Social Bots versus Real Humans: The Framing of “Trump’s Wall” on Twitter

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

SOCIAL BOTS VERSUS REAL HUMANS: THE FRAMING OF “TRUMP’S WALL” ON TWITTER

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a candidate for the degree of master of strategic communication,

and hereby certify that, in their opinion, it is worthy of acceptance.

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TABLE OF CONTENTS

FIGURES AND TABLES

Figures

Tables

ABSTRACT

Around the globe, elites are using social media and computational propaganda to manipulate public opinion, (Bradshaw & Howard, 2018) increasingly degrading the traditional news media's gatekeeping function while building a symbiotic relationship with ideological media that forgo objectivity (Entman & Usher, 2018). Although a number of studies have examined framing of content in social media, including Twitter, no study known to the author has isolated bot-generated tweets to understand if they are capable of framing issues and how they frame them compared to real humans. The current research explores this issue by using a machine-learning (ML) software that detects whether a post came from a social bot account versus a real human with up to 100 percent accuracy for political bots (Yang et al., 2019). After an extensive manual data collection procedure, the current research goes through three steps: 1) identify whether a Twitter post originated from a social bot vs. real human, 2) determine the frame(s) and sentiment used in the post, 3) determine if the results fall in line with an asymmetrical cascading network activation model where the posting of right-leaning content is more automated than left-leaning content (Entman & Usher, 2018). To explore the existence of a new cascading network activation model that is asymmetrical, the content examined had to be polarizing. Thus, the context selected for the study is President Donald Trump's current Mexico border wall campaign. In addition to the data capture method described, a content analysis method is also utilized to make comparisons between frames used by social bots versus real humans and the right versus the left.

KEYWORDS: Social bots, political bots, framing, content analysis, cascading network activation, Trump's Mexico border wall, Botometer

INTRODUCTION

Researchers estimate that approximately nine to fifteen percent of Twitter accounts are controlled by bots (Varol, Ferrara, Davis, Menczer, & Flammini, 2017), and a Pew Research study conducted in 2017 found that approximately two-thirds of all links to popular websites shared on Twitter were shared by bots (Wojcik, Messing, Smith, Rainie, & Hitlin, 2018). Additionally, social bots on Twitter have been found to play a significant role in promoting polarizing political content during major political movements across the globe (Bessi & Ferrara, 2016; Howard & Kollanyi, 2016; Howard et al., 2016; Howard et al., 2017; Howard et al., 2018; Stella et al., 2018). Although Twitter claims to have shut down millions of fake accounts in 2018, the bot problem persists and continues to interfere in political discussions on the platform (Kosoff, 2018).

Social bots tasked with political manipulation on Twitter pose a threat to democracy because they are often utilized to spread fake news, manufacture consensus, exacerbate conflict online, (Bessi & Ferrara, 2016; DiResta, 2018, and Stella, Ferrara, & De Domenico, 2018) and even increase our exposure to violent and inflammatory content (Stella, et al., 2018). “There is methodological work to be done, however, when it comes to understanding communication driven by…political bots” (Wooley, 2018, p. 139). Communication researchers should concern themselves with this work, not only because social bots are a new tool used in political communications (Woolley & Howard, 2016), but also because their activity conflicts with the very principles journalists strive to uphold in their work: seek and promote the truth (Hodges, 1986).

Around the globe, government agencies and political parties are using social media and computational propaganda to manipulate public opinion (Bradshaw & Howard, 2018). Howard and Woolley (2016) believe that to understand modern communication, "we must now investigate the politics of algorithms and automation" (p. 1). Understanding these systems is "crucial for sustaining the public value of social media" (p. 3). Howard and Woolley (2016) also think researching how algorithms and automation structure our lives is the next great challenge of the social sciences. Furthermore, Entman and Usher (2018) find that automation on social platforms is more prevalent and more advanced on the political right in the U.S. than it is on the left, saying "the right-wing, but not left-wing ecosystem has reached digital maturity" (Entman & Usher, 2018, p. 130).

To better understand how automation on social media platforms influences public opinion, we need to understand how social bots can frame issues. As of today, there has been little research conducted on how bots frame polarizing political issues (Bessi & Ferrara, 2016; Stella et al., 2018). This study aims to take a deep dive into individual tweets around one polarizing issue in the U.S. to understand the various ways the issue is framed and if framing differs between humans and bots. It also aims to find if bots more heavily promote right-leaning frames. A recent issue that has divided the American public along Democratic and Republican lines is President Trump's proposed border wall with Mexico. Eighty-two percent of Republicans favor the expansion of the border wall with Mexico, while ninety-three percent of Democrats oppose it (Gramlich, 2019).

This study seeks to answer the following question: How are social bots being used, if at all, to promote polarizing frames of President Donald Trump's border wall on

Twitter? To answer this question, a content analysis will be conducted on a selection of 1,980 tweets from a particularly volatile period for the border wall issue (February 2019). The tweets will be coded for political leaning and valence, and a tool called Botometer will be used to determine if each tweet was posted by a bot. Once the tweets are coded and the accounts are analyzed, an analysis of the data will determine the dominant political leaning of bots versus humans in addition to the sentiment of bot tweets versus human tweets. This study will differ from others conducted on bots (Bessi & Ferrara, 2016; Howard et al., 2017; Howard & Kollanyi, 2016; Stella et al., 2018) in that it will not use machine learning tools to analyze frames or sentiment. This will enable the researcher to examine visual content such as images, videos, and GIFs as well as linked content to determine framing and sentiment. It also differs in that the study sample will be collected manually and retroactively rather than using a streaming API (application programming interface).

Key Concepts and Definitions

To understand the content of this study, several terms related to computational propaganda must be explained. Firstly, computational propaganda can be defined as "the assemblage of social media platforms, autonomous agents, and big data tasked with the manipulation of public opinion" (Howard & Woolley, 2016, p. 3). Social bots are part of these so-called autonomous agents. Social bots can be defined as "a version of automated software used on social media platforms to undertake tasks and mimic real users. They are social media accounts equipped with algorithms that post, tweet, or message of their own accord" (Howard, Woolley, & Calo, 2018, p. 83). These so-called "fake" accounts can also retweet, and "like" or "favorite" the tweets of other users. Some of these social bots are intelligent agents, meaning, they are “specifically designed to observe and act upon a given computational environment in order to achieve certain goals” (Howard et al., 2018, p. 84). In this study, we will be looking at social bots that are political bots. Political bots are “software-driven social actors that can be used to spread propaganda and obstruct activism” (Woolley, 2018, p.127). They are specifically designed to manipulate public opinion (Woolley & Howard, 2016). Lastly, we need to understand the definition of autonomous agents. Autonomous agents are “software programs which respond to states and events in their environment independent from direct instruction by the user or owner…” (Bosser, 2001, p. 1002). This study focuses on political bots on Twitter, which by definition participate in computational propaganda.

BACKGROUND AND LITERATURE REVIEW

The origins of social bots can be traced back to 1950 when Alan Turing designed a test to answer the question, "Can machines think?" (Ferrara et al., 2016). Simply put, for a machine to successfully pass the Turing Test, it had to be able to fool a human into believing he or she was communicating with another human being. Turing's test spurred decades of debates and attempts to design machines that can emulate human communication, and it is considered by some to be the beginning of artificial intelligence (Saygin, Cicekli, & Akman, 2000). In the late 1980s, machine learning algorithms assisted in the advancement of natural language processing (Woolley, 2018). In the 1990s, chatbots were developed and deployed to represent humans online (Woolley, 2018). Today, millions of social bots are deployed on Twitter (Newberg, 2017), and they are programmed for a variety of purposes. Some of them are chatbots that assist with customer service (Ferrara et al., 2016). Others are deployed by marketers to send spam messages that contain advertising, and some celebrities and influencers purchase bot followers to artificially inflate their follower numbers (Woolley, 2018).

Some social bots are more sophisticated than others. There are bots that simply retweet content, while others can engage with users by replying and commenting on posts (Yang, Varol, Davis, Ferrara, Flammini, & Menczer, 2019). They are programmed to follow the temporal posting patterns of humans, and the most sophisticated ones copy profile names, photos, and usernames from real human accounts (Yang et al., 2019). In the last 6 years, we have witnessed the development and deployment of social bots for the purpose of political manipulation (Woolley, 2018). Specific functions of social bots include influencing user opinion on single issues, padding follower lists of political leaders, and promoting content produced by major political parties and PACs. They are also used to promote and "spin" news during political crises (Howard et al., 2018). This literature review explores studies on social bot activity during recent political movements and crises, as well as bot-to-human interactions. Later, framing theory is examined to explain the functions and the effects of political bots on social media.

