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Understanding and Diagnosing Antimicrobial Resistance on Social Media: A Yearlong Overview of Data and Analytics

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ABSTRACT
To better understand user conversations revolving around antibiotics and antimicrobial resistance (AMR) on Twitter, we used an online data collection and analysis toolkit with full firehose access to collect corpuses of tweets with "antibiotic" and "antimicrobial resistance" keyword tracks. The date range included tweets from November 28, 2015, to November 25, 2016, for both datasets. This yearlong date range provides insight into how users have discussed antibiotics and AMR and identifies any spikes in activity during a particular time frame. Overall, we found that discussions about antibiotics and AMR predominantly occur in the United States and the United Kingdom, with roughly equal gender participation. These conversations are influenced by news sources, health professionals, and governmental health organizations. Users will often defer to retweet and recirculate content posted from these official sources and link to external articles instead of posting their own musings on the subjects. Our findings are important benchmarks in understanding the prevalence and reach of potential misinformation about antibiotics and AMR on Twitter.

Antimicrobial resistance (AMR) is a rapidly worsening health crisis that affects millions across the globe (Levy & Marshall, 2004). If AMR continues at its current rate, it is estimated that by 2050 it will cause 10 million deaths per year and cost the world US$100 trillion in medical costs and reduced gross domestic product (Review on Antimicrobial Resistance, 2014). Hospitals still rely heavily on antibiotics and antimicrobials to treat a variety of conditions: in 2014, nearly half of US hospital patients received some form of antimicrobial drug treatment (Magill, Edwards, Beldavs, Dumyati, Janelle, Kainer, Richards, 2014). Given this high rate of use, the lack of knowledge about AMR among the general populace is troubling (McCullough, Parekh, Rathbone, Del Mar, & Hoffmann, 2016; Scanfeld D., Scanfeld V., & Larson, 2010; Smith, M'ikanatha, & Read, 2015). While clinicians and medical personnel tend to be blamed for the development of AMR, significant portions of the population also fail to recognize common causes of AMR, such as excessive antibiotic use (McCullough et al., 2016).

In efforts to address this issue, health organizations have undertaken campaigns across Europe and the United States to educate clinicians and patients about antibiotic misuse (Goossens et al., 2006). Nearly all campaigns correlated with lowered rates of antibiotic use in the targeted areas, although causation remains elusive due to the amount of confounding factors (Goossens et al., 2006; Huttner, Goossens, Verheij, & Harbarth, 2010). In general, successful campaigns utilized local interventions and staff, often as a complement to broader, long-term approaches (Belongia et al., 2005; Perz et al., 2002). These campaigns targeted both physicians and patients, and often expressed positive messages about behavior change rather than using scare tactics (Goossens et al., 2006; Huttner et al., 2010).

Despite these efforts, AMR remains a globally threatening issue that requires multidisciplinary research, attention, and action (Smith et al., 2015). With more adults seeking health-related information on the Internet and through their social networks, often relying on such information in making health-related decisions, understanding online conversations about AMR may help equip policymakers and communication scholars with tools needed to combat this issue. In this study, we seek to do just that. By mining and analyzing tweets made about antibiotics and AMR over a 1-year period, this study investigates informal information networks about AMR on Twitter, through which misinformation has the potential to spread. Specifically, we seek to identify influential nodes in the Twitter AMR information network and the extent of those nodes' influence, as well as identify key terms being used with AMR. In doing so, we map not only influential individuals (i.e., Twitter handles) but also key terms being used in relation to AMR on Twitter.

Literature review

A review of information online

American adults are increasingly using the Internet to seek and share health-related information. From 2009 to 2014, the

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number of American adults who used the Internet to seek health-related information rose from 61% to 72% (Pew Research Center, 2009, 2014). Among adults already familiar with the Internet, that number is estimated to be closer to 90% (Tennant et al., 2015). Within these searches, medicine- and drug-related information is a major topic. In 2004, medicine was the third most frequent category of health-related searches (Eysenbach & Köhler, 2004); a more recent study found that 45% of all health-related searches concerned medicine, particularly prescription drugs (Pew Research Center, Pew Internet and American Life Project, 2009).

