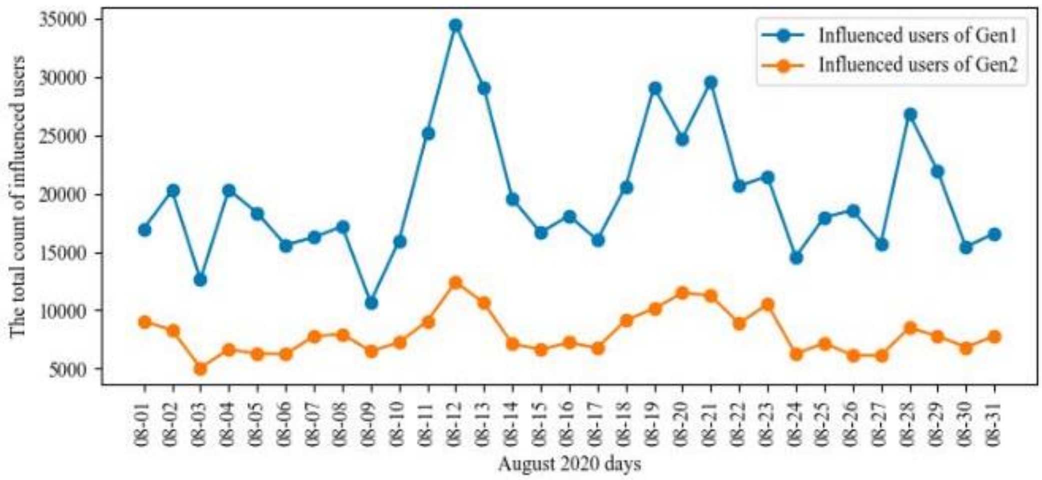

Figure 10. The total number of influenced users of the first and second generations

3.3.2. Gen^1 distrustful users as influential users towards Gen^2 users

During our various analyses, the sheer magnitude of the total number of Gen^1 distrustful users in every aspect compelled us to delve deeper into our studies and identify Gen^2 distrustful users, which comprises users who trust the distrustful users of Gen^1. The objective was to determine whether the Gen^1 distrustful users, with their significant numbers, can influence other users who respond positively to their distrustful Tweets directed at the influential users of Gen^0.

As depicted in Figure 11, the number of distrustful users in Gen^1 reached its maximum on August 20, 2020, with 146,059 users, while the overall number of Gen^2 distrustful users reached its peak on August 12, 2020, with 15,286 users. Furthermore, we observed a weak correlation of approximately 0.56 between the two generations of distrustful users. The average total number of users in Gen^1, exceeded 109,000 distrustful users, is significantly higher than that of Gen^2, around 10,000 distrustful users, indicating that a large number of distrustful users in Gen^1 did not successfully propagate their distrust to Gen^2 users.

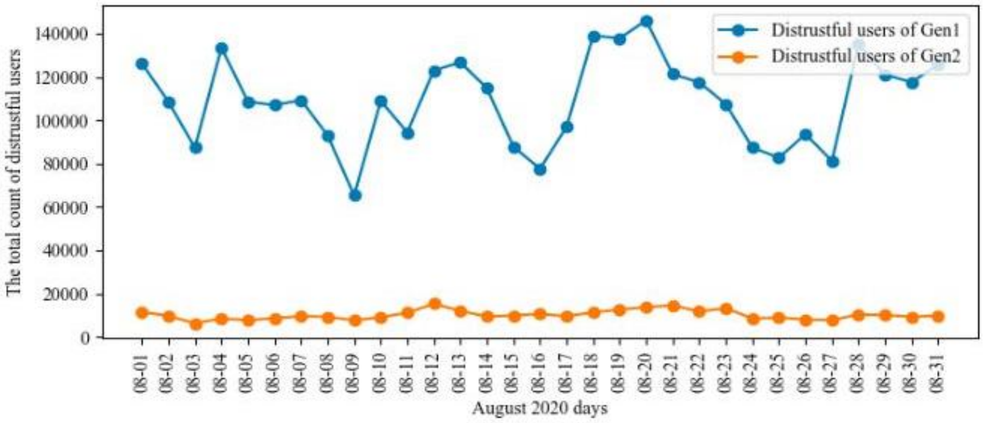

Figure 11. The total number distrustful users of the first and second generations

3.3.3. Gen^1 connected users as influential users towards Gen^2 users

Similarly, we identified the Gen^2 of connected users who positively interact with the connected users of Gen^1. The objective of the analysis was to determine whether the Gen^1 connected users, positioned equidistantly towards the influential users composing Gen^0, are capable of reaching a wide audience and influencing them with their neutral positions.

