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Influencers, Amplifiers, and Icons: A Systematic Approach to Understanding the Roles of Islamophobic Actors on Twitter

Lawrence Pintak[1,2], Brian J. Bowe[3,4], and Jonathan Albright[5]

Abstract

In the 2018 U.S. midterm elections, an unprecedented number of American Muslims ran for public office, including the first two Muslim women elected to Congress. This study analyzes the anti-Muslim/anti-immigrant Twitter discourse surrounding Ilhan Omar, one of these two successful candidates. The results identify three categories of accounts that linked Omar to clusters of accounts that shaped the Islamophobia/xenophobic narrative: *Influencers, Amplifiers*, and *Icons*. This cadre of accounts played a synergistic and disproportionate role in raising the level of hate speech as a vast network containing a high proportion of apparently inauthentic accounts magnified the messages generated by a handful of provocateurs.

Keywords

Twitter, Islamophobia, hate speech, bots, influencers, social media

Introduction

For Muslim Americans, Donald J. Trump's election as U.S. president was apocalyptically described as "the most pronounced threat to their collective political well-being in history" (Calfano et al., 2019, p. 477). Trump's use of Islamophobic rhetoric on the

[1]The Aga Khan University, Nairobi, Kenya
[2]Washington State University, Pullman, USA
[3]The American University in Cairo, Egypt
[4]Western Washington University, Bellingham, USA
[5]Columbia University, New York, NY, USA

Corresponding Author:
Lawrence Pintak, Dean and Professor, Graduate School of Media and Communications, The Aga Khan University, P.O. Box 30270, Nairobi 00100, Kenya.
Email: Lawrence.Pintak@aku.edu

campaign trail and in office, followed by the institution of a ban on travelers from several Muslim-majority countries, was accompanied by a rise in violence and vandalism against Islamic communities across the United States (Lajevardi & Oskooii, 2018; Tesler, 2018).

This spike in Islamophobia created fear, but it also galvanized and mobilized the U.S. Muslim community. An unprecedented number of Muslims were motivated to seek elected office in the 2018 midterm elections, overcoming a traditional hesitancy to engage in electoral politics (Siddiqui et al., 2016). At least 166 Muslims ran in the 2018 primaries for offices ranging from local school boards to the governorship of Michigan and the U.S. Congress (Pintak et al., 2019), and by election day, some commentators were even referring to the results as a "Muslim wave" (Ghanem, 2018). Two Muslims were elected to Congress—Rep. Rashida Tlaib (D. MI) and Rep. Ilhan Omar (D. MN).

This push-and-pull dynamic of Islamophobia and engagement is emblematic of the uncomfortable space Muslims occupy in the United States. Since Donald Trump began his campaign for the U.S. presidency in earnest, incidents of anti-Muslim activities have been on the rise (Anti-Muslim Activities in the United States, 2019). There is long-standing evidence that non–Muslim Americans who know a Muslim personally harbor less Islamophobic attitudes (Mogahed & Mahmood, 2019). However, Muslims make up a relatively small proportion of the U.S. population, and because of this, secondhand mediated discourses take on a greater importance in the formation of beliefs and attitudes about Muslims among the general public. In the social media era, anti-Muslim rhetoric has found a home on social media platforms like Twitter, which have become a particularly fertile ground for the so-called "Cyber Islamophobia," in which Muslims are perpetually constructed as a violent outgroup incompatible with U.S. society (Aguilera-Carnerero & Azeez, 2016).

This phenomenon is important to understand because Twitter has become a key component of political discourse in the United States, especially in the wake of Trump's extensive use of the platform. The central research question addressed in this study examines the roles played by different categories of influential accounts in shaping the Islamophobic narrative around Ilhan Omar during her campaign for Congress and how do they work to reinforce each other. This study is based on a large-scale network analysis of Twitter discourse involving Omar in the run-up to the election. Omar, a naturalized U.S. citizen who fled Somalia with her family when she was a child and spent years in a refugee camp before immigrating to the United States, was chosen because she is the highest profile Muslim on the U.S. political landscape, in part because she has been specifically singled out for attack by President Trump, who has held her up as a symbol of the alleged threat posed by Muslims (Haberman & Stolberg, 2019; McCarthy, 2019). In addition, the number of tweets in her network during the period studied was more than 7 times that of the next Muslim candidate, Rep. Rashida Tlaib (90,193 vs. 12,492).

In an attempt to better understand the mechanisms of influence behind online rhetoric involving Muslim candidates in the 2018 election, this research examines the Twitter networks that linked Omar to clusters of those accounts posting tweets that contained Islamophobic or xenophobic language or other forms of hate speech to identify the roles played by three categories of Twitter accounts—Influencers, Amplifiers, and Icons—in the propagation of Islamophobic rhetoric. This study explores the respective roles of these accounts to understand to what extent each serves a purpose in the Twitter ecosystem and how some work together.

Influence can be measured quantitatively through centrality and network metrics (Gruzd et al., 2014). Users identified as influential, however, must be categorized according to audience, content, and context (Romero et al., 2010). The degree to which a user can influence others is a composite measure that includes their activities, audiences, and the platform's affordances (Bruns & Burgess, 2011). Put together, influence is a research construct that must be applied on a case-by-case basis to understand processes within sociotechnical systems (Ellison & Vitak, 2015).

Furthermore, this study examines the authenticity and autonomy of accounts driving the narrative, since this measure makes it possible to determine the degree to which the narrative is being shaped by bots and other forms of manipulative behavior. Given the rising importance of social platforms in political life, an understanding of these underlying mechanisms is crucial far beyond the focus of the current research.

Literature Review

Although Islamophobia is a contested term, it has been defined conceptually as indiscriminate or unfounded negative or hostile attitudes and emotions directed at the religion of Islam, which results in discrimination against Muslims and their exclusion from the public sphere (Bleich, 2011; Conway, 1997). The rise of Islamophobia post-9/11 has been linked to deep-seated fears of the Muslim "Other" (Pintak, 2006), exacerbated by fears of terrorism and, particularly, the onset of "homegrown" violence by Muslim Americans or Muslims residents in the United States (Ernst, 2013; Esposito & Kalın, 2011).

