

“Make A-meme-rica great again!”: Studying the memers among Trump supporters in the 2020 US presidential election on Twitter via hashtags #maga and #trump2020

by

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Abstract

The study, consisting of three parts and based on the theoretical framework of social network analysis, political spamming, and framing theory, analysed a corpus of 220,336 tweets from 96,820 unique users posted on Twitter between October 27 and November 2, 2020. It investigates the participation of social media, particularly Twitter, and internet memes in political discourse, positioning such concepts in the political context of the 2020 US presidential election. The study attempts to better understand Donald Trump, his community of supporters, and their political discourse and activities during the 2020 US presidential election; thus, an investigation into their Twitter social network should prove fruitful.

By probing into the community of supporters of the incumbent Donald Trump, specifically the group of internet memers (an internet slang describing people who create or distribute memes), on Twitter during the 2020 US presidential election, the study reveals the most active and influential users within the network, the likelihood of those users being spamming bots, and their tweets' content. Such analysis is relevant in understanding Twitter users related to the hashtags, their affiliations, and the nature of such accounts. Systematic, objective, and quantitative content analysis of internet memes found in the corpus should determine (1) the memes' target, (2) how were the targets portrayed in the memes, and (3) the main themes, or ideas, of the internet memes posted within the community of Donald Trump supporters. Finally, findings shall be discussed, from which assessment, prediction, and serviceable data are provided in the hope that the study can contribute to building a solid foundation for future research concerning internet memes, social media, and political communication.

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Dedication

This thesis is dedicated to my mother who has always supported my choice however bad it may turn out to be. Fortunately, I was raised well.

To my grandfathers who had always believed that I was born for greatness but did not live long enough to follow my academic journey and witness my achievements, I hope I have not disappointed you.

To the A. Q. Miller School of Journalism & Mass Communications at Kansas State University where I found a true family in everyone instead of just a pit-stop as I initially planned, it has been a privilege being a humble member of your school. You will always be in my heart.

I would also like to take the opportunity to raise awareness on the conversation regarding mental health issues in academia via this thesis. Even before becoming an early-career researcher, dealing with mental health difficulties had been a significant part of my life. These problems can be devastating, sometimes fatal; thus, I hope that universities, colleges, and educational institutions worldwide would take the matter seriously and provide students, faculty members, and staff with the assistance they need to stay sane. Better be safe than sorry, since Agent K (Men in Black) once argued that the most destructive force in the universe was not sugar, but regret.

Chapter 1 - Introduction

On June 9, 2016, the Republican nominee for the US presidential election, Donald J. Trump, criticised Barack Obama on Twitter because the then-president of the United States had publicly endorsed the Democratic nominee Hillary Clinton; Clinton was Obama's Secretary of State from 2009 to 2013. In response, Hillary Clinton posted a tweet that would eventually become the second-most retweeted political message of the year and Twitter's representative for the hashtag #Election2016, "Delete your account", an internet meme (Berland, 2016; Collins, 2016). In both the 2012 and 2016 US presidential elections, Democrats and Republicans had employed internet memes as a means of online political campaigning and iconography to raise awareness, support, and funds from citizens (Foster, 2014; Zannettou et al., 2018).



Figure 1. Hillary Clinton's tweet, which is an internet meme, was the second-most retweeted political message of 2016 and Twitter's representative for the hashtag #Election2016

While the participation of social media and internet memes in political discourse, particularly presidential elections, is not a new phenomenon, its influence in the 2016 US presidential election was 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 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, Bellio, Crestini, & Arkoudas, 2020). The Democratic candidate spent most of her tweets discussing political issues (27.3%) and attacking Trump, his views, ideas, and statements (27.89%). Her opponent, meanwhile, adopted a fundamentally different approach, blasting not only politicians but also anyone else who dared to publicly criticise the candidate in 43.96% of his tweets (Lee & Quealy, 2019). Trump also dedicated another 11.44% of the tweets to himself, insisting that he was the only candidate who could “make America great again, defeat terrorism, contrast illegal immigration, and self-fund his campaign”.

In 2020, 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). His online activities prompted social platform providers, including Twitter and Facebook, to stamp political content posted before, during, and after the general election day, including those from Donald Trump and Joe Biden, his Democratic opponent. Such efforts, while limited and maybe not enough “to save democracy”, represented Big Tech’s endeavours in combating misleading and premature claims about the election on their platforms (Geoffrey, 2020; Graham & Rodriguez, 2020; Shepardson & Culliford, 2020). Eventually, after political fanatics attacked the Capitol on January 6, 2021, Donald Trump, who was accused of inciting the insurrection, was banned from numerous social platforms such as Facebook, Instagram, Twitter, Snapchat, Twitch, Shopify (permanently), Reddit (by deleting and banning several related subreddits), Amazon

Web Service, LiquidWeb (indirectly via termination of hosting services for far-right platforms Parler and Oath Keepers), and YouTube (Colarossi, 2021; Denham, 2021; Eisen & Reisner, 2021; Savage, 2021; Twitter Inc., 2021).

The utilisation 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 maximising television as a campaign tool (Newman, 1994; Verser & 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, Bellio, Crestini, & Arkoudas, 2020; Ott, 2016). His victory in the 2016 US presidential election 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, including Twitter and Facebook (Groshek & Koc-Michalska, 2017; Oliver & Rahn, 2016). It was suggested that Twitter, along with its simplicity, impulsivity, and incivility, might have signalled the inevitable ascent of Donald Trump despite him being offensive, bullying, and abusive on the platform. Additionally, the general media agenda was so heavily affected by populism content, and voters' viewpoints and decision-making process were being shaped by misinformation and fake news, that the outcome of the election was influenced (Benkler, Faris, Roberts, & Zuckerman, 2017; Ott, 2016). However, Groshek and Koc-Michalska (2017) contended that, from both theoretical and empirical standpoints, it was "tempting but maybe somewhat premature" to assert that liberal democracy in the United States was

being harmed by social media, especially through its filter bubbles, or if those bubbles were among the causes of the evidently growing populism in the United States.

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). Nevertheless, the significance of internet memes, an integral aspect of communication on social media, to recent US presidential elections, and politics in general, might have been underestimated although the primary political involvement of millions of American people during the 2016 presidential election “was limited to tweeting and retweeting snarky anti-Clinton or anti-Trump memes to like-minded individuals” (Ott, 2016). Despite increasingly becoming relevant and impactful, internet memes are still more often considered laughing matters rather than legitimate conveyors of information, and scholars have little understanding of their influence and propagation (Shifman, 2014; Zannettou et al., 2018). Little literature exists to reflect the importance of internet memes to mass communications and, furthermore, society. To better understand Donald Trump, his community of supporters, and their political discourse and activities during the 2020 US presidential election, an investigation into their Twitter social network should prove fruitful.

This study consists of three parts and builds on the theoretical framework of social network analysis, political spamming, and framing theory to fill in the gap by probing into the community of supporters of the incumbent Donald Trump, specifically the group of internet memers (an internet slang describing people who create or distribute memes) among them, on Twitter during the 2020 US presidential election. In the first portion, by collecting and analysing a corpus of tweets containing either the hashtags #maga (an abbreviation for Donald Trump’s campaign motto, Make America

Great Again) or #trump2020 posted between October 27 and November 2 (i.e., one week before the general election day), the study explores the community of Trump supporters on Twitter. Patterns, such as the most active and influential users, the likelihood of those users being spamming bots, and their tweets' content, are revealed. The second part looks forward to identifying the group of memers among Trump supporters on Twitter via a subset of the original corpus, which contains tweets with memes. Like the first part, specific user and content patterns are expected to be revealed by analysing the subset. These patterns are then compared to those found in the first part to identify differences and similarities.

The third portion, via content analysis of the internet memes found, aims to determine the targets of the memers and learn how memers among the community of Donald Trump supporters framed their memes and their targets. Finally, findings shall be discussed, from which assessment, prediction, and serviceable data are provided in the hope that the study can contribute to building a solid foundation for future research concerning internet memes, social media, and political communication.

Chapter 2 - Literature Review

2.1. Memes and internet memes

The term “meme” was coined by the English ethologist, evolutionary biologist, and author Richard Dawkins in his 1976 acclaimed publication, *The selfish gene*. He described his conceptualisation as follow:

We need a name for the new replicator, a noun that conveys the idea of a unit of cultural transmission, or a unit of imitation. “Mimeme” comes from a suitable Greek root, but I want a monosyllable that sounds a bit like “gene”. I hope my classicist friends will forgive me if I abbreviate mimeme to meme. If it is any consolation, it could alternatively be thought of as being related to “memory”, or to the French word mème. It should be pronounced to rhyme with “cream”. Examples of memes are tunes, ideas, catch-phrases, clothes fashions, ways of making pots or of building arches. (Dawkins, 2016, p. 378–379)

Meme made its first appearance in the definitive record of Oxford English Dictionary in 1997 before being fully revised in 2001, initially defined as “a cultural element or behavioural trait whose transmission and consequent persistence in a population, although occurring by non-genetic means (esp. imitation), is considered as analogous to the inheritance of a gene.” Meanwhile, internet memes are the memes which can be found in virtually every place and space in the modern world, including but not limited to social networks (e.g., Facebook, Instagram, Snapchat, or Twitter), forums (e.g., Reddit, 4chan), user-generated video and micro-video platforms (e.g., YouTube, TikTok, or the now-archived Vine), or any random website on the internet, television series, news reports, podcasts, postcards, or printed image-macros at birthdays or Halloween parties.

The Oxford English Dictionary defines an internet meme as an image, a video, a piece of text typically humorous in nature that is copied and spread rapidly by internet users, often with slight variations. Nevertheless, the conceptualisation of memes, mainly internet memes, has been shifted and modified throughout history and is, to a certain extent, different from, or perhaps simpler than, Dawkins' original ideas (Juza, 2013). The exact origin of the first internet meme as they are understood today, i.e., where, when, and how it emerged, has not been determined yet by scholars. Fulton (2017) believed that the first internet meme was Dancing with the Baby (circa 1996). Others, including Davison (2012), perceived emojis as the preliminary form of internet memes. 4chan is widely believed to be the first meme community on the internet. None of these assumptions stands on solid ground.

2.2. Characteristics of internet memes

Pepe the Frog was initially an anthropomorphic frog character in Matt Furie's comic series Boy's Club before being memefied (i.e., turned into a meme) into a Nazi Trump-supporter and used as an alt-right symbol in multiple series of popular image macros. The possibility of Pepe's interpretation is endless, but eventually, he means whatever his conjurers want him to mean (Nuzziu, 2017). Pepe the Frog is an exemplary example of internet memes, along with Bad Luck Brian, Moon Moon, Confused Cat at Dinner, Baby Yoda, or the recently famous Tiger King or Bardcore. They are often perceived as shallow, insignificant, silly jokes sent around to be soon forgotten (Nissenbaum & Shifman, 2017).

Dawkins (2016) posited that memes propagated themselves in the meme pool "by leaping from brain to brain" via imitation and compared the process to that of genes wherein they propagated themselves in the gene pool "by leaping from body to body via

sperms or eggs”. He considered fidelity, fecundity, and longevity as the three key characteristics of memes. Knobel and Lankshear (2007) argued that internet memes were too newly emerged that no form of revolutionary longevity could have been established; however, they believed the current ideas about internet memes were not radically different from Dawkins’ understanding of memes. Humour, intertextuality richness, and anomalous juxtaposition were also posited as three additional fundamental components of popular internet memes, which drew deeply on popular internet culture. Davidson (2012) added the incredible speed of transmission, the ability to overcome physical obstruction and time, and replicability to the batch. Bebić and Volarevic (2018) considered the primary purpose of an internet meme was merely to become well-known, actual, and humorous in order to be easily noticed while also quickly spread in a social network.

Thompson (1995) identified five characteristics of mass communications: “comprises both technical and institutional methods of production and distribution”, “involves the commodification of symbolic forms”, “has separate contexts between the production and reception of information”, “can reach to those ‘far removed’ in time and space in comparison to the producers”, and “conducts mass information distribution”. While memers seldom put a price-tag on their works (i.e., internet memes are not made to be sold), internet memes can be indirectly commercialised via meme-related merchandises such as clothing or souvenirs. Moreover, free-to-use social platforms for user-generated content (e.g., YouTube, Facebook, Twitter, or Reddit) are built upon the basic bargain principle, which means providers provide free and open platforms while users provide the contents. Providers can then monetise “the individualised data gathered from the social and creative activities, interests, and communication of users”

by selling those data to advertisers (Soha & McDowell, 2016). Those data include the creation, usage, and patterns of internet memes. McQuail (1969) posited that the seven characteristics of mass communications include the complexity and formality of organisation, a massive audience, the heterogeneity of the audience, the ability to reach multiple individuals at the same time, public accessibility to contents, one-directional flow and impersonality, and the mass audience as a creation of modern society. Thus, internet memes, with the internet acting as an intermediate mean of transmission, should be qualified and perceived as a fundamental form of mass communication since they fit into both the above-mentioned conceptualisations of mass communications.

While they have been leaping into the broad daylight of public recognition at a quick and steady pace, the concept of memes and internet memes has been the subject of heated and constant academic debate between enthusiastic apostles and dismissive sceptics, as well as the target of derision and sometimes outright dismissal (Aunger, 2000; Shifman, 2012; Shifman, 2014). There is, in fact, memetics, the study of information and culture describing how an idea can be propagated based on a Darwinism analogy; however, it has been contended by critics as untested, unsupported, and incorrect (Kantorovich, 2014; Marks, 2002; Polichak, 2000). The study of memes is not an exception. Although memetics and memes are, indeed, novel and contemporary topics among academia, there are studies investigating internet memes' origin, definition, and inherent characteristics (Davison, 2012; Knobel & Lankshear, 2007; Zannettou et al. 2018) as well as their cultural, social and political participation (Milner, 2013; Nissenbaum & Shifman, 2017; Szablewicz, 2014).