Social Bots in Political Movements

The rise of social bots as a tool in political communication is a global phenomenon (Howard & Kollanyi, 2016). Examples of polarizing social bot activity during political movements include the Catalan referendum for independence (Stella et al., 2018), the U.S. 2016 presidential election (Howard et al., 2018), the Brexit vote (Howard & Kollanyi, 2016), and the nomination of Brett Cavanaugh to the U.S. Supreme Court (de Haldevang, 2018).

Howard and Kollanyi (2016) conducted a study around social bot activity on Twitter during the United Kingdom's referendum to withdraw from the EU, commonly known as Brexit, in June 2016. Howard and Kollanyi collected a data set of over 1.5 million tweets based on hashtags they designated as pro-Brexit, anti-Brexit, and neutral. They collected this data using Twitter's streaming API. Although an even number of hashtags were used for each point of view, the study sample contained a much larger number of tweets in support of Brexit (approximately 660,000 pro-Brexit tweets and 180,000 anti-Brexit tweets). The study also found a heavier use of automation (50 or more posts per day) to promote pro-Brexit tweets and a much larger quantity of bots making pro-Brexit tweets (842 pro-Brexit versus 196 anti-Brexit). Lastly, the study found that seven of the top ten Twitter accounts analyzed (those that tweeted the most about the issue) were bots. A potential flaw in this study is that the Brexit hashtag was largely used in neutral contexts, but it was counted as a pro-Brexit hashtag in this study (Howard & Kollanyi, 2016).

In another example, Howard et al. (2018) found that then presidential candidate Donald Trump had several supportive Twitter followers with Latino names such as Pepe Luis Lopez, Francisco Palma, and Alberto Contreras who were not real people; they were bots. They also found that U.S. politicians increasingly use bots to mislead the public about their popularity. Additionally, politicians use bots to "disrupt the communications strategy of a rival" (Howard et al., 2018). They report that during the 2016 presidential election, social bots promoted political rumors and fake news from Russian sources (Shao, Ciampaglia, Varol, Flammini, & Menczer, 2017 as cited in Howard et al., 2018). Another social bot study on the 2016 presidential election sampled 22 million tweets and analyzed those containing specified pro-Trump, pro-Clinton, and/or neutral hashtags related to the election during November 2016 (Howard, Bolsover, Kollanyi, Bradshaw, & Neudert, 2017). They found that 57% of the tweets used pro-Trump hashtags, 20% used pro-Clinton hashtags, and 13% contained neutral hashtags. Additionally, they found 47% of the news stories shared in the sample were from untrustworthy sources (not from a known professional news organization). However, their sample turned out to contain only 2% bots, though there were other accounts in the sample that were highly automated. A likely reason for the low percentage of bots in this study is that the sample tweets were taken only from accounts that indicated they were based in Michigan, and bot accounts usually don't provide geographic information (Howard et al, 2017).

Yet another study conducted on tweets during the U.S. election season (September and October 2016) estimated that in a data set of over 20 million tweets and 2.8 million users, 400,000 of those users were bots (Bessi & Ferrara, 2016). Bessi and Ferrara used Indiana University's Botometer (at the time referred to as BotOrNot) to test 50,000 of the most active Twitter accounts in the sample. Of these 50,000 accounts, they found 7,183 of these were bots, and they were responsible for over 2.3 million tweets in the sample. This means bot accounts contributed to nearly 19% of the total conversation on the topic. The researchers then extrapolated this percentage of bot accounts to the rest of the sample to estimate there were approximately 400,000 bot accounts within the sample of 2.8 million users. This tweet sample was also collected based on hashtags that were pro-Trump, pro-Clinton, anti-Trump, and/or anti-Clinton.

Another Twitter bot study conducted during the Catalan referendum for independence in 2017 found that out of 3.6 million tweets, 24% were produced by bots (Stella et al., 2018). Interestingly, they also found that of the tweets that were replies, 39% were generated by bots. The sample used in the study included hashtags that were pro-independence, anti-independence, and/or neutral. Additionally, Stella et al. (2018) found that bots were used to promote violent content that was targeted at Independentists and exacerbated social conflict online.

In essence, bots increase the public's exposure to negative content (Stella et al., 2018) and can negatively impact political discussion (Bessi & Ferrara, 2016). In other words, bots are being used to "deliberately pollute" communication among citizens and communication between the media and the public (Entman & Usher, 2018, p. 305). These findings are worrisome due to the part bots have played in influencing political elections in recent years, successfully playing a part in shaping our political realities. According to Howard and Kollanyi (2016), “Political bots tend to be developed and deployed in sensitive political moments when public opinion is polarized” (p. 1).

Bot-Generated Tweets vs Human-Generated Tweets

Of the bot studies mentioned in this literature review, only two venture deeper than political leaning to examine how bot-generated tweets differ from human-generated tweets. Bessi and Ferrara (2016) conducted a sentiment analysis on the tweets they collected posted by United States-based users during the 2016 election season. They used a machine learning tool called SentiStrength to determine the sentiment of the tweet sample. The tool is between 60.6 and 72.8 percent accurate in determining positive and negative sentiment of short, informal texts, including emoticons (Bessi & Ferrara, 2016). Their sentiment analysis found that bot-generated tweets that supported Trump were the most positive as a data set, but in general, in all the categories (pro-Trump, anti-Trump, pro-Clinton, anti-Clinton), overall bot sentiment matched overall human sentiment. One interesting conclusion made in the study was that negative tweets made by Clinton supporters “address in large majority the candidate herself, rather than her opponent” (Bessi & Ferrara, 2016, p. 10). This could be an indication that determining political leaning solely based on hashtags is not the most accurate way to conduct this research, and that a more in-depth analysis of the framing of each tweet is required to code for political leaning.

In addition to examining sentiment, they found that humans and bots retweet each other at approximately the same rate; however, humans engage in interactions (replies) with other humans significantly more than they do with bots, and bots engage more with other bots. This indicates that while social bots share content that humans share, and they can create an illusion of consensus, they aren't yet sophisticated enough engage in meaningful interactions with humans (Bessi & Ferrara, 2016).

Stella et al. (2018) studied several aspects of bot-generated tweets versus human-generated tweets in their political bot study of the Catalan Referendum. They found that bots and humans followed a similar circadian rhythm, with a similar post volume by hour between the two groups. Like Bessi and Ferrara (2016), they also found that humans interact mostly with other humans. However, their analysis of tweet sentiment dives deeper into bot-human interaction. Stella et al. (2018) found that retweets directed to bots do not deviate significantly from neutral, while tweets directed at humans are drastically more positive or negative. They also found that bots tended to target the most influential human users, and in this study, bots targeted Independentists with largely negative messaging and "associating hashtags with negative connotations" (Stella et al., 2018, p. 12,439). The findings in this study support a hypothesis that bots accentuate "the exposure to negative, hatred-inspiring, inflammatory content, thus exacerbating social conflict online" (Stella et al., 2018, p. 12,439). To conduct their sentiment analysis, Stella et al. studied the co-occurrence of hashtags with individual tweets to determine sentiment. They hand-coded a small subset of tweets (approximately 2,500) to determine accuracy.

Exploring Framing Theory

To fully understand the political leaning and messaging of tweets, it is necessary to examine the way problems are framed and how their causes and solutions are interpreted in each tweet. Entman defines framing as "to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (1993, p. 52). When the salience of content or a piece of information is increased, it becomes more meaningful and more easily recalled by its target audience (Entman, 1993). Essentially, framing can be seen as the construction of meaning (Benford & Snow, 2000).

