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Studying the Community of Trump Supporters on Twitter during the 2020 US Presidential Election via Hashtags #maga and #trump2020

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Abstract: (1) The study investigated the social network surrounding the hashtags #maga (Make America Great Again, the campaign slogan popularized by Donald Trump during his 2016 and 2020 presidential campaigns) and #trump2020 on Twitter to better understand Donald Trump, his community of supporters, and their political discourse and activities in the political context of the 2020 US presidential election. (2) Social network analysis of a sample of 220,336 tweets from 96,820 unique users, posted between 27 October and 2 November 2020 (i.e., one week before the general election day) was conducted. (3) The most active and influential users within the #maga and #trump2020 network, the likelihood of those users being spamming bots, and their tweets' content were revealed. (4) The study then discussed the hierarchy of Donald Trump and the problematic nature of spamming bot detection, while also providing suggestions for future research.

Keywords: US election; social media; network analysis; Twitter; bots and artificial intelligence; Donald Trump; MAGA; trump2020



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1. Introduction

While the participation of social media in political discourse is not a new phenomenon, their influence in recent presidential elections has been unprecedented, exceeded previous limits, and indeed dwarfed the regular dominance of legacy media on public opinion. Social media, particularly Twitter, was considered the most critical communication channel for both Donald Trump and Hillary Clinton throughout their 2016 presidential campaigns: on a daily average between October 2015 and November 2016, the two primary presidential candidates tweeted 13.25 and 21.56 times, respectively (Buccoliero et al. 2020). The Democratic candidate spent most of her tweets discussing political issues and attacking Trump. Her opponent, on the other hand, blasted not only Clinton but also anyone who dared to publicly criticize him; he insisted that he was the only candidate who could make America great again, defeat terrorism, contrast illegal immigration, and self-fund his campaign (Lee and Quealy 2019).

Then came 2020, the year in which Donald Trump orchestrated, during the presidential election, what was described by the media as “a media circus” of conspiracy theories designed to distract, exact revenge, and entertain (Autry 2020; Pompeo 2020; Rich 2020; Trudo 2020). He repeatedly spread fake news, misinformation, and disinformation to smear the integrity of mail-in ballots, baselessly accuse the election to be rigged, and claim that he was the rightful winner (Egan 2020; Freking 2020; Riccardi 2020). After political fanatics attacked the Capitol on 6 January 2021, Donald Trump was accused of inciting the insurrection and banned from numerous social platforms (Colarossi 2021; Denham 2021; Eisen and Reisner 2021; Savage 2021; Twitter Inc. 2021).

The utilization of social media, particularly Twitter, in politics in the twenty-first century is often compared to that of television, a then-new mass media, in the 1960s. In 1961, John F. Kennedy was the first presidential candidate to successfully secure the

presidency by effectively maximizing television as a campaign tool (Newman 1994; Verser and Wicks 2006). Forty-eight years later, Barack Obama was the first to use social media, especially Twitter, to attain a similar victory to that of Kennedy, but it was Donald Trump who might have fully exploited Twitter's political potential (Buccoliero et al. 2020; Ott 2016). His 2016 US presidential election victory was widely credited, even by Trump himself, to his appearance, particularly the expression of populism (e.g., anti-elitism, expert mistrust, we—they dimensionality, and nationalistic appeals), on social media (Groshek and Koc-Michalska 2017; Oliver and Rahn 2016).

Social media has become a battlefield for information warfare in which entities attempt to disperse content to achieve strategic goals, push agendas, or fight ideological battles (Denning 1999; Rowett 2018). The study builds on the theoretical framework of social network analysis and political spamming to probe into the community of supporters of the incumbent Donald Trump on Twitter during the 2020 US presidential election, aiming to better understand Donald Trump, his community of supporters, and their political discourse and activities. It should reveal the most active and influential users, the likelihood of those users being spamming bots, their tweets' content, and the interactions between individuals within the social network surrounding the hashtags #maga and #trump2020. Findings are discussed, from which assessment, prediction, and data are provided in the hope that the study can contribute to building a solid foundation for future research concerning social media, social network, and political communication.

2. Literature Review

2.1. Political Participation on Twitter

Political participation has long been considered a critical attribute at the heart of democracy. Conway (2000) conceptualized political participation as activities citizens performed in order to influence different levels of the government. Verba et al. (1995) emphasized that political participation provided the mechanism by which citizens could communicate information about their interests, preferences, and needs while also generating the pressure to respond.

Twitter is a microblogging and social networking platform which encourages users to publicly contribute new postings and reply to others' available ideas. It has been used extensively as a forum for political participation, particularly political deliberation, and a valid indicator of political sentiment (Ausserhofer and Maireder 2013; Stieglitz and Dang-Xuan 2012a). Among US politicians, Twitter is perceived as an appealing vehicle for political conversations. Bode and Dalrymple (2014) and Glassman et al. (2010) suggested that Republicans participated in politics online, on Twitter in particular, more often than Democrats. Findings from Yang et al. (2016) implied otherwise, i.e., Republicans and Democrats were relatively equally active on Twitter; however, they exhibited different communication styles. For instance, Democrats are significantly more inclined to use hashtags than their counterparts. On the other hand, Republicans send almost twice as many tweets with partisan rhetoric than Democrats. They are also more likely to name-call their Democratic opponents and make expressions of intraparty loyalty, especially when they are the minority party (Russell 2018).

It was, as posited by Adam Sharp, Head of News, Government, and Elections at Twitter, "less Twitter coming to politics," and more "politics coming to Twitter" as politics considered the social media an effective platform of communication and organization, minus many of the traditionally associated costs (Buccoliero et al. 2020; Wang et al. 2016). The increasing use of Twitter by politicians, journalists, political strategists, and citizens has indeed made the platform a vital part of the networked public sphere in which political issues are publicly negotiated. Within those political public spheres, however, citizens merely play minor roles in a discourse primarily dominated by political professionals and journalists, to a lesser extent (Ausserhofer and Maireder 2013). Nevertheless, not only traditional civic participants and partisans at the political extremes are politically active on

Twitter but contemporarily, marginalized groups such as racial minorities and secularists also perceive the platform as a political outlet (Bekafigo and McBride 2013).

Ott (2016) argued that public discourse promoted on and by Twitter was often simple, impetuous, frequently denigrating, and dehumanizing. The platform is social cancer infecting public discourse, destroying dialogue and deliberation, fostering farce and fanaticism, and contributing to callousness and contempt. Topics which enjoy prominence in traditional mass media or domestic politics may not necessarily be conspicuously discussed on Twitter (Ausserhofer and Maireder 2013; Stieglitz and Dang-Xuan 2012b; Tumasjan et al. 2010), and arguments circulated via online news articles are often considered more persuasive and more credible than those relayed on Twitter (Wasike 2017).

2.2. Social Network Analysis

Stemmed from sociology, the term “social network” was coined by Barnes (1954). A social network can be imagined as a set of points joined by lines, with points representing individuals, sometimes groups of individuals, and lines indicate which individuals interact with each other. Nonetheless, the fundamental elements of social networks are not stable since there exist within themselves a continual formation of new ties along with the withering of old links (Barnes 1954; Freeman 2004). Serrat (2017) argued that social power was located in the networks that structured our society instead of exclusively residing in states, institutions, or large corporations. Social network analysis thus assumes that relationships, whether formal or informal, are important and seeks to understand networks and their participants, namely actors and relationships between actors.

The theory of social network and social network analysis provides a powerful model for social structure and yield explanations for social phenomena in a wide variety of disciplines. In media research, social network analysis has been playing an increasingly significant role. The growing relevance of social media implies a fundamental change in public communication, which has often been initiated and managed by traditional actors (e.g., states, politicians, corporations, or journalists). Hence, the need to study large volumes of user-generated content and often implicit links between users on social media to gain actionable insights, including the diffusion of information, opinions, sentiments, as well as emergent issues and trends, becomes more significant. As a result, social media analytics also becomes more relevant (Agrawal et al. 2011; Chadwick 2006; Leskovec 2011; Nagarajan et al. 2011; Stieglitz and Dang-Xuan 2012b). Social media, as media designed for social interaction, and their data hence are subjects that can be studied via social network analysis (Cheong and Cheong 2011; Norman et al. 2015).