Lu and Fan (2018) investigated the relationship between self-mocking internet memes and psychological well-being among college students in China, suggesting that

the need for humour and narcissism encouraged participants to use internet memes as both a self-protection strategy and a social strategy. Entertainment and self-expression were the motives encouraging postgraduate communication students in Indonesia to use memes; informativeness, however, did not have any connection with or influence on the audiences (Cahya & Triputra, 2017). Memers who are students in Western countries perceive internet memes as an instrument for political engagement, self-expression, social identity, and entertainment (Leiser, 2019). Meanwhile, Wells (2018) proposed internet memes as a plausible device in developing critical thinking and evidence-based argument skills in students.

2.3. Internet memes in political discourse

In December 2012, the exuberant “Gangnam Style” became the first video in history to hit one billion views on YouTube. It did not then take too long for a meme craze to sweep across the world wide web, leading to the creation of a myriad of variations, imitations, and parodies. Despite an often lack of seriousness, internet memes are a unique product of the current digital culture that typifies many of its underlying qualities; they, to an extent, have been playing a vital part in defining and shaping the twenty-first century (Shifman, 2014). The humorous nature of memes indeed makes them an ideal venue for political critique and commentary, as humour has been a method for skewering both people and institutions in the highest echelons of power (Miltner, 2018). Zannettou et al. (2018) believed internet memes, apart from their usual humorous intention, have been weaponised to sway and manipulate public opinion; they can be considered one of the most impactful media for propagation in the modern world as their popularity gradually increases. Still, Dean (2019) suggested that the attitude of political science towards social media and digital politics had long been

an unease, or even squeamishness, which hindered their ability to appreciate the texture and character of contemporary digitally mediated politics. Political scientists, therefore, should perceive the production and exchange of digital visual media, notably internet memes, not as some frivolous activity on the margins of politics but as increasingly central to the everyday practices of politically engaged citizens.

It is not difficult to recognise the rapidly growing presence of internet memes within political contexts. Bebić and Volarevic (2018) posited that *Ćaća se vraća* (*The Father is Coming Back*), a sarcastic Facebook initiative, successfully employed internet memes to influence the way the media portrayed Ivo Sanader; he was then the former prime minister of Croatia and had just been released from prison. Sanader was presented usually positively and as a problem solver on *Ćaća se vraća*. Chagas, Freire, Rios, and Magalhães (2019) argued that during the 2014 elections in Brazil, Dilma Rousseff and Aécio Neve were candidates who most profited from persuasive memes. Eduardo Jorge, an outsider candidate dubbed as “The King of Memes” due to his performances during the debates, exaggerated gestures, funny responses, and atypical behaviours, was also the character of many political internet memes, particularly those about grassroots actions and public discussions. During the anti-government protests in Ukraine between 2013 and 2014 and in Venezuela in 2019, both pro- and anti-government communities took advantage of internet memes’ visual appeal and memorability to gain influences and propagate their political agendas (Makhortykh & González Aguilar, 2020). In both countries, internet memes were revealed to be used by anti-government communities to articulate forms of creative critique, symbolic resistance against the regime, or a coping mechanism and tended to incite positive emotions. Their counterparts, on the other hand, employed internet memes for

polarisation and propagation, using strong affective stimuli to mobilise the audience. Findings also highlighted that neo-authoritarian regimes had been increasingly adopting internet memes as a communicative measure against protest activities.

The spread of political internet memes, which does not necessarily follow an S-shaped dynamic, contrasts with typical findings of the literature regarding the diffusion of information. Instead, memes can either focus on idiosyncratic political issues, hence capture high levels of attention in a short amount of time. They, on the other hand, can include established themes routinely discussed throughout the legislative process, in which case the dynamics conforming to a linear fashion (Gurciullo, Herzog, John, & Mikhaylov, 2015). The combination of dialogue and conflict in political memes is indeed a critical element that increases the popularity of a meme and thus makes it viral (Lukianova, Shteynman, & Fell, 2019).

On social media, state-sponsored accounts have been known to utilise the expressive power of images and pictures (i.e., using politically and ideologically imbued internet memes) to advance agendas (Rowett, 2018; Zannettou, Caulfield, Bradlyn, De Cristofaro, Stringhini, & Blackburn, 2020). For example, Zannettou et al. (2020) analysed a dataset of 8 million images from the 9 million tweets released by Twitter in October 2018 that, according to the social networking service, had been posted by 3.6 thousand accounts identified as being controlled by the Russian Internet Research Agency (IRA). The study suggested that internet memes, while some were meant to be funny, possessed strong political nature and were exploited by the accounts mentioned above to disseminate their ideology. The internet memes sharing pattern, interestingly, coincides with real-world events, further indicating the accounts' intention to create discord during dividing events. Those campaigns were effective since they evoked a

strong emotional response with a stark partisan divide that drove consumers' behaviours; thus, misinformation and disinformation, some expressed in the form of internet memes, could rapidly spread throughout social media channels. However, exposure to media literacy can shift the behaviours of audiences with the most partisan views who are usually considered "hard to reach and hard to teach"; indeed, after the exposure, 8% to 17% of the political partisans, both left and right, are less likely to feel positive about a disinformation meme. Labelling propaganda and pinpointing the sources of materials also reduces the likelihood of partisan audiences sharing disinformation items. Nonetheless, the process of identifying and labelling disinformation is often not accomplished as punctually as needed which means by the time the pieces of disinformation are flagged, they have already done reaching their targeted audiences (Todd, James, Marek, & Danielle, 2020).

2.4. Political participation on Twitter

Political participation has long been considered a critical attribute at the heart of democracy. The practice involves activities such as voting, aiding political campaigns, donating money or making other forms of contributions to political causes, working informally in the community, contacting government officials, serving on local governing boards, as well as protesting, demonstrating, boycotting, and buying products for political reasons (Park, 2013; Verba, Schlozman, & Brady, 1995). Conway (2000) defined political participation as activities citizens performed in order to influence different levels of the government. Verba, Schlozman, and Brady (1995) emphasised that the exercise provided the mechanism by which citizens could communicate information about their interests, preferences, and needs while also generate pressure to respond.

Twitter, a microblogging and social networking platform which encourages users to publicly contribute new postings and reply to others' available ideas, has been used extensively as a forum for political participation, particularly political deliberation, and a valid indicator of political sentiment (Ausserhofer & Maireder, 2013; Stieglitz & Dang-Xuan, 2012). For instance, during election campaigns, especially right before the election day, there often is a dramatic surge in political candidates' number of social media postings; after the decisive day, that number often drops. Candidates who engage with audiences via social media, particularly Twitter, receive more votes than those who do not, and their tweets are characterised by interactivity (i.e., the inclusion of interactive features such as mentions, hashtags, or retweets) and personalisation (i.e., the inclusion of their emotions, private life, and activities) (Kruikemeier, 2014). Stieglitz and Dang (2012) studied 108,000 political tweets published before the two Landtag (state parliament) elections in the populous states of Baden-Württemberg and Rheinland-Pfalz in Germany in 2011. They suggested that tweets containing words reflecting affective processes, either positive or negative, were retweeted more often than those that did not. Hence, in online political contexts, both information and sentiment, which possess the ability to influence the political opinion-making process, can be disseminated.

Among US politicians, Twitter is perceived as an appealing vehicle for political conversations. Bode and Dalrymple (2014) and Glassman, Straus, and Shogan (2010) suggested that Republicans participated in politics online, on Twitter in particular, more often than Democrats. Yang, Chen, Maity, and Ferrara (2016) findings implied otherwise, i.e., Republicans and Democrats were relatively equally active on Twitter; however, they exhibited different communication styles, with Democrats significantly

more inclined to use hashtags than their counterparts. Additionally, 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, notably as the minority party (Russell, 2017).

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 organisation, minus many of the traditionally associated costs (Buccoliero, Bellio, Crestini, & Arkoudas, 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 more minor roles in a discourse primarily dominated by political professionals, as well as journalists to a lesser extent (Ausserhofer & Maireder, 2013). Nevertheless, not only traditional civic participants and partisans at the political extremes are politically active on Twitter, but contemporarily, marginalised groups such as racial minorities and secularists also perceive the platform as a political outlet (Bekafigo & McBride, 2013). Twitter users who have political intents are more likely to have obtained higher education (70.5% have a bachelor’s degree while the percentage of the general population is 24.4%) and income (\$62,000 annually, compared to \$49,777 of the general population). They are, in many ways, the ideal subpopulation with which political elites might choose to communicate (Bode & Dalrymple, 2014).

Ott (2016) argued that public discourse promoted on and by Twitter was often simple, impetuous, frequently denigrating, and dehumanising. 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 & Maireder, 2013; Stieglitz & Dang-Xuan, 2012; Tumasjan, Sprenger, Sandner, & Welp, 2010), and arguments circulated via online news articles are often considered more persuasive and more credible than those relayed on Twitter (Wasike, 2017).

Chapter 3 - Theoretical Framework

3.1. Social network analysis

Stemmed from sociology, the term social network was coined by Barnes (1954). He described social networks as a social field with no units, boundaries, or coordinating organisations; such a social field “is made up of the ties of friendship acquaintance which everyone [...] partly inherits and largely builds up for himself”. A social network can be imagined as a set of points joined by lines, with points represent 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 assumes that relationships, whether formal or informal, are important and seeks to understand networks and their participants, namely actors and relationships between actors. Scholars, however, have not been able to construe networks’ public and organisational power in ways that could harness their full potential. The theory of social network and social network analysis is a gold mine for social scientists, providing a powerful model for social structure and yielding explanations for social phenomena in a wide variety of disciplines. Its application can be found in studies of kinship structure, social mobility, science citations, contacts among members of deviant groups, corporate power, international trade exploitation, class

structure, among many other areas of social sciences (Borgatti, Mehra, Brass, & Labianca, 2009; Scott, 1988; Serrat, 2017).

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, Budak, & Abbadi, 2011; Chadwick, 2006; Leskovec, 2011; Nagarajan, Sheth, & Velmurugan, 2011; Stieglitz & Dang-Xuan, 2012). Social media, as media designed for social interaction, and their data are subjects that can be studied via social network analysis (Cheong & Cheong, 2011; Norman, Nordin, Din, Ally, & Dogan, 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. Their 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, Kim, and Park (2021) examined consumer behaviours 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 indeed needed to comprehensively analyse elements in group communication, including media use (Haythornthwaite, Wellman, & Mantei, 1995).

3.2. Political spam

Political spamming is not a novel phenomenon. However, few academic research has been done to examine the topic, and such research failed to provide a clear conceptual definition of political spam while also neglected the networked and collaborative aspect of it (Al-Rawi, Groshek, & Zhang, 2019; Najafabadi, 2017). Spam used to be merely conceptualised as unsolicited emails sent in bulk, and scholars posited that the first noticeable widespread use of unsolicited bulk email for political purposes, or political spam, was recognised in 1998 and 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 behaviour of humans or the system itself, at the direct or indirect, immediate or long-term advantage of the spammer(s)” (Ferrara, 2019). Al-Rawi, Groshek, and Zhang (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 (Gao, Hu, Wilson, Li, Chen, & Zhao, 2010; Just, Crigler, Metaxas, & Mustafaraj, 2012; Sridharan, Shankar, & Gupta, 2012). The use of political spamming on Twitter has been recognised in political events such as the 2008 US congressional elections (Metaxas & Mustafaraj, 2009), the Massachusetts senate race in 2010 (Mustafaraj & Metaxas, 2010), and the 2010 municipal elections in Ottawa, Canada (Raynauld & Greenberg, 2014). Such spamming efforts aimed to discredit journalist and liberal media outlets, flood the network with unsolicited information, or overwhelm the original content in an attempt to silence dissent. Al-Rawi, Groshek, and Zhang (2019) argued that political spamming was prevalent in the context of political discourse on Twitter despite Metaxas and Mustafaraj (2009) and Himelboim, McCreery, and Smith (2013) suggested contradictorily.

Political spam has been consistently exempted from regulations by federal and state governments under the rationales that (1) politicians would not exploit the annoyance factor of political spam, (2) political spam cannot be regulated since it constitutes constitutionally protected political speech, and (3) imposing regulations could cripple the development of email, and internet-based media in general, as tools for political campaigns. Grossman (2004) contended that those beliefs were, nevertheless, misguided, and political spam should and could be regulated in various ways. It may prove vital, especially in contemporary contexts, since social media hosts, apart from human users, the participation of automated agents called social bots or sybil accounts, which 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 also 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 performing terrorist propaganda and recruitment activities (Boshmaf, Muslukhov, Beznosov, & Ripeanu, 2013; Davis et al., 2016; Lee, Eoff, & Caverlee, 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 jeopardise democracy and influence the outcome of elections have been observed. 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, Conover, Meiss, Gonçalves, Flammini, & Menczer, 2011). Similar activities occurred in the Massachusetts special election of 2010 (Metaxas & 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 as employers of the power of political spamming (Najafabadi, 2017). Examples of such efforts can be found in the US (Fielding & Cobain, 2011), Syria (Qtiesh, 2011), China during pro-Tibet movements (Segal, 2012), South Korea during its 2012 presidential election (McCurry, 2017), Mexico during the 2014 Iguala mass kidnapping (Finley, 2015), or Ecuador (Woolley, 2015).

Political spamming may endanger democracy, create panic during emergencies, and affect the stock market. Furthermore, 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 polarisation of political discussion. They can alter the perception of social media influence, artificially popularising certain people or ruin the reputation of others for commercial or political purposes (Boshmaf et al., 2013; Conover, Ratkiewicz, Francisco, Gonçalves, Menczer, & Flammini, 2011; Edwards, Edwards, Spence, & Shelton, 2014; Hwang, Pearce, & Nanis, 2012; Messias, Schmidt, Oliveira, & Souza, 2013). Hence, studying political spam and social media bots under mass communication lenses is vital in contemporary contexts. 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.