Since before the invention of the Internet, politicians and governments have used frames to increase public support for their initiatives (Entman, 1993; Manor & Crilley, 2018). Frames are an instrument of power because they “can shape people’s world view, opinions, and actions” (Manor & Crilley, 2018, p. 371, see also Ravazzani & Maier, 2017 and Entman, 1993). For example, the Israeli government used frames in social media communications to frame the West’s view of Hamas and the Palestinians and construct the view that Israel is the only legitimate democracy in the East (Manor & Crilley, 2018). In 2011, President George W. Bush and his administration framed the 9/11 attacks as terrorist attacks carried out by Islamic extremists, repeating divisive frames such as “they hate us” and “they hate our freedoms” (Bartolucci, 2012, p. 567). The Bush administration reiterated conflict frames that promoted dichotomous worldviews and provoked an *us against them* mentality. Bush also stressed morality frames, saying that Islamic extremists were “coldblooded killers” and their “hatred cannot be satisfied” and that God told him to strike Al Qaida (Bartolucci, 2012, p. 568-571). He also stated, “Either you are with us or with the terrorists” (Bartolucci, 2012, p. 571) Thus, Bush designated the United States and anyone else on its side as the good guys, and anyone not on its side as the bad guys. This framing of Islamists as terrorists spread around the world and has also been adopted by authoritarian governments to legitimize attacks on innocent citizens (Edel & Josua, 2018). “Elites usually do not invent their strategies from scratch, but draw on sources of inspiration and examples” (Edel & Josua, 2018, p. 885). This can be referred to as “frame diffusion” (Benford & Snow, 2000, p. 627). Common frames governments have used to justify repression against a certain group of people include outlining them as perpetrators of criminal behavior, terrorism, intimidation, and disruption of daily life, law, and order (Edel & Josua, 2018). Both Uzbekistani and Egyptian government elites framed non-violent protestors as Islamist terrorists to the international community when they killed 600-1,000 of them in Rabi’a ‘Adawiya Square in Egypt in 2013 and in Andijon in Uzbekistan in 2005. They also carried out mass arrests using military force (Edel & Josua, 2018).

Governments, activists, and elites use framing as a tool to construct meaning through articulation and amplification (Ravazzani & Maier, 2017). The public also constructs meaning through framing by “participating in public deliberation” (Borah, 2011, p. 250). The articulation of frames is a process that involves the collection and alignment of events and experiences to make them more compelling. “Slices of observed, experienced, and/or recorded ‘reality’ are assembled, collated, and packaged” (Benford & Snow, 2000, p. 623), thus constructing a particular viewpoint. “Most frames are defined by what they omit as well as include” (Entman, 1993, p. 54). For instance, the Uzbekistani government omitted the fact that women and children were killed when lethal force was used against protestors (Edel & Josua, 2018), and Bush omitted the fact that the administration really didn’t know who was behind the 9/11 attacks in his initial speeches to the public (Bartolucci, 2012). The amplification process involves highlighting certain “issues, events, or beliefs” (Benford & Snow, 2000, p. 623) to make them more salient than others and can also involve “idealization, embellishment, clarification, or invigoration of existing values or beliefs” (p. 624). Amplification links a frame to a culture’s existing values or belief systems (Benford & Snow, 2000).

Five dominant types of frames have emerged through analyses of U.S. and European news frames (Matthes, 2009; Neuman, Just, & Crigler, 1992; Semetko & Valkenburg, 2000; Valenzuela, Piña, & Ramirez, 2017).

Conflict frame. Conflict frames highlight conflict between groups or individuals. When used by the news media, conflict frames are often employed to capture attention (Semetko & Valkenbug, 2000). But, when employed by governments, they can be used to divide people and garner support against a common enemy (Bartolucci, 2012). Conflict frames often involve stories that are told from an “us versus them” standpoint and imply that there are winners and losers (Neuman et al., 1992).

Human interest frame. Human interest frames are employed to provoke emotions, particularly sympathy and compassion, through the communication of personal experiences that highlight the humanitarian impact of an issue or event (Neuman et al., 1992; Semetko & Valkenburg, 2000). An example of human-interest framing can be seen in the recent highlighting of difficulties migrants face crossing the U.S.-Mexico border with a photograph of a drowned migrant father and his daughter after they attempted to cross the Rio Grande (Linthicum, 2019).

Economic consequences frame. Economic frames highlight the economic impact an issue, event, or problem that could affect or is affecting a particular group or individual (Semetko & Valkenburg, 2000). A common example of an economic consequences frame around the U.S.-Mexico border wall issue is that not physically closing the border results in immigrants stealing American jobs (Crenshaw, 2019). Another common example is the framing of immigrants as taking advantage of public resources and taxpayer dollars by using health and other public services "for free." While the media commonly use technical terms when employing economic frames, people will typically overlay economic frames with a moral perspective (Neuman et al.,1992).

Morality frame. Morality frames are used to place an issue, problem, or event in a religious or moral context (Semetko & Valkenburg, 2000). These frames often create dichotomy and highlight one course of action as the "right" choice. Bush's attempt to frame his choices as analogous to God's choices is one example of morality framing (Bartolucci, 2012). Morality frames can employ religious tenets or values, such as freedom and justice (Neuman et al., 1992).

Responsibility frame. Responsibility frames are used to "attribute responsibility for its cause or solution" to a particular group or individual (Semetko & Valkenburg, 2000, p. 96). While Semetko and Valkenburg (2000) identify responsibility as a frame type, Neuman et al. (1992) do not. Semetko and Valkenburg (2000) cite Iyengar (1987 & 1991) in relation to the responsibility frame type, but while Iyengar did study how attribution of responsibility affects framing, Iyengar (1990 & 1991) identifies frames as episodic or thematic and argues that frames influence how people assign responsibility. Iyengar seems to identify responsibility as an effect of framing and not a frame type per se.

These frames can be represented not only linguistically but also visually (Ravazzani & Maier, 2017). "Social media are inherently visual platforms" (Manor &

Crilley, 2018, p. 385). They are also multimodal communication platforms where users can employ visuals, sounds, and animation to frame issues (Ravazzani & Maier, 2017). Scholars have noted the importance of a visual analysis to understand the framing of conflict, which indicates images serve an important function in framing that language does not, such as iconicity, implicitness, and indexicality (Manor & Crilley, 2018). Because of this, I argue that comparing hashtags and conducting sentiment analysis using machine learning tools provides valuable insights, but the technology is not sophisticated enough for analyzing the visual framing of issues. Machine learning tools used in current social bot studies (see Bessi & Ferrara, 2016; Howard et al., 2017; Howard & Kollanyi, 2016; Stella et al., 2018) did not analyze the sentiment of images, videos, links, and GIFs shared in tweets, which are helpful (or essential if it is the only content of a tweet) in determining how an issue is being framed. In this study, human-generated and bot-generated tweets will be analyzed and coded based on the way they frame problems and interpret causes both verbally and visually.

Lastly, why is it important to study how bots are framing issues on social media? Frames can "shape public perceptions of political issues" (Semetko & Valkenburg, 2000, p. 94). Based on this literature review, it is apparent that strategic framing can influence public opinion about an event or a group of people (Bartolucci, 2012; Benford & Snow, 2000; Edel & Josua, 2017), and it can also provoke people to act. Two hundred violent attacks on Muslim Americans were recorded in the three days following 9/11 (Bartolucci, 2012). This result makes it especially alarming that bots are successfully disseminating violent frames on Twitter (Stella et al, 2018).

The Cascading Network Activation Model

Part of what this study hopes to find is based on Entman's cascading network activation model. In 2004, Entman developed his model to show how political issues are framed in the U.S., starting with the White House, flowing to Congress and non-administration elites to the mass media, and finally, to the public. In this model, the public could communicate their thoughts and ideas back to the mainstream media but rarely were they able to open communication channels with the elite. However, because social media "platforms allow elites to bypass institutional media by connecting directly to the public" (Entman & Usher, 2018, p.301), Entman and Usher propose a revised cascading network activation model that shows how elites are using the Internet and social media to bypass the mainstream media and communicate directly with the public. Entman and Usher (2018) also proposed adding five new digital "pump valves" to the model, as these aid the flow of framed political information. These pump valves include: platforms (social media), analytics (e.g., Cambridge Analytica), algorithms, ideological media (e.g., Breitbart, InfoWars), and rogue actors. Entman and Usher define these rogue actors as "technology-empowered hackers, fake news creators, and bots" (p.302).