This online information plays a considerable role in people's health behavior. The majority of people who researched health information online felt that the information had an impact on how they cared for themselves, including which types of questions they asked their doctors and how they managed chronic pain (Pew Research Center, Pew Internet and American Life Project, 2009). Aware of this reliance on online information, health experts have expressed concerns over the accuracy of the information (Moturu, Liu, & Johnson, 2008; Wilson, 2002), especially considering that many users have neither the motivation nor the knowledge to evaluate health sources for themselves (United States Department of Health and Human Services, 2010). To remedy these shortcomings, recommendations have been made to require quality ratings and trust assessments of all major health websites (Motoru, Liu, & Johnson, 2008).

However, with the dawn of social media, health information seekers no longer rely on only health-specific websites; they also use social networking sites such as Facebook and Twitter to find and share health information (Pew Research Center, Pew Internet and American Life Project, 2009; Tennant et al., 2015; Thackeray, Crookston, & West, 2013). This behavior spans across the demographics of gender, age, and race: so long as an individual has a social media account, he or she is likely to use it for health-related research at some point. It is perhaps not surprising that people rely on their own social networks for information, as Americans now rank their peers higher in trustworthiness than their government (Edelman, 2016).

The microblogging platform Twitter is a particularly popular source of information. When choosing a social media platform for news-related information, people prefer Twitter to Facebook, especially for breaking news (Pew Research Center, 2015). About 10% of the American population uses Twitter for news, and that number rises to 63% among current Twitter users. Twitter users also follow more news organizations and reporters than Facebook users do.

As a whole, research suggests that individuals perceive the Internet as a source of health information that is trustworthy and reliable enough to change their health-related behavior (Edelman, 2016; Pew Research Center, Pew Internet and American Life Project, 2009; Tennant et al., 2015; Thackeray et al., 2013). Therefore, it is crucial to understand and limit health misinformation on social networks and especially on Twitter, given Twitter's renowned status as a source of real-time information.

Misinformation online

Misinformation is defined as "false or inaccurate information, especially that which is deliberately intended to deceive" (Kumar & Geethakumari, 2014, p. 3). Several models of the spread of misinformation focus on the role of influential communicators within a social network (Acemoglu, Ozdaglar, & ParandehGheibi, 2010; Budak, Agrawal, & El Abbadi, 2011; Kumar & Geethakumari, 2014). Acemoglu et al. (2010) refer to these influential communicators as "forceful agents," in contrast to the "regular agents" that comprise the rest of the network (p. 196). Forceful agents exhibit greater influential power in a network due to both personality-driven factors, such as stubbornness and fanaticism, and role-driven factors, such as social status and access to media. Forceful agents propagate information that drives their community toward consensus on a particular issue. Because regular agents cannot easily counterbalance the messages propagated by forceful agents, it is imperative to identify and manage forceful agents in order to prevent the spread of misinformation.

Kumar and Geethakumari (2014) describe social networks as a series of nodes, some more influential than others and all of which can be infected with misinformation. Decontamination of specific nodes, especially influential ones, is quite difficult: even when presented with accurate information, people may deny or ignore it. Kumar and Geethakumari (2014) argue from a cognitive psychology perspective that decontaminating individual nodes is less effective than launching wide-scale preventative (or counter-) campaigns. Budak et al. (2011) extend and refine this viral metaphor – the decontamination of a single node may not always lead to the spread of accurate information. Rather, the positive effects may remain limited to the individual node, particularly if it is not an influential one. Budak et al. (2011) argue that a node's level of influence does not derive from number of connections, but rather from its position within a network. Therefore, it remains useful to map out and track influential users in the AMR conversation.