3.3. Framing theory

The definition of framing in social sciences, cognitive sciences, and sub-fields of political sciences has been hitherto diversified as its implementation can be universally found throughout disciplines. Scholars, including those who work in social movements, bargaining behaviour, foreign policy decision making, jury decision making, media effects, political psychology, public opinion and voting, campaigns, and others, have been utilising the framing approach (Druckman, 2001). Gitlin (1980) considered framing principles of selection, emphasis, and presentation composed of little tacit theories about what existed, what happened, and what mattered. Jamieson and Cappella (1997) reduced the interpretation of framing to how the story was written or produced, including orienting headlines, specific word choices, rhetorical devices employed, and

narrative forms, among others. Iyengar (1991) referred to the concept of framing as subtle alterations in the statement or presentation of judgment and choice problems.

The interdisciplinary roots of frames and framing can be traced back to sociology (Gamson & Modigliani, 1989; Gamson & Modigliani, 1994; Goffman, 1974), psychology (Kahneman, 2003; Kahneman & Tversky, 1979; Kahneman & Tversky, 2013), and linguistics (Lakoff & Johnson, 1980). The idea was first described by Bateson (1972) as a spatial and temporal bounding of a set of interactive messages, then further explained by Goffman (1974); framing can be understood as the practice of interpreting information within a familiar context. Druckman (2001) identified two distinct treatments of frames. Frames in thought, based on the groundwork laid by Goffman (1974), Kahneman and Tversky (2013), and Sweetser and Fauconnier (1996), refers to an individual's (cognitive) understanding of a given situation and what the individual sees as relevant to understanding a situation. On the other hand, frames in communication, following Gitlin (1980), Iyengar (1991), and Jamieson and Cappella (1997), refers to the words, images, phrases, and presentation styles that an informant uses when relaying information to another. The chosen frame may, in turn, express what the informant sees as relevant to the topic at hand.

To mass communication, framing theory refers to how the media chooses to package and present information to the public, i.e., "the frame" through which messages are delivered to the audiences that may influence their choice-making process (Baran & David, 2011; Hallahan, 2008; Littlejohn & Foss, 2010). DeVreese (2005) posited communication as a dynamic process involving frame-building (i.e., how frames emerged) and frame-setting (i.e., the interplay between media frames and audience predispositions). Frames have several locations, including the communicator, the text,

the receiver, the culture; they are integral to a process of framing that consists of distinct stages: frame-building, frame-setting, and individual and societal level consequences of framing (D'Angelo, 2002; De Vreese, 2003; Entman, 1993; Scheufele, 2000).

The notion of framing has gained momentum in communication disciplines, especially in media analysis and media-effects research (DeVreese, 2005; Nwabueze & Egbra, 2016). Scholars have been extensively applying framing theory to examine virtually every subject of news coverage, including politics. De Vreese, Peter, and Semetko (2001) posited that journalists, while reporting political and economic news, focused more on framing conflict rather than economic consequences. Strömbäck and Van Aelst (2010) dug deeper into the coverage of political elections in the media, considering commercialism as the driving force behind the framing of politics, and the type of media mattered when it came to the meta-framing of politics. Commercial news media and tabloids were more likely to frame politics as a game instead of issues compared to public service news media and quality newspaper, respectively.

Patterson (2000) also acknowledged the impacts of commercialisation, as well as the relationship between media commercialism and their inclination to frame politics as a strategic game in which politicians competed under universal terms. He further argued that by neglecting hard news (i.e., information which was presumably essential to citizens' ability to understand and respond to the world of public affairs such as coverage of breaking events involving top leaders, significant issues, or critical disruptions in the daily routines) and prioritising soft news (i.e., news that were not "hard"), the media contributed to declining interest in the news. Thus, hard news approaches would be a viable response to a hyper-competitive media environment.

On Twitter, during environmental protests against the operation of Cerattepe gold mine in Turkey in 2016, the framings of political economic and environmental justice were adopted by the protest network, and those frames fostered stable connections between activist groups (Doğu, 2019). Findings on the 2014 Colombian presidential election suggested a radical difference between the focus of journalists and the public on Twitter. While journalists pay attention to the issue frame (i.e., fundamental socioeconomic and political concerns), the public was more interested in the conflict frame (i.e., conflicts between individual, groups, or institutions). Likewise, while journalists employed the hate frame, the public attends to the peace frame (Garcia-Perdo, 2017). Hemphill, Culotta, and Heston (2013) found members of the US Congress to actively use social media, viz Twitter, to frame issues by choosing topics to discuss and employing explicit hashtags to highlight aspects of the topics. They also posited that those politicians spent their best efforts to frame recognisably divisive issues such as healthcare, jobs, energy policy, equal pay, and immigration. Furthermore, voting patterns generally aligned with tweeting patterns, i.e., US politicians tweeted and voted along the same polarised lines.

3.4. Research questions

Conforming to the design and objectives of the study, and after reflecting on the literature review and the theoretical framework explained above, the following research questions are proposed:

- RQ1a.** Who were the most active and influential users among the social network of Trump supporters on Twitter during the 2020 US presidential election?
- RQ1b.** What is the likeliness of those users being spamming bots?

- RQ2.** What were the most associated hashtags and the most retweeted tweets among the particular social network?
- RQ3.** Who were the most active memers among the social network of Trump supporters on Twitter during the 2020 US presidential election?
- H1a.** Memers among the community of Trump supporters on Twitter during the 2020 US presidential election primarily used internet memes to express grassroots support for Donald Trump
- H1b.** Memers among the community of Trump supporters on Twitter during the 2020 US presidential election primarily used internet memes to create an unfavourable, sometimes menacing, portrayal of Joe Biden

Chapter 4 - Methods

4.1. Data collection and study objectives

4.1.1. Part 1: Exploring the community of Trump supporters on Twitter

This study used the dataset provided publicly by Chen, Deb, and Ferrara (2020). Text files containing dehydrated tweet ids posted between October 27 and November 2 were collected via Subversion (GitHub, n.d.), 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 or #trump2020, posted between October 27 and November 2, 2020, was generated. The timeframe between October 27 and November 2 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, their affiliations, and their supporters during this period of time is generally expected (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 should reveal 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 examines the relationship between those groups of users. Details, such as those handles' likeliness of being spamming bots, would be 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 analysed 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, Groshek, & Zhang, 2019).

4.1.2. Part 2: Identify the memers

A subset of 18,172 tweets from the initial corpus that were original tweets and contained at least one internet meme in their content was generated. Internet memes, as identified in this part of the study, were repeating video loops (i.e., GIFs), image macros, or photographs with words superimposed on them to create commentary for the image (Foster, 2014). The second part of the study aims to identify the most active memers among the social network of Trump supporters during the 2020 US presidential election and evaluate the likeliness of those most active users being spamming bots.

4.1.3. Part 3: A content analysis of the internet memes

For this portion, the study referred to a corpus of 33,558 tweets containing either the hashtags #maga or #trump2020, and posted between October 27 and November 2, 2020 (i.e., one month before the general election day). A content analysis of the internet memes was conducted, with the codebook for analysing the content of internet memes adopted from Foster (2014) and Chagas, Freire, Rios, and Magalhães (2019) with adjustments following the objectives (see Appendix A).

Content analysis is a frequently used media research method which provides an effective way to investigate media content. The method alone, however, cannot serve as the basis for making statements about the effects of content on an audience (Wimmer &

Dominick, 2013). Walizer and Wienir (1978) defined content analysis as a “systematic procedure devised to examine the content of recorded information”. Krippendorf (2004) saw the method as “a research technique for making replicable and valid references from data to their context”. Nonetheless, content analyses should be conducted systematically, objectively, and quantitatively following its fundamental characteristics.

The goal of content analysis in this part of the study was to determine (1) whom did the memes target, (2) how were the targets portrayed in the memes, and (3) what were the main themes, or ideas, of the internet memes posted within the community of Trump supporters.

4.2. Twitter Capture and Analysis Toolset (TCAT)

The Twitter Capture and Analysis Toolset (TCAT) is a set of tools which allows users to retrieve and collect publicly available tweets from Twitter and analyse them in various ways. Apart from methodological transparency, the software provides robust and reproducible data capture and analysis while also interlinks 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”. This study utilises 4CAT, a variation of TCAT designed to capture and analyse 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 ODYCCEUS project (Peeters & Hagen, 2018).

TCAT and its application can be found extensively in contemporary communication research and has been mentioned, tested, and discussed in several studies. TCAT provides representative samples of tweets which are relatively

proportional to the total volume of tweets being posted at any given time, although it cannot give extensive and comprehensive access to all historical tweets (Bruns & Burgess, 2016; Gerlitz & Rieder, 2013; Groshek, de Mees, & Eschmann, 2020). Al-Rawi, Groshek, and Zhang (2019) used a dataset of 14,300,463 tweets by 2,493,949 unique users to study the propagation of #fakenews on Twitter. Groshek and Tandoc (2016) studied 4,231,684 tweets by 1,432,681 users, positing that legacy news organisations and affiliated journalists were least present and only marginally engaged in covering, while Twitter users emerged as far more prominent gatekeepers during the racially charged protests in Ferguson, Missouri in 2014. Huang and Wang (2019) explored how the Chinese government utilised a network of diplomatic Twitter accounts to “tell China stories well”, i.e., build a communication network and pursue external propaganda goals set by the Communist Party of China. Skrubbyeltrang, Grunnet, and Tarp (2017), via an analysis of a corpus of 3,913 tweets, examined users’ counter-narratives surrounding #RIPINSTAGRAM suggested that while technological advancement was generally welcomed and celebrated among users, their resistance towards algorithmic personalisation was increasing.

4.3. Gephi

Gephi, an open-source application for interactive graph analysis, network analysis, and visualisation, is among the most utilised one of its kind 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 allows for spatialising, 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, Heymann, & Jacomy, 2009; Groshek, de Mees, & Eschmann, 2020).

A plethora of mass communication research has adopted the power of Gephi to visualise and analyse networks, including social media networks on Twitter (Al-Rawi, Groshek, & Zhang, 2019; Bruns, 2012; Bruns & Highfield, 2013; Groshek & Tandoc, 2016; Larsson & Moe, 2012). Bruns (2012) argued that Gephi was the most appropriate tool to analyse and visualise the @reply networks between participating users around specific #hashtags on Twitter due to the active, highly responsive open-source development community and its focus on dynamic network visualisation despite the existence of competitive software packages.

4.4. Botometer

Botometer (at <https://botometer.iuni.iu.edu>) is a bot-evaluation API developed by a team from Indiana University whose 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, Groshek, & Zhang, 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). Botometer currently identifies six types of Twitter bots:

- Echo-chamber bots, or accounts that engage in follow back groups, as well as sharing and deleting political content in high volume.
- Fake follower bots, or bots purchased to increase follower counts.
- Financial bots, or bots that post using cashtags.
- Self-declared bots from botwiki.org.
- Spammers, or accounts labelled as spambots from several datasets.
- Other, or miscellaneous other bots obtained from other sources such as manual annotation or user feedback.

For example, Botometer evaluates the ten most followed Twitter accounts as of May 2020 (Clement, 2020) as follow. Noted that while a score of 3 or above indicates a high likeliness of the Twitter handle being a social bot, Al-Rawi, Groshek, and Zhang (2019) argued that the average bots’ score was 2.3.

Table 1. Bot scores, evaluated by Botometer, for the 10 most followed Twitter accounts as of May 2020

Position	Handle	Number of followers (in millions)	Botometer score
1	@barackobama	118.09	2.8
2	@justinbieber	111.78	1.1
3	@katyperry	108.5	0.5
4	@rihanna	96.94	0.1
5	@taylorswift13	86.14	1
6	@Cristiano	85.05	1.2
7	@ladygaga	81.5	1
8	@realDonaldTrump	80.46	—*
9	@TheEllenShow	80.15	0.8
10	@ArianaGrande	74.1	0.8

*The Twitter handle @realDonaldTrump, which belongs to Donald Trump, was permanently suspended by Twitter “due to the risk of further incitement of violence” after close review on January 8, 2021

(Twitter Inc., 2021). Thus, Botometer could not provide a score for the account. However, on a previous test conducted on November 25, 2020, @realDonaldTrump received a score of 3.4.

Interestingly, among these evaluations, while verified celebrities' accounts (e.g., Justin Bieber, Rihanna, Kary Perry, or Cristiano Ronaldo) secured understandably low bot scores (from 0.1 to 1.2), two verified politicians' accounts, namely those belonging to Barack Obama and Donald Trump, received relatively high bot scores (2.8 and 3.4, respectively). Other politicians, such as Joe Biden, Kamala Harris, and Mike Pence, were awarded above-average bot scores as well; they received 3.1, 2.7, and 2.8, respectively. Botometer often gives politicians' accounts high scores on Astroturf and Other; they admit to sometimes categorising "organisational accounts" as bot accounts, and that bot detection "is a hard task".

Nevertheless, 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; Yang et al., 2020).

Chapter 5 - Data analysis and results

Between October 27 and November 2, 2020, an average of 31,476.43 tweets containing the hashtags #maga or #trump2020 ($M = 31,019$, $SD = 7,196.03$) 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 ($M = 18,105$, $SD = 4,566.93$) posted on Twitter every day. November 2 had the highest number of unique Twitter users (29,459) while October 28 had the lowest (17,403).