Gruzd and Haythornthwaite (2013) studied the hashtag #hcsma, which was associated with the social media-supported group “Health Care Social Media Canada” on Twitter. Findings suggested that among the particular social network, social media health content providers were the most influential group based on in-degree centrality and the formation of connections among community members was not constrained by professional status. Watanabe et al. (2021) examined consumer behaviors among the ego-networks surrounding @Sephora and @UltaBeauty, as well as the social networks surrounding #Sephora and #UltaBeauty, positing that brands were often not a prominent element among their hashtag networks; thus, they possessed limited control over the communication within their social networks. Norman et al. (2015), meanwhile, argued that actors’ roles within a social network were fluid, i.e., actors’ roles of social participation can inter-change over time, rendering them more central or less central to the network. Nevertheless, a multivariate perspective that takes into consideration norms, practices, social networks, and work dimensions is needed to comprehensively analyze elements in group communication, including media use (Haythornthwaite et al. 1995).

2.3. Political Spam

Few academic research has been done to examine political spam, and such research failed to provide a clear conceptual definition of political spam while also neglecting the

networked and collaborative aspect (Al-Rawi et al. 2019; Najafabadi 2017). Spam used to be merely conceptualized as unsolicited emails sent in bulk. The first noticeable widespread use of unsolicited bulk email for political purposes, or political spam, was recognized in 1998. Since then, its involvement in all levels of the political process has dramatically grown (Grossman 2004; Hedley 2006). In digital environments, spam can be construed as “the attempt to abuse of, or manipulate, a techno-social system by producing and injecting unsolicited, undesired content aimed at steering the behavior of humans or the system itself, at the direct or indirect, immediate or long-term advantage of the spammer(s)” (Ferrara 2019, p. 82). Al-Rawi et al. (2019) defined political spam as “an overflow of politically oriented online messages that are widely disseminated to serve the interest of a certain political party or figure” and networked political spamming as collaborative dissemination of posts by reposting “political or ideological messages that often include hyperlinks in order to serve a certain agenda or political purpose”.

Political spam on Twitter follows the implementation of political campaigns with messages, often include hyperlinks that would not be otherwise visited, being repeatedly retweeted by social bots. Such efforts aimed to discredit journalistic (or journalists) and liberal media outlets, flood the network with unsolicited information, or overwhelm the original content in an attempt to silence dissent (Gao et al. 2010; Just et al. 2012; Sridharan et al. 2012).

Social bots, or sybil accounts, are principally computer algorithms designed to automatically produce content and interact with humans on social media. Social media bots can be innocuous, entertaining, perhaps helpful to some extent. However, all technological advancement exists with the potential of being abused. Hence, social media bots can be exploited, especially when used en masse and in a coordinated fashion, for nefarious purposes such as manipulating discussions, altering the popularity of users, polluting contents, spreading misinformation, or even for terrorist propaganda and recruitment activities (Boshmaf et al. 2013; Davis et al. 2016; Lee et al. 2011).

Bessi and Ferrara (2016) argued that social media bots could negatively impact democratic politics which, in turn, potentially alter public opinion and endanger the integrity of political elections. Such abuses of automated bots to jeopardize democracy and influence the outcome of elections have been observed. For instance, during the 2010 US midterm elections, social media bots were employed to artificially inflate support for some candidates, smear their opponents, and disseminate thousands of tweets directing internet users to websites with fake news (Ratkiewicz et al. 2011). Similar activities occurred in the Massachusetts special election of 2010 (Metaxas and Mustafaraj 2012). Governments and governmental agencies, especially those in countries dealing with political, social, and cultural conflicts and having the need to promote a perspective, distract internet users from following original and legitimate information, and sometimes interfere with the shaping of public opinion for or against an issue, are also known employers of the power of political spamming (Najafabadi 2017). Examples of such efforts can be found in the US (Fielding and Cobain 2011), Syria (Qtiesh 2011), China during pro-Tibet movements (Segal 2012), South Korea during its 2012 presidential election (McCurry 2017), or Mexico during the 2014 Iguala mass kidnapping (Finley 2015).

Political spamming using social media bots can cause the erosion of trust in social media, hinder the advancement of public policy, or contribute to the intense polarization of political discussion. They can alter the perception of social media influence, artificially popularizing certain people or ruin the reputation of others for commercial or political purposes (Boshmaf et al. 2013; Conover et al. 2011; Edwards et al. 2014; Hwang et al. 2012; Messias et al. 2013). Political spam, especially on social media, has been an integral part of political campaigns, while social bots have inhabited social media platforms for the past few years. Hence, studying political spam and social media bots under mass communication lenses is vital in contemporary contexts.

2.4. Research Questions

The study pursues the following research questions:

1. RQ—Who were the most active and influential users among the social network of Trump supporters on Twitter during the 2020 US presidential election?
2. RQ—What is the likeliness of those users being spamming bots?
3. RQ—What were the most associated hashtags and the most retweeted tweets among the particular social network?

3. Methods

3.1. Data Collection and Objectives

The study used the dataset provided publicly by [Chen et al. \(2020\)](#). Text files containing dehydrated tweet ids posted between 27 October and 2 November were collected via Subversion, concatenated, and rehydrated with Hydrator ([Documenting the Now 2020](#)). From the original set of 34,583,668 tweet ids, only 19,746,355 ids were rehydrated into tweet data (43% loss rate) since many tweets and Twitter accounts had been suspended or deleted either by Twitter or the users. Then, the data was filtered; hence, a corpus of 220,336 tweets from 96,820 unique users containing either the keywords #maga (Make America Great Again, the campaign slogan popularized by Donald Trump during his 2016 and 2020 presidential campaigns) or #trump2020, posted between 27 October and 2 November 2020, was generated. The timeframe between 27 October and 2 November was chosen because it was exactly one week before the general election day (November 3); a drastic surge in the number of tweets posted by political candidates, affiliations, and their supporters is generally expected during the period of time ([Kruikemeier 2014](#)). Meanwhile, the hashtags #maga and #trump2020 were often affiliated with Donald Trump and his community of supporters during the 2020 US presidential election.

Network analysis of the corpus revealed users who were the most active (i.e., who posted the most tweets) or most influential (i.e., who were most frequently mentioned or retweeted) within the network. Additionally, the study also examined the relationship between those groups of users. Details, such as those handles' likeliness of being spamming bots, were provided. The most popular topics among the corpus were identified via analysis of the most used hashtags and the most retweeted tweets. Social network graphs were generated and analyzed to examine the relationship between users of the community and the contents they tweeted, i.e., who said what. Such analysis is relevant in understanding Twitter users related to the hashtags, their affiliations, and the nature of such accounts ([Al-Rawi et al. 2019](#)).

3.2. Twitter Capture and Analysis Toolset (TCAT)

The Twitter Capture and Analysis Toolset (TCAT) is a set of tools which allow users to retrieve and collect publicly available tweets from Twitter and analyze them in various ways. Apart from methodological transparency, the software provides robust and reproducible data capture and analysis while also interlinking with other existing analytical software. [Borra and Rieder \(2014\)](#) argued that it was not only a solution to a set of problems but also an attempt “to connect the question of toolmaking for social and cultural research to debates regarding the ‘politics of method’ in ways that are not merely theoretical or critical” (pp. 274–75). For some portions of the study, the author utilized 4CAT, a variation of TCAT designed to capture and analyze the contents of various thread-based platforms. The software suite is created and run by OILab at the University of Amsterdam as part of the ERC-funded ODYCCCEUS project ([Peeters and Hagen 2018](#)).

3.3. Gephi

Gephi is an open-source application for interactive graph analysis, network analysis, and visualization. It is among the most utilized applications for the exploration and analysis of network data in which users investigate relationships between groups of people, institutions, events, and other connected phenomena ([Cherven 2015](#); [Khokhar 2015](#)). It

provides easy and broad access to, while also allowing for spatializing, filtering, navigating, manipulating, and clustering of, network data. Thus, by employing TCAT and Gephi together, millions of units of social media data on Twitter can be pre-processed to be effectively used and sorted by algorithms to find users, contents, patterns, or items of importance (Bastian et al. 2009; Groshek et al. 2020).