Islamophobia is often discussed at the individual level as the motivating force behind discrete acts of violence or vandalism (Shyrock, 2010). However, the Runnymeade Trust (Conway, 1997) highlighted "the exclusion of Muslims from mainstream political and social affairs" as an outcome of Islamophobia (p. 4). Given the rise of overt violence against Muslims in the United States, Beydoun (2018) criticized the dominant definitions of Islamophobia as being too focused on individual animus while eliding the state structures that have promoted it and allowed it to metastasize. In a wide-ranging report, Ali et al. (2011) documented a well-funded network of individual donors and foundations that perpetuate Islamophobic ideas in the political sphere. Similarly, Bail (2015) described a "rapidly expanding network of civil society organizations" whose affiliated think tanks, churches, and social movement organizations wield influence on media, government, law enforcement, and political spheres to "shift American public opinion against Islam" (p. 3).

Although Islamophobia has roots in the United States that predate independence from Britain in 1776 (GhaneaBassiri, 2010), it rose to the fore in the aftermath of the al-Qaeda attacks of 9/11 and then saw a resurgence with the rise of Islamic State in Syria and Iraq, providing fertile ground for the anti-Muslim, xenophobic messaging of Donald Trump.

Islamophobia has also been linked to tribalism on the part of White Americans, fearful of demographic and economic shifts that they blame on Muslims and other immigrants (Chua, 2018). As such, Islamophobia is strongly intertwined with racism, although it is only rarely discussed as such in the academic literature or media discourse (Beydoun, 2018; Love, 2017; Meer, 2013; Moosavi, 2015; Taras, 2013).

Exacerbating this situation in the United States has been an obnubilation of Muslims into the broader category of "brown foreigners" (Islam, 2018). This is noteworthy because, of the many Muslim candidates for office in the 2018 midterms, almost all were people of color, and many were from families with recent immigration stories. This includes Ilhan Omar who wears a hijab and who came to the United States with her family as a refugee from Somalia. Omar is the highest profile member of this cohort, featured on the cover of *Time* magazine and hailed as "a new national voice against [Trump] administration policies" (Karnowski, 2018; "The Legislator: Ilhan Omar," 2017). But her intersectional identities left Omar with multiple burdens to carry when entering the public sphere and made her a prime target for Islamophobia online.

Cyber Islamophobia and Online Influencers

Cyber Islamophobia is a multifaceted phenomenon that includes spreading false statements about Muslims and Islam, attributing despicable acts to it, mocking its practices, and making threats or meting out verbal abuse in social media channels, thereby propagating reductive stereotypes and misrepresentations that perpetually place Muslims as outsiders in conflict with "the West" (Aguilera-Carnerero & Azeez, 2016). Such rhetoric reifies Huntington's (2011) problematic notion that "Islam's borders are bloody and so are its innards" (p. 258), which makes inevitable a "clash of civilizations" between the world's Muslims and the West.

However, Islamophobic Twitter debates do not magically appear online fully formed. Rather, they are the result of an interlocking and symbiotic ecosystem of influencers. As Benkler et al. (2018) note, "To understand media and politics, we must understand the entire ecosystem: the outlets and influencers who form networks, the structure of networks, and the flow of information in networks" (p. 45). The phenomenon of rising online Islamophobia may be related to the volatile—but still little understood—interaction between social media use, political polarization, the rise of disinformation, and the health of democracy itself (Tucker et al., 2018).

On Twitter, the notion of "influence" can be conceptualized in a variety of ways. It can be defined as the mentions, tweets, and impressions assigned to an individual user (Borgmann et al., 2016). Topical influencers can be considered experts on a particular subject who wield the ability to cause others to share information (Zengin Alp & Gündüz Öğüdücü, 2018). Influencers may exhibit a wide variety of desirable attributes, such as credibility, expertise, enthusiasm, connectivity, or centrality, "that allows them to influence a disproportionately large number of others" (Bakshy et al., 2011). This multiplicity of ways to think about and measure "influence" on Twitter is one of the complications of studying communication on the platform.

Rather than considering Twitter influence as a monolithic construct, this research uses three different measures to understand the different roles accounts play in shaping the Twitter conversation. These roles are labeled *Influencers, Amplifiers*, and *Icons*. Each group plays a particular part in the Twitter ecosystem and, sometimes, helps the Twitter discourse spill over into the broader political discourse beyond social media. Each of these kinds of influencers has been studied in the past; this research's contribution is to consider all of them working in concert.

Influencers. The first way this research measures the degree to which an account shapes the Twitter conversation is through the PageRank, an algorithm that shows the "propagation of influence along the network of web pages, instead of just counting the number of other web pages pointing at the web page" (Kwak et al., 2010, p. 595). The importance of these accounts relative to others in the candidate's network reflects the degree to which they are central to the narrative by showing up in retweets or mentions by other accounts (Kouznetsov & Tsvetovat, 2011; Tommasel & Godoy, 2015). The tool is used by Google to measure the influence of webpages (Brin & Page, 1998), but it has also been adopted to determine the level of authority and trust of Twitter accounts by other users (Caverlee et al., 2008; Frahm & Shepelyansky, 2012; Gimenez-Garcia et al., 2016; Wei et al., 2017; Weng et al., 2010). PageRank has been employed to access the level of influence of Twitter accounts in studies involving the 2015–2016 Zika outbreak in the United States, in health care (Desai et al., 2016), the 2012 London Olympics (Willis et al., 2015), and other situations.