Figure 2. Distribution of tweets and unique users mentioning #maga or #trump2020 between October 27 and November 2, 2020

5.1. Part 1: Exploring the community of Trump supporters on Twitter

5.1.1. The users

The approach to investigating RQ1a and RQ1b, due to noise and irrelevant content on social media, was to select top lists following previous studies that examined large datasets (Al-Rawi, 2017; Al-Rawi, 2019; Al-Rawi, Groshek, & Zhang, 2019; Wilkinson & Thelwall, 2012). Regarding the most active users among the network of Trump supporters on Twitter during the 2020 US presidential election, it can be seen that @Drizzle_500, who posted 550 tweets during the seven days between October 27 and November 2, 2020, appeared to be a Chinese account supporting Donald Trump and ranked first in the most-active chart (Table 1), followed by @cogitarus (453 tweets), @ReimTopher (341 tweets), @HassanYadollahi (341 tweets), and @Beorn1234 (268 tweets). Together, these top 100 most active users posted a total of 12,858 tweets ($Mean = 128.58$, $M = 108.5$, $SD = 70.41$), 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.

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).

Table 2. The top 100 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	.5
7	christo31129690	Deleted	229	-
8	Tony_Eriksen	Unverified	199	1.5
9	srogers0612	Unverified	198	.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	.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
26	JmkWalkow	Unverified	138	1.2
27	GracieMcKay7	Unverified	136	2
28	Una_Paloma1	Unverified	134	3.3

29-	dreamchqser	Unverified	133	1.4
29-	GwasiraT	Unverified	133	1.8
31-	Jjones8025M	Unverified	132	3
31-	PersianPatrio10	Unverified	132	3.3
33	pak_cyrus	Unverified	131	1
34	sarvnaz_e_hosn	Unverified	130	3.8
35	IrishRick3	Unverified	128	.6
36	SMC3141	Unverified	127	1.4
37	theendisnear04	Unverified	123	.5
38	QRESTARTMIGA	Unverified	121	1.2
39-	121Shahram	Unverified	119	1.4
39-	pstjeffanderson	Unverified	119	.4
41-	homarestart	Unverified	118	4.2
41-	MariaSo92340189	Unverified	118	4.1
43	mozzzzhiii	Unverified	117	1.7
44-	mitchsnnyder45	Unverified	116	4.8
44-	TolTak	Unverified	116	.7
46-	debbietuggleFL	Unverified	113	3.6
46-	raieskarimi	Unverified	113	1.4
46-	sobhan_samn	Unverified	113	.5
46-	TrulyUnique7	Unverified	113	.4
50	RestartYaar	Unverified	109	3.1
51-	biubiubiu7979	Unverified	108	1.6
51-	ciaocostarica	Unverified	108	1.1
51-	Spinn360	Unverified	108	0
54	CutGovt	Unverified	107	2.9
55-	chrysoils1	Unverified	105	1
55-	Janicedeshield1	Unverified	105	1
57	Amir_ZZAA	Unverified	104	1
58-	VALLEMULTICOLOR	Unverified	103	.6
58-	vote_Trump__	Unverified	103	.4

60	witrayler	Unverified	101	4.2
61	Restart44800571	Unverified	100	3.6
62-	dw4u2u	Unverified	99	2.4
62-	GasmiaMohamed_R	Unverified	99	1.4
62-	samsam767676	Unverified	99	1
65	VforVen93798340	Unverified	96	2.9
66	denniso805a	Unverified	95	3.7
67	Vladimi81231035	Unverified	93	4.4
68	edmondson_lisa	Unverified	92	.2
69-	CHPSRE	Unverified	91	3.7
69-	elham02168942	Unverified	91	2
69-	TonyToez	Unverified	91	.4
72	Amambo12Carlos	Unverified	90	.3
73-	eraseism	Unverified	89	4.4
73-	JD_FutUREPres	Unverified	89	3.7
75-	DavidDuvall8	Unverified	88	1
75-	pip1985	Unverified	88	3.7
75-	RSTfatima93	Unverified	88	4.6
78	Fardin15044871	Unverified	87	2.2
79-	bledsoe_wes	Unverified	86	2.2
79-	Fery_wise	Unverified	86	3.4
79-	miketow70210566	Unverified	86	1.1
82-	delfonik	Unverified	85	.8
82-	RezaTrump2020	Unverified	85	2.9
84-	DrAutismMum1	Unverified	84	1.6
84-	RogueQ5	Unverified	84	1.4
86-	Alaskag48809544	Unverified	83	1.6
86-	CindyB_717	Unverified	83	.5
86-	emily20960718	Unverified	83	1.3
86-	RLTraveler	Unverified	83	.6
90	Gerald_Weaver_	Unverified	82	3

91-	Jennife19080225	Unverified	81	1.4
91-	NewsLinksNet	Unverified	81	4.8
91-	VenezuelaNOdesm	Unverified	81	4.2
94	America1Cactus	Unverified	79	1.8
95-	doo_001	Unverified	78	4.8
95-	kolbe_Marie_jp2	Unverified	78	3.9
95-	mcleod	Unverified	78	1.3
95-	WB6DYN	Unverified	78	.4
99-	RubysPizza	Unverified	77	.6
99-	TrumpVirusUS1	Suspended	77	4 ^(*)

(*) By April 9, 2021, the Twitter handle @TrumpVirusUS1 has been permanently suspended by Twitter. Thus, Botometer could not provide a score for the account. However, on a previous test conducted on March 16, 2021, @TrumpVirusUS1 received a bot score of 4.

To determine the most influential users, top lists of the most mentioned users (Table 2) and the users whose tweets were most retweeted by 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 with 9,301 mentions, followed by his opponent Joe Biden (@JoeBiden, 3,678 mentions), Biden’s vice-president nominee Kamala Harris (@KamalaHarris, 1,050 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 chart are verified and can be categorised into groups of Republican politicians (e.g., Donald Trump (@realDonaldTrump, #2), Jack Posobiec (@JackPosobiec, #9), Kayleigh McEnany (@kayleighmcenany, #13), Dan Scavino (@DanScavino, #23), and Mike Pence (@Mike_Pence, #35)), Democratic politicians (e.g., Joe Biden (@JoeBiden, #2), Kamala Harris (@KamalaHarris, #3), Nancy Pelosi (@SpeakerPelosi, #21), Alexandria Ocasio-

Cortez (@AOC, #25), and Chuck Schumer (@SenSchumer, #48)), the media (e.g., CNN (@CNN, #14–), Fox News (@FoxNews, #29), Sean Hannity (@seanhannity, #31–), The Washington Post (@washingtonpost, #44–), and Jake Tapper (@jaketapper, #49)), celebrities (e.g., James Woods (@RealJamesWoods, #4), Lady Gaga (@ladygaga, #5), Lil Wayne (@LilTunechi, #20), Kirstie Alley (@kirstiealley, #27), and Brett Favre (@BrettFavre, #34)), and others.

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, Schmidt, Weaver, & Wilson, 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, ten 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).

Table 3. The top 50 most mentioned users

Rank	Handle	Account status	Times mentioned	Botometer score
1	realDonaldTrump	Suspended	9,301	-(1)
2	JoeBiden	Verified	3,678	2.2
3	KamalaHarris	Verified	1,050	2.5
4	RealJamesWoods	Verified	668	.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	.6
10	DonaldJTrumpJr	Verified	329	1.4
11	dbongino	Verified	317	-(2)
12	HillaryClinton	Verified	305	1.8
13	kayleighmcenany	Verified	293	.8
14-	CNN	Verified	283	4.2
14-	thehill	Verified	283	4.2
16-	EricTrump	Verified	239	.2
16-	IvankaTrump	Verified	239	1
18	DrBiden	Verified	212	.6
19	restartleader	Suspended	209	-
20	LilTunechi	Verified	185	.5
21	SpeakerPelosi	Verified	178	2
22	MSNBC	Verified	175	2.7
23	DanScavino	Verified	169	2
24	Acosta	Verified	165	.4
25	AOC	Verified	164	1.9
26	FreeCryptopia	Suspended	159	-
27	kirstiealley	Verified	157	.4
28	PeteButtigieg	Verified	153	1.2

29	FoxNews	Verified	152	3.4
30	BarackObama	Verified	151	2.1
31–	catturd2	Unverified	149	.7
31–	seanhannity	Verified	149	1.8
33	IngrahamAngle	Verified	147	.6
34	BrettFavre	Verified	135	1
35	Mike_Pence	Verified	130	2.4
36	WhiteHouse45	Verified	126	1.9
37	ScottPresler	Verified	123	3.8
38	POTUS45	Verified	120	3.7
39	ProjectLincoln	Unverified	119	1
40	charliekirk11	Verified	118	2.8
41	Beorn1234	Unverified	116	3.2
42–	GenFlynn	Suspended	115	-
42–	HKrassenstein	Unverified	115	1.4
44–	marklevinshow	Verified	111	1.6
44–	washingtonpost	Verified	111	4
46	nypost	Verified	104	4.6
47	CNNPolitics	Verified	103	3.8
48	SenSchumer	Verified	96	2.8
49	jaketapper	Verified	94	.4
50	ericcervini	Unverified	93	.1

⁽¹⁾ The Twitter handle @realDonaldTrump, which belongs to Donald Trump, was permanently suspended by Twitter “due to the risk of further incitement of violence” after close review on January 8, 2021 (Twitter Inc., 2021). Thus, Botometer could not provide a score for the account. However, on a previous test conducted on November 25, 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.

The former White House Deputy Chief of Staff for Communications Dan Scavino (@DanScavino), retweeted 18,013 times, led the top retweeted chart. He was retweeted about 4.5 times more than his runner-up, the conservative media outlet Right Side Broadcasting Network (@RSBNetwork, 4,006 times). They were followed by the incumbent vice-president and Republican vice-president nominee for the 2020 US

presidential election Mike Pence (@Mike_Pence, 3,195 times), Donald Trump’s daughter and senior advisor Ivanka Trump (@IvankaTrump, 2,747 times), and conservative media personality Lou Dobbs (@LouDobbs, 1,557 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, @honnnie2 (#36–, 4.8), received a bot score of 4 or above. The handle, self-described as “um [†] clTexas 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 #VoteRedToSaveAmerica) 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.

Table 4. The top 50 most retweeted users

Rank	Handle	Account status	Times retweeted	Botometer score
1	DanScavino	Verified	18,013	2

2	RSBNetwork	Verified	4,006	0
3	Mike_Pence	Verified	3,195	2.4
4	IvankaTrump	Verified	2,747	1
5	LouDobbs	Verified	1,557	1
6	larryelder	Verified	1,143	1.2
7	DiamondandSilk	Verified	1,130	1
8	jack_hikuma	Unverified	1,084	1.7
9	RealMattCouch	Unverified	803	3.2
10	sergiodireita1	Unverified	752	1.6
11	KarenPence	Verified	714	1.4
12	JennaEllisEsq	Verified	686	.4
13	chiakiasami	Unverified	630	1.6
14	Pismo_B	Unverified	623	1.4
15	BGOnTheScene	Unverified	621	2.2
16	eortner	Verified	556	.4
17	Beorn1234	Unverified	532	3.2
18	ksorbs	Verified	517	1
19	IWashington	Verified	512	.6
20	iwantbamboo	Unverified	465	.2
21	JasonMillerinDC	Verified	436	.9
22	TheLeeGreenwood	Verified	428	.7
23	abigailmarone	Unverified	404	.8
24	TheDailyEdge	Unverified	334	3.7
25	ColumbiaBugle	Unverified	332	1.6
26	AbediAA	Unverified	321	0
27	EricTrump	Verified	320	.2
28	MarleneFFL	Unverified	319	2.9
29	NicoleArbour	Verified	297	.1
30	sobhan_samn	Unverified	296	.6
31	LindaSuhler	Unverified	270	1.8
32	davidmweissman	Verified	267	.8

33	RichardGrenell	Verified	248	.6
34	PamBondi	Verified	247	1
35	mikandynothem	Unverified	240	3.9
36–	honninnie2	Unverified	232	4.8
36–	kinguilfoyle	Verified	232	1.4
38	aubrey_huff	Verified	225	0
39	CarlosSimancas	Unverified	214	1.6
40	BotSentinel	Unverified	212	3.6
41	w_terrence	Verified	211	1
42	SergioGor	Unverified	195	1.1
43	deAdder	Unverified	187	.3
44	EdanClay	Unverified	181	3.8
45	daniellesouzag	Unverified	179	.5
46	HizbkKhan	Unverified	175	2.2
47	sattarkhan121	Unverified	170	3.6
48–	bigredwavenow	Unverified	169	.4
48–	NINENEWSNANCY	Unverified	169	3.6
50	Feriii86681620	Unverified	166	1

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, ten users received a bot score of 3 or above, and @honninnie2 (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 popularising Restart, a fringe dissident community of Iranian opposition and conspiracy groups similar to QAnon (e.g., #MIGA, #RestartMIGA, or #restartleader) (Tabatabai, 2020).

To analyse the influential users and communities of users within the #maga and #trump2020 network during the 2020 US presidential election beyond simple frequency analysis of user mentions, a social network graph by mentions (Figure 3) 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 1,197 nodes, representing the most influential unique users, and 4,406 directed edges, representing mentions. Nodes were sized by weighted degree metrics, emphasizing users' influence within the network by their activity in mentioning other users and being mentioned by other users. The modularity algorithm detected communities within the network; colours highlighted these communities. The spatialization method of choice was OpenOrd (with Noverlap), which works well on real-world datasets while also produces visually appealing and globally accurate layouts for large datasets (Martin, Brown, Klavans, & Boyack, 2011). The graph is [available online in a dynamic interactive interface](#).

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 green cluster), and those who were related to @JoeBiden and @KamalaHarris (i.e., the violet cluster). There were also smaller and fragmented clusters of users, such as the orange cluster (with the most prominent social vortices being @JackPosobiec and

@RealJamesWood), the dark-grey cluster (with the most prominent social vortices being @TeamTrump and @TrumpWarRoom), or the blue cluster (with the most prominent social vortex being @Drizzle_500). @realDonaldTrump was mentioned 2,813 times by 394 different users and 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).