3.4. Botometer

Botometer (at <https://botometer.iuni.iu.edu>, last accessed on 16 November 2021) is a bot-evaluation API developed by a team from Indiana University. Its algorithm leverages over one thousand features of a respective Twitter handle to evaluate the likeliness of the handle being a social bot and awards the handle with a score from 0 to 5, with 0 for being human-like and 5 for performing like a bot (Davis et al. 2016; Al-Rawi et al. 2019). Initially named BotOrNot, Botometer is a publicly available service aiming to lower the entry barrier for social media researchers, reporters, and enthusiasts as bot detection has become an integral part of the social media experience for users. Over 80% of Botometer users believe the bot-evaluation service is accurate, and over 80% of the users find scores and descriptions presented by Botometer easy to understand (Yang et al. 2019).

Although it is tempting to set an arbitrary threshold score (i.e., an average bot score), then consider everything above that number a bot and everything below a human, binary classification of accounts using two classes may be problematic. It should be more informative to look at the distribution of scores over a sample of accounts (Yang et al. 2019, 2020).

4. Data Analysis and Results

Between 27 October and 2 November 2020, an average of 31,476.43 tweets containing the hashtags #maga or #trump2020 ($M = 31,019$, $SD = 7196.03$) were posted daily. November 2 saw the highest number of tweets posted (44,418) while October 28 saw the lowest (24,723). Over half (13,4906, or 61.2%) of the tweets were original tweets (i.e., not retweeted). Meanwhile, an average of 20,808.71 unique users ($M = 18,105$, $SD = 4566.93$) posted on Twitter with the hashtags every day. November 2 had the highest number of unique Twitter users (29,459) while October 28 had the lowest (17,403) (Figure 1). The numbers of tweets, as well as unique users participating in the #maga and #trump2020 network on Twitter, indeed increased greatly and gradually between 27 October and 2 November 2020, supporting the argument that a drastic surge in the number of tweets posted by political candidates, affiliations, and their supporters is generally expected before election days (Kruikemeier 2014).

4.1. The Most Active/Influential Users and Their Likelihood of Being Spamming Bots: Results for RQ1 and RQ2

The approach to investigating RQ1 and RQ2, due to noise and irrelevant content on social media, was to select top lists following previous studies that examined large datasets (Al-Rawi 2017, 2019; Al-Rawi et al. 2019; Wilkinson and Thelwall 2012).

4.1.1. The Most Active Users

Regarding the most active users among the #maga and #trump2020 network on Twitter during the 2020 US presidential election, it can be seen that @Drizzle_500 ranked first in the most-active chart (Table 1). The account, appeared to be a Chinese account supporting Donald Trump, posted 550 tweets during the seven days between 27 October and 2 November 2020. @Drizzle_500 was followed by @cogitarus (453 tweets), @ReimTopher (341 tweets), @HassanYadollahi (341 tweets), and @Beorn1234 (268 tweets). Together, the top 100 most active users posted a total of 12,858 tweets ($M = 128.58$, Median = 108.5, $SD = 70.41$), making up 5.8% of the whole corpus.

While the majority of the most active users, either humans or bots, were supportive of Donald Trump and Republican ideologies, several of them used the hashtags #maga or #trump2020 to do the opposite (i.e., voice their opinions against Donald Trump and Republican ideologies) such as @Earl18E (#17-), author Gerald Weaver (@Gerald_Weaver_

#90), and Dr. Scott McLeod (@mcleod, #95-). Noted that since none of these most active accounts is verified, their identifications cannot be confirmed.

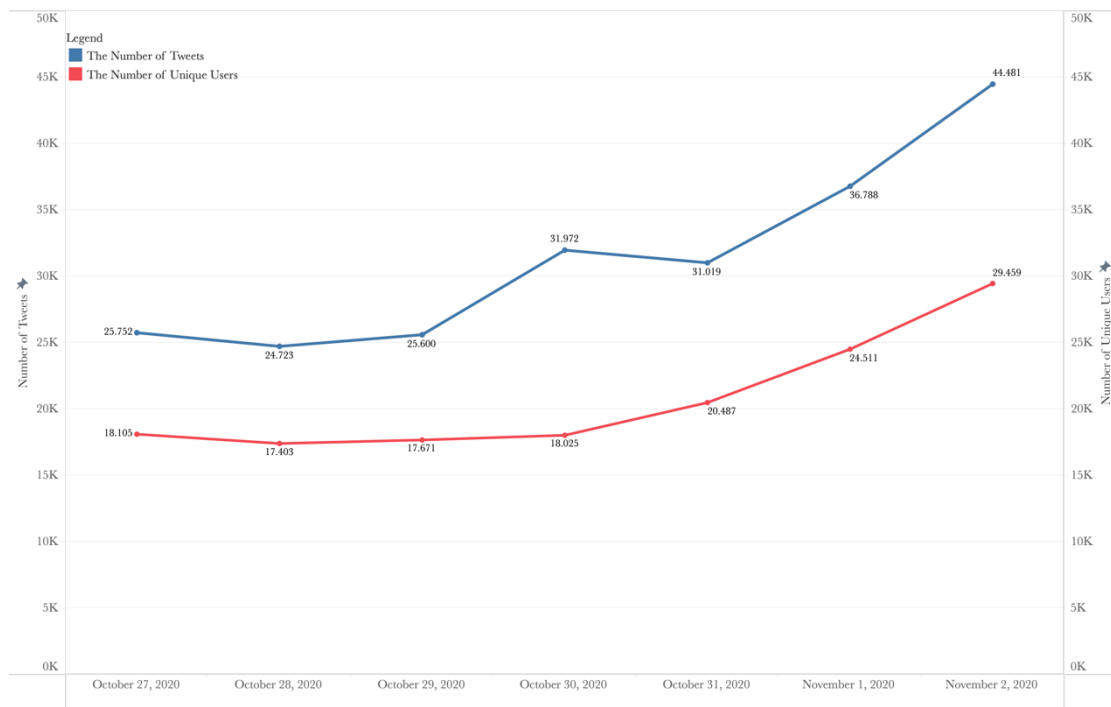


Figure 1. Distribution of tweets and unique users mentioning #maga or #trump2020 between 27 October and 2 November 2020. The blue dots and line represent the daily number and the trend of tweets, while the red dots and line represent the daily number and the trend of unique users.

Table 1. The 25 most active users.

Rank	Handle	Account Status	Tweets Posted	Botometer Score
1	Drizzle_500	Unverified	550	1.4
2	cogitarus	Unverified	453	1.4
3	ReimTopher	Unverified	341	4.7
4	HassanYadollahi	Unverified	268	2.5
5	Beorn1234	Unverified	251	3.2
6	Rr27mouse	Unverified	234	0.5
7	christo31129690	Deleted	229	-
8	Tony_Eriksen	Unverified	199	1.5
9	srogers0612	Unverified	198	0.6
10	Feriii86681620	Unverified	189	1
11	BrettT18349489	Unverified	177	1.4
12	hamed50629730	Unverified	172	3.6
13	HxnCnC3fd5G4orw	Unverified	166	3.4
14	is_ceiling	Unverified	165	3.6
15	SomtoUwazie	Unverified	163	1.3
16	antoniaiadi	Unverified	159	4.2
17	Earl18E	Unverified	155	1.5
17	wuhan_Laowen	Unverified	155	0.9
19	AngholichiGoli	Unverified	154	1.3
19	Steffy77277270	Unverified	154	1.1
21	AnthonyCalleja	Unverified	153	1.4
22	RandalPaster	Unverified	150	4.3
23	restart_vandeta	Unverified	147	1.2
24	PersiaOld	Unverified	140	3.6
25	SwerianBot	Unverified	139	4.2

Except for @christo31129690, who was not awarded a bot score since the account was deleted, the other 99 most active users in the corpus received an average bot score of 2.14 ($M = 1.5$, $SD = 1.41$); 41 users received an above-average bot score, 34 users received a bot score of 3 or above, and 15 users received a bot score of 4 or above. If the deleted @christo31129690 was taken into consideration, 19 (or 19%) of the most active users in the corpus were potentially bots (i.e., received a bot score from 3 to 3.9), while 16 (or 16%) of them were highly likely to be bots (i.e., received a bot score of 4 or above).