In the context of Twitter, users demonstrate a strong desire to share helpful and relevant information, especially during crises (Abdullah, Nishioka, Tanaka, & Murayama, 2015). Therefore, information (and misinformation) on Twitter has the potential to spread rapidly. Twitter users also exhibit the tendency to question rumors or unofficial information (Mendoza, Poblete, & Castillo, 2010) and prefer sharing information from official sources (Chew & Eysenbach, 2010; Pew Research Center, 2015; Sullivan et al., 2012). When misinformation is spread, users follow up with a "crowd-correction" of the inaccurate information (Starbird, Maddock, Orand, Achterman, & Mason, 2014). However, these corrections rarely reach the same number of users as the original misinformation. Due to its users' emphasis on spreading relevant and accurate information, Twitter presents an ideal platform to combat AMR misinformation. To do so, influential users must be identified and their networks of influence mapped.

Twitter in the context of Health 2.0

Twitter – and similar social networks – represents the next step in the development of Health 2.0. Health 2.0 refers to the use of Web 2.0 technologies, such as wikis, blogs, and tagging systems, to distribute health information (Hughes, Joshi, & Wareham, 2008; Van De Belt, Engelen, Berben, & Schoonhoven, 2010). Initially, physicians and healthcare providers disseminated information in a unilateral direction. Since then, Health 2.0 has become increasingly collaborative and user-focused, with users creating communities that circulate their own information (Van De Belt et al., 2010). Physicians have also recognized the value of interactive interfaces that facilitate conversations between patients and their healthcare providers.

Social media serves a dual purpose in the Health 2.0 landscape. Firstly, healthcare providers can use social media to track health conditions. Twitter is a particularly useful tool in this area. Twitter reacts quickly to real-world events and accurately reflects the offline behaviors and attitudes surrounding these events (Bollen, Mao, & Pepe, 2011). Twitter has been used to track symptoms (Lamb, Paul, & Dredze, 2013; Paul & Dredze, 2012), the spread of an illness (Broniatowski, Paul, & Dredze, 2013), adverse reactions to drugs (Frefield et al., 2014), and health risk factors such as smoking and self-medicating (Dredze, 2012).

Secondly, Twitter can be used in the same manner as the general Health 2.0: as a source of health information, as well as a gauge of the general population's understanding of various health issues. An analysis of concussion-related tweets revealed that users were generally knowledgeable and conscientious about concussions, although they also expressed some common misconceptions (Sullivan et al., 2012). A third of the information tweeted about concussions was derived from reliable news sources and health organizations. This is in line with the expectation that Twitter users value news sources and accurate, helpful information.

An evaluation of H1N1-related tweets yielded similar results (Chew & Eysenbach, 2010). Only about 4.5% of the sampled tweets included misinformation. More impressively, over 90% of informational tweets provided a link to a source, with news organizations being the most popular source category. A study on vaccination tweets also concluded that Twitter users share predominantly reputable information from official sources (Love, Himelboim, Holton, & Stewart, 2013). However, these results do not hold true in every situation. Oyeyemi, Gabarron, and Wynn (2014) analyzed Ebola-related tweets in Guinea, Liberia, and Nigeria during 2004. They found that a staggering 58.9% of sampled tweets included misinformation, as compared to only 38% with accurate information.

In terms of AMR specifically, Scanfeld D., Scanfeld V., and Larson (2010) examined a sample of antibiotics-related tweets. The two most popular categories of tweets concerned antibiotic use and general (accurate) information about antibiotics. Misinformation ranked as the sixth category, representing roughly 6% of the sampled tweets. The researchers estimated that this 6% reached a total audience of over 1 million followers. The most common types of misinformation concerned antibiotic use for treating the flu and colds: the latter combination (flu + antibiotics) reached an estimated audience of over 850,000 followers.

Past studies confirm Twitter's position as a new, integral component of Health 2.0. Twitter users participate in far-reaching conversations about many different health topics. Because users prioritize reliable information from reputable sources, they circulate relatively small amounts of health misinformation. But as Scanfeld et al. (2010) revealed, even a small percentage has the potential to reach over a million individuals.