This research labels accounts with a high PageRank as Influencers. Acknowledging the inherent ambiguity of the term "influencer," Bakshy et al. (2011) conceptualized it as the ability to "seed" content that then cascades through Twitter as it is shared by other users. This tranche of accounts includes those that "seed" the Twitter narrative, originating content like ideas, memes, or hashtags (Bakshy et al., 2011). However, that is not true of all accounts with a high PageRank. The mechanics of their participation vary and include tweeting, retweeting, replying, liking, or tweeting a screenshot of the original tweet. Previous researchers have referred to the most active of these influencers as Idea Starters (Tinati et al., 2012; Tommasel & Godoy, 2015; Wang & Zheng, 2014). Such accounts are highly engaged in social media and connected to an intricate network of trusted, high-quality online relationships (Tinati et al., 2012).

Amplifiers. While the Influencers were measured via PageRank, a second kind of conversation-shaping account was measured through weighted-out degree, which is the sum of the individual edges—for example, all references to candidates—from any account that references another and whose post is directed toward the central actor. Those accounts were labeled Amplifiers. The Influencers originate the Twitter discourse or contribute to its early development, but the Amplifiers perform the main work of dissemination. These Amplifiers collate and share the thoughts, ideas, and opinions of others, serving as "the firehose of knowledge" (Tinati et al., 2012, p. 1163).

This amplification happens in several ways: by retweeting or replying to others who mention or reply to a candidate's account; by tagging or adding a candidate's handle to threads on which they were not included; or by replying to or retweeting the candidates themselves. Amplifiers function as *net contributors* or *top engagers-activists*, as this measure prioritizes the most active accounts by total frequency relative to the candidate whose network is depicted. Amplifiers generally retweet a large amount of content, reply to a large number of conversations, and begin conversations by tagging other users (Tommasel & Godoy, 2015). However, the actual number of retweets is less important than their strategic network connections that allow their retweets to be relayed to accounts that themselves are strategically connected to other Amplifiers and the broader network.

Amplifiers have a symbiotic relationship with the Influencers. Amplifiers have larger numbers of followers, and those followers retweet them heavily (Tommasel & Godoy, 2015). "Amplifiers tend to be the individuals that are part of [a] small trusted network of certain" influential accounts, "taking their original ideas and sharing them to a larger, more visible audience" (Tinati et al., 2012, p. 1163). Without the Influencers, there would be *nothing* to talk about. Without the Amplifiers, there would, in relative terms, be *no one* to talk about it.

Icons. A third category of impact is measured by the simple number of followers for a particular account, which is usually reflective of the account holder's prestige. These are the social media influencers in the classic sense; political, entertainment, and news celebrities; major media organizations; and similar accounts that have huge networks of followers. In this study, they are labeled *Icons*. Their relative rank is based on total follower count in the Twitter universe, not their influence within the individual candidate's network. This combination of media outlets, celebrities, and organizations can also be referred to as "elite users" (Wu et al., 2011) who concentrate public attention and sometimes contribute to the polarization of political discourse (Morales et al., 2015).

While Influencers and Amplifiers are important within a network, Icons serve as a bridge between the network and the broader social conversation. Such high-value users remain important in the social media era because, as Wu et al. (2011) note, "while attention that was formerly restricted to mass media channels is now shared among other 'elites,' information flows have not become egalitarian by any means" (p. 710). In other words, although members of the general public have the same access to Twitter that a celebrity does, that does not mean all tweets carry equal weight. Previous research has found celebrity tweets are perceived as more authoritative, trustworthy, and competent, making them particularly useful, for example, in generating word-of-mouth about products (Jin & Phua, 2014; Pal & Counts, 2011).

The Icons only appear on a particular account's network map if they have, in some way, interacted with other accounts in that account's network. This activity is not necessarily influential inside the captured networks, but it is important for the diffusion of awareness and information outside the candidate's network to the rest of Twitter and the world. They are useful for showing topical attention and candidate coverage by the mainstream media and for showing references from highly influential support and opposition actors. While it is important to acknowledge the existence of this category, it does not play a significant role in this study as the most prominent Icons in the Omar network were not engaged in tweeting hate speech or Islamophobic messaging.

Trolls

Within these categories are individual accounts that exhibit characteristics of "trolls." Researchers have yet to agree on a single definition of "troll" or "trolling" because the act is strongly subjective and contextual, therefore it may have multiple and inconsistent definitions (Coles & West, 2016; Fornacciari et al., 2018, p. 258). The behavior of a troll is analogous to that of a fisherman dragging a lure through the water to provoke a feeding frenzy (Baker, 2001; Binns, 2012).

One commonly used definition characterizes a troll as "an individual adopting an antisocial behavior that provokes and irritates other users of an online social platform" (Fornacciari et al., 2018, p. 258). The rise of political polarization, intolerance, and bullying in society in recent years (Korostelina, 2017; "Political Polarization, 1994-2017," 2017; van Prooijen & Krouwel, 2016) has been accompanied by increased levels of antisocial behavior online (Korostelina, 2017; Ott, 2017; van Prooijen & Krouwel, 2016). The *online disinhibition effect* means that individuals often act differently online than they would in the physical world; the most negative iteration of this phenomenon is the *toxic disinhibition effect* in which suppressed anger and violence are expressed (Suler, 2005). Thus, individuals who might not engage in antisocial activities in the "real world" are more likely to do so if their online community involves rising levels of vitriol and are also affected by shifting attitudes within their particular societal milieu (Cheng et al., 2017, p. 2). When discussing trolls, it is important to include information about context and proportionality to understand the marginal position many trolls occupy in the broader discourse (MacKinnon & Zuckerman, 2012). For the purposes of this study, we are defining trolling as the act of posting or retweeting multiple messages containing Islamophobic, xenophobic, or other forms of hate speech. While an argument can be made that all accounts that tweet or retweet at least one example of offensive comments could be considered trolls, we are not broadening the definition to include those accounts.

Bots and Inauthentic Accounts

The Twitter discourse examined here shows some evidence of "bots," which are automated social media accounts designed to execute a variety of tasks. Some tasks are benign, such as sending tweets and following users (Kollanyi, 2016). However, bots also play a key role in disseminating and normalizing political disinformation online through sheer volume (Ferrara et al., 2016; Ratkiewicz et al., 2011; Shaffer, 2017). Signs of bots include inexplicably large numbers of followers, tweets, or likes; random strings of letters and numbers in the account name; or scant personal identifying information.