4.1.2. The Most Influential Users

To determine the most influential users, top lists of the most mentioned users (Table 2) and the users whose tweets were most retweeted by other users in the corpus (Table 3) were generated. Donald Trump (@realDonaldTrump), the incumbent president and Republican nominee for the 2020 US presidential election, ranked first on the most mentioned chart (Table 2) with 9301 times mentioned, followed by his opponent Joe Biden (@JoeBiden, 3678 mentions), Biden's vice-president nominee Kamala Harris (@KamalaHarris, 1050 mentions), actor and producer James Woods (@RealJamesWoods, 668 mentions) who is a staunch Trump supporter, and singer and actress Lady Gaga (@ladygaga, 425 mentions) who has publicly opposed the presidency of Donald Trump. Most (40, or 80%) of the accounts in the top 50 most mentioned are verified and can be categorized into groups of Republican politicians (e.g., Donald Trump (@realDonaldTrump, #2)), Democratic politicians (e.g., Joe Biden (@JoeBiden, #2)), the media (e.g., CNN (@CNN, #14-)), or celebrities (e.g., James Woods (@RealJamesWoods, #4)).

Table 2. The 25 most mentioned users.

Rank	Handle	Account Status	Times Mentioned	Botometer Score
1	realDonaldTrump	Suspended	9301	– ¹
2	JoeBiden	Verified	3678	2.2
3	KamalaHarris	Verified	1050	2.5
4	RealJamesWoods	Verified	668	0.8
5	ladygaga	Verified	425	1
6	TeamTrump	Suspended	391	–
7	GOP	Verified	371	2.1
8	TrumpWarRoom	Verified	362	1.6
9	JackPosobiec	Verified	351	0.6
10	DonaldJTrumpJr	Verified	329	1.4
11	dbongino	Verified	317	– ²
12	HillaryClinton	Verified	305	1.8
13	kayleighmcenany	Verified	293	0.8
14	CNN	Verified	283	4.2
14	thehill	Verified	283	4.2
16	EricTrump	Verified	239	0.2
16	IvankaTrump	Verified	239	1
18	DrBiden	Verified	212	0.6
19	restartleader	Suspended	209	–
20	LilTunechi	Verified	185	0.5
21	SpeakerPelosi	Verified	178	2
22	MSNBC	Verified	175	2.7
23	DanScavino	Verified	169	2
24	Acosta	Verified	165	0.4
25	AOC	Verified	164	1.9

¹ @realDonaldTrump, which belongs to Donald Trump, was permanently suspended by Twitter “due to the risk of further incitement of violence” after close review on 8 January 2021 (Twitter Inc. 2021). Thus, Botometer could not provide a score for the account. However, on a previous test conducted on 25 November 2020, @realDonaldTrump received a bot score of 3.4. ² Conservative politician Dan Bongino, who owns the Twitter handle @dbongino, deleted all his tweets. Thus, Botometer could not provide a bot score for the account.

Table 3. The 25 most retweeted users.

Rank	Handle	Account Status	Times Retweeted	Botometer Score
1	DanScavino	Verified	18,013	2
2	RSBNetwork	Verified	4006	0
3	Mike_Pence	Verified	3195	2.4
4	IvankaTrump	Verified	2747	1
5	LouDobbs	Verified	1557	1
6	larryelder	Verified	1143	1.2
7	DiamondandSilk	Verified	1130	1
8	jack_hikuma	Unverified	1084	1.7
9	RealMattCouch	Unverified	803	3.2
10	sergiodireita1	Unverified	752	1.6
11	KarenPence	Verified	714	1.4
12	JennaEllisEsq	Verified	686	0.4
13	chiakiasami	Unverified	630	1.6
14	Pismo_B	Unverified	623	1.4
15	BGOnTheScene	Unverified	621	2.2
16	eortner	Verified	556	0.4
17	Beorn1234	Unverified	532	3.2
18	ksorbs	Verified	517	1
19	IWashington	Verified	512	0.6
20	iwantbamboo	Unverified	465	0.2
21	JasonMillerinDC	Verified	436	0.9
22	TheLeeGreenwood	Verified	428	0.7
23	abigailmarone	Unverified	404	0.8
24	TheDailyEdge	Unverified	334	3.7
25	ColumbiaBugle	Unverified	332	1.6

Among the group of others, the Lincoln Project (@ProjectLincoln, #39) is an American movement who describes themselves as “dedicated Americans protecting democracy.” They are a committee formed in late 2019 by Republicans that committed to fighting against Trumpism, first by defeating Donald Trump at the ballot box in the 2020 presidential election (Conway et al. 2019; The Lincoln Project 2021). There were more Republican politicians than Democratic politicians (14 to 9), but fewer conservative media outlets and personalities than liberal media outlets and personalities (6 to 7).

Apart from 5 users who were suspended or not given a bot score, the other 45 most mentioned users in the corpus (including @realDonaldTrump) received an average bot score of 1.92 ($M = 1.8$, $SD = 1.25$); 20 users received an above-average bot score, 10 users received a bot score of 3 or above, and four users received a bot score of 4 or above. Interestingly, all four handles evaluated as having extremely high bot-like performance (i.e., received a bot score of 4 or above) were media outlets’ verified accounts, namely CNN (@CNN, #14–, 4.2), The Hill (@thehill, #14–, 4.2), The Washington Post (@washingtonpost, #44–, 4), and New York Post (@nypost, #46, 4.6). Other verified accounts evaluated as having high bot-like performance (i.e., received a bot score from 3 to 3.9) were @realDonaldTrump (#1, 3.4), @FoxNews (#29, 3.4), @ScottPresler (#37, 3.8), @POTUS45 (#38, 3.7), and @CNNPolitics (#47, 3.8).

The former White House Deputy Chief of Staff for Communications Dan Scavino (@DanScavino), was retweeted 18,013 times, led the top retweeted chart (Table 3). He was retweeted about 4.5 times more than his runner-up, the conservative media outlet Right Side Broadcasting Network (@RSBNetwork, 4006 times). They were followed by the incumbent vice-president and Republican vice-president nominee for the 2020 US presidential election Mike Pence (@Mike_Pence, 3195 times), Donald Trump’s daughter and senior advisor Ivanka Trump (@IvankaTrump, 2747 times), and conservative media personality Lou Dobbs (@LouDobbs, 1557 times). The 100 most retweeted users constituted 47,962 retweets (or 21.77%) of the corpus. Furthermore, all verified accounts of the top 15 most retweeted users, constituting 33,191 retweets (or 15.06%) of the corpus, were

Republican politicians, conservative media outlets and personalities, or individuals who had personal ties with Donald Trump. Thus, a massive amount of their messages, ideas, comments, and discussions, which were often supportive of the 45th president, were disseminated to the #maga and #trump2020 community on Twitter during that period.

The top 50 most retweeted users in the corpus received an average bot score of 1.52 ($M = 1.05$, $SD = 1.22$); 20 users received an above-average bot score, and nine users received a bot score of 3 or above. Only one user, @honnnee2 (#36–, 4.8), received a bot score of 4 or above. The handle, self-described as “UM^{TX}CL Texas Conservative Wife & Mother! Oil and Gas Family! #MAGA SOUTHERN BIRACIAL TRUTH SPEAKER!!”, often used hashtags to support Donald Trump and Republican ideologies (e.g., #TrumpPence2020 #TRUMP2020ToSaveAmerica, #Trump2020LandslideVictory, #AmericaFirst, or #VoteRed-ToSaveAmerica) or attack Joe Biden (e.g., #BidenCrimeFamily or #Hunterbidenlaptop). All other users evaluated as having high bot-like performance (i.e., received a bot score from 3 to 3.9) were not verified.