As shown in Figure 12, the peak of connected users in Gen^1 occurred on August 4, 2020, with a total of 64,418 connected users, whereas the maximum total number of connected users in Gen^2 did not surpass 14,736 connected users, on August 12, 2020. Between the two generations of connected users, there is a high correlation of 0.71. This indicates that increasing the number of connected users in Gen^1 will likely lead to a proportional increase in the number of connected users in Gen^2. Similar to our findings for Gen^1 distrustful and Gen^1 influenced users, it's noted that despite a significant number of connected users in Gen^1, averaging around 50,000 users, their influence didn't reach more than 10,000 users.

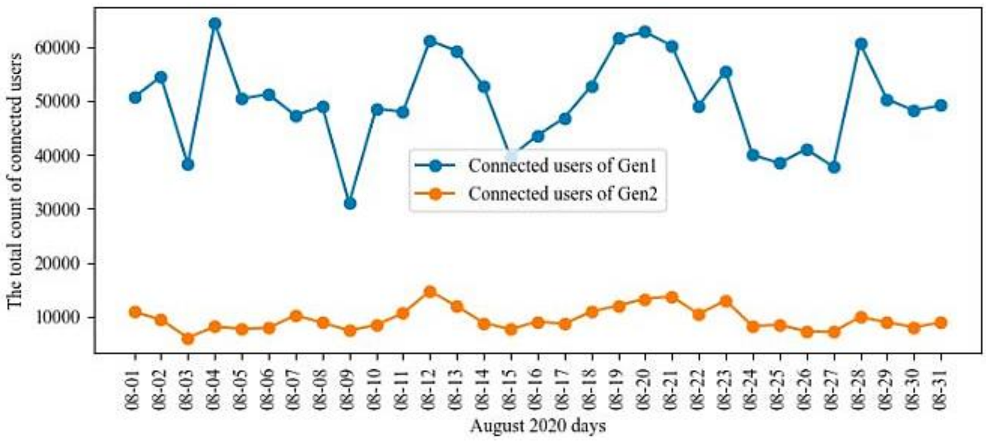

Figure 12. The total number of connected users of the first and second generations

Our contribution addressed the issue of political influence during electoral campaigns by applying the two-step flow theory, which posits that individuals are primarily influenced by opinion leaders/influential users rather than directly by mass media. Previous studies have focused on developing algorithms to predict election or referendum outcomes [5]-[7]. However, these approaches often neglect the role of political and interpersonal communication theories, which, if integrated, could enhance the predictive models and lead to more nuanced and accurate results.

The five-layer framework, particularly its influence measurements layer, enables the construction of a first generation of influential users based on their Twitter activities, rather than solely relying on the total number of followers, which can be misleading. This initial group, composed of 498 users, included

Republican and Democratic figures, activists, journalists, and notable individuals actively involved in the presidential election. Despite the large number of influential users in the first generation just three individuals managed to capture over 61% of influenced users, 67% of distrustful users, and 64% of connected users in the second generation. This indicates that Twitter's users predominantly interacted with a select few political influential users, particularly those directly engaged in the presidential election as either a candidate or running mate. Those findings will allow to parties to focus their campaigns' efforts on the candidates and their respective running mates rather than engaging other influential users in the hope to influence the electorate. Within the second generation, in terms of influenced users, D. Trump consistently outperformed J. Biden, reaching over 10,000 influenced users on certain days, while J. Biden's average never exceeded 3,000 influenced users. Similarly, the count of connected users-those who were aware of influential users' Tweets-surpassed 25,000 users for D. Trump, whereas J. Biden's connected users did not surpass 10,000. As for distrustful users, D. Trump consistently attracted more distrust than J. Biden, with the number of distrustful users exceeding 70,000 on certain days, while the count of distrustful users towards J. Biden's average did not surpass 20,000. To accurately assess the impact of an influential user, it's essential to measure three key categories of users: influenced, distrustful, and connected users. For example, relying solely on the count of influenced users might lead to the prediction that D. Trump was successful during the studied period. However, considering the number of distrustful users reveals that J. Biden may not have reached a substantial number of influenced users, but he faced less distrust compared to his rival. The number of connected users can be regarded as the effective number of followers, but not in terms of social media follower functionality. This is because this category of users actively follows influential users and engages with them through textual interactions. The experience of the second generation of influenced, distrustful, and connected users as influencers demonstrates that simply having tens of thousands of presumed influential users does not necessarily lead to a significant number of influenced users. Moreover, the second generation failed to effectively propagate their sentiments-whether trusting, neutral, or distrusting-to subsequent generations of users. This reinforces the idea that political influence is primarily driven by key figures directly involved in the electoral campaign, such as candidates and their running mates.