Social media bots represent one kind of Twitter activity that is classified as "inauthentic," but they are hard to positively identify because they use sophisticated algorithms to mimic human behavior (Ferrara et al., 2016). The presence of such inauthentic activity on Twitter presents problems for a political ecosystem by introducing nonexistent issues or by overstating the actual support for an issue (Keller & Klinger, 2019). It also presents a challenge for researchers because it complicates linking observed data to actual people or genuine opinions (Crosset et al., 2018).

Method

This study is based on an analysis of tweets (N = 90,193) captured between September 21, 2018, and November 4, 2018. The beginning date coincided with the race's final primaries, while November 4 was set as the cutoff date to avoid distorting the data with the flurry of get-out-the-vote posts on November 5 and congratulatory or sympathy posts after the results were announced on November 6.

Data were collected for references made to Omar's Twitter handle (@IlhanMN) with or without @, through an ongoing query to Twitter's Search API and filtered for the desired date range. Only English-language tweets that included a mention of the candidate's name or Twitter handle were included in the corpus (references to "Ilhan Omar" or "Omar" only were not included because there are thousands of people named Omar on Twitter and the results would have been irrelevant and unmanageable). Although the Search API avoids the sampling issues of the platform's Streaming API, there are two standard limitations that should be mentioned: (a) Twitter imposes a restriction on records returned per query to a maximum of 1,000 records (i.e., tweets) every 15 min, and (b) tweets older than 7 days are not available. This was not an issue in this study as the collection was carried out in real time. Furthermore, there is the possibility of certain tweets being algorithmically defected and removed by the platform upon posting, and thus not returned in the 15-min query intervals. This is unlikely to be a factor in this focused data set, however, as a tweet referencing a candidate would need to be taken down in less than 15 min to be omitted from the corpus. Given the extended time range of collection, the relatively low volume of tweets over the time of the collection, and considering the study's cutoff time before the midterm results, the Search API is a reliable and representative source of data for the purposes of this study (Thelwall, 2015).

All tweets were read and individually coded by one of the study's authors on a single variable: the presence of Islamophobic sentiment or language. A test of intercoder reliability was conducted with a graduate student research assistant. There is much conflicting advice about the amount of content required for measuring intercoder reliability. Published guidelines suggest somewhere between 5% and 10% of the entire corpus are necessary, while others recommend an amount of more than 50 items but rarely more than 300 (Lombard et al., 2018; Neuendorf, 2017; Riffe et al., 2014). A formula provided by Riffe et al. (2014) suggested that this study could have used as few as 101 tweets in the reliability sample. To ensure the entire character of the discourse was represented, two coders coded 2,000 tweets from the entire body of collected tweets. The observed agreement was 91.2%. Correcting for chance agreement, Krippendorff's alpha was .822, which is widely accepted as a sufficient level of reliability (Krippendorff, 2006; Lombard et al., 2018; Neuendorf, 2017; Riffe et al., 2014).

Tweets were coded to identify those that contained Islamophobic language or sentiment. The lexicon used to identify Islamophobic and xenophobic language and other forms of hate speech was based on the Hatebase.org database, supplemented by a compilation of additional terms added by the authors, drawn from their previous experience studying Islamophobic hate speech.

Examples of tweets that were included in that category were those that referred to Muslims as "animals," "termites," "dogs," and "muzzrats." Others attacked Allah as a "false god" or "Satan" as in this tweet that tagged Omar's Twitter account, @IlhanMN:

> Allah exists but he is not god. Allah is Baal the moon God. A very evil, demonic creature who infests the world with his presence through Islam. One billion people are enslaved by this bloodletting creature of doom. There is a better Way but they are forced not to seek it.

Others expressed fear of Islam:

> @IlhanMN It isn't "Pisslamaphobia" when they really ARE trying to kill you.

Many of the tweets categorized as Islamophobic, xenophobic, or containing hate speech combined examples of all three, such as this one:

> @IlhanMN Bringing incest to the West, along with FGM [female genital mutilation], beating wives and hiding the scars under a niquab [sic] or burka, girls wearing a hijab so as not to excite the men, marrying children. Doesn't sound like a culture that can co-exist with Western values.

Categorization of the top "conservative" or "pro-Trump" accounts was based on a combination of factors. Those accounts associated with media organizations were checked against the classifications on the political rating site mediabiasfactcheck.com, political categorizations of media in the Lexis/Nexis database, the Southern Poverty Law Center classifications, and a database released by NewWhy, a web marketing firm that developed the list to allow advertisers to prevent their ads from appearing on alt-right, racist, or sexist websites. Organizations or individuals not included in these lists were categorized after an examination of the content of the account or political positions stated in its content.

In addition to collecting structured API data (i.e., usernames, posting times, textual content, profile information, user bio, user location, etc.), relationship (i.e., graph) data were also obtained from the search API in the form of node and edge tables. The resulting files were saved as gexf files and imported into Gephi, an industry-standard open-source visualization tool. Statistics were run for core metrics, including weighted and unweighted degree, indegree, outdegree, modularity, and PageRank. The modularity algorithm for community partitioning was run at a setting of 0.5.

To identify bots, accounts were run through Botcheck.me software (Albadi et al., 2019; Labs, 2017), a process-focused tool that uses machine learning "to recognize the differences between regular human profiles and these politically-charged accounts that exhibit bot-like behavior" (Bhat & Krishnaswamy, 2017). When a suspected bot was not flagged by the software, it was examined for other characteristics that indicate a potential "inauthentic" account, one whose provenance is not as presented, including high retweet rates, a disproportionate number of followers and likes, account name, and iconography (Ferrara et al., 2016; Ratkiewicz et al., 2011). Such accounts are often automated or part of groups of accounts controlled by a single individual or organization and used to distribute similar or identical content to increase impact and appear to be part of a synergistic narrative (Douek, 2020).