Method

To better understand user conversations revolving around antibiotics and AMR on Twitter, we used an online data collection and analysis toolkit with full firehose access to collect corpuses of tweets with "antibiotic" and "antimicrobial resistance" keyword tracks. The date range included tweets from November 28, 2015, to November 25, 2016, for both datasets. This yearlong date range provides insight into how users have discussed antibiotics and AMR, highlights any spikes in activity during a particular time frame, and identifies potential instances of misinformation.

Results

Dataset 1: Search term "antibiotic"

Tweet activity metrics

The first dataset we analyzed was the "antibiotic" dataset. On Sysomos, we set our search parameters to collect all tweets including the word "antibiotic." We then filtered our results to obtain tweets in English only. We collected a total of 602,100 tweets in this dataset (from 552,569 users) (Figure 1).

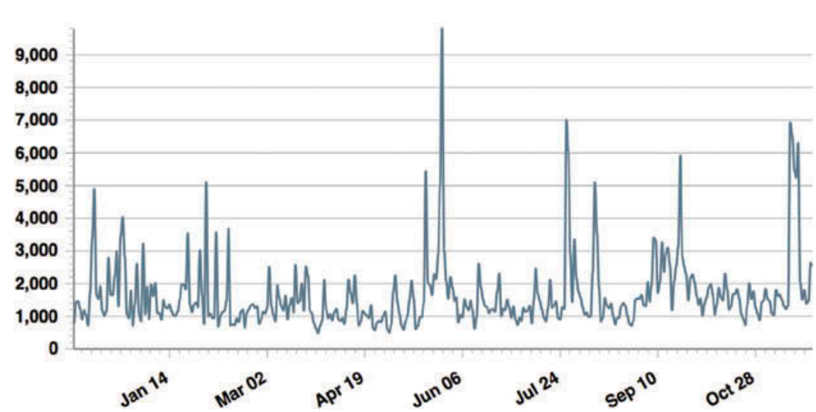

Figure 1. Distribution of "antibiotic"-related tweets.

The graph above shows many spikes in the dataset which indicate higher frequency of conversation revolving around antibiotics. The biggest spike occurred on May 27, 2016, with over 9,700 tweets including the term "antibiotic." Upon further investigation, this spike was found to be in response to news reports (from sources such as CNBC, BBC, *Washington Post, New York Times*) claiming the first antibiotic resistant superbug had been found in the United States. According to the *Washington Post*, the most cited article of the group, a woman in Pennsylvania was diagnosed with a strain of *Escherichia coli* resistant to the antibiotic colistin. While the woman's condition was treatable with other antibiotics, researchers began to fear that the colistin-resistant gene would spread to other bacteria that have other antibiotic resistance. On Twitter, conversations within the "antibiotic" dataset revolved around the news story (Figure 2).

As seen in the word association graph below, which Sysomos calls a BuzzGraph, the most popular words used together in this dataset during the May 27th spike have the darkest and boldest interconnecting lines or "linkages." These words include "colistin," "resort," "resistant," and "resistance." These words indicate that, when users discuss the antibiotic resistance story, they employ terms such as "superbug" and "resistance" into their conversation.

User demographics

We analyzed the user demographics of this dataset and found that 56% of users were male and 44% were female. It is important to note that organizations such as news outlets and companies are excluded from this portion of the analysis (Sysomos, 2011). If a user is a health organization, news outlet, or a company, it is categorized differently than individual users. Sysomos recognizes these accounts as organizations and does not automatically assign a gender to the account from their gender association algorithms, which is based off of self-reported data or other indicators from the metadata, such as the names of users (Sysomos, 2011).

We also analyzed our dataset by location. Approximately 47% of users were from the United States and 15% of users were from the United Kingdom. This country breakdown is not surprising given our filtering parameters and exclusion of languages outside of English.

Hashtags

We also analyzed the most popular hashtags associated with "antibiotic" on Twitter. The top 10 hashtags were as follows: #antibiotic, #eurekamag, #antibioticresistance, #amr, #health, #antibioticguardian, #msgproducts4u, #antibiotics, #news, #science (Figure 3).