Additionally, elites have the monetary resources to command armies of social bots that further their agendas, frame issues, and exploit algorithms (Howard & Woolley, 2016) while members of the general public do not. "Political elites have been learning and applying communication innovations [like social bots] by activists as tools for social control" (Howard & Kollanyi, 2016, p. 5). Entman and Usher (2018) propose that rogue actors along with the four other digital pump valves leave the public more exposed to frames developed by elites than to frames originating from true grassroots campaigns. Furthermore, they propose that this new model is asymmetrical in the United States, in the sense that the flow of communication directly from the elite to the public via digital channels is stronger on the political right than it is on the left. This is in large part due to the right's strong and loyal following of ideological and dogmatic, non-traditional media outlets (Entman & Usher, 2018). Bots are often programmed to promote this type of content on social media. Social media bots can "fool people and algorithms, spread disunity, and undermine collective action" (Entman & Usher, 2018, p. 303). They are also used to manufacture consensus by forcing a message or frame to trend on Twitter, fooling people into believing a large number of people feel a certain way when they do not (DiResta, 2018).

This study will contribute to the research corpus on social bots through the lens of issue framing and Entman and Usher's updated cascade activation model by examining Twitter communications regarding a recent polarizing political issue in the U.S. This brings us to the primary research question that drives this study: How, if at all, are social bots being used to promote polarizing frames of President Trump's border wall on Twitter? The specific research questions guiding the study include the following:

RQ1: What is the proportion of bot-generated to human-generated tweets regarding the U.S./Mexico border wall and border security within the sampled tweets?

RQ2: Are more bots versus humans promoting primarily left- or right-leaning frames of the U.S./Mexico border wall and border security on Twitter?

RQ3: Does the sentiment (i.e., valence) of tweets differ for bots versus humans regarding the border wall and border security?

RQ4: Do bots use common media frames, and if so, do bots frame the U.S./Mexico border wall and border security differently than humans?

METHODOLOGY

Design

The design chosen for this study is a case study consisting of a data capture method and content analysis. A case study is a study design “in which a particular instance or a few carefully selected cases are studied intensively” (Grinell 1981, cited in Kumar, 2011, p.123). A case study can be used to provide “an overview and in-depth understanding of a case(s), process and interactional dynamics within a unit of study” (Kumar, 2011, p. 123). A content analysis is a method that involves collecting and analyzing content from written, verbal, visual, printed, and/or electronic resources (Hamad, Holmes, Johnson, Kinsella, & Savundranayagam, 2016). It is a method “specifically intended for the study of messages” (Lombard, Snyder-Duch, & Bracken, 2006). A content analysis “consists of coding raw data...according to a developed or predefined classification scheme (a coding manual)” (Hamad et al., 2016, p.3).

The case study selected for this study is Trump’s border wall campaign. This issue was selected because it is recent which is essential given the short life span of many bot accounts (they are sometimes deleted by Twitter when identified or shut down once they have served their purpose). The issue must also be polarizing in order to test Entman and Usher’s theory that the new cascade model is asymmetrical. As previously mentioned, Trump’s wall is a highly polarized issue with eighty-two percent of Republicans supporting expansion of the border wall with Mexico and ninety-three percent of Democrats opposing it (Gramlich, 2019).

The content analysis for this study evaluates messages in electronic resources -- tweets. Content analyses have been used successfully in multiple studies using framing theory and social media content to examine communications around a specific issue (Chew & Eysenbach, 2010; Edel & Josua, 2018; Manor & Crilley, 2018; Ravazzani & Maier, 2017; Wasike, 2013). A content analysis is an obvious choice for this study, as it involves the analysis of raw data to determine the framing of an issue. In this study, the researcher must analyze content that has already been generated without the researcher's ability to shape output (unlike interviews or focus groups). The content collected for analysis in this study consists of tweets pertaining to Trump's border wall campaign that fall within a selected time frame. The tweets will be coded for political leaning, valence, and frame type.

Sampling Method

Because bots are particularly prevalent on Twitter, the current study chose to focus on Twitter as the social media context. This selection is justified in light of a Pew Research Center study of 1.2 million tweeted links in which two-thirds were found to be generated by bots (Wojcik et al., 2018). Although Facebook is more frequently used by Americans than Twitter (Smith & Anderson, 2018), social bot researchers have focused more on Twitter because Facebook is a much more private and closed platform. People are more open to communicating with strangers on Twitter, while Facebook is mostly used by people to connect and communicate with others already within their social networks (Johnston, Chen, & Hauman, 2013). Because many Facebook users do not make their profiles public, and because users only see posts from accepted "friends," it's much more difficult for bots to infiltrate discussions. Twitter also has a convenient advanced search feature, enabling researchers to search all publicly posted content based on username, topics and time frames (Tidey, 2017).

Twitter's advanced search feature was used to find original tweets and replies related to Trump's border wall by searching for the following hashtags: #BuildTheWall, #BuildThatWall, #NoWall and #BorderWall. #BuildTheWall and #BuildThatWall were counted as the same hashtag because they are completely synonymous and interchangeable. #BuildTheWall and #BuildThatWall are predominantly used in right-leaning tweets, while #NoWall is a predominantly left-leaning tweet. #BorderWall is used in both types of tweets as well as neutral tweets. Hashtag sampling was chosen for this study because it is centered around specific events and a specific political theme, and hashtags are useful for the "formation of ad hoc publics around specific themes and topics" (Bruns & Burgess, 2011, p. 1). The selected hashtags helped the researcher hone in on tweets related to Trump's border wall.

These specific hashtags were chosen because they were the predominant ones in each category (right, left and neutral), which was discovered after a period of social listening and an analysis of tweets about the border wall on Twitter. A Google search for "popular Trump border wall hashtags" also revealed that these were among the most popular left-leaning and right-leaning hashtags related to Trump's border wall. Once the chosen hashtags were entered into Twitter's advanced search tool, "English only" was selected as a parameter in Twitter's advanced search feature, and "safe search" mode was turned off to ensure the inclusion of any content that might be offensive to some users. Disregarding "unsafe" tweets would skew the data (Boyd & Crawford, 2012) and potentially ignore some bot accounts, resulting in a misleading sample.

To reduce the volume of tweets and make them more manageable for this study, the study focuses on two key dates: February 11 and February 15, 2019. These dates were chosen because three significant events related to Trump's border wall campaign occurred in this time frame. Beto O'Rourke (a prominent Texas Democrat, 2020 presidential candidate, and border wall dissenter) and President Trump held rallies simultaneously in El Paso on Monday night of February 11 (Tacket, 2019). Then, on the morning of Friday, February 15, President Trump declared a national emergency at the United States' southern border (Paschal, 2019). Also, to make the scope of the study manageable for one researcher, a limited number of tweets per hour were selected in this 48-hour period. The most tweets per hour (70) were selected during high-traffic times and the smallest number of tweets collected per hour (20) were collected during low-traffic times (12:00 am to 6:00 am CST). A total of 1,980 tweets will be analyzed (990 per day). Due to the tendency of some organizations and savvy individuals with social media tools to automate posts that go out every hour on the hour, the researcher did not select the first tweets in each hour. Instead, the researcher followed a time cycle. For example, if the first round of tweets ended at 12:42 am, the researcher started collecting the next hour's sample at 1:43 am.

Repeat content was ignored, such as popular photos like the one shown in Figure 1, which was posted repeatedly after Joy Villa was photographed wearing a "build the wall" dress at the 2019 Grammy Awards. Tweets were collected, however, if they contained original content in addition to the repeat content. If one user tweeted multiple times in the same hour, only the first tweet was examined in an effort to analyze as many different users as possible. Advertisements, or paid promotional content, were also discounted from the sample.

Figure 1. Joy Villa at the 2019 Grammy Awards

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Unit of Analysis

The units of analysis in this study are individual original tweets in their entirety. While retweets and likes can create an illusion of consensus (Woolley & Guilbeault, 2017), they were not counted or analyzed for bot activity in this study because they do not contain original messages, and therefore do not contain frames. However, if the author of a post added their own commentary to a retweet, then it will be counted and analyzed in this study. The components of each tweet that will be recorded include the account that posted the tweet (to determine whether it is a bot account), the content of the tweet itself, links within the tweet, memes, images, videos, and emoji. Links within posts will be opened, and content on these URLs will be taken into consideration when coding the tweet for political leaning and valence. If emoji (also known as emoticons) are used in a tweet, they can be especially helpful in determining the sentiment of a post, as can memes and images. "...[E]moticons largely function as non-verbal cues do in face-to-face communication” (Chang, Hecht, Johnson, Miller, Terveen & Thebault-Spieker, 2016, p. 260). As these will serve as our “body language” for interpreting tweets, they will be included in the analysis as a component of a tweet’s content. Memes are also used to frame issues, as they can be used to understand a “culture at large” and as “visual rhetoric” to persuade an audience to accept a particular interpretation (Huntington, 2013). The “culture at large” in this case is Democratic or Republican culture.