The issue of whether and when to name the authors of hostile Twitter posts is one much debated in the literature. For the purpose of this article, we have only named those accounts that belong to public figures, such as politicians, celebrities, and individuals who have used their Twitter account to raise their public profile. For purposes of credibility in the context of the prevalence of "fake news," we have provided links to tweets cited. In some cases, those lead to accounts that have been suspended or removed.

Findings

The Twitter discourse surrounding Omar is measured in three ways: PageRank for Influencers, weighted-out degree for Amplifiers, and follower count for Icons. Each of these rankings is a different way to look at the same network, with each highlighting a different set of accounts that shapes the narrative in a different way.

This study is primarily concerned with the Islamophobic content in the narrative: who is creating it and who is amplifying it. Therefore, this study focuses on those accounts that have in some way been connected to tweets containing such sentiment. However, the fact that an account has been tied to that narrative does not necessarily mean it has posted Islamophobic/xenophobic tweets or those containing hate speech; rather, it has somehow been linked into the narrative. For example, @MPRNews, the Twitter account of Minnesota Public Radio, is ranking highly among accounts tied to the anti-Muslim narrative not because it is tweeting anti-Omar content, but because it is being tagged on tweets that do contain such sentiment. Quite often prominent news organizations and politicians—such as House Speaker Nancy Pelosi—are tagged in tweets containing sentiment directly contrary to their own views in the hopes of provoking them. This is the very nature of trolling.

Influencers

Table 1 shows the most influential accounts in the Omar network based on PageRank. This sector includes accounts that are in some way linked to those trolling Omar with Islamophobic/xenophobic hate speech content, along with other accounts that are being tagged in those tweets. The most prominent account is that of Laura Loomer (@LauraLoomer) who dominated the Islamophobic Twitter narrative around Omar. Loomer's PageRank puts her 13th among all accounts of every political viewpoint in the Omar network, but first among accounts posting anti-Muslim/xenophobic content.

Table 1. Top Conservative Influencers.

Account	PageRank	Network rank
LauraLoomer	0.007167	13
Jen4Congress	0.004442	18
AlphanewsMN	0.003528	25
RealDonaldTrump	0.00344	26
HireLearning	0.001011	140
IngrahamAngle	0.000622	149
PoliticalIslam	0.000531	154
PamelaGeller	0.000304	177
Cernovich	0.000101	279
BreitbartNews	0.000093	294

That ranking reflects the account's central role in the narrative. Loomer is an *agent provocateur* who specializes in staging media events and leveraging them on Twitter (Mansell, 2018). She previously worked for Project Veritas, a conservative organization that secretly records liberal figures to entrap them (Mayer, 2016; Nelson, 2018). The account is more influential than those of the news organizations posting about Omar, including @PioneerPress, the Twitter account of Minnesota's main newspaper, which ranked 82 overall in the network, and significantly higher than that of the next most influential conservative or pro-Trump account in the network, Jennifer Zielinski (@Jen4congress), the Republican nominee running against Omar.

The Loomer account was extremely active. It seeded the narrative with posts that were widely retweeted. For example, in October 2018 she posted the following:

> .@IlhanMN why did you marry your brother? Why did you vote against making female genital mutilation a felony? Why are you campaigning with Linda Sarsour? Why did you refuse to take your oath on a Constitution, but took it on a Quran? Why do you hate Jews I have more. https://t.co/4ORzqPN3EQ[1]

That comment was directly retweeted 900 times and was also widely quoted in other tweets. In addition, aside from Omar herself, Loomer's account is the most heavily tagged of any among the conservative accounts in Omar's network.

@Jen4Congress, which had the second-highest PageRank among the conservative accounts in the Omar network, was the campaign account of Jennifer Zielinski, the Republican candidate who ran against Omar for the Congressional seat in her district. But, while this account had a high PageRank, Zielinski did not post a single tweet that could be considered Islamophobic or containing hate speech. Rather, she was widely tagged by others who were posting such offensive content. Similarly, the third most influential account based on PageRank, @AlphanewsMN, did not post a single Tweet tagging Omar. However, it was influential because some of its articles—particularly those accusing the candidate of committing immigration fraud by allegedly marrying her brother—were widely circulated on Twitter in tweets authored by other accounts, rather than posts by the account itself. The account is associated with Alphanews.com, a conservative Minnesota blog and aggregation site that was responsible for generating some of the disinformation about Omar. It was also widely tagged by accounts posting allegations about Omar that it was hoped Alphnews.com would investigate and report, such as this Loomer Tweet:

> @IlhanMN, a Somali immigrant who supports Sharia, FGM & insurance payouts to families of terrorists was arrested in 2013 for Trespassing in Minnesota. She resisted arrest & was aggressive w/ police. She is running for CONGRESS IN MINNESOTA! @AlphaNewsMN https://t.co/d49rhHJI5Q[2]

Of the most influential conservative accounts in the Omar network, some actively contributed to the discourse (@LauraLoomer and @HireLearning); others played more supporting roles (@Cernovich, @Jen4Congress, @AlphanewsMN), whereas other accounts were present because they were widely tagged in the hope they would retweet or write about anti-Omar allegations and that the tagging would bring the tweets to the attention of their followers (@RealDonaldTrump, @IngrahamAngle, @PamelaGeller, @BreitbartNews, @PoliticalIslam). As such, examining PageRank only tells one part of the story.

Amplifiers

Weighted-out degree provides another way to rank conservative accounts in the Omar network that are, in some way, linked to Islamophobic/xenophobic/hate speech content. This view shows those conservative accounts with the highest weighted-out degree. These are the Amplifiers. Thus, @LauraLoomer loses her position of dominance, replaced by accounts that have a larger virtual megaphone effect. There is another difference between the Amplifier rankings and those of the Influencers. Where all the top Influencers were "authentic" accounts, 14 of the top 20 Amplifiers are suspected "inauthentic" accounts and two others were suspended by Twitter for violating its rules regarding inauthentic behavior or offensive content (Table 2).