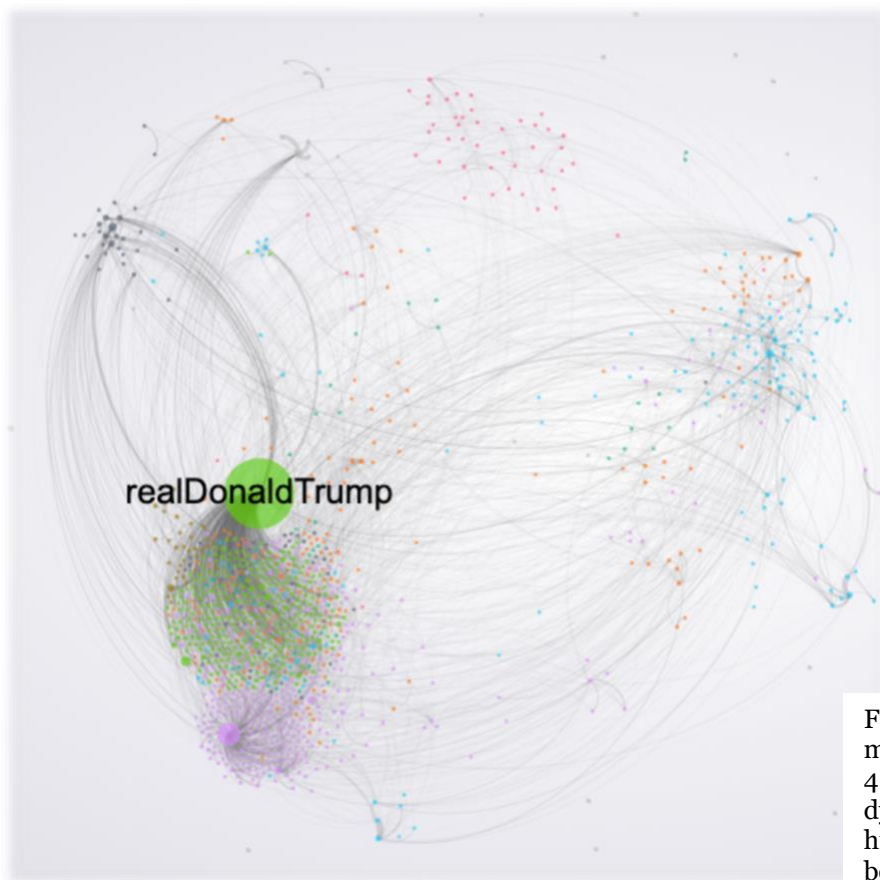


Figure 3. A social network graph by mentions of 1,197 nodes (users) and 4,406 directed edges (mentions); a dynamic interactive version with higher resolution and more details can be found [here](#)

@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 nine different users 142 times and was mentioned by three different users 114 times. The

account, curiously, mentioned itself 110 times; thus, its connection was somewhat limited, its 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.

5.1.2. The content

A list of the 50 most frequently used hashtags (case insensitive) among the community was generated (Table 4) to answer RQ2. 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, 6,667 times; #trump2020tosaveamerica, #12, 6,289 times; #trump Pence2020, #25, 1,864 times; #trumptrain, #28, 1,608 times; #trump2020nowmorethanever, #35, 1,311 times) and the Republican party (e.g., #gop, #21, 2,061 times; #redwave, #26, 1,767 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, 4,536 times) and urged eligible voters to cast their ballots (e.g., #vote, #5, 15,406 times; #vote2020, #46, 1,045 times), particularly for Donald Trump and his Republican allies (e.g., #votered, #16, 3,119 times; #voteredtosaveamerica, #27, 1,742 times; #votetrump2020, #38, 1,206 times; #voteredtosaveamerica2020, #45, 1,062 times; #voteredlikeyourlifedependsonit, #50, 917 times). Donald Trump received support from several social and political movements

on Twitter as well, including #miga (#10, 7,467 times) which is related to the dissident Restart community in Iran, #blexit (#30, 1,418 times) which convinces African American voters to stop supporting the Democratic party, #walkaway (#31, 1,405 times) which encourages liberals to flee from the Democratic party, and #latinosfortrump (#36, 1,281 times) which is a coalition of Latino supporters of Donald Trump.

Table 5. The top 50 most used hashtags

Rank	Hashtag	Frequency	Rank	Hashtag	Frequency
1	trump2020	95582	26	redwave	1767
2	maga	92451	27	voteredtosomeamerica	1742
3	maga2020	17062	28	trumptrain	1608
4	trump2020landslide	15866	29	electionday	1522
5	vote	15406	30	blexit	1418
6	trump	11574	31	walkaway	1405
7	election2020	10860	32	trumprally	1397
8	trump2020landslidevictory	10070	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	trump Pence2020	1864	50	voteredlikeyourlifedependsonit	917

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 2,832 times, followed by #bidenharris2020 (#19, 2,780 times) and #joebiden (#22–, 1,993 times). The Democratic presidential nominee and his family were primarily accused of corruption (e.g., #bidencrimefamily, #33, 1,394 times; #bidencorruption, #40, 1,121 times; #bidencrimefamily, #41, 1,113 times); ironically, #bidencrimefamily, which had a typo in itself, appeared more frequently in the corpus than #bidencrimefamily. 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 running for the presidential office in 2016, Donald Trump had repeatedly used the motto #draintheswamp (#39, 1,143 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, Helderman, & Fahrenthold, 2020). The term “drain the swamp” was first used in 1903 by Social Democratic Party organiser Winfield R. Gaylord to metaphorically describe how socialists wish to deal with big business (Know Your Meme, 2017; Polpik, 2010).

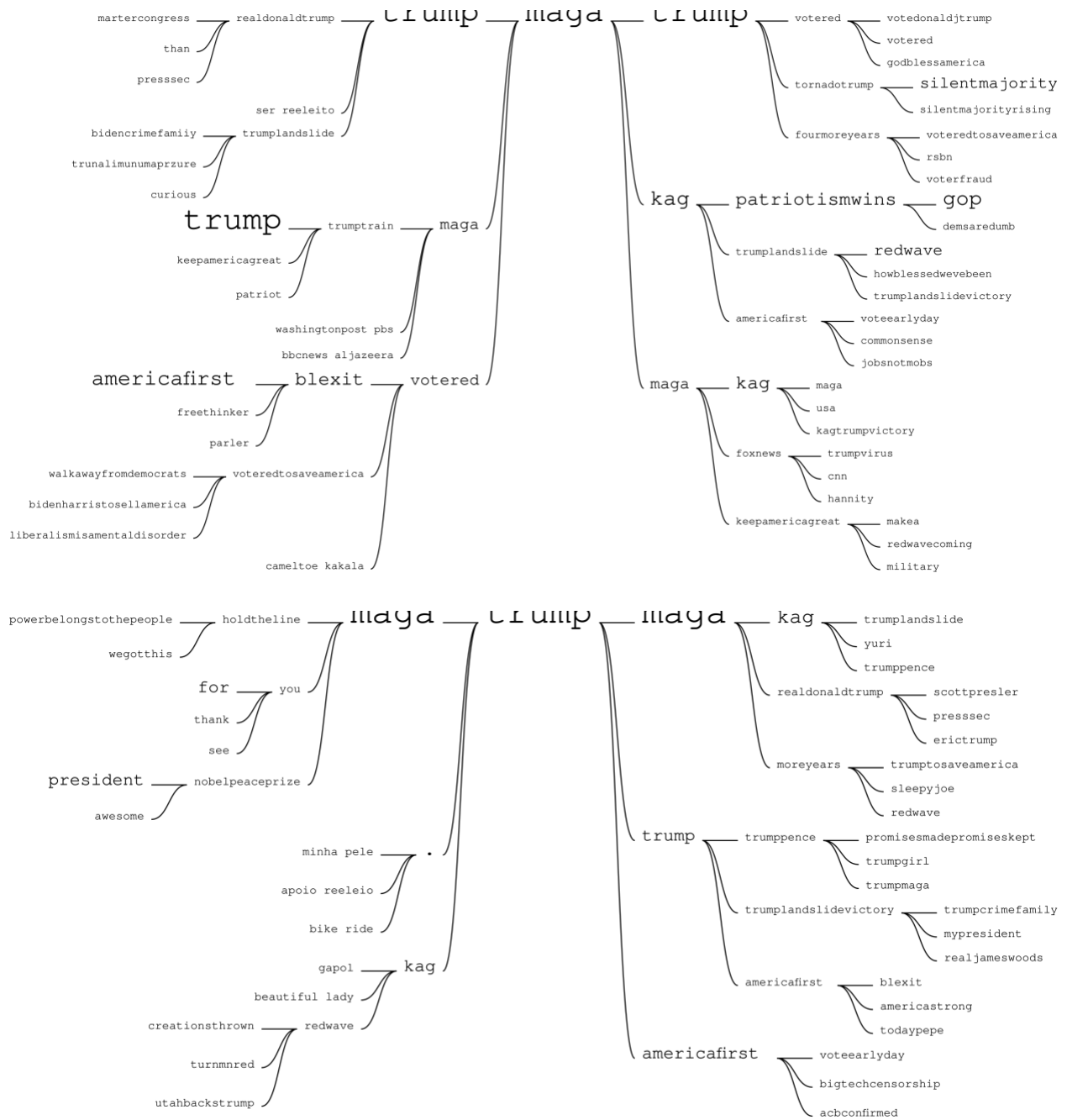


Figure 4. Word trees for “maga” and “trump” (Wattenberg & Viégas, 2008)

#covid19 (#24, 1,878 times) was another topic of discussion. As of November 1, 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 (CDC, 2020; WHO, 2020). Although Donald Trump and his

supporters gave him “a 10 out of 10” on his efforts against COVID-19, experts generally criticised the Trump administration’s response to the coronavirus disease, arguing that their strategy was “lack of candour”, “lack of science”, and “very likely did cost lives” (Chalfant, 2020; Howard & Kelly, 2021; Stracqualursi, 2021). #michigan (#43, 1,073 times) and #pennsylvania (#44, 1,070 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 & Martina, 2020; Schulte & Eggert, 2020) while 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 5) 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 2,628 nodes, representing hashtags, and 10,4492 undirected edges, representing hashtag co-occurrences. Nodes were sized by weighted degree metrics, emphasizing hashtags’ frequency and their connection with other hashtags. 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). 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 (Gephi, 2011). The graph is [available online in a dynamic interactive interface](#).

#trump2020 and #maga co-occurred with 2,344 and 2,298 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, 6,568 times; #trump2020-#4moreyears, 5,140 times; #trump2020-#election2020, 4,704 times; #trump2020-#americafirst, 3,380 times; #trump2020-#blexit, 2,302 times; #maga-#election2020, 16,264 times; #maga-#kag, 10,520 times; #maga-#americafirst, 4,420 times; #maga-#trump2020landslide, 3,382 times; #maga-#kag2020, 2,898 times). The third most frequently used hashtags among the network, #trump2020landslide, co-occurred 59,902 times with 1,464 different hashtags, including #trump2020 (6,642 times), #maga (3,382 times), and other hashtags supportive of Donald Trump or against Joe Biden such as #kag (922 times), #4moreyears (674 times), #redwave (622 times), or #bidencrimefamily (570 times).

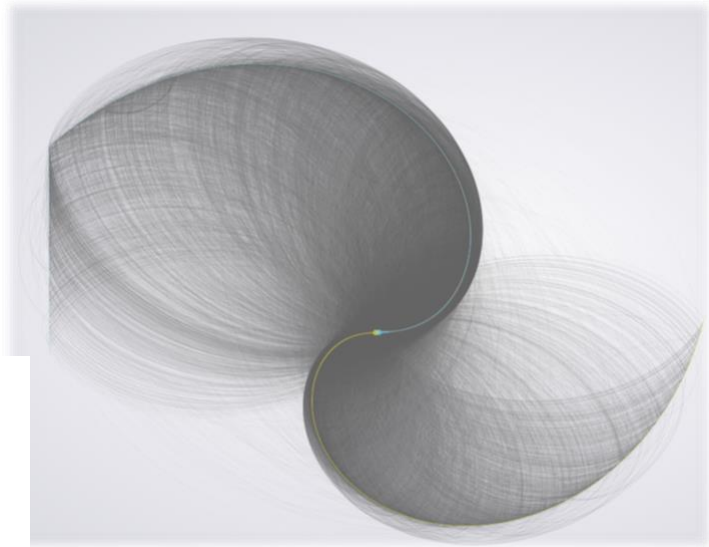


Figure 5. A social network graph by hashtag co-occurrences of 2,628 nodes (hashtags) and 104,492 undirected edges (co-occurrences); a dynamic interactive version with higher resolution and more details can be found [here](#)

#biden and #bidenharris2020 were related to the #trump2020 cluster while #joebiden belonged to neither of the two major clusters. #covid19, on the other hand,

was categorised 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), #trumpliespeopledie (32 times), and #trumphasnoplan (30 times).

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.

A chart of the top 50 most retweeted tweets (Table 5), which were 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, 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; #33 by @abediaa (retweeted 321 times) sarcastically made fun of "MAGA-heads"; #43 by @davidmweissman (retweeted 256 times) supported Joe Biden, believing him and like-minded politicians such as Barack Obama, Hillary Clinton, and Kamala Harris to be the actual fighters for the people's rights. The former White House Deputy Chief of Staff for Communications Dan Scavino (@DanScavino) dominated the most retweeted tweets

chart with 21 tweets that were retweeted 16,475 times, constituting 58.28% of the retweet volume of the 50 most retweeted tweets.

Table 6. The 50 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	3,086
2	RT @DanScavino: HAPPENING NOW! #MAGAus 🇺🇸	1,997
3	RT @RSBNetwork: 🎵🎵🎵 "I will vote for Donald Trump!" 🎵🎵🎵 Miami is PARTYING as they wait for @realDonaldTrump to arrive!! 🇺🇸🇺🇸🇺🇸 #MAGA #MiamiForTrump	1,674
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	1,637
5	RT @DanScavino: Happening now in Goodyear, ARIZONA! 6 DAYS!! LET'S WIN, WIN, WIN!!! #MAGAus 🇺🇸	1,064
6	RT @DanScavino: LET'S GO PENNSYLVANIA! #Election2020 #MAGAus 🇺🇸	1,037
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.	556

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!