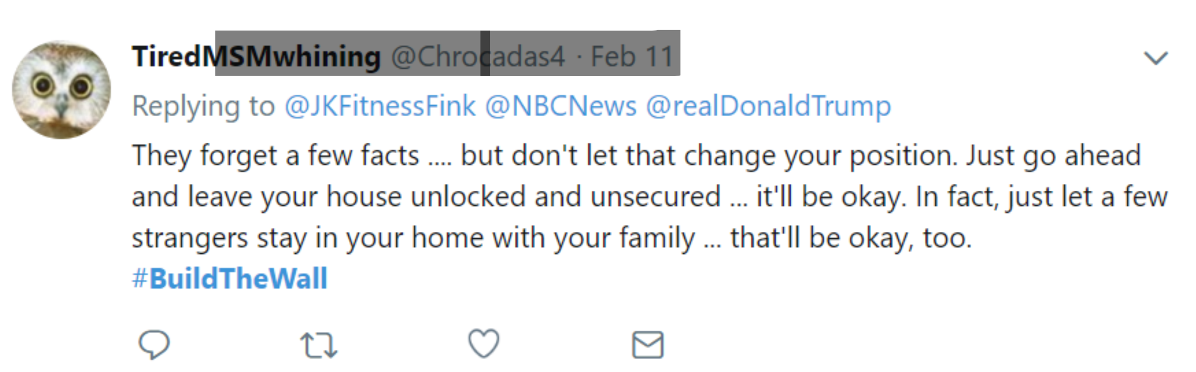
Coding Categories

Framing theory serves as the guide for coding categories in this study. As previously mentioned, framing is “to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (Entman, 1993, p. 52). Therefore, to analyze how the selected tweets are framed, they will be coded as left-leaning, right-leaning, or neutral based on their problem definition, causal interpretation, moral evaluation and/or treatment recommendation pertaining to immigration and border security.

Coding for Right-Leaning Content

Conservatives tend to value authority, loyalty, and purity more than liberals, and they are more likely to favor a strict assimilation to American “traditional values” (Gries, 2016). Some widely accepted traditional American values established by sociologist Robin M. Williams include pragmatism, individualism, patriotism, and volunteerism, among others (1970). Some scholars argue that there are also modern conservative values, such as laissez-faire economics, anti-socialism, anti-regulation, and anti-civil rights with a pretext of moral decay (Phillips-Fein, 2009). These values influence the conservative stance against illegal immigration and their preference for stricter border policies (Gries, 2016). To better understand the framing of the border wall from the right, the transcript from Trump's speech declaring a national emergency at the border on February 15, 2019, was analyzed for overarching themes. The main problem statement that emerged is that the U.S. is experiencing an "invasion of drugs, invasion of gangs, [and] invasion of people" and this invasion is coming from "the southern border." Right-leaning op-eds on the border wall were also examined to find agreement among conservatives that border walls are an effective border security solution (O'Connel, 2019 and Crenshaw, 2019). Besides drugs, gangs and human traffickers coming across the border, other problems cited included immigrants taking American jobs and illegal immigrants straining the country's social welfare system (Crenshaw, 2019). Sampled tweets that contain such references will be coded as right-leaning. If tweets contain a moral interpretation that the border wall is good and/or tweets contain the treatment recommendation of building a wall, the content will also be coded as right-leaning. Essentially, tweets that are interpreted to be in favor of the border wall will be coded as right-leaning.

Figure 2. A right-leaning tweet analyzed in this study

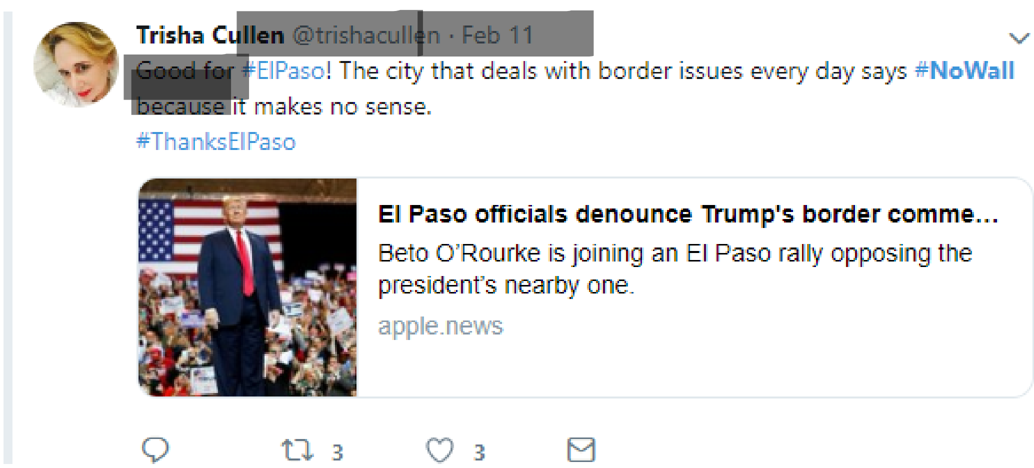


Coding for Left Leaning Content

Liberals tend to value fairness, compassion, and communitarian ideals more than conservatives, and are more likely to buy into "open and fair" immigration policies (Gries, 2016). They also tend to support "government economic intervention" and the "expansion of personal freedoms" (Swedlow, 2008, p. 160). Democrats are much more likely than Republicans to take the position that immigrants strengthen the country (Thompson, 2018).

Left-leaning content may allude to immigration being non-problematic and reference immigrants as hard workers who contribute to our economy and do jobs that many Americans won't do -- the opposite of the conservative framing of immigrants taking Americans' jobs. However, left-leaning individuals do identify drugs and the trafficking of contraband as a problem (Ramos, 2019). To get a clear picture of liberal framing of Trump's border wall, recent left-leaning op-eds from *The New York Times* and *The Guardian* were examined. Themes that emerged include: the inefficacy of a border wall when illegal drugs flow in through legal ports of entry, a majority of immigrants remain in the country by overstaying their temporary visas, the right to seek asylum in the United States (Ramos 2019 and Gawthorpe 2019), and money would be more effectively spent proactively reducing violence and border crossings with anti-gang programs in Central America and the United States (Kristof & Thompson, 2019). The analyzed pieces implied Trump's wall would be largely ineffective at stopping illegal immigration, terrorism and illegal drugs, and that the wall itself is a symbol of racism (Ramos, 2019) and the manifestation of a "need for separation" (Gawthorpe, 2019). The left-leaning causal interpretation will differ in that drugs/criminals/contraband mostly enter the country at ports of entry, not at random points along the southern border. Treatment recommendations would not include building a wall and could include allocating more funding toward alternative forms of border security and for processing immigrants. The moral interpretation is that immigration is good for the country and the border wall is bad. Essentially, tweets that are interpreted to be against Trump's border wall will be coded as left-leaning.

Figure 3. A left-leaning tweet analyzed in this study



Coding for Neutral Content

Tweets that only contain the hashtag #BorderWall are more likely to be neutral than tweets using the other three hashtags analyzed in this study. Content that appears to be neither for nor against the construction of Trump's border wall will be coded as neutral. An example of this type of content might include objective commentary on how many miles of border wall already exist, where the country stands in the political process of approving or rejecting funding for the wall, how a mix of partial border wall and other security measures are effective, or how much extending the border wall would cost with no opinion or emotion provided by the user. An example of a neutral tweet is shown in figure 4.