Some accounts showed signs of being inauthentic coordinated bot accounts—"inauthentic" because they use fake names and "coordinated" because they work together to spread misleading information ("Community Standards—Misrepresentation," n.d.; Friedberg & Donovan, 2019). Other accounts appeared to be sockpuppets, which are also known as "coordinated authentic" accounts designed to "mislead others about who they are" (Kerner, 2018). A final group showed evidence of being automated "cyborg" accounts (Kramer, 2017).

In other words, at most, only four accounts *did not* show evidence of being some version of the automated bot, sockpuppet, or cyborg. This is logical, given that the purpose of bots in a political context is to automatically retweet content that supports the owner's ideological message, but, given their very nature, they do not (for the most part) generate new content. What is most striking about the anti-Muslim Amplifiers is

Table 2. Top Conservative Amplifiers.

Status	W/O degree	Network rank
Inauthentic	734	3
Inauthentic	513	5
AUTHENTIC	424	7
Inauthentic	392	10
Inauthentic	313	12
Inauthentic	306	13
AUTHENTIC	288	14
AUTHENTIC	287	15
AUTHENTIC	274	16
Inauthentic	238	19
Inauthentic	231	21
Inauthentic	229	22
Inauthentic	199	26
Inauthentic	185	29
Inauthentic	174	30
Inauthentic	167	31
Inauthentic	167	32
Inauthentic	162	34
Inauthentic	160	35
SUSPENDED	155	36

where they rank versus other accounts tweeting about Omar. Four of the 10 highest ranked Amplifiers in the network were those forwarding anti-Muslim content, and almost half of the highest ranked Amplifiers were those giving voice to Islamophobic messaging or hate speech. Contrast this with the fact that the highest ranked anti-Muslim Influencer account, @LauraLoomer, did not even make the top 10 among all Influencers, and only three other anti-Muslim Influencer accounts even made the top 100, as measured by PageRank. In other words, only a handful of accounts that seeded the anti-Muslim narrative were as influential as accounts that were spreading other kinds of messaging, but those accounts that provided a digital megaphone for the anti-Muslim messaging were very prominent, based on weighted-out degree, when compared with other accounts.

The most prominent apparent "authentic" Amplifier of anti-Muslim/xenophobic messaging is primarily an Amplifier of a broadly pro-Trump, conservative line, with occasional Islamophobic threads, such as the following:

> @IlhanMN You do understand the quran calls for the death of all infadels. And i believe it, because right before the islamic terrorist shoot at you, they yell allahu akbar.[3]

The next three accounts among the top five apparently "authentic" conservative Amplifiers are more clearly focused on trolling Omar for her Muslim faith and for what they claim is her “anti-Semitic” position on Israel, such as this tweet from an account that has since been suspended for violating Twitter standards that ban, among other things, “hateful conduct” and “platform manipulation” (“Rules and policies,” 2019):

> @IlhanMN Oh look a far left progressive socialists democrat is a Jew hater Muslim sharia law loving grooming child bride pedophile and female mutilation #Minnesota #AntiSemitism the New Democratic Party #WalkAway #RedWave[4]

One of those accounts was a crossroads for anti-Palestine/pro-Israel content:

> @ClearYourDay @PerryYielding @LauraLoomer I’m sure she’s worried about you and your following of 53. Now go back to your anti-semitic Democrats literally calling for the media to “stop humanizing Jews!” -@lsarsour, or @IlhanMN & @RashidaTlaib. All three host & attend fundraisers for Hamas & terrorists killing Jews.[5]

The next apparently “authentic” account among the top conservative Amplifiers is @HireLearning, an account run by Marni Hockenberg, whose bio on her Twitter account described her as “Jewish-American activist. Advocating for anti-Sharia ‘American Laws for American Courts’ laws.” The account’s relationship with @LauraLoomer is symbiotic: Loomer is the dominant Influencer in the Islamophobic/xenophobic sector of Omar’s network; Hockenberg’s @HireLearning account was (until it was suspended) the primary Amplifier of that narrative. Hockenberg heads a Minneapolis corporate recruiting firm and is a close ally of Loomer, whose penchant for political theater she has emulated:

> Yesterday the Muslim American Society singled me out of the audience as I was waiting to hear @keithellison & @IlhanMN speak & made me leave. They said I’m “on a list” of ppl they don’t want at their events. And here’s a video that explains why! #ShariaKills #WakeUpAmerica https://t.co/EdNjl9pATT[6]

Such Tweets reflect the fact that Hockenberg plays two roles in the network, she is a primary Amplifier, but she is also an Influencer.

The top five apparent “authentic” accounts are rounded out by an account that primarily retweets conservative content about Minnesota politics, with dozens of attacks on Omar.

Icons

A final perspective on Omar’s network is presented through follower count. In this case, the accounts of major celebrities, news organizations, and others with huge numbers of followers are seen intervening into the network (Table 3). Bette Midler is one example. The singer posted one tweet in support of Omar. It was retweeted about 400 times, but her true influence is reflected in the fact that her account has 1.55 million followers, thus the overall impact of that tweet outside the Omar network was vast. Lena Dunham, creator and star of the HBO series *Girls* who also posted just one tweet,

Table 3. Icons.