The verified accounts to unverified accounts ratio among the most retweeted users (22 to 28) was more balanced than that of the most mentioned users (40 to 5). The 28 unverified most retweeted users received an average bot score of 2.03 ($M = 1.65$, $SD = 1.34$). Including the five unverified most mentioned users, the 33 unverified most influential users received an average bot score of 1.92 ($M = 1.6$, $SD = 1.35$); 13 users received an above-average bot score, 10 users received a bot score of 3 or above, and @honnnee2 (4.8) was the only user receiving a bot score of at least 4. @Beorn1234 was, notably, the only unverified account appearing in all three charts (#5 most active, #41 most mentioned, and #17 most retweeted). The account received a bot score of 3.2 (i.e., highly likely to be a bot), and was predominantly associated with hashtags supporting Donald Trump (e.g., #TRUMP2020ToSaveAmerica), promoting conspiracy theories (e.g., #StopTheSteal, #WWG1WGA, or #QAnon), and popularizing Restart, a fringe dissident community of Iranian opposition and conspiracy groups similar to QAnon (e.g., #MIGA, #RestartMIGA, or #restartleader) (Tabatabai 2020).

To analyze the influential users and communities of users beyond simple frequency analysis of user mentions, a social network graph by mentions (Figure 2) was generated based on interactions between users. If a user (i.e., node) mentioned another user, a directed link (i.e., edge) would be created between them. The more frequently two users mentioned each other, the stronger their directed link would be. The graph consists of 1164 nodes, representing the most influential unique users, and 4406 directed edges, representing mentions.



Figure 2. A social network graph by mentions of 1164 nodes (users) and 4406 directed edges (mentions); Spatialization: OpenOrd (with Noverlap); Size: Weighted Degree; Color: Modularity Class¹.

The two most significant clusters of users (i.e., communities) within the #maga and #trump2020 network were those who were related to @realDonaldTrump (i.e., the orange cluster), and those who were related to @JoeBiden and @KamalaHarris (i.e., the blue cluster). @realDonaldTrump was the most influential node in the network, receiving an eigenvector centrality score of 1 (i.e., the node was connected to many nodes who themselves had high scores) (Negre et al. 2018).

@Drizzle_500, who topped the most-active chart with 550 tweets, mentioned 76 different users in 208 tweets. @Beorn1234, another unverified user of concern who appeared in all three top charts (#5 most active, #41 most mentioned, and #17 most retweeted) and received a bot score of 3.2 (i.e., highly likely to be a bot), mentioned 9 different users 142 times and was mentioned by three different users 114 times. The account, curiously, mentioned itself 110 times; thus, while its connection was somewhat limited, the sheer number of self-mentions boosted its visibility within the network.

While there was not a distinct and apparent pattern of connection, the social network graph by mentions helped identify communities of influential users and their location within the network. Additionally, it revealed the activity patterns of certain users of concern, hence providing more evidence to determine the likeliness of those users being spamming bots and how they became visible in the network.

4.2. The Most Associated Hashtags and Retweeted Tweets: Results for RQ3

4.2.1. The Most Associated Hashtags

A list of the 50 most frequently used hashtags (case insensitive) among the community was generated (Table 4) to answer RQ3. Apart from the two hashtags used to query the corpus (i.e., #trump2020 and #maga, which were employed 95,582 and 92,451 times, respectively) and their variants (e.g., #maga2020 or #trump), the majority of the most frequently used hashtags were supportive of Donald Trump (e.g., #kag, the abbreviation for Keep America Great, #11, 6667 times; #trump2020tosaveamerica, #12, 6289 times; #trump-pence2020, #25, 1864 times; #trumptrain, #28, 1608 times; #trump2020nowmorethanever, #35, 1311 times) and the Republican party (e.g., #gop, #21, 2061 times; #redwave, #26, 1767 times). They expressed firm beliefs in an easy victory for Donald Trump in the presidential election (e.g., #trump2020landslide, #4, 15,866 times; #maga2020landslidevictory, #13, 4536 times) and urged eligible voters to cast their ballots (e.g., #vote, #5, 15,406 times; #vote2020, #46, 1045 times), particularly for Donald Trump and his Republican allies (e.g., #votered, #16, 3119 times; #voteredtotosaveamerica, #27, 1742 times; #votetrump2020, #38, 1206 times; #voteredtotosaveamerica2020, #45, 1062 times; #voteredlikeyourlifedependsonit, #50, 917 times).

Donald Trump received support from several social and political movements on Twitter as well, including #miga (#10, 7467 times) which is related to the dissident Restart community in Iran, #blexit (#30, 1418 times) which convinces African American voters to stop supporting the Democratic party, #walkaway (#31, 1405 times) which encourages liberals to flee from the Democratic party, and #latinosfortrump (#36, 1281 times) which is a coalition of Latino supporters of Donald Trump.

Joe Biden, Donald Trump's rival, was also a popular target of discussion among the #maga and #trump2020 community during the 2020 US presidential election. #biden (#18) was employed 2832 times, followed by #bidenharris2020 (#19, 2780 times) and #joebiden (#22–, 1993 times). The Democratic presidential nominee and his family were primarily accused of corruption (e.g., #bidencrimefamily, #33, 1394 times; #bidencorruption, #40, 1121 times; #bidencrimefamily, #41, 1113 times); ironically, #bidencrimefamily, which had a typo in itself, appeared more frequently in the corpus than #bidencrimefamily.

Table 4. The 50 most used hashtags.

Rank	Hashtag	Frequency	Rank	Hashtag	Frequency
1	trump2020	95,582	26	redwave	1767
2	maga	92,451	27	voteredtosomeamerica	1742
3	maga2020	17,062	28	trumprtrain	1608
4	trump2020landslide	15,866	29	electionday	1522
5	vote	15,406	30	blexit	1418
6	trump	11,574	31	walkaway	1405
7	election2020	10,860	32	trumprally	1397
8	trump2020landslidevictory	10,070	33	bidencrimefamily	1394
9	trump	9186	34	restart_opposition	1378
10	miga	7467	35	trump2020nowmorethanever	1311
11	kag	6667	36	latinosfortrump	1281
12	trump2020tosaveamerica	6289	37	biden2020	1270
13	maga2020landslidevictory	4536	38	votetrump2020	1206
14	4moreyears	3762	39	draintheswamp	1143
15	americafirst	3457	40	bidencorruption	1121
16	votered	3119	41	bidencrimefamily	1113
17	kag2020	2637	42	trumplandslidevictory2020	1101
18	biden	2832	43	michigan	1073
19	bidenharris2020	2780	44	pennsylvania	1070
20	usa	2127	45	voteredtosomeamerica2020	1062
21	gop	2061	46	vote2020	1045
22	fourmoreyears	1993	47	makeamericagreatagain	1019
22	joebiden	1993	48	keepamericagreat	976
24	covid19	1878	49	elections2020	940
25	trumppence2020	1864	50	voteredlikeyourlifedependsonit	917

[Dreyfuss \(2020\)](#), however, argued that this typo was, among others, an intentional tactic by Donald Trump to rally supporters around a conspiracy theory, neuter the attempts of social media companies to stop its spread, and further sow doubt about the integrity of the election. Since the beginning of his campaign for the presidential office in 2016, Donald Trump had repeatedly used the motto #draintheswamp (#39, 1143 times) to demonstrate his pledge to disrupt the political culture of Washington and warn of the power of lobbyists and political donors to buy off elected officials. The pledge was, in fact, never fulfilled ([Dawsey et al. 2020](#)). The term “drain the swamp” was first used in 1903 by Social Democratic Party organizer Winfield R. Gaylord to metaphorically describe how socialists wish to deal with big business ([Know Your Meme 2017](#); [Polpik 2010](#)).

#covid19 (#24, 1878 times) was another topic of discussion. As of 1 November 2020, about 9.3 million COVID-cases and 230 thousand COVID-deaths had been reported in the US, while 46 million COVID-cases and 1.2 million COVID-deaths had been reported globally ([Centers for Disease Control and Prevention—CDC 2020](#); [World Health Organization—WHO 2020](#)). Although Donald Trump and his supporters gave him “a 10 out of 10” on his efforts against COVID-19, experts generally criticized the Trump administration’s response to the coronavirus disease, arguing that their strategy was “lack of candor,” “lack of science,” and “very likely did cost lives” ([Chalfant 2020](#); [Howard and Kelly 2021](#); [Stracqualursi 2021](#)).