Figure 4. A neutral tweet analyzed in this study

Coding for Valence

Valence refers to "whether message content solicits positive or negative feelings in message receivers" (Stefanone, Saxton, Egnoto, Wei, & Fu, 2015, p. 1790). It can also be defined as the "intended emotionality of a message" (Stefanone et al., 2015, p. 1790). Tweets containing words, images, and emoji that convey joy, love, hope, accomplishment, gratefulness and other positive emotions were coded as positive (see the code book in Appendix A). Tweets containing words, images, and emoji that convey fear, anger, contempt, shame, anxiety, sadness and similar emotions were coded as negative. These words have been successfully used in previous studies (Danner, Snowdon & Friesen, 2001) to code for valence. Tweets that did not demonstrate emotion were coded as neutral, and tweets that contained equally positive and negative elements were coded as ambiguous.

Coding for Frame Types

This study takes a deductive approach to frame type analysis, as the frame types are pre-defined, and the content is analyzed for the extent to which these frames appear in the sample (Semetko & Valkenburg, 2000). The sample of tweets will be coded to be one or more of the following four frame types or as having no relevant frame: conflict, morality, economic consequences, and human interest. The author found much overlap between the morality and responsibility frames as outlined by Semetko and Valkenburg and also took into account Iyengar's studies on frame types and attribution of responsibility (1990 & 1991) and opted not to include it as a frame type. Additionally, the responsibility frame type was not recognized in other studies of generic frame types (see Neuman et al, 1992; Valenzuela, Piña, & Ramirez, 2017). See appendix A for more details on coding for frame types.

Intracoder Reliability

Determining the coder reliability of a content analysis is critical to its validity (Lombard et al., 2006). To determine the reliability of analyzing the chosen categories based on the definitions provided, ten percent of the total sample of tweets were reviewed and coded. Holsti's formula will be used to calculate the percent of agreement between the original coded sample and the second round of coding. Agreement for each variable was calculated separately to maximize reliability by not hiding low levels agreement in one calculated average of agreement across all variables (Lombard et al., 2006). To maximize reliability with one coder, the sample was also coded at the beginning, middle, and end of the sample. The minimum acceptable level of agreement for this study would be an alpha coefficient of .8 (Holsti, 1969).

$$\text{Reliability} = \frac{\text{M (number of decisions where coder agrees)}}{\text{N (number of coding decisions)}}$$

Reliability for each of the four variables examined in this study is as follows:

Content type: 1.0

Political leaning: 1.0

Valence: .9

Frame type: .9

Machine-Learning Tool

To address RQ1, "What is the proportion of bot-generated to human-generated tweets regarding the U.S./Mexico border wall and border security within the sampled tweets?" this study will utilize Indiana University's Botometer to determine the likelihood of examined tweets coming from accounts controlled by social bots. Botometer is a publicly available tool developed in collaboration between researchers from the Indiana University Network Science Institute and the Center for Complex Networks and Systems Research (CNetS). Botometer was designed using a machine learning algorithm that was trained to identify bots using 15,000 manually identified bot accounts and 16,000 verified human accounts (Varol et al., 2017). The tool classifies bots by evaluating 1,150 account features that are divided into six categories: user-based features (number of friends and followers, profile description, and settings), friends features (which include retweets and mentions by other accounts and their language and geographic locations), network features (which include retweet, mention, and hashtag networks), temporal features (such as rate of content production and time intervals between posts), content and language features (which includes an analysis of word length, entropy, and Part-of-Speech or POS tagging), and sentiment features or valence (Varol et al., 2017). The newest version of Botometer also analyzes time zone information, device metadata, and content deletion patterns to determine whether an account is a bot (Yang et al., 2019).

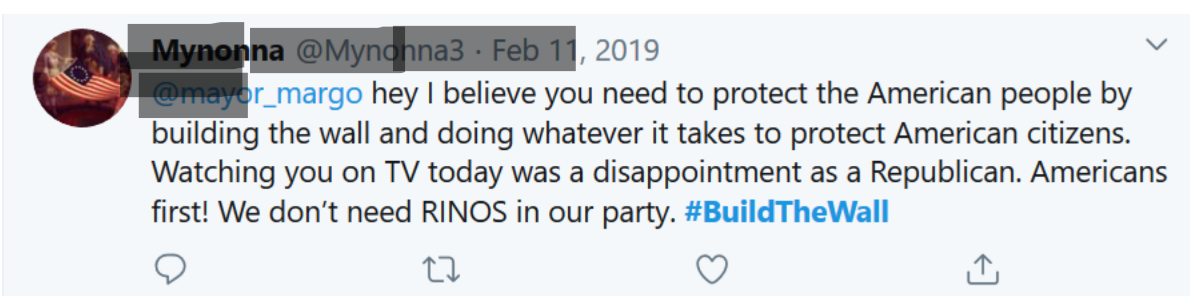
Studies using Botometer (Varol et al., 2017 and Wojcik et al., 2018) have found the percentage of bots on Twitter to be between 9 percent and 15 percent. However, these estimates could be conservative if accounts that are partially automated are included (Davis et al., 2017). The most recent study of the tool's accuracy (Varol et al., 2019) determined the tool to have a high prediction accuracy (between 0.95 and 0.97 AUC). To help users determine whether a Twitter account is a bot, Botometer provides a probability score, referred to as a CAP score (Complete Automation Probability). Accounts may have a score between 0 percent (human) and 100 percent (bot). In previous studies, researchers used a threshold of .5 or 50 percent to separate bots from humans. A recent political bot study by Luceri, Deb, Giordano, and Ferrara (2019) use a CAP score of .3 as an acceptable threshold. Any account with a CAP score higher than 30% was counted as a bot due to the "emergence of increasingly more sophisticated bots." The author of this study chose to take a more conservative approach to bot scoring and will designate accounts with a CAP score of 70 percent and above as bots. Additionally, the author will divide sampled accounts into three categories: most likely humans, most likely bots, and unidentified, as done by Broniatowski, Jamison, Qi, Alkulaib, Chen, Benton, …& Dredze (2018) in a health communications study that also used Botometer to score bots. This author finds this approach to provide the most accurate analysis, as Botometer "cannot make an accurate assessment for all accounts" (Broniatowski et al., 2018, p. 1379).

ANALYSIS

In total, 1,980 tweets were analyzed and coded. The vast majority of tweets sampled (1,868) had a CAP score of .2 or lower and are most likely humans. A small portion of accounts sampled (101) fell into the unidentified range. This group not only contains those accounts with a score between. .21 and .69 – it also contains accounts that were unable to be scored by Botometer because they were suspended, closed, designated as private (unreadable by Botometer), or the username changed over the course of the study (less than 1% of the sample).

This study sought to find if bots were contributing to the U.S.-Mexico border wall discussion, and if so, how did this compare to the volume of human-generated tweets. While the number of bots found in this sample were few, the content of bot-generated tweets indicated that bots are capable of framing content and that the types of frames they use are consistent with those used by humans. The tweet shown in Figure 5 comes from an account with a CAP score of 83%. The tweet employs a moral frame by implying that protecting American citizens is a mayor's moral duty and overlays a conflict frame, indicating that this mayor (the mayor of El Paso, TX) is not a Republican (one of us), referring to him as a RINO (Republican in name only).

Figure 5. Tweet from sample with a CAP score of 83%



In this sample, the proportion of bot-generated tweets to human-generated tweets was 9 to 1,868. In other words, only .5% of the accounts sampled were most likely bots according to a CAP score of .7 and above.

RQ1: What is the proportion of bot-generated to human-generated tweets regarding the U.S./Mexico border wall and border security within the sampled tweets?

Table 1: *Occurrence of bot vs. human-generated tweets*

	CAP Score	Totals
Most likely bots	70-100%	9
Unidentified	21-69%	103
Most likely humans	0-20%	1868

The study also sought to explore left-leaning versus right-leaning tweets generated by bots compared to humans. Bots promoted right-learning frames more than left-leaning frames, but this was also true of humans and partially automated accounts. The majority of tweets sampled (72%) were coded as right-leaning tweets. This was consistent across categories, with two-thirds of bot-generated tweets and over two-thirds (72%) of human tweets and (71%) unidentified tweets consisting of right-leaning content.

RQ2: Are more bots versus humans promoting primarily left- or right-leaning frames of the U.S./Mexico border wall and border security on Twitter?

Table 2: Political Leaning of bots vs. humans

	Right	Left	Neutral	Ambiguous
Most likely humans	1337	361	95	75
Unidentified	73	15	9	6
Most likely bots	6	1	2	0

Next, the study sought to find if the valence of bot-generated tweets differed from human-generated tweets. In all categories, the tweets were mostly negative. In the human and unidentified categories, neutral tweets were more frequent than positive tweets. However, bot tweets were more frequently negative than human tweets, with 54 percent of human tweets and 78 percent of bot tweets being negative.