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
26	RT @IvankaTrump: Happy Halloween 🎃 from Youngstown, Ohio! 🤔🙄 #MAGA	431
27	RT @JennaEllisEsq: This makes me so proud to be an American. us THE BEST IS YET TO COME!!! #Trump2020	397
28	RT @IvankaTrump: ❤️ Pennsylvania! #MAGA	371

29	RT @DanScavino: Happening Now—another massive MAKE AMERICA GREAT AGAIN rally in SCRANTON, PENNSYLVANIA! Get out and VOTE to #MAGA, Pennsylvania! Let's WIN! http://Vote.DonaldJTrump.com	356
30	RT @Mike_Pence: RT @Mike_Pence: MICHIGAN FOR TRUMP! Thank you to some incredible American patriots for a great night in Flint! #MAGA us	354
31	RT @Mike_Pence: On my way, Wilmington, North Carolina! #MAGA	338
32	RT @TheLeeGreenwood: MAGA! #Trump2020 #GodBlessTheUSA	333
33	RT @abediaa: MAGA-heads giving Iblis a shoutout for supporting Trump. What they don't realize is that Iblis = Satan in Arabic 🗡️👹 #MAGA #Trump #TrumpRally #TrumpMeltdown #Iblis #Satan	321
34	RT @IvankaTrump: Great to be in Sarasota! 🌟 Excited to see everyone at the rally this afternoon! #MAGA us	316
35	RT @DanScavino: Sunday, November 1, 2020—Washington Township in Macomb County, Michigan! #MAGAus 🗡️	313
36	RT @NicoleArbour: I'm Nicole Arbour, and heck yeah I endorse @realDonaldTrump for President. #Trump2020	297
37	RT @larryelder: On my street, all you see are Biden signs. But this one's a little different. #Trump2020	292
38	RT @IvankaTrump: Thank you Sarasota! #MAGA	290
39	RT @DanScavino: WOW!!!! #MAGAus 🗡️	287
40	RT @DanScavino: HAPPENING NOW—President @realDonaldTrump in Green Bay, Wisconsin! #MAGAus 🗡️	275
41	RT @chiakiasami: 民主党・バイデン支持者の仕業?? 狂気でしかない... #MAGA #VOTE #MakeAmericaGreatAgain #トランプ大統領の再選を断固支持します	265
42	RT @Mike_Pence: TUCSON is ready for FOUR MORE YEARS of President @realDonaldTrump! #MAGA #VOTE us	260
43	RT @davidmweissman: #MAGA, troll me all you want. President Obama, Hillary Clinton, Joe Biden & Kamala Harris do not want to take our rights away. Fighting for rights of others will not infringe on your rights, I promise you that, you can hold me to that. This election is a moral one, not political.	256

44	RT @DanScavino: President @realDonaldTrump departing WISCONSIN! Next stop, NEBRASKA! #MAGAus 🇺🇸 🌐 https://Vote.DonaldJTrump.com	248
45	RT @IWashington: Fxck These Masks! #MAGA us	242
46	RT @Mike_Pence: Wheels up! See you soon North Carolina for a GREAT #MAGA event!	241
47	RT @sergiodireita1: O fenômeno Trump. Contemplem! um #TrumpLandslide #MAGA	237
48-	RT @BGOnTheScene: Nuns for Trump in the front row for today's rally #TrumpRally #NunsForTrump #Trump2020	236
48-	RT @Mike_Pence: It's going to be a GREAT day on the campaign trail! Let's get it done! #MAGA us Latrobe, PA us Erie, PA us Traverse City, MI us Grand Rapids, MI	236
50	RT @aubrey_huff: The polls are bullshit! Don't let it fool you. @realDonaldTrump wins big! #Trump2020LandslideVictory	224

A bipartite social network graph by hashtag-user co-occurrences (Figure 6) 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 visualised 5,212 nodes, representing 3,672 users and 1,540 hashtags, and 48,396 undirected edges, representing user-hashtag co-occurrences. Nodes were sized by weighted degree metrics, emphasizing users' influence within the network by their activity in using hashtags, hashtags' frequency, and the connection between users and hashtags within the network. User nodes were coloured in a violet shade based on their weighted degree metrics; the darker their colour was, the more active they were in using hashtags within the network. Meanwhile, hashtag nodes were classified into three clusters, namely the #trump2020 cluster (i.e., the yellow cluster), the #maga cluster (i.e., the blue cluster), and others (i.e., the grey clusters). The

spatialization layout of choice was dual circle, which distributed nodes in a circle while located high-degree nodes on a separate circle. In this bipartite graph, #trump2020 and #maga were identified as the high-degree nodes. Other hashtag nodes and user nodes were arranged on a circular layout around those high-degree nodes. The graph is [available online in a dynamic interactive interface](#).

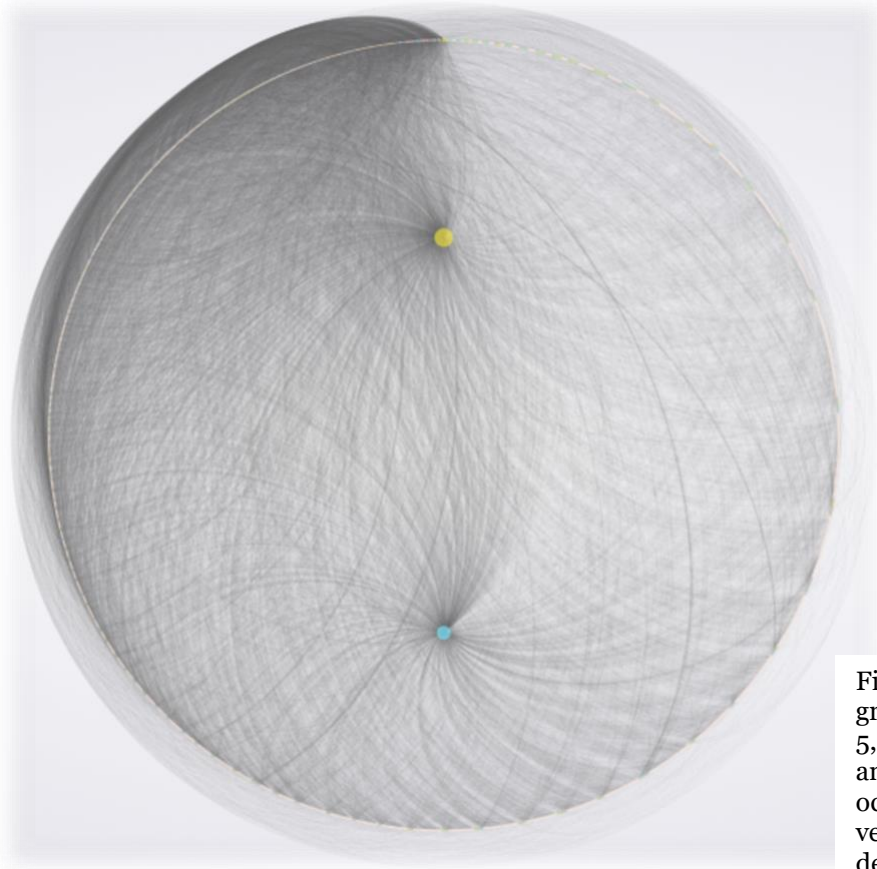


Figure 6. A bipartite social network graph by hashtag-user co-occurrences of 5,212 nodes (3,672 users, 1,540 hashtags) and 48,396 undirected edges (co-occurrences); a dynamic interactive version with higher resolution and more details can be found [here](#)

#trump2020 was employed by 2,773 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 favourites, 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) being their most frequently used hashtags. Another high-degree hashtag, #maga, was employed by 2,523 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.

#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 employing #bidencorruption (288 times) and #bidencrimefamily (271 times), attempting to illustrate an ill-favoured 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' favourite 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.

5.2. Part 2: Identify the memers

Among the original corpus of 220,336 tweets, 18,172 (or 8.25%) of them were original (i.e., not retweeted) tweets that have at least a photo or a gif in their content. Regarding RQ3, the most active visual storytellers within this subset of 18,172 tweets were @Tony_Eriksen (199 memes, ranked #8 among the most active users in the corpus) followed by @Steffy77277270 (124 memes, #19– most active) @MariaSo92340189 (111 memes, #41– most active), @VALLEMULTICOLOR (78 memes, #58– most active), and @CutGovt (76 memes, #54 most active). Their Twitter content suggested that they were Donald Trump and Republican supporters. @Feriii86681620, the #21 most active memers, were one of the only two most active memers who appeared in the most retweeted chart at #50. @Beorn1234 appeared again in the most active memers chart at #26–, thus becoming the only Twitter account who had a position in every user chart in this study.

Some of the most active accounts (e.g., @Gerald_Weaver_, an author who ranked #12 among most the active memers and #90 among the most active users), as mentioned previously, used the hashtags #maga and #trump2020 to oppose Donald Trump and support Joe Biden. Again, since none of the most active memers' account was verified by Twitter, their identities could not be confirmed. Twenty (or 40%) of the most active memers also featured in the top 100 most active users chart (Table 1). The 50 most active memers were accounted for 2,526 original tweets, merely 1.72% of original tweets, and received an average bot score of 2.06 ($M = 1.5$, $SD = 1.42$); 18 users received an above average bot score, 17 users received a bot score of 3 or above, and eight users received a bot score of 4 or above. Thus, 9 (or 18%) of the most active memers were potentially bots (i.e., received a bot score from 3 to 3.9) while eight (or

16%) of them were highly likely to be bots (i.e., received a bot score of 4 or above), a roughly similar ratio of suspected spamming bots compared to Table 1.

Table 7. The 50 most active memers

Rank	Handle	Account Status	Memes posted	Botometer score
1	Tony_Eriksen	Unverified	199	1.5
2	Steffy77277270	Unverified	124	1.1
3	MariaSo92340189	Unverified	111	4.1
4	VALLEMULTICOLOR	Unverified	78	.6
5	CutGovt	Unverified	76	2.9
6	Amambo12Carlos	Unverified	75	.3
7-	SwerianBot	Unverified	74	4.2
7-	TonyToez	Unverified	74	.4
9	mitchsnyder45	Unverified	69	4.8
10-	BorisGreybeard	Unverified	68	.4
10-	is_ceiling	Unverified	68	3.6
12	Gerald_Weaver_	Unverified	66	3
13	delfonik	Unverified	59	.8
14	BrettT18349489	Unverified	53	1.4
15	WB6DYN	Unverified	52	.4
16	DrAutismMum1	Unverified	49	1.6
17	restart_vandeta	Unverified	47	1.2
18	JOHNAVATARcom	Unverified	46	1
19-	Eric51399692	Unverified	45	4.2
19-	urgent_logo_652	Unverified	45	4.1
21	Feriii86681620	Unverified	44	1
22	otiose94	Unverified	43	1
23	moralesch	Unverified	40	1
24	PersiaOld	Unverified	38	3.6
25	RussiaIfYouAre	Unverified	36	.8

26-	Beorn1234	Unverified	35	3.2
26-	MadnessWhiskey	Unverified	35	4.4
28	H3ow12t17	Unverified	33	3.8
29-	OBJECONCIENCIA	Unverified	30	1.2
29-	qjersey2	Unverified	30	2
31	ILIYA1981	Unverified	29	1.4
32	myriamwinner1	Unverified	29	1.2
33	SNOWMAN2020641	Unverified	28	3.4
34	sharoncabana	Unverified	27	0
35	JESUSisKINGOD	Unverified	26	1.6
36	LarkspurShorty	Unverified	25	4.6
37-	ChechekinGolo	Unverified	24	1.8
37-	GeneMcVay	Unverified	24	3.8
37-	ImWenXiao	Unverified	24	1.4
37-	OLulaEstaPreso	Unverified	24	1.4
41-	FreedomWarro	Unverified	23	1.8
41-	mjr1900_rl	Unverified	23	.2
41-	Satire_huch	Unverified	23	3.2
41-	TheXrayDave	Unverified	23	1.5
45-	America14697952	Unverified	22	1
45-	JohnBorden	Unverified	22	.9
45-	MaeSubtle	Unverified	22	3.6
45-	Str8Say	Unverified	22	1.6
45-	SusanMThom	Unverified	22	1
45-	TrumpVirusUS1	Suspended	22	4*

(*) By April 9, 2021, the Twitter handle @TrumpVirusUS1 has been permanently suspended by Twitter. Thus, Botometer could not provide a score for the account. However, on a previous test conducted on March 16, 2021, @TrumpVirusUS1 received a bot score of 4.

5.3. Part 3: A content analysis of the internet memes

For this portion, the study referred to a corpus of 33,558 tweets containing either the hashtags #maga or #trump2020, and posted between October 27 and November 2,

2020 (i.e., one month before the general election day). The corpus was generated via 4CAT. Four-hundred and ninety-one internet memes from the corpus were collected and analysed to identify the type of political memes, their target, and how the target was portrayed. A codebook, adopted from Foster (2014) and Chagas, Freire, Rios, and Magalhães (2019) with adjustments can be found in Appendix A. Two coders performed the coding process. Krippendorff's α for intercoder reliability on 50 memes (i.e., approximately 10% of the sample) indicated strong results: .878 for type of political memes, .939 for portrayal, and 1 for offensive words, target, extremist affiliation, and sentiment (Freelon, 2010, 2013).