#michigan (#43, 1073 times) and #pennsylvania (#44, 1070 times) also appeared in the most used hashtags chart since, perhaps, Donald Trump was then repeatedly attacking Michigan’s Democratic Governor Gretchen Whitmer for her coronavirus response, accusing her of being dishonest ([Mason and Martina 2020](#); [Schulte and Eggert 2020](#)). In Pennsylvania, his campaign filed lawsuits attempting to challenge the state’s poll-watching law and limit mail-in ballots ([Levy 2020](#); [Sherman 2020](#)). Michigan and Pennsylvania were considered crucial swing states during the 2020 US presidential election; Joe Biden won in both states.

A network graph by hashtag co-occurrences (Figure 3) was generated to further investigate the association between hashtags within the network. If two hashtags (i.e., nodes) appeared in the same tweet, a link (i.e., edge) would be created between them. The more often hashtags appeared together, the stronger their link would be. The graph consists of 2628 nodes, representing hashtags, and 104,492 undirected edges, representing hashtag co-occurrences. The spatialization layout of choice was radial axis which groups nodes and draws the groups in axes (or spars); thus, it helps study homophily by showing distributions of nodes inside groups with their links.

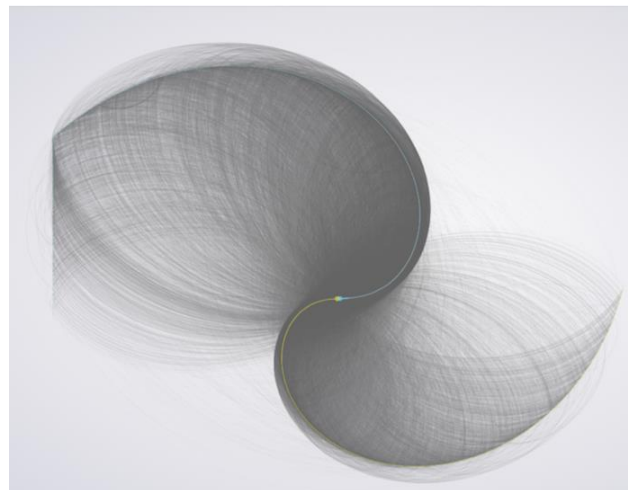


Figure 3. A social network graph by hashtag co-occurrences of 2628 nodes (hashtags) and 104,492 undirected edges (co-occurrences); Spatialization: Radial Axis Layout; Size: Weighted Degree; Color: Modularity Class².

Two significant clusters of hashtags were identified via the modularity algorithm, namely the #trump2020 cluster (i.e., the yellow cluster) and the #maga cluster (i.e., the blue cluster). #trump2020 and #maga co-occurred with 2344 and 2298 different hashtags, respectively. They co-occurred 20,060 times and were often paired with other hashtags expressing support for Donald Trump and the Republican party (e.g., #trump2020–#kag, 6568 times; #trump2020–#4moreyears, 5140 times; #trump2020–#election2020, 4704 times; #trump2020–#americafirst, 3380 times; #trump2020–#blexit, 2302 times; #maga–#election2020, 16,264 times; #maga–#kag, 10,520 times; #maga–#americafirst, 4420 times; #maga–#trump2020landslide, 3382 times; #maga–#kag2020, 2898 times).

The third most frequently used hashtags among the network, #trump2020landslide, co-occurred 59,902 times with 1464 different hashtags, including #trump2020 (6642 times), #maga (3382 times), and other hashtags supportive of Donald Trump or against Joe Biden such as #kag (922 times), #4moreyears (674 times), #redwave (622 times), or #bidencrime-famiily (570 times).

#biden and #bidenharris2020 were related to the #trump2020 cluster while #joebiden belonged to neither of the two major clusters. #covid19 was categorized into the #maga cluster. There were several hashtags paired with #covid19 to express displeasure towards the Trump administration's response to the coronavirus, such as #trumpvirus (262 times), #trumpliespeoplelie (32 times), and #trumphasnoplan (30 times).

A bipartite social network graph by hashtag-user co-occurrences (Figure 4) was generated to further investigate the association between hashtags and users within the network. If a user (i.e., a user node) posted a tweet with a certain hashtag (i.e., a hashtag node), a link (i.e., edge) would be created between that user and the hashtag. The more frequently a user employed a hashtag, the stronger their link would be. The bipartite social network graph visualized 5212 nodes, representing 3672 users and 1540 hashtags, and 48,396 undirected edges, representing user-hashtag co-occurrences.

#trump2020 was employed by 2773 different Twitter users with @Drizzle_500, our most active user among the corpus, using it 551 times. The account employed a total of 41 hashtags with #yourchoice, #election, #votered, #vote2020, and #4moreyears being some of their favorites, being used 529, 528, 506, 502, and 502 times, respectively. Meanwhile, @cogitarus, the runner-up in the most active chart, used 16 different hashtags in his tweets with #americafirst (452 times), #blexit, #votered, #maga, #kag, and #patriotismwins (451 times each) being their most frequently used hashtags. Another high-degree hashtag, #maga, was employed by 2523 different users, including some eminent ones such as @dreamchqser (259 times, #29–most active), @Beorn1234 (249 times, #5 most active, #41

most mentioned, and #17 most retweeted), and @Tony_Eriksen (199 times, #8 most active). In comparison, #trump2020 was employed more frequently, by more users among the network than #maga.

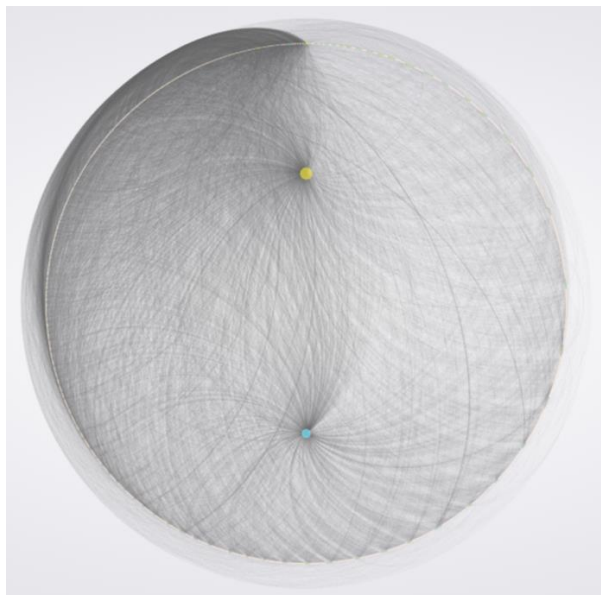


Figure 4. A bipartite social network graph by hashtag-user co-occurrences of 5212 nodes (3672 users, 1540 hashtags) and 48,396 undirected edges (co-occurrences); Spatialization: Dual Circle Layout; Size: Weighted Degree; Color: Modularity Class³.

#biden, #bidenharris2020, and #joebiden (#18, #19, and #22– most used hashtags) were employed by 490, 340, and 348 unique users, respectively. It can be seen that the number of users who used Biden-supporting hashtags were significantly, and understandably, lower than users who used Trump-supporting hashtags. Nevertheless, a user employing certain candidate-supporting hashtags did not necessarily mean that the user supported the particular candidate. For instance, among users who used #maga were @Earl18E (152 times) and @mcleod (78 times) whose Twitter activities indicated that they were Trump opposers. Similarly, @Drizzle_500 used #joebiden (60 times) while also employing #bidencorruption (288 times) and #bidencrimefamily (271 times), attempting to illustrate an ill-favored portrayal of the Democratic candidate.

Not only did the bipartite social network graph by hashtag-user co-occurrences help investigate the association between hashtags and users within the network, but it also assisted in examining certain users and hashtags of concern, thus revealing users' favorite hashtags and general sentiment, how hashtags were employed and whether they were employed following their original purpose (e.g., using #maga against Donald Trump instead of supporting him), and users' strategies of using hashtags to disseminate their messages, arguments, and ideologies within the social network.

The network graph by hashtag co-occurrence, while unable to comprehensively describe and explain tweets' content, helped identify the clusters of the most used hashtags, their relationship and association with each other, and how they were employed by users within the social network. It also assisted in studying particular hashtags of concern, partially revealing whether such hashtags were used intentionally or merely added as a mass-tagging strategy.