Account	Followers	Network rank
lenadunham	5,645,121	1
nymag	1,774,506	2
theatlantic	1,718,355	3
bettemidler	1,478,571	4
thecut	1,410,584	5
ocasio2018	889,338	6
hrc	814,912	7
vanjones68	803,688	8
brianstelter	604,804	9
theintercept	532,703	10
amyklobouchar	510,983	11
cernovich	451,140	12
mehdihasan	414,303	13
ebonymag	400,260	14
razarumi	387,523	15
lindasuhler	373,069	16
essence	331,797	17
moveon	323,119	18
tinastuffracing	316,594	19
pattyarquette	295,400	20

is prominent because her account has 5.6 million followers. Major media organizations can also periodically intervene in a network. In this case, both the *Atlantic* magazine and The Cut section of *New York* magazine wrote articles about Omar generating significant discussion within the network but, more importantly, bring discussion of Omar to a much wider audience outside the network. Only one of the top 20 Icons in Omar's network, conservative radio host Mike Cernovich, was linked to the anti-Muslim dialogue. Two others, columnist and TV host Mehdi Hasan and Pakistan-American columnist Raza Ahmed Rumi, were Muslims involved in fighting Islamophobic rhetoric. The fact that Icons are not a significant factor in the discussion around Islamophobia and xenophobia in the Ilhan Omar network reflects the fact that the entertainment and media world figures who tend to have the largest Twitter following tend to be liberal and not espouse anti-Muslim sentiment, and the major media organizations who also command large numbers of followers are, for the most part, not propagating anti-Muslim and anti-immigrant views.

Discussion

Twitter influence has been conceptualized and measured in a variety of different ways, including using PageRank, weighted outdegree, and the number of followers. This research suggests that by examining these metrics simultaneously, it is possible to gain a nuanced understanding of the underlying mechanisms of the Twitter ecosystem. Analyzing the Omar Twitter network in these three different ways revealed the underlying structure of the debate and showed different roles that *Influencers, Amplifiers*, and *Icons* played in the construction of Islamophobic/xenophobic rhetoric during the campaign.

It is not that one of these methods is a better way of measuring influence, it is that the three together provide a detailed picture of how these main topics spread. Each of these different kinds of Twitter influence does a different kind of work in the ecosystem. By looking at them together, it is possible to see their relative influence and interdependence.

Two of these three categorizations, Influencer and Amplifier, have been used separately and/or in different contexts. However, as far as the authors know, this is the first time these categorizations, along with the Icon label, have been used together to show the way that different measures can provide a full picture of the roles of individual accounts and the interactions between them. This methodology was used to examine anti-Muslim and xenophobic sentiment in Ilhan Omar's network but can be applied to any study of online influence.

Agents Provocateurs

In particular, this combination of approaches helps unpack the nature of the Islamophobic and xenophobic discourse surrounding Omar. Fifty percent of the tweets tagging Omar contained overtly Islamophobic or xenophobic language or other forms of hate speech. In addition, 67% of all tweets were posted by accounts that had posted at least one hateful tweet. On the surface, those figures give the impression of a substantial Islamophobic/xenophobic and racist Twitter movement against the candidate. However, close analysis simultaneously using these three methods of mapping, combined with careful coding, reveals a very different picture. A handful of Influencers—in this case, *agents provocateurs*—were responsible for authoring, or giving initial impetus to, the majority of the offensive tweets, which were then relayed to the broader Twitter universe by a larger, but still finite, network of Amplifiers, many of which were either identified as a form of bot or showed signs of the kind of "coordinated inauthentic activity" that characterize bots.

Meanwhile, coding revealed that of the 32,445 accounts in the Omar network that posted or retweeted offensive comments, 61% posted or retweeted just one such tweet. This underlines the fact that the overwhelmingly Islamophobic/xenophobic narrative was being fueled and manipulated by a small cadre of accounts working in close coordination and actively trolling the candidate, which then inspired action on the part of the rest. The role of the majority of accounts retweeting offensive messages might be best described as engaging in Islamophobic/xenophobic slacktivism ("Slacktivism," n.d.), rather than overtly acting as protagonists in the anti-Muslim/xenophobic narrative. The term "slacktivism" is most commonly associated with the willingness of liberals "to perform a relatively costless and effortless token display of support for a social cause" (White & Kristofferson, 2018), such as clicking "like" in Facebook; in this case, it involves a Twitter user who retweets an ugly missive.

The Icons, the elite accounts controlled by celebrities and media organizations with millions of followers, played virtually no role in the overarching anti-Muslim narrative of these two candidates, in part because the Icons intervening in the networks were either politically liberal celebrities or news organizations that had written generally positive articles. No anti-Muslim or right-wing individuals or organizations with a comparable following were present, likely for the reasons speculated upon above.

Tracking Emerging Thought Leaders

In the specific context of the Islamophobic/xenophobic narrative and the implications for Muslim candidates in the 2020 election, the analysis shows the emergence of new thought leaders sparking the anti-Muslim conversation. The top 20 conservative Influencers identified in this study (excluding suspected bots/cyborgs) included several accounts from individuals not previously included among influential anti-Muslim voices. Two accounts that are now suspended—@LauraLoomer and @HireLearning—led the discussion. These accounts nudged out more established voices, such as Laura Ingraham's Fox show *The Ingraham Angle*, Pamela Geller, @Breitbartnews, and Richard Spencer of @JihadWatch, who have been repeatedly named as leaders of the anti-Muslim lobby (Ali et al., 2011; Steinback, 2011). Another influential newcomer was Peter Boykin, the founder of Gays for Trump, who has campaigned against *sharia* law, has made positive comments about White supremacist organizations (Bond, 2018), and was the only one to troll Omar, Tlaib, and a third Muslim Congressional candidate, California Republican Omar Qudrat.

Laura Loomer eclipsed all other anti-Muslim activists in her ability to shape the online narrative around Ilhan Omar. She sits at the nexus of the anti-Muslim/xenophobic online debate. The Omar network maps show a dense cloud of accounts clustered between Loomer and Omar, as well as several other Muslim candidates, reflecting the fact that she is tagged on vast numbers of tweets trolling those candidates.

That underlines the central role played by Loomer in shaping the dialogue around Omar. Hers is the most influential account in the anti-Omar narrative. However, as noted above, the key to the influence of the Loomer account was its symbiotic relationship with the top conservative Amplifiers in the Omar network, which included six apparent bots and @HireLearning and Goldilox_io1, both of which were subsequently suspended by Twitter for violating its terms of service.