RQ3: Does the sentiment (i.e., valence) of tweets differ for bots versus humans regarding the border wall and border security?

Table 3: Sentiment of bots vs. humans

	Positive	Negative	Neutral	Ambiguous
Most likely humans	267	1014	361	226
Unidentified	19	46	25	13
Most likely bots	0	7	1	1

Lastly, the study sought to find if bots were capable of framing tweets about the border wall, and if those frames differed from the frames of human tweets. This study found that bots are indeed capable of generating tweets with frames. Conflict was the predominant frame used across categories in this sample, and morality was the next most frequently employed frame in all categories. The study results indicate that bots employ frames in a similar way to humans.

RQ4: Do bots use common media frames, and if so, do bots frame the U.S./Mexico border wall and border security differently than humans?

Table 4: Frame Types across Categories

	Moral	Human Interest	Conflict	Economic Consequence
Most likely humans	335	50	839	101
Unidentified	13	3	42	1
Most likely bots	3	0	4	2

It is worth noting that Luceri et al. (2019) used a CAP score of 30% as the dividing line between bots and humans due to increasing bot sophistication. It is highly probable that several of the accounts in the unidentified group (scores above 20%) are at least partially automated, especially since this group also contains suspended accounts. Researchers have struggled with the categorization of “hybrid” social media accounts that are partially automated and partially controlled by humans. These techniques are employed to “bypass bot and bot-coordination detection systems,” (Yang et al., 2019). This is why some likely bots will not receive a high enough CAP score to be officially considered bots. This is also the reason for the inclusion of an unidentified group in this study. If we add the unidentified group (which includes the same framing patterns) to the bot group, there is further evidence to support bots frame issues along the same lines as humans.

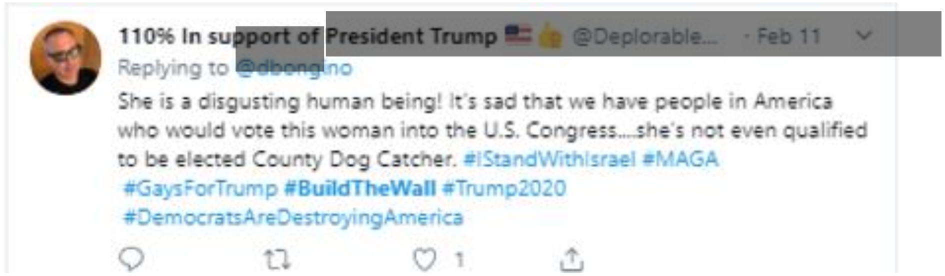
DISCUSSION

This study was designed to examine the framing capabilities of social bots. Recall Entman's definition of framing as "to select some aspects of a perceived reality and make them more salient in a communicating text…" (1993, p. 52). The common frames found within bot-generated tweets (moral, conflict, and economic consequence) in the sample suggest that social bots are indeed capable of making perceived aspects of reality more salient to their audience. This is interesting information for mass media researchers who have previously only attributing framing capabilities to humans. In future studies, when bot accounts are identified and separated from human accounts, the tweets of these bots should be examined for their framing capabilities in addition to the temporal patterns, sentiment, and reply and content sharing frequency that are often analyzed in big data studies. This will help us better understand the growing sophistication of bots and how well they can emulate human communication.

This study was also designed to examine Twitter activity related to President Trump's border wall on the right versus the left. Recall that Entman and Usher (2018) proposed five digital pump valves to add to their Cascading Network Activation model, two of which were social media and bots. They also proposed that the adoption of this model is politically asymmetrical, with the right being more advanced in the adoption and use of these tools. From the small sample of bots found, six out of nine generated right-leaning tweets. Though it is a small number, it is in line with Entman and Usher's theory. Additionally, it is interesting to note that out of the 1,980 tweets analyzed, 1,416 were right-leaning. This could be an indicator that the right's use of social media to promote their political perspectives is far more successful than efforts on the left. The results support Entman and Usher’s statement that, “the right wing, but not left-wing ecosystem has reached digital maturity” (Entman & Usher, 2018, p. 130). Many of the sampled right-leaning tweets were shared directly from the accounts of Republican politicians, including President Trump’s Twitter account. A suggestion for future research to further investigate Entman and Usher’s theory would be to analyze another political issue on Twitter and calculate how many right-learning tweets versus left-leaning tweets share content from the accounts of their respective politicians. This would provide more of an indication of the power of political elites to directly influence the people on social media and the success of each side.

An interesting observation made from the sample is that right-leaning users employed their hashtags, #BuildtheWall and #BuildthatWall, much more frequently than the left used the #NoWall hashtag. #BuildtheWall hashtags were used in right-leaning tweets even when they weren’t related to the border wall. As shown in Figure 6, #BuildtheWall was used on tweets as if it were a campaign banner, along with #MAGA, #Trump2020, and other hashtags developed by the right to promote their positions. When viewing right-leaning tweets about the border wall in sequence, it gives an illusion of a strong, cohesive movement of united supporters around a cause, while left-leaning tweets appear to be random and isolated in comparison.

Figure 6. A tweet using right hashtags as banners



Another interesting aspect of the use of hashtags in this sample is that the left sometimes used the right's hashtags to get their attention (Figure 7). As shown in Table 5, in 35 out of 377 tweets, left-leaning users employed a #Buildthewall or #Buildthewall hashtag. This is nearly 10 percent of left-leaning tweets. This unexpected use of hashtags is worth noting for future research that conducts big data studies on bots. As previously noted, these studies often only use hashtags to organize their sample by political ideology.

Table 5: Hashtags and political leaning

	#BuildtheWall/#BuildthatWall	#NoWall	#BorderWall
Left-leaning tweets	35	247	100
Right-leaning tweets	1359	1	57

Figure 7. Left-leaning tweet with right-leaning hashtags

Practical Implications

The findings of the current research in combination with related studies (Howard & Kollanyi, 2016; Howard et al., 2017) have practical implications for political communicators, social media companies, and regulators. Professional political communicators on the left should take note that their colleagues on the right appear to be out-performing them on digital channels. Based on the results of this study and several related studies, it appears they are not utilizing the five pump valves (platforms, analytics, algorithms, and ideological media) with the same efficacy as the right. Is this because they are putting less time, effort, and resources into data analysis related to online behavior and digital communications? Is it that Twitter is not the best platform to reach Democratic voters? Or, is it that the right is more effectively leveraging offline activities for online engagement?

Recall that Beto O’Rourke held an anti-border wall rally the same day President Donald Trump held is pro-wall rally in El Paso, Texas, yet there were far fewer left-leaning tweets sampled on this day. Also recall that Joy Villa wore a “build the wall” dress to the 2019 Grammy Awards, which was shared and commented on proliferously by the right. Content about this dress occurred multiple times in this sample. Camila Cabello opened the same award ceremony with a performance that contained the message, “build bridges not walls” (Garcia Lawler, 2019). This message was mentioned exactly once within the sample, and it was framed from a politically neutral standpoint. Practitioners can test these questions in the field to understand why Twitter engagement surrounding political issues is higher on the right in an effort to improve their digital reach and impact.

Perhaps another reason the left has been slower to adopt some of the five digital pump valves is because there are ethical implications. When it comes to political communication online, what is fair? Is it unacceptable to use bots to promote political causes and political candidates? If so, is it also unacceptable to use partially automated accounts? How much, if at all, should political strategic communicators employ algorithms, analytics, and rogue actors (bots) to sway public opinion? It is also worth noting that extreme and violent content was shared in the discussion of Trump’s border wall on Twitter. Should the rules be the same when it comes to extreme, violent, or intentionally divisive content? Regulators and leaders of social media companies must discuss and arrive at answers to these questions to help establish a level playing field in the arena of political communications.

Figure 8. An extreme and divisive tweet from the border wall sample

Finally, another area where social bot research is lacking is research on platforms besides Twitter, such as Facebook. Automated, fake accounts created for political manipulation have been found on Facebook (Fandos & Roose, 2018), and Facebook is the most commonly used social platform in the United States (Smith & Anderson, 2018), yet there is no scholarly research that quantifies bots on Facebook or examines their communications in this medium.