4.2.2. The Most Retweeted Tweets

A chart of the top 25 most retweeted tweets (Table 5), which were collectively retweeted 28,267 times, making up 12.8% of the corpus, was generated, indicating the types of messages Twitter users among the network were primarily engaged with and interested in

retweeting. It further affirmed that such content was those expressing grassroots support for Donald Trump and the Republican party, believing in an easy victory for Donald Trump in the presidential race, urging eligible voters to cast their ballots, particularly for Donald Trump and his Republican allies, and smearing Joe Biden and his allies. Only #13 by @eortner, retweeted 556 times, framed the #maga community negatively by accusing #MAGA protestors in New York of being racist towards a black Lyft driver.

Table 5. The 25 most retweeted tweets.

Rank	Tweets	Frequency
1	RT @DanScavino: EPIC!! 30,000+ in Rome, Georgia! Let's WIN! #VOTE #Election2020 #MAGAus 🇺🇸 🌐 http://Vote.DonaldJTrump.com	3086
2	RT @DanScavino: HAPPENING NOW! #MAGAus 🇺🇸	1997
3	RT @RSBNetwork: 🎶🎶🎶"I will vote for Donald Trump!"🎶🎶🎶Miami is PARTYING as they wait for @realDonaldTrump to arrive!!🎶🎶🎶#MAGA #MiamiForTrump	1674
4	RT @DanScavino: It's 12:35amE in Opa-locka, FLORIDA, and there's a #MAGA Rally in progress! Stop #5! Let's MAKE AMERICA GREAT AGAIN! Get out and VOTE #TrumpPence2020! 🌐 http://Vote.DonaldJTrump.com	1637
5	RT @DanScavino: Happening now in Goodyear, ARIZONA! 6 DAYS!! LET'S WIN, WIN, WIN!!! #MAGAus 🇺🇸	1064
6	RT @DanScavino: LET'S GO PENNSYLVANIA! #Election2020 #MAGAus 🇺🇸	1037
7	RT @DanScavino: A view from above in BUTLER, PENNSYLVANIA! Unbelievable!! Get out and #VOTE to #MAGAus 🇺🇸 🌐 http://Vote.DonaldJTrump.com	830
8	RT @DanScavino: 🌐 http://Vote.DonaldJTrump.com #Election2020 #MAGAus 🇺🇸	716
9	RT @IvankaTrump: I'll give you one guess who we're voting for??? #Trump2020 ususus	659
10	RT @DanScavino: 5 DAYS!!! #VOTE #MAGAus 🇺🇸	652
11	RT @DanScavino: Happening now—President @realDonaldTrump arrives in Las Vegas, Nevada after awesome #MAGAus 🇺🇸 rallies in MICHIGAN, WISCONSIN, and NEBRASKA! http://Vote.DonaldJTrump.com	613
12	RT @DanScavino: 10/27/20—Lansing, Michigan! #VOTE #MAGAus 🇺🇸	566
13	RT @eortner: #MAGA protestors trying to "keep Rodeo Drive & Beverly Hills great" swarmed my @lyft driver yelling racial attacks at her because she was black. She handled it with grace (While I the NYer still in me gave the 1 finger salute). us owes Tanishia better. Make these racists famous!	556
14	RT @IvankaTrump: One day, four states! Ending strong . . . We love you Pennsylvania! #MAGA	549
15	RT @LouDobbs: #LDTPoll: Who are you voting for? #MAGA #AmericaFirst #Dobbs	545
16	RT @ksorbs: Just voted with my son, it was his first time, couldn't be prouder! #Trump2020	517
17	RT @DanScavino: HAPPENING NOW—Waterford Township, in MICHIGAN! #Election2020 #MAGAus 🇺🇸	504
18	RT @DanScavino: #Election2020 #MAGAus 🇺🇸 🌐 https://Vote.DonaldJTrump.com	478
19	RT @DanScavino: 6 DAYS!!#VOTE #MAGAus 🇺🇸	471
20	RT @LouDobbs: Tireless Effort: @RudyGiuliani says he is working day and night to expose the corruption of The Biden Crime Family. #MAGA #AmericaFirst #Dobbs	460
20	RT @RealMattCouch: This is how we roll in Northwest Arkansas for Trump! #TrumpTrain #Trump2020 #Trump2020Landslide	460
22	RT @DanScavino: Happening Now in Nebraska! #VOTE #MAGAus 🇺🇸 🌐 https://Vote.DonaldJTrump.com	459
23	RT @DanScavino: THANK YOU for everything your doing, Brandon—we're grateful, your making a difference. Let's #MAGA! #Election2020	447
24	RT @DanScavino: HAPPENING NOW in ARIZONA! #VOTE #MAGAus 🇺🇸 🌐 https://Vote.DonaldJTrump.com	439
25	RT @iwantbamboo: There's a Train running the Biden Bus out of Texas! #keeptexasred #leadright #maga	435

5. Discussion

This study is, perhaps, one of the earliest to probe into and provide insights on the community of Trump supporters and their communications during the 2020 US presidential elections. It attempted to not only better understand Donald Trump, his community of supporters, and their political discourse and activities, but to also investigate the participation of social media, particularly Twitter, in political discourse, positioning such concepts in the political context of the 2020 US presidential election.

5.1. The Hierarchy of Donald Trump

Donald Trump was understandably the most influential individual among the #maga and #trump2020 community on Twitter during the 2020 US presidential election, so significant as to the point that, as shown in Figure 2, no other individual or institution among the particular network, even those on his side, could compete with him. In Figure 2, Trump had a weighted degree of 2813, 3.37 times more significant than his runner-up Joe Biden (834), 13.14 times more significant than the Republican party itself (214), and 44.65 times more significant than his running-mate, Vice-President Mike Pence (63). It should be noted that by the time this study was conducted, Donald Trump's Twitter handle @realDonaldTrump had been permanently suspended by Twitter "due to the risk of further incitement of violence" after close review on 8 January 2021 (Twitter Inc. 2021), which means that his tweets could not be taken into consideration. Between 27 October and 2 November 2020, Donald Trump posted 366 original tweets via his handle, or 52.29 tweets per day on average (Median = 60, SD = 15.71) (Trump Twitter Archive 2016). He would rank third in the most active chart (Table 1) had his handle not been suspended. Imagine how even bigger and significant his node would be in Figure 2 had his 366 tweets been calculated.

In many ways, the activities, behaviors, and expressions of Donald Trump and his supporters, particularly on Twitter, showed characteristics of a cult of personality, a phenomenon referred "to the idealized, even god-like, public image of an individual consciously shaped and molded through constant propaganda and media exposure" (p. 29). Such idealized, or God-like, figure can then use their influence of public personality to manipulate others although their perspective often focuses on the cultivation of relatively shallow, external images (Wright and Lauer 2013). Hickman (2019) found similarities on the dimensions of cognition negative, contract negative, and performance negative via verbal characteristics between Donald Trump and charismatic leaders. Those charismatic leaders included Benito Mussolini, Joseph Stalin, Adolf Hitler, Vladimir Putin, Jim Jones, David Koresh, Mao Tse-tung, and Winston Churchill, among who were dictators (e.g., Benito Mussolini, Joseph Stalin, Adolf Hitler, and Mao Tse-tung) and notorious cult leaders (e.g., Jim Jones and David Koresh). Reyes (2020) also focused on Donald Trump's cult of personality and self-representation, positing that the 45th president of the United States had built his candidacy and presidency around his persona, distancing himself from the Republican party, traditional politics, and traditional politicians.

The media plays a crucial, instrumental role in the creation of leaders' cults of personality. The charismatic leader, especially in politics, has increasingly become the product of media and self-exposure (Wright and Lauer 2013). Gaufman (2018) used the Russian analytical paradigm of carnival culture to explain the popularity and political success of Donald Trump, arguing that the age of misinformation on the mass media, among other factors, had presented Donald Trump with a unique opportunity to leverage the power of social networks to his advantage. For instance, traditional mass media constantly reported about Donald Trump, conveniently boosting his visibility and disseminating his messages despite seldom taking him seriously. Findings of this study affirmed that the content posted among the #maga and #trump2020 community on Twitter during the 2020 US presidential election was primarily grassroots support for Donald Trump and, to a much lesser extent, his allies. Such results, and the fact that Donald Trump was seemingly the most prominent figure on his side (he was 13.14 times bigger than the party he represented), might suggest that Trump supporters' backing for him was somewhat unquestioning, and they merely

regurgitated his rhetoric rather than doing their research and coming up with original contents.