Finally, although the Icons in this study serve as broad-based thought leaders, they were entering a discourse whose boundaries had already been dictated by the Influencers and Amplifiers. Celebrities and major media organizations were not leading the conversation, but rather bringing it to the attention of others outside the network through engagement that was mostly glancing and superficial. In this case, with the abovementioned exception of Loomer, they ignored the dominant anti-Muslim discourse within the network and broadcast the minority positive messaging.

Bots

Complicating the dynamics of this ecosystem was the presence of bots. Of the top 40 Amplifiers spreading Islamophobic/xenophobic messages in Omar's network, only 11 could be determined to be authentic accounts. In July 2019, 8 months after data capture ended, we went back and reexamined the network. We found that almost 15% of the accounts that existed in the fall of 2018 had vanished, either shut down by Twitter for violations of its standards or self-deleted by their owners, a tactic used to prevent detection after the bot served its purpose.

These inauthentic accounts represent hidden forces, which have a real effect on the discourse, serving as automated megaphones that, in the case of anti-Muslim and xenophobic hate speech, transform the Twitter "dialogue" into a one-way monologue of hate. Together, these shadowy accounts function to poison the political narrative, drawing in both likeminded and unsuspecting individuals who retweeted their posts, disproportionately amplifying—and, for some, normalizing—the message of intolerance.

Concluding Remarks

As Omar entered the political ring, she was confronted with a highly organized digital smear campaign on Twitter that was not only infused with racist, misogynist, xenophobic, and Islamophobic hate speech but was also highly automated with the hallmarks of organized actors. While that did not prevent her from winning her contest, it provided a strong headwind that has continued into her first term. As politics becomes ever more accustomed to the media logic of platforms like Twitter, contemporary democracies face an "epistemic crisis" as they buckle "under the pressure of technological processes that had overwhelmed our collective capacity to tell truth from falsehood and reason from its absence" (Benkler et al., 2018, p. 4). This is why media literacy demands a broader understanding of the network characteristics and content created by different kinds of influencers. McGregor and Molyneux (2020) found that "the routinization of Twitter into news production affects news judgment" (p. 597). In particular, the political journalists who use Twitter uncritically as some sort of valid barometer of public sentiment may be fueling an inauthentic narrative created by the bot network sponsors that amounts to electronic sound and fury, signifying nothing. The specifics of the attacks on the Omar campaign is particular to the United States, but the broader strategies are of crucial importance internationally.

A decade ago, Kwak et al. (2010) may have been overly idealistic when they wrote that Twitter users "have the power to dictate which information is important and should spread by the form of retweet, which collectively determines the importance of the original tweet," further positing "the emergence of collective intelligence" (p. 598). Through this process, Twitter has become a crucial broker in the contemporary attention economy, which is influenced as much by engagement metrics as it is by ideas and, as such, is sensitive to message amplification (Zhang et al., 2018). But with the presence of coordinated bot networks propping up the work of shadowy Influencers and their associated Amplifiers, the distorted intelligence that emerges may indeed be artificial.

Just because a large proportion of the tweets studied here were artificial does not mean they were inconsequential. Rather, they played an important role in distorting online civic discourse, in part when journalists and interested members of the public interacted with this material. This research illuminated a complex part of the Twitter ecosystem by measuring different parts of a network and showing how they worked together. However, Twitter is only a small portion of the larger media ecology. Future researchers should look at the agenda-setting effects of this inauthentic discourse to try to grapple with its real-world implications on political campaigns and democratic discourse writ large, especially people from traditionally marginalized populations.

There is a large emerging body of literature that is beginning to map out the polarizing consequences of this confluence of social media affordances and disinformation (see Tucker et al., 2018), but there is work that remains to build an understanding of this fast-changing area. As Keller and Klinger (2019) note, "It becomes impossible for a society to monitor itself when machines disguised as societal members enter and manipulate the marketplace of ideas" (p. 174). This dynamic is particularly important when it comes to conversations that intersect with Islamophobia, racism, misogyny, or xenophobia because the act of amplifying hate speech can serve to normalize it.

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ORCID iDs

Lawrence Pintak https://orcid.org/0000-0003-4460-6170
Brian J. Bowe https://orcid.org/0000-0002-1991-6532

Notes

1. https://twitter.com/LauraLoomer/statuses/1054801592619196416 (Account suspended)
2. https://twitter.com/LauraLoomer/statuses/1052533545636425729 (Account suspended)
3. https://twitter.com/Joroe40/statuses/1057303510847578112
4. https://twitter.com/kgore50/statuses/1056990348302528513 (Tweet blocked)

5. https://twitter.com/Goldilox_Lo1/statuses/1055152651606900736 (Account suspended).
6. https://twitter.com/HireLearning/statuses/1051443697651474432 (Account suspended)

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Author Biographies

Lawrence Pintak, PhD is an award-winning journalist and media development expert who has reported from four continents and led media development projects in the Middle East, South Asia, Africa and the Caucuses. He is dean of the Graduate School of Media and Communications at The Aga Khan University in East Africa and was previously the founding dean of The Edward R. Murrow College of Communication at Washington State University (2009-2016).

Brian J. Bowe (Ph.D., Michigan State) is an associate professor at Western Washington University with an appointment to the Journalism and Mass Communication Department at the American University in Cairo. His research focuses on representation of Muslims in news coverage, as well as journalism curriculum design and assessment. With a strong interest in the Middle East and North Africa, Bowe served as a 2019 Fulbright scholar to the University of Jordan and is principal investigator of an ongoing grant-funded project in Tunisia.

Jonathan Albright (Ph.D., University of Auckland) is the former director of the Digital Forensics Initiative at the Tow Center for Digital Journalism and was previously an assistant professor of media analytics in the school of communication at Elon University. Albright's work focuses on the analysis of socially-mediated news events, misinformation/propaganda, and trending topics, applying a mixed-methods, investigative data-driven storytelling approach.