Limitations

One challenge to this study is that bots are continuously evolving as developers enhance their techniques to evade detection by tools, such as Botometer (Luceri et al., 2019; Rauchfleisch & Kaiser, 2020). Another challenge is that tweets were sampled retroactively rather than collected in real time via streaming API. This poses a problem because bot accounts are sometimes identified by Twitter and shut down, or they are shut down by those who deployed them after they have served their purpose. Another issue with allowing time to pass between tweet posting and collection is that Twitter users sometimes change their usernames. Once a username has changed, or an account has been suspended or closed, Botometer can no longer analyze and score the account's activity. However, it will not always be possible for researchers to identify a target date or event in advance to be able to collect tweets in real time.

Because this study analyzes such a small number of tweets in comparison to other social bot studies, and it does not examine simple retweets, it likely does not paint an accurate picture of the overall proportion of bots to humans tweeting about the border wall. However, it does provide an in-depth analysis of how bots frame tweets versus how humans frame tweets on the left and on the right. It was also able to account for subtle nuances in tone and language and unexpected uses of hashtags that machine learning tools are still likely not advanced enough to catch.

Lastly, another limitation lies in the increasingly blurred line between social bots and humans and the varying accuracy of Botometer as a detection tool. Many people and organizations use software tools to schedule social media posts, such as Spout Social and Hootsuite, and users of these automation tools are growing. Hootsuite began in 2008 with zero users, and they now have 18 million (Hootsuite.com, 2020). Because of this, a user may appear to be a bot when it is only partially automated. Another factor that adds to this confusion is that Botometer's user CAP scores vary over time, and the tool can produce false positives and false negatives. For example, a user might have a CAP score of 80% at the time a researcher analyzed it, but weeks later the account might have an entirely different score. Perhaps a user was posting at an unusually high frequency or from a different time zone for a brief period. This is because Botometer bases its CAP score on only the most recent 200 tweets. Botometer's accuracy also varies by data set (Rauchfleisch & Kaiser, 2020). Future research with bot detection tools should reevaluate Twitter accounts examined in a study after 14 days or more and compare initial scores to final scores for greater accuracy.

CONCLUSION

Social bots are capable of framing issues using the common generic frames identified in framing research (conflict, moral, and economic consequence) and applying them to political content. This research adds a drop to a nearly empty pool of research that should be conducted on bots' framing capabilities to better understand how well they can emulate humans online and their effects on human behavior. The small number of bot accounts found in this study (far below the established baseline of 9-15%) could be an indication that Twitter is successfully taking action against bot accounts and shutting them down in a timely manner, and it could also be an indication that social bots are becoming increasingly more sophisticated. Bot behavior more closely resembles that of humans than it did just four years ago (Luceri et al., 2019). In either case, bots remain a problem, and they are currently capable of successfully emulating human framing capabilities on Twitter.

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APPENDIX A

CODEBOOK

Every tweet selected within the given date range will be coded. Advertisements and promoted tweets posted by organizations and companies are excluded from analysis. Repeat content is also excluded from analysis.

Coding for Political Leaning

Right-leaning tweets

Right-learning tweets in this sample will show support for Trump's border wall and likely include the hashtags:

- #BuildTheWall
- #BuildThatWall
- #MAGA
- #QAnon

#MAGA and #QAnon will not be coded, but they are often used in tweets that are in tweets that are in favor of building the border wall. These tweets may contain references to immigrants wasting our money and/or resources. Additionally they:

- May refer to people who cross the southern border as drug dealers, terrorists, traffickers, and/or criminals
- May include negative references to President Obama
- May include negative references to Democrats
- May include negative references to Latin Americans
- May include negative references to Beto O'Rourke

- May show support of Trump’s national emergency declaration

Left-leaning tweets

Left-leaning tweets in this sample will demonstrate disapproval of Trump’s border wall and might use the #NoWall hashtag. They also:

- May contain negative references to President Trump.
- May contain negative references to Republicans.
- May show disapproval of Trump’s national emergency declaration.
- May demonstrate support of Beto O’Rourke.

Politically neutral tweets

Neutral tweets will not demonstrate support for or against the border wall and will likely include the hashtag #borderwall and none of the other hashtags in the study.

Coding for Emotional Valence

Emotionally positive tweets

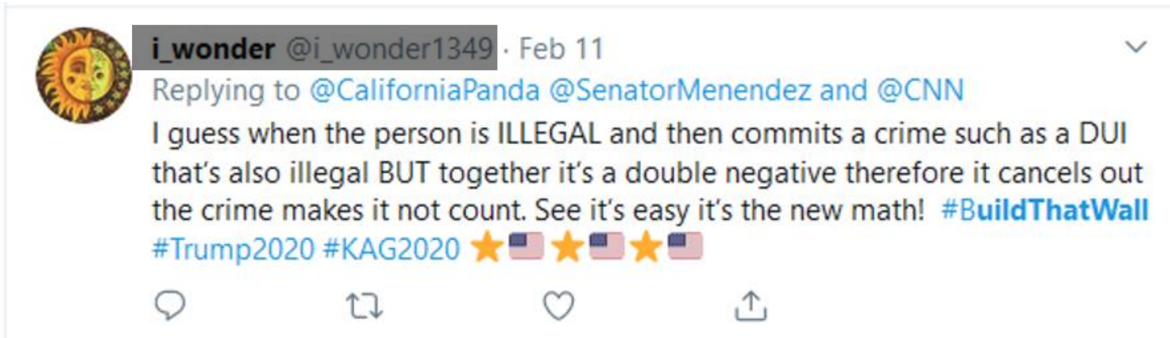
Positive tweets demonstrate joy, love, hope, relief, accomplishment, gratefulness, and optimism, among other positive emotions. See an example of a positive right-learning tweet that expresses optimism below.

Positive tweets may contain the following emoji:

- smiling face
- heart
- wide grin
- kiss
- hug

Emotionally negative tweets

Negative tweets demonstrate fear, anger, disgust, contempt, shame, frustration, suffering, confusion, anxiety, hopelessness, negativity, sarcasm, and/or sadness. Negative tweets may contain threats or warnings of danger. Sarcasm may sometimes be difficult to detect and largely depends on the context and political leaning of the tweet. See an example of a sarcastic right-learning tweet below.



Negative tweets may contain the following emoji:

- angry face
- sad face
- scared face
- confused face
- vomiting
- crying

Coding for Frame Types

Conflict frames

Conflict frames highlight conflict between groups or individuals and take an "us versus them" approach. Tweets that highlight the difference between liberal and conservative viewpoints will be coded as conflict frames. Also tweets that take an "us versus them" approach when it comes to the media versus the people, Congress versus the presidency, or immigrants versus Americans will be coded as conflict frames.

Human interest frames

Human interest frames are employed to provoke emotions and highlight the humanitarian impact of an issue or event (Semetko & Valkenburg, 2000) and provoke feelings of sympathy or compassion through the retelling of personal or individual experiences. Left-leaning tweets employing a human interest frame in this study will likely outline particular cases of difficulties migrants faced when crossing the border or navigating the U.S. immigration process (or lack thereof). Right-leaning tweets employing this frame might mention specific cases of human trafficking, murder, or drug-related deaths. See an example of a human interest frame below. (Note, the link is from a fake news site.)

Economic consequences frames

These frames highlight the economic impact an issue or event has on particular group or individual. In the sample collected, tweets that use this frame will likely emphasize the economic cost of building or not building the border wall. They might also mention the economy and jobs lost to immigrants.

Note that while the media commonly uses technical terms when employing economic frames, people will typically overlay economic frames with a moral perspective (Neuman et al.,1992).

*Morality frame*s

Morality frames are used to place an issue, problem, or event in a religious or moral context and might provide moral prescriptions to problems (Semetko & Valkenburg, 2000). An example of a morality frame that might appear in this sample is a moral obligation to help or protect those fleeing violence or hardship in their home countries. For example, content sampled in this study might invoke the quote from the

Statue of Liberty, “Give me your tired, your poor, your huddled masses yearning to breathe free…” Morally framed tweets might also prescribe a solution, saying something ought to be done. They may also place blame, saying someone is bad or evil for taking/not taking a certain action. See an example of a moral frame that employs American values below.