These popular hashtags indicate that conversations as a whole revolve around antibiotics and news regarding antibiotic resistance and AMR. While some hashtags are straightforward, such as #antibiotic and #health, our team further analyzed indeterminate hashtags. #eurekamag refers to the magazine Eureka Mag, which posts frequent updates on life and health science. #msgproducts4u is associated with the company MSG All Trading, a company that promotes healthy and organic foods with healthy "antibiotics" as alternatives to processed foods. As a whole, these hashtags imply that conversations using the term "antibiotic" encompass health news, sources, and products.

Influential users

We then identified the most "influential" users within our dataset. Sysomos declares users as influential when they have a wide reach, high engagement rates, and large following on Twitter. We chose to focus on the top 5 influencers within the dataset as they have the highest reach and engagement according to Sysomos' algorithms. In addition, our team was more focused on identifying the types of influential users (i.e., news sources or medical workers) rather than detailing an exhaustive list of influencers. Our main goal for this section

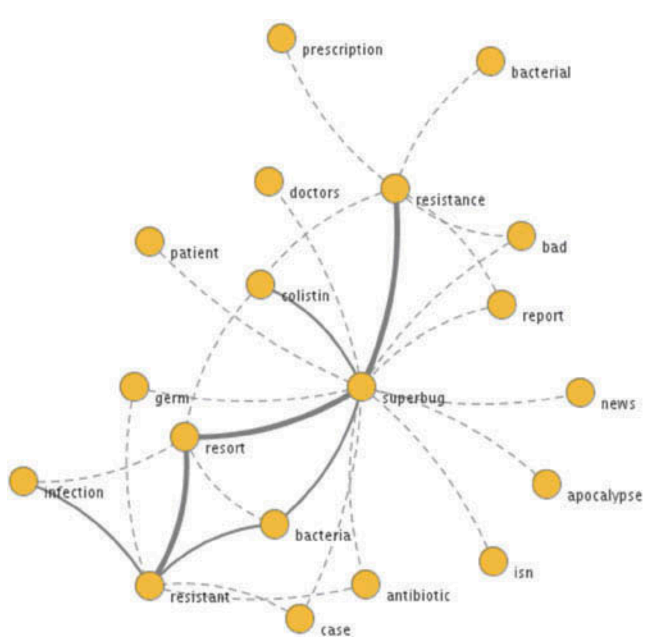

Figure 2. BuzzGraph for search term "antibiotic" during May 27, 2016 spike.

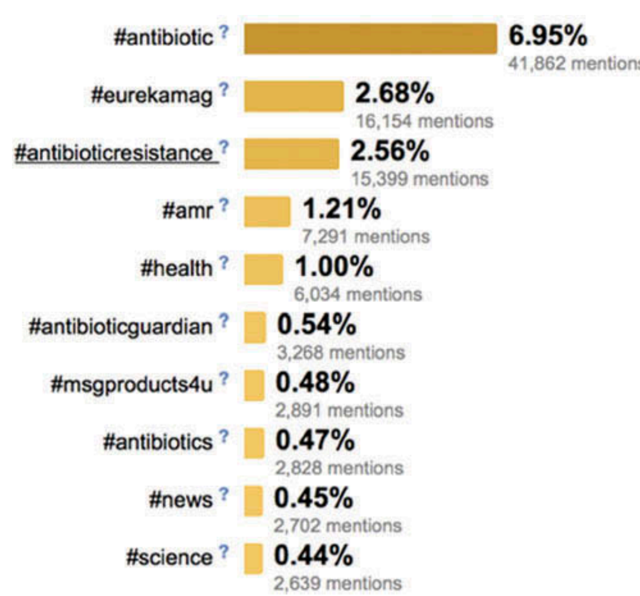

Figure 3. Commonly used hashtags associated with "antibiotics."