Figure 7. A picture wall consists of 120 memes collected from the subset of 33,558 tweets containing either the hashtags #maga or #trump2020, and posted between October 27 and November 2, 2020

Donald Trump, his allies, Republican politicians, or conservatives (identified as “the Trump side” for Part 3) were portrayed in 343 internet memes (69.86%) while Joe Biden, his allies, Democratic politicians, or liberals (identified as “the Biden side” for Part 3) were the targets of 141 internet memes (28.72%). The target of seven memes could not be identified or clarified. Two-hundred memes (40.73%) were grassroots

action memes, 157 memes (31.98%) were persuasive memes, and 134 memes (27.29%) were public discussion memes. Only 28 memes (5.7%) contained one or more offensive words; offensive language can be used to signify a number of emotions such as anger, frustration, joy, or surprise (Jay, 2009).



Figure 8. Examples of the types of political memes

Over half (284, or 57.8%) of the memes portrayed the target positively while only 186 memes (37.9%) portrayed their target negatively. Pearson’s χ^2 test with simulated p-value indicated a statistically significant association between the memes’ target and their sentiment ($\chi^2(4, 491) = 430.36, p < .001$, Cramer’s $V = .66$). The sentiment towards the Biden side was predominantly negative (in 134 memes, or 95%) while the sentiment towards the Trump side was mostly positive (in 277 memes, or 80.8%). Fifty-two memes (15.2%) portrayed the Trump side negatively and another 14 memes (4.1%) portrayed them neutrally (Table 7).

Table 8. Crosstabulation regarding the association between the memes' target and their sentiment

	Negative		Neutral		Positive	
	N	%	N	%	N	%
The Biden side	134	95%	0	0%	7	5%
The Trump side	52	15.2%	14	4.1%	277	80.8%
Unspecified	0	0%	7	100%	0	0%
Total	186	37.9%	21	4.3%	284	57.8%

One hundred and eighty-six memes (37.9%) portrayed their target as an ideal politician, candidate, or sure winner. Ninety-eight memes (20%) portrayed their target as a populist or a candidate that the people supported. Meanwhile, the loser (or the incapable) and the menace (or the criminal) frames were both employed in 94 memes (19.1%) each. The target's portrayal in 19 memes (3.9%) could not be specified. Pearson's χ^2 test with simulated p-value indicated a statistically significant association between the memes' target and their portrayal ($\chi^2(8, 491) = 450.67, p < .001$, Cramer's $V = .68$). As can be seen, the community of Trump supporters on Twitter used internet memes primarily to support Donald Trump and his side as they were framed as the politician (or the ideal candidate) and the populist 182 times (53.1%) and 96 times (28%), respectively. On the other hand, they attacked Joe Biden and his side rather mercilessly, framing him as the loser (or the incapable) and the menace (or the criminal) 59 times (41.8%) and 75 times (53.2%), respectively. Donald Trump was also a target of dissent, although much less frequently than Joe Biden, portrayed as the loser (or the incapable) 35 times (10.2%) and the menace (or the criminal) 19 times (5.5%).

While opposers of Donald Trump focused their criticism on Trump's failures, incapability, and improper acts and remarks during his presidential term, and accused him of spreading hate, discrimination, and fake news, as well as being lawless and a liar, those who were against Joe Biden based their arguments on seemingly unsubstantiated claims. For instance, they branded the former vice-president a paedophile, a puppet of the Chinese Communist Party, or a disappointment who had achieved nothing in his political career. They also launched personal attacks towards the Biden side; for example, they directed their aggression toward Hunter Biden, Joe Biden's son, on his alleged connection with the Ukrainian government and his drug addiction.

Table 9. Crosstabulation regarding the association between the memes' target and their portrayal

	The politician, or the ideal candidate		The populist		The loser, or the incapable		The menace, or the criminal		Other	
	N	%	N	%	N	%	N	%	N	%
The Biden side	4	2.8%	2	1.4%	59	41.8%	75	53.2%	1	.7%
The Trump side	182	53.1%	96	28%	35	10.2%	19	5.5%	11	3.2%
Unspecified	0	0%	0	0%	0	0%	0	0%	7	100%
Total	186	37.9%	98	20%	94	19.1%	94	19.1%	19	3.9%

The majority (430, or 87.58%) of memes were not portrayed along with, or attached to, symbols or implications of extremist affiliations. Twenty-six memes (5.3%) included symbols, images, or paraphernalia that are usually connected to extreme left-wing ideologies and activities, 20 memes (4.07%) included symbols, images, or paraphernalia that are usually connected to extreme right-wing ideologies and activities, and 15 memes (3.06%) included other extremist affiliations such as terrorist organisations, proto-states, or other foreign-influenced affiliations. Pearson's χ^2 test with simulated p-value indicated a statistically significant association between the memes' target and the extremist affiliations portrayed along with them ($\chi^2(6, 491) = 61.37, p < .001, \text{Cramer's } V = .25$). The Biden side was connected to left-wing extremist affiliations in 23 memes (16.3%) and other extremist affiliations in nine memes (6.4%), while the Trump side was connected to right-wing extremist affiliations and other extremist affiliations in 19 memes (5.5%) and six memes (1.7%), respectively.

Table 10. Crosstabulation regarding the association between the memes' target and extremist affiliations

		The Biden side	The Trump side	Unspecified	Total
No extremist affiliations	N	108	315	7	430
	%	76.60%	91.80%	100%	87.60%

Left-wing extremist affiliations	N	23	3	0	26
	%	16.30%	0.90%	0%	5.30%
Right-wing extremist affiliations	N	1	19	0	20
	%	0.70%	5.50%	0%	4.10%
Other extremist affiliations	N	9	6	0	15
	%	6.40%	1.70%	0%	3.10%

Pearson's χ^2 test with simulated p-value indicated a statistically significant association between the memes' target and the type of internet memes they were ($\chi^2 (4, 491) = 112.9, p < .001$, Cramer's $V = .34$). Memes targeting the Trump side were predominantly grassroots action memes (190 memes, or 55.4%), followed by persuasive memes (93 memes, 27.1%). Meanwhile, memes targeting the Biden side could be primarily categorised into public discussion memes (71 memes, 50.4%) and persuasive memes (63 memes, 44.7%).

Table 11. Crosstabulation regarding the association between the memes' target and the types of internet memes they were

	Persuasive memes		Grassroots action memes		Public discussion memes	
	N	%	N	%	N	%
The Biden side	63	44.7%	7	5%	71	50.4%
The Trump side	93	27.1%	190	55.4%	60	17.5%
Unspecified	1	14.3%	3	42.9%	3	42.9%
Total	157	32%	200	40.7%	134	27.3%

Among the 141 internet memes targeting the Biden side, Pearson's χ^2 test with simulated p-value indicated a statistically significant association between the types of internet memes and the memes' sentiment ($\chi^2 (2, 141) = 22.42, p < .001$). Memers within the network of Trump supporters on Twitter used persuasive memes and public discussion memes mainly to depict a negative, unfavourable portrait the Biden side,

while the sentiment of grassroots action memes targeting those individuals and entities were more balanced (42.9% positive and 57.1% negative).

Table 12. Crosstabulation regarding the association between the types of internet memes and the sentiment among the 141 internet memes targeting Joe Biden, his allies, Democratic politicians, and liberals

	Positive		Negative	
	N	%	N	%
Persuasive memes	2	3.2	61	96.8%
Grassroots action memes	3	42.9%	4	57.1%
Public discussion memes	2	2.8%	69	97.2%
Total	7	5%	134	95%

Among the 343 memes targeting The Trump side, Pearson’s χ^2 test with simulated p-value indicated a statistically significant association between the types of internet memes and the memes’ sentiment ($\chi^2(4, 141) = 73.36, p < .001$). The percentage of positive sentiment towards the Trump side was highest among grassroots action memes (182 memes, 95.8%), followed by persuasive memes (59 memes, 63.4%) and public discussion memes (36 memes, 60%). On the other hand, only 31 persuasive memes (33.3%) and 20 public discussion memes (33.3%) were framed negatively against Donald Trump and his side. The only grassroots action meme that portrayed Donald Trump negatively had an American flag in its content along with the text: “I’d rather be an American than a Trump supporter”. While only a few memes (14 memes, or 4.1%) framed the Trump side neutrally, half of them were grassroots action memes.

Table 13. Crosstabulation regarding the association between the types of internet memes and the sentiment among the 343 internet memes targeting Donald Trump, his allies, Republican politicians, and conservatives

	Positive		Neutral		Negative	
	N	%	N	%	N	%

Persuasive memes	59	63.4%	3	3.2%	31	33.3%
Grassroots action memes	182	95.8%	7	3.7%	1	.5%
Public discussion memes	36	60%	4	6.7%	20	33.3%
Total	277	80.8%	14	4.1%	52	15.2%

Findings of Part 3 supported H1a and H1b in positing that memers among the community of Trump supporters on Twitter during the 2020 US presidential election primarily used internet memes to express grassroots support for Donald Trump, his allies, Republican politicians, and conservatives while also attempt to create an unfavourable, sometimes menacing, portrayal of Joe Biden, his allies, Democratic politicians, and liberals.

Chapter 6 - Discussion

This study is, perhaps, one of the earliest in its field 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, and internet memes in political discourse, positioning such concepts in the political context of the 2020 US presidential election.

The hierarchy of Donald Trump

Donald Trump was 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 3, no other individual or institution among the particular network, even those on his side, could compete with him in imposing their influence on other members. In Figure 3, Trump had a weighted degree of 2,813, 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 January 8, 2021 (Twitter Inc., 2021), which means that his tweets could not be taken into consideration. Between October 27 and November 2, 2020, Donald Trump posted 366 original tweets via his handle, or 52.29 tweets per day ($M = 60$, $SD = 15.71$) (Trump Twitter Archive, 2016). He would rank third in the most

active chart (Table 1) was his handle not suspended, and imagine how even bigger his node would be in the social network graph were his 366 tweets calculated.

The rise of Donald Trump, which reflected long-standing political and economic currents both domestically and globally, happened in an era in which anti-Black violence, violence against Native American activists, police brutality, civilian hate crimes, and the ritual miscarriages of justice had gone viral (Rosa & Bonilla, 2017). Bouie (2016) argued that many whites among Trump supporters were those who became hyperaware of their racial status under the Obama administration and turned themselves into victims of white fragility. White fragility is, as described by DiAngelo (2018), a state in which even a minimum amount of racial stress became intolerable, triggering a range of defensive moves (e.g., the outward display of emotions such as anger, fear, and guilt) and behaviours (e.g., argumentation, silence, and leaving the stress-inducing situation). As a result, Donald Trump became their hope to restore the racial hierarchy upended by his predecessor. Pettigrew (2017) argued that five major social psychological phenomena, including authoritarianism, social dominance orientation, prejudice, relative deprivation, and intergroup contact, could help in describing Trump supporters; thus, two common traits among Trump supporters were that they had a rigidly hierarchical view of the world and they deferred to authority.

In many ways, the activities, behaviours, and expressions of Donald Trump and his supporters, particularly on Twitter, showed characteristics of a cult of personality, a phenomenon “refers to the idealised, even god-like, public image of an individual consciously shaped and moulded through constant propaganda and media exposure”. Such idealised, 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 & Lauer, 2013). This argument is supported by Hickman (2019) in which the author 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 as the charismatic leader, especially in politics, has increasingly become the product of media and self-exposure (Wright & 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. On social media, Donald Trump dedicated a considerable portion of his posts to endorse himself, insisting that he was the only candidate who could "make America great again, defeat terrorism, contrast illegal immigration, and self-fund his campaign" (Lee & Quealy, 2019). 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. Rawi, Groshek, and Zhang (2019) highlighted that Donald Trump also dominated the #fakenews community on Twitter between January 3 and May 7, 2018, using his influence to manipulate supporters and allies into reinforcing his agenda, i.e., associating mainstream media with fake news and vilifying major news organisations, particularly CNN.

History has shown that cults of personality would lead to virtually nothing but devastating consequences (e.g., the Fascist Italy, the Third Reich in Germany, or The Great Purge in the Soviet Union). The legacy of the cult of personality of Donald Trump on Twitter, while fortunately may not be as grim as a genocide, will unfortunately be carried on by his supporters. For instance, there is already an America First Caucus launched by Donald Trump's loyalists (e.g., Georgia Representative Marjorie Taylor Greene and Arizona Representative Paul Gosar) which expressed their intention to "follows in President Trump's footsteps" using numerous dog whistles (Mathis-Lilley, 2021; Wang & Itkowitz, 2021), although the handle @realDonaldTrump is now suspended and he is not sitting in the White House anymore.

The problematic nature of bot detection

The most active users in the corpus received an average bot score of 2.14. The average bot score was lower than the binary thresholds defined by Al-Rawi, Groshek,

and Zhang (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 signalled 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 October 27 and November 2, which was equivalent to averagely 78.57 tweets per day, or roughly one tweet every 18 minutes, nonstop. Similarly, @cogitarus tweeted 453 times in seven days, averagely 64.71 tweets every day, or roughly one tweet every 22 minutes. Such frequencies of tweeting seem inhuman even for social media addicts. Howard, Kollanyi, and Woolley (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".

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 and @cogitarus a bot score of 1.4, which suggested that those users were 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 sometimes, 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, Kollanyi, & Woolley, 2016). 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 criticised the approach of bot detection tools, including Botometer and Bot Sentinel, as extremely limited (Roth & 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 controlled by both human and bots (i.e., semi-automated and semi-

manual) (Rauchfleisch & Kaiser, 2020), it can be concluded that the media also employ a certain level of automation to disseminate their agenda and contents.

Memetic political discourse in the 2020 US presidential election

Findings were consistent with Moody-Ramirez & Church (2019) in positing that the political party difference between the two presidential candidates contributed to variations in their representations in the political internet memes. However, while Donald Trump was primarily memed negatively during the 2016 US presidential election with his hairstyle and facial expressions being the targets, political memes criticising him during the 2020 US presidential election focused on his failures, incapability, and improper acts and remarks during his presidential term. They also accused him of spreading hate, discrimination, and fake news, as well as being lawless and a liar. The study supported Ross and Rivers (2017) in finding that the (de)legitimization strategies of authorisation, moral evaluation, rationalization and mythopoesis were employed in internet memes to not only help creators share their views and spread their messages in the attempt to influence others, but also to delegitimize the target of the memes as to bring about their desired political result.