5.2. The Problematic Nature of Bot Detection

The most active users in the corpus received an average bot score of 2.14, lower than the binary thresholds defined by [Al-Rawi et al. \(2019\)](#) (2.3) and [Keller and Klinger \(2019\)](#) (3.8), roughly equal to [Wojcik et al. \(2018\)](#) (2.15), and higher than [Zhang et al. \(2019\)](#) (1.25). The average bot score also generally signaled that Botometer's classifier could not be sure about the nature of this group of users. There were 34 users who received a bot score of 3 or above and if the deleted account of @christo31129690 was taken into consideration, it could be said that 35 (or 35%) of the most active users among the #maga and #trump2020 community on Twitter during the 2020 US presidential election were bots. Still, the bot-score evaluation approach using Botometer may be problematic.

Take @Drizzle_500 for example: the account tweeted 550 times during the seven-day period between 27 October and 2 November which was equivalent to averagely 78.57 tweets per day, or roughly one tweet every 18 minutes, nonstop. Such frequency of tweeting seems inhuman even for social media addicts. [Howard et al. \(2016\)](#) identified accounts having a high level of automation as those who posted at least 50 times a day since it was very difficult for human users to maintain such rapid pace of social media activity "without some level of account automation" (p. 4).

Nevertheless, on a scale from 0 to 5, with 0 for being human-like and 5 for performing like a bot, Botometer awarded both @Drizzle_500 a bot score of 1.4, which suggested that the user was relatively human-like. [Rauchfleisch and Kaiser \(2020\)](#) argued that Botometer bot scores were imprecise, especially if tweets were written in a language other than English, which consequently led to false negatives (i.e., bots being classified as humans) and false positives (i.e., humans being classified as bots) in estimating bots. Botometer admits that bot detection via software is a hard task and even trained eyes can be wrong, and the best approach to Botometer is to use the tool to complement instead of completely replacing human judgement. Additionally, binary classification of accounts using two classes (e.g., bot or not) can be problematic since few accounts are completely automated. While such approach to classify bots is not encouraged, a number of studies in social science research still adopt it for bot classification and estimation.

Theoretically, extremely active human users might achieve the "high level of automation" pace of social activity (i.e., posting at least 50 times a day), especially if they were merely retweeting contents ([Howard et al. 2016](#), p. 3). Thus, it is suggested that this study's results regarding the estimation of spamming bots among Twitter users should be used as a reference rather than a definitive conclusion. Although bots did not account for the majority of the most active users, a percentage of 35% of the whole group was still alarming. Twitter claimed that their technological power to proactively identify and remove malicious usage of automation "is more sophisticated than ever," and they permanently suspended millions of accounts that were maliciously automated or spammy every month. They also criticized the approach of bot detection tools, including Botometer and Bot Sentinel, as extremely limited ([Roth and Pickles 2020](#)). Twitter's efforts, however, seem to be insufficient.

Many handles evaluated as having extremely high bot-like performance (i.e., received a bot score of 4 or above) or high bot-like performance (i.e., received a bot score from 3 to 3.9) were media outlets' verified accounts (e.g., CNN (@CNN, 4.2 and @CNNPolitics, 3.8), The Hill (@thehill, 4.2), The Washington Post (@washingtonpost, 4), New York Post (@nypost, 4.6), and Fox News (@FoxNews, 3.4)). Since Twitter accounts can be simultaneously controlled by both human and bots (i.e., semi-automated and semi-manual) ([Rauchfleisch and Kaiser 2020](#)), it can be concluded that the media also employ a certain level of automation to disseminate their agenda and contents.

6. Conclusions

Twitter has been, and will indeed continue to be, a forum for political participation, particularly political deliberation, a valid indicator of political sentiment, and an appealing vehicle for political conversations as discussed by [Ausserhofer and Maireder \(2013\)](#), [Stieglitz and Dang-Xuan \(2012a\)](#), and [Yang et al. \(2016\)](#). Twitter's political participation and influence in at least the four presidential elections in the last 13 years is evident. For instance, as 34,583,668 tweets were originally tweeted between 27 October and 2 November 2020, about the 2020 US presidential election, a tremendous amount of political information was created, disseminated, and absorbed by Twitter users, which might affect their decision-making process regarding who they should trust in and, eventually, vote for.

Nevertheless, the 2020 US presidential election result suggested that candidates' activity and prominence on social media, particularly Twitter, should not be perceived as a valid predictor of election outcomes. Donald Trump was apparently the circus master of the media circus he generated during the election (i.e., he was the most prominent and most significant figure, not only on social media but also all other media channels); still, it was Joe Biden who won the presidential race instead of the 45th president securing his second term in the White House. Thus, the study agrees with [Groshek and Koc-Michalska \(2017\)](#) in challenging the idea that liberal democracy in the United States was being harmed by social media, especially through its filter bubbles.

The study believes that the ugly and malicious sides of social media, particularly Twitter, will persist. Users with predetermined agendas will believe what they want to believe, utilize arguments that support their confirmation bias, and intentionally and strategically ignore science, truths, and facts. On the other hands, the study also concludes that while social media have flaws and limitations, they provide valuable political outlets and civic engagement opportunities for marginalized groups and people who are often considered politically and civically inactive (e.g., youths). These social platforms and formats are more appealing and accessible than traditional and conventional, typically drier, forms of political communication ([Penney 2019](#)). Additionally, if social media indeed have the power to carry an individual to the top, they can also take that individual down to rock-bottom, especially if their actions and behaviors violate standardized moral, decency, and social values.

Limitations and Future Study

The study recognized several of its limitations and, at the same time, proposed viable approaches for future research concerning internet memes, social media, and political communication. Due to Twitter's permanent suspension of Donald Trump's account, as well as many other Twitter handles who were spamming bots, their tweets, as discussed above, could not be included in the dataset. It might consequently make the dataset somewhat incomplete and, to some extent, unable to fully portray and characterize users and contents of the targeted social network. Still, the study is confident that the dataset was representative of the #maga and #trump2020 community during the 2020 US presidential election. Therefore, the data provided was adequate to examine Donald Trump's community of supporters and their political discourse and activities. Additionally, as the study identified some problematic aspects of the bot detection and estimation method, future studies on the topic are encouraged so that more refined, precise, appropriate, and trustworthy bot detecting methods can be offered to the social science community.

While the study probed into the Twitter community and their communication during the 2020 US presidential election, it only investigated the social network of Trump supporters rather than the networks surrounding both candidates. Thus, future research can examine the community of Biden supporters using hashtags equivalent to #maga and #trump2020. Comparative assessment of the two communities of supporters can be then provided, from which contrasts in their actions, behaviors, sentiment, and civility are highlighted. The social networks of political supporters and political contents on legacy

media, as well as other social media channels such as Facebook, Reddit, Parler, or 4chan, should also be considered in future studies.

Finally, since the study referred solely to Twitter data, users' demographics could not be identified and analyzed. The media effects could not be determined via content analysis. Hence, ethnographic methods, such as interviews or surveys, are further needed to complement the findings of this study.

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Informed Consent Statement: All data collected and used in this study, including tweets and Twitter accounts, were publicly available via Twitter Public APIs. While some scholars argue that tweets and Twitter handles should not be quoted in research papers without users' consent, the author of this study believes that public Twitter data should be perceived as private data on public display on the basis of ongoing consent under contract (Gold 2020). Thus, as long as the data remain publicly visible, the normal ethical requirement of individual informed consent can be waived.

Data Availability Statement: Data available on request.

Conflicts of Interest: The author declares no conflict of interest.

Notes

- ¹ A dynamic interactive version of the social network graph by mentions with higher resolution and more details can be found at http://gorilladragon.org/dat_t/MDPI/Graph1/index.html (last accessed on 16 November 2021).
- ² A dynamic interactive version of the social network graph by hashtag co-occurrences with higher resolution and more details can be found at http://gorilladragon.org/dat_t/Graph2/index.html (last accessed on 16 November 2021).
- ³ A dynamic interactive version of the bipartite social network graph by hashtag-user co-occurrences with higher resolution and more details can be found at http://gorilladragon.org/dat_t/Graph3/index.html (last accessed on 16 November 2021).

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