was to see if the influencers were predominantly reputable sources or misinformative users, in addition to identifying potential contacts in the AMR field. These top 5 influential users include @Jinariggs1, @GeorgeMonbiot, @Medscape, @SCMP_News, and @NICECOMMS. The top influencer in this dataset is @Jinariggs1, a licensed pharmacologist who promotes different types of drugs and treatments that users can purchase in Canada. She has 221k followers on Twitter. The next influencer is @GeorgeMonbiot, a reporter who discusses controversial topics. He recently tweeted about how antibiotic resistance is one of the main crises that modern society faces. He has 163k followers on Twitter. The next influencer is @Medscape, a source that covers updates in the medical field, drug references, and diseases. @Medscape has 118k followers. The fourth influencer is @SCMP_News, a source that provides news and analysis on China and Asia as a whole. This account has over 345k followers. The last influencer in this list is @NICEcomms, the official account for the National Institute for Health and Care Excellence. This account provides updates in the medical field and drug treatments. @NICEcomms has 114k followers. From this list of users, it is evident that news sources, health organizations, and those working within the health fields are the most influential sources discussing antibiotics.

Identical tweets (retweets)

We then looked at the most retweeted content within the "antibiotic" dataset. The top 5 most retweeted posts are outlined in Table 1.

The top 2 most retweeted were the same joke regarding a patient wanting to "surprise bacteria" and not take medication at the time recommended by a doctor. The third most retweeted was by @WHO, the World Health Organization. This tweet promoted World Antibiotic Awareness Week. The following top most retweeted posts were news stories regarding antibiotic resistance and testing. With the exception of the humorous posts, the most retweeted items were news updates in the antibiotics field of medicine.

Network analysis (BuzzGraph)

We also examined the BuzzGraph for the entire "antibiotic" dataset (Figure 4).

As seen in the graph below, the most prominent words in the dataset are "resistant," "superbug," "resistance," "bacteria," and "infection." This means that, when users talk about "antibiotics," they are also discussing bacterial resistance and superbugs. Although this is the "antibiotic" dataset, users are incorporating stories of antibiotic resistance into their conversation. Users on Twitter are discussing the resistance to antibiotics specifically, not just antibiotics in general.

Dataset 2: Search term "antimicrobial resistance"

The second dataset we analyzed was the "antimicrobial resistance" dataset. On Sysomos, we set our search parameters to collect all tweets including the phrase "antimicrobial resistance." We then filtered our results to obtain tweets in English only. We collected a total of 45,976 tweets (from 40,233 users) in this dataset, which was fewer than the "antibiotic" dataset. Our results for the "antimicrobial resistance" dataset are presented in Figure 5.

The graph below shows two major spikes in the dataset, which indicate higher frequency of conversation revolving around AMR. The biggest spike occurred on March 11, 2016, with over 2,500 tweets including the phrase "antimicrobial resistance."

Upon further investigation (using the search feature on Twitter and analyzing Sysomos word association graphs), this spike in activity was found to be in response to news reports regarding three trending AMR stories: (1) the 61st anniversary of Alexander Fleming's death and the issue of antibiotic resistance, (2) Labour MEP's voting for the ban of antibiotics in farm animals in the European Union, and (3) the U.S. Food and Drug Administration's AMR Monitoring team winning a government award to design a public health surveillance mobile application.

On Twitter, conversations within the "antimicrobial resistance" dataset revolved around these news stories (Figure 6).

As shown in the word association graph below, these most in the dataset include "antibiotic," "livestock," "epidemiology," "cmo (chief medical officer)," and "AMR." These words indicate that users were discussing antibiotic resistance stories. Similar to the "antibiotic" dataset, user discussions and activity in the "antimicrobial resistance" dataset include reputable news stories and field updates. There are no instances of false news or bots promoting harmful content.

User demographics

We analyzed the user demographics of this dataset and found that 53% of users were male and 47% were female. This indicates that each gender is equally participating in

Table 1. Most common retweeted content for search term "antibiotic."

Original tweet	Username	Date tweeted	Number of retweets
Antibiotics DOCTOR: why did you take your antibiotic Medicine at 6 am, when I told you 9 am? PATIENT: I wanted to surprise the Bacteria	@akashahghazi	June 23, 2016	7,096
Doctor: Why did you take your antibiotic medicine at 6 a.m when I told you 9 a.m? Patient: I wanted to surprise the Bacteria..	@Azaammmmmmmmmmm	August 9, 2016	4,031
It's World Antibiotic Awareness Week! #AntibioticResistance is one of the biggest threats to global health https://goo.gl/Lutlmz	@WHO	November 14, 2016	3,456
Sleep as a target of antibiotic use in chronic fatigue syndrome? - http://allscienceglobe.com/sleep-as-a-target-of-antibiotic-use-in-chronic-fatigue-syndrome/…	@MoreScienceNews	February 6, 2016	2,851
Biologists develop method for antibiotic susceptibility testing - http://ln.is/allscienceglobe.com/CsGoE …	@MoreScienceNews	January 31, 2016	2,457

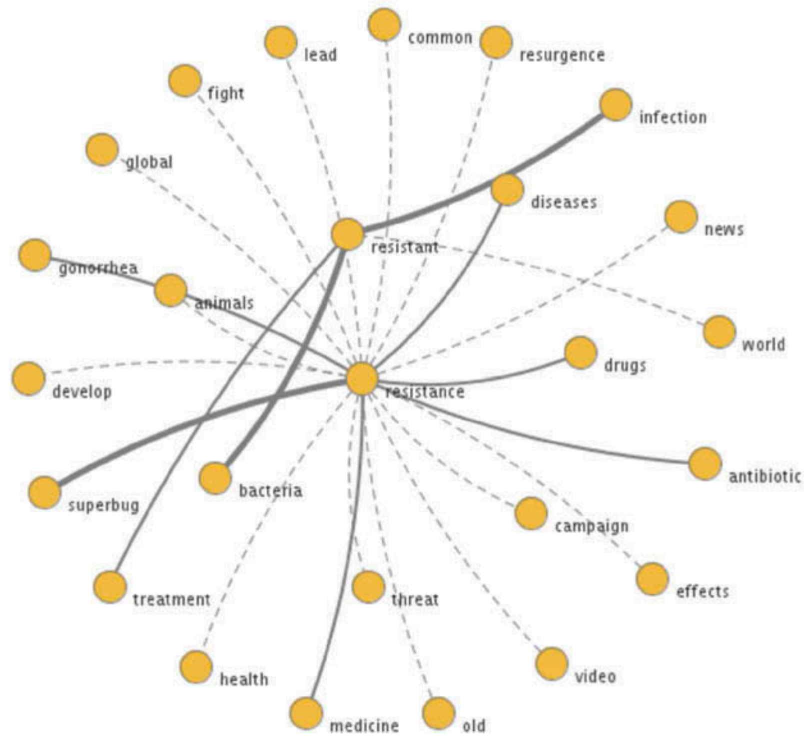

Figure 4. BuzzGraph for search term "antibiotic" during the 1-year time period.

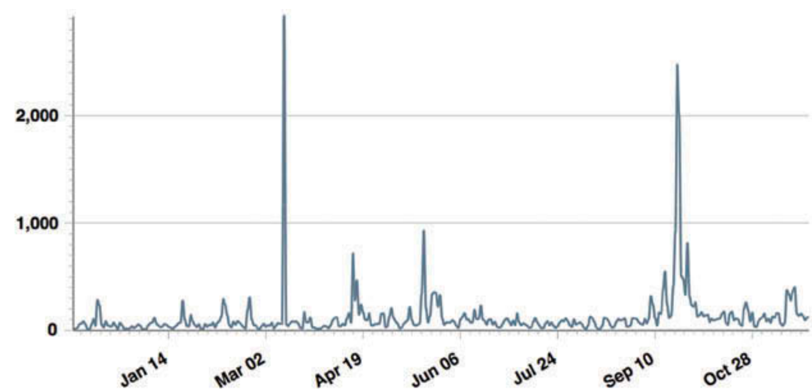

Figure 5. Distribution of "antimicrobial resistance"-related tweets.

discussions regarding AMR