Donald Trump most benefited from grassroots action memes while Joe Biden was portrayed negatively in 95% of his memes, which is understandable since the study was investigating the community of Trump supporters. Nonetheless, the #maga and #trump2020 community on Twitter during the 2020 US presidential election did not comprise only of Trump supporters, but also those who opposed him and those who supported his opponent, Joe Biden. Chagas, Freire, Rios, and Magalhães (2019) posited that there were two ways in which politicians were laughed at (or being discussed) via internet memes, one of which happened when they really mattered. This was the case

for Donald Trump and Joe Biden during the 2020 US presidential election, in which supporters and opposers engaged in communication battles to support their candidate, oppose his opponent, and perhaps secure the right to satirise both sides. Internet memes are subject to biased cognitive processing, particularly selective judgment or motivated scepticism; thus, political internet memes may be a vehicle for political messages that contribute to a polarised media environment despite their fleeting nature (Huntington, 2018). It should also be noted that many political memes analysed in the study did not feature humour, an inherent characteristic of internet memes discussed in the literature review. Instead, they included rather serious messages or calls for actions.

Campbell, Arredondo, Dundas, and Wolf (2018) posited that internet memes evoked civil religion, an idea rooting in nationalist ideologies in which religion becomes a tool to interpret politics (Coleman, 1970; Rousseau, 2018). The civil religion discourse in memes was done via God Talk (i.e., religious worldviews are used to interpret and justify certain political actions, and vice versa), and was predominantly spoken in the voice of Conservative American Christians and from a viewpoint often closely associated with a Republican agenda. Such findings were consistent with this study as there were memes depicting Donald Trump as god-sent, or what he (and his Republican allies) was doing was in accordance with Christian beliefs or God's teachings and voting for Donald Trump was sometimes portrayed as a religious decision. Duerringer (2016) argued that the incorporation of evangelical Christianity with mainline Republican was politically problematic and inherently unstable. Still, embedding evangelical Christianity to traditional conservatism, as well as strands of libertarianism, neoliberalism, and neoconservatism, was a Republican strategy to continue to appeal to the mass of people and drive voters to the poll. While it may be the case, McLoughlin and Southern (2020)

suggested that the level of policy information in political memes was low, which means consumers would be unlikely to increase their political knowledge from digesting memes. Nevertheless, there was not enough evidence to determine if incidental exposure to political content in internet memes had any impact on meme consumers' perspective and attitude, or they simply laughed at the content then resume scrolling.

Chapter 7 - Conclusion

Three conclusions were taken out of the study. Firstly, 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 (2012), and Yang, Chen, Maity, and Ferrara (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 October 27 and November 2, 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, this 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. Social media, however, will remain 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).

Secondly, Benkler, Faris, Roberts, and Zuckerman (2017) and Ott (2016) argued that Twitter's simplicity, impulsivity, and incivility, as well as populism, misinformation, and fake news, might have assisted the ascension of Donald Trump despite him being offensive, bullying, and abusive on the platform. Ott (2016) further described Twitter as social cancer infecting public discourse, destroying dialogue and deliberation, fostering farce and fanaticism, and contributing to callousness and contempt. While the study agrees that a considerable amount of populism contents, fake news, and misinformation were frequently circulated within the community of Trump supporters on Twitter during the 2020 US presidential election, it does not have enough empirical evidence, hence the confidence, to determine the impact of Twitter on Donald Trump's political success and, in a broader scope, public deliberation and political discourse.

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, utilise arguments that support their confirmation bias, and intentionally and strategically ignore science, truths, and facts. On the other hands, it also perceives that while social media have their flaws and limitations, they provide valuable political outlets and civic engagement opportunities for marginalised 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 behaviours violate standardised moral, decency, and social values.

Thirdly, the weaponisation of political internet memes during the 2020 US presidential election in the attempt to sway public opinion was evident, supporting Zannettou et al. (2018) argument. Such strategies to exploit the expressive power of politically and ideologically imbued internet memes was also employed by various entities in previous elections, namely the 2012 and 2016 ones (Foster, 2014; Zannettou et al., 2018). As a communication medium, internet memes have several advantages compared to other forms of mass communication media. They are funnier, more concise, easier to understand, more relatable, and more vivid.

Thus, the study agrees with Miltner (2018) in positing that the humorous nature of memes indeed makes them an ideal venue for political critique and commentary. It also supports Dean (2019) in suggesting that communication and political scholars should perceive the production and exchange of digital visual media, notably internet memes, not as some frivolous activity on the margins of politics but as increasingly central to the everyday practices of politically engaged citizens. The study argues that since internet memes are a unique product of the current digital culture that typifies many of its underlying qualities and they, to an extent, have been playing a vital part in defining and shaping the twenty-first century (Shifman, 2014), it is now inappropriate to treat them merely as regular laughing stocks, but instead an integral agent of daily societal life, a fundamental communication medium, and a serious research subject of social science.

Chapter 8 - Limitations and future research

The study recognised 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 are incredibly highly likely to be 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 characterise users and contents of the targeted social network. Still, the study is confident that the dataset was representative of the community of Trump supporters 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, behaviours, sentiment, and civility are highlighted. The social networks of political supporters, political contents, and political internet memes 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 analysed. The media effects, particularly of the political internet memes, 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. There were also difficulties in determining the status of memes of some units of analysis (e.g., selfies and family pictures) similar to Chagas, Freire, Rios, and Magalhães (2019). Thus, a proper and consensus conceptualisation and definition of memes, particularly political memes, may need to be developed.

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Appendix A - Codebook

Adopting the codebooks in Foster (2014) and Chagas, Freire, Rios, and Magalhães (2019) for analysing contents of political internet memes disseminated during presidential elections (with adjustments to fit the study's purposes), the following variables are coded:

A. Offensive words

Whether the meme contained offensive words following Kaye and Sapolsky (2004) definition and categorisation or not (0 = no, 1 = yes). Offensive words might include:

1 – Seven dirty words, following the Federal Communications Commission guidelines for the seven words that cannot be used on television, which are shit, piss, cunt, fuck, cocksucker, motherfucker, and tits.

2 – Sexual words, or words based on sexual body parts and sexual acts, such as penis, balls, vagina, or jerking off.

3 – Excretory words, or words related to excrement or excretory body parts, such as poop, ass, or asshole.

4 – Other strong or mildly offensive words that do not fit into the above categories, such as bitch, bullshit, damn, or hell, or words that are disputed.

B. Target

The primary individual(s) or organisation(s) portrayed in the memes. They could be either:

1 – Joe Biden, his allies, Democratic politicians, or liberals.

2 – Donald Trump, his allies, Republican politicians, or conservatives.

3 – there was not a clear target, or both (1) and (2) were portrayed in the meme.

C. Portrayal

How the target was primarily portrayed in the memes to represent the main theme or idea. The portrayal can either be:

1 – The politician, or the ideal candidate: The target fulfilled the ideal picture of a traditional leader by posing with other leaders, looking serious, or having empathy and compassion. The target should either look like state-people or be seen expressing compassion towards their followers (Grabe & Bucy, 2009). Indicators of the ideal candidate theme may include, but not limited to:

- Elected official, including other people of power or elected officials.
- Patriotic symbols, such as flags, monuments, and military machinery.
- Symbols of progress, such as economic growth or technology.
- Identifiable entourage, including security personnel, reporters, and aids.
- Campaign paraphernalia, such as visible symbols, logos, or names on posters and other campaigning materials.
- Political hoopla, such as confetti, balloons, and streamers.
- Religious symbols, such as places of worship, religious figures, or other religious symbols such as crosses or pulpits.
- Formal attire, such as a tuxedo, a black-tie, or conventional business suit.
- Personal interaction, both physical interactions or affinity gestures, such as waving, hugging, embracing, kissing, or shaking hands, with supporters. These interactions should be personal, i.e., one-on-one.

- Family associations, including the appearance of family members or personal connections to historical family ties.

2 – The populist: The target appeared as one of the people, often be seen in semi-professional or casual clothes, and did ordinary things (Goodnow, 2013; Grabe & Bucy, 2009). Indicators of the populist theme may include, but not limited to:

- Celebrities, such as actors, musicians, television or online personalities, influencers, and athletes.
- Audiences, in which supporters tightly pack into a limited space, or a mass of supporters that can be seen applauding, waving, cheering, and wearing campaign paraphernalia.
- Crowd interaction, such as rapid, anonymous handshakes and touches to groups of supporters without an indicator of personal interaction.
- Informal attire, including semi-profession clothing (e.g., rolled-up shirtsleeves, or a suit without a jacket) and casual dress (e.g., khaki pants, slacks, or jeans; shirt, sport coats, jean jackets, sweaters or other causal garments).
- Ordinary people, including common folks, members of disadvantaged communities, or workers in manufacturing plants.
- Physical activities, including common athletic or recreational activities, or other physical or social work such as serving meals or chopping wood.

3 – The loser, or the incapable: The target was described as ridiculous, incapable, often in an undesired or unexpected situation, or showing unapproving facial

expressions (Goodnow, 2013; Grabe & Bucy, 2009). Indicators of the loser theme may include, but not limited to:

- Disapproving audiences, in which attendants can be seen booing, jeering, making hostile hand gestures (e.g., flipping the bird, or giving a thumbs-down), falling asleep, or showing any signs of bore or disinterest. The crowds' size is usually small, with only a few supporters scattered around and empty chairs are visible.
- Weaknesses, include falling, tripping, a lack of coordination, or an illness.
- Defiant gestures, such as punching the air, pounding the podium, pumping fists, pointing fingers, or wringing hands.
- Inappropriate non-verbal displays, including facial expressions, gestures, or moods that are incongruent with the context of the meme.
- Political failures, scandals, or the inability to “keep promises”.

4 – The menace, or the criminal: The target was described as evil, cunning, villainous, or having criminal schemes that intentionally caused devastating consequences to the country and its people, either politically, socially, or economically. Indicators of the menace theme may include, but not limited to:

- Accusations of criminal intents or actions.
- Affiliations with crime organisations, syndicates, or families.
- Prisons and related symbols, images, or paraphernalia such as handcuffs, chains, electric chairs, or prison bars.
- Symbols, images, or paraphernalia related to the devil, such as having horns or fangs, holding the devil trident, or exercising antichrist activities.

- Improper, immoral, or illegal sexual activities such as sexual harassment, paedophilia, or incest.

5 – Other: The portrayal could not be categorised in any of the above themes.

D. Extremist affiliation

Whether the target was portrayed along with, or attached to, symbols or implications of extremist affiliations. Extremist affiliations may include:

0 – No extremist affiliation was found.

1 – Left-wing extremist affiliations: The target portrayal was attached with symbols, images, or paraphernalia that are usually connected to extreme left-wing ideologies and activities. They can be, for example, communism, socialism, anarchism, the symbol of hammer and sickle, or the Soviet Union.

2 – Right-wing extremist affiliations: The target portrayal is attached with symbols, images, or paraphernalia that are usually connected to extreme right-wing ideologies and activities. They can be, for example, fascism, Nazism and neo-Nazism, nationalism, white supremacy, the Swastika, the Confederate flag, or the QAnon symbol.

3 – Other extremist affiliations: The target portrayal is attached with symbols, images, or paraphernalia that are usually connected to other extremist individuals, organisations, or movements such as terrorist organisations, proto-states, or other foreign-influenced affiliations.

E. Type of political memes

Chagas, Freire, Rios, and Magalhães (2019) identified three types of political memes:

1 – Persuasive memes, which may include in their content:

- Propositional rhetoric or pragmatic appeal: The content suggested or referred to a candidate's proposals, raised a discussion that points out voters' rational calculus, or touched on matters related to themes discussed in the election and the candidates' opinions.
- Seducing or threatening rhetoric or emotional appeal: The content used explicitly subjective and emotional aspects, such as portraying a candidate as a "protector, or father, of the poor", placing him among children, or even appealing to emotions like fear or hope.
- Ethical and moral rhetoric or ideological appeal: The content examined scandals, criticised corruption or inadequate public resources management, and mentioned rivalries between different political factions.
- Critical rhetoric or appeal to the credibility of the source: The content was anchored in sources such as statements by third parties, the media, opinion surveys, or others to ensure the greater credibility of a given candidate or the content itself.

2 – Grassroots action memes, which may include in their content:

- Dynamics of collective action and networks curated by organisations: The content was explicitly sponsored by party organisations (and not by supporters), companies, NGOs, professional category, or specific syndicate entities. In this classification, memes created by campaign strategists were included.
- Dynamics of hybrid connective action and networks catalysed by organisations: The content was the result of supportive action without connections to party organisations or other entities. In this classification,

content created by supporters or for supporters to show their preferences were included.

- Dynamics of connective action and self-organised networks: The content was created by an informal group, such as the Occupy movement. Such content was spontaneously generated with some level of political engagement.
- Dynamics of casual connective action: The content resulted from a trend or behaviour not necessarily related to a particular political engagement, such as photo fads or selfies. In this codification, TV photos during the electoral debate were included.

3 – Public discussion memes, which may include in their content:

- Literary or cultural allusions: The content mentioned cultural products (e.g., series or movies) or popular culture in general, including references to popular expressions, internet slang, famous characters, or celebrities.
- Jokes about political characters: The content presented comments about specific characters on the political scene.
- Situational jokes: The content presented comments about candidates' facial, gesture, or body reactions in certain situations.

F. Sentiment

Whether the general sentiment towards the target(s) of the memes was 1 – positive, 2 – neutral, or 3 – negative.