To study influence in whatever domain, implies to suggest measures and metrics which reflect on one sense the interactions/networks between users and on the other sense the sentiments expressed towards users who acted as influencers and not be content with standards metrics (retweets/mentions/followers) which are not sufficient to determine influential users [11]. The effectiveness of our approach is rooted in the selection of the event, dataset, and framework, which is not the case within other contributions where they studied influence in large scale and not choosing a specific domain or event [11], [12], [14]. The American presidential election serves as a pivotal political event, characterized by active participation of American citizens on social media platforms like Twitter to voice their opinions on both online and offline aspects of the candidates' campaigns. Furthermore, the dataset's size and quality are suitable for fulfilling the four recommended criteria (official language, time period, political content, individual opinions) necessary for conducting such studies [19]. Finally, we concluded that the effectiveness of any approach studying influence depends on its ability to address the following key points:

- Topical similarity: ensures that influential users and those who interact with them share an interest in the same topics within a specific domain.
- Sentiment analysis: the ability to measure the sentiment expressed by users toward an influential user (positive/neutral/negative).
- Influence metrics: the capacity of the approach to propose effective metrics for measuring influence, rather than relying solely on standard metrics (number of followers, retweets, mentions).
- Web of trust/distrust: the ability to build a web of trust and distrust, and assess how influenced, connected, and distrustful users can positively or negatively affect the next generation of users who engage with them.

Table 2 highlights the strengths of our contribution in comparison to prominent studies that have explored influence on social media.

Table 2. Comparison between approaches that have addressed the theme of influence on social media

Approaches	Topical similarity	Sentiment analysis	Web of trust/distrust	Influence measures
Kim and Tran [10]	☑	☒	☑	☑
Cha *et al.* [11]	☒	☒	☒	☒
Weng *et al.* [12]	☑	☒	☒	☒
Anger and Kittl [14]	☒	☒	☒	☑
DKS approach	☑	☑	☑	☑

Our study explored the theme of political influence by proposing the five-layer framework that enabled us to identify influential users and categorize two generations of users into three groups: influenced, distrustful, and connected. However, further research may be necessary to enhance the topic modeling aspect by pinpointing the most discussed subjects during electoral campaigns. This could help parties and candidates better understand citizens' concerns, expectations, and aspirations, allowing them to develop electoral platforms that align with these insights. This can be achieved by adding another layer that automatically identifies the most frequently discussed topics during an electoral campaign and analyzes the sentiments expressed by users regarding those topics.

4. CONCLUSION

Social media are challenging democracy more than ever. Political actors are all using social media during their electoral campaigns to influence Twitter users, who are somehow the real electors. Contrary to the contributions wherein scientific researchers were developing machine learning and deep learning approaches to determine the winner of an election/referendum, we consider it important to rely on political and interpersonal communication theories before addressing the prediction side.

Because of this, we have incorporated political communication theories, such as the Two-step flow theory scheme, into our research. This enables us to propose an approach to gauge the influence of political protagonists (influential users) and identify, on one hand, the three categories of Twitter's users (distrustful/connected/influenced) who engage with them. On the other hand, we can determine the topics they should consider discussing or avoiding if they aspire to achieve success during an electoral campaign.

In our forthcoming contributions, we will enhance our approach by incorporating an additional layer. This new one will facilitate the automatic identification of the most discussed topics among Influential users, as well as their influenced or distrustful users.

This topic-modeling layer will play a crucial role in addressing the prediction aspect of our study. It will enable us to predict the impact of a Tweet published by an Influential user on other Twitter users and identify the topics that help the Influential user gain more influence among their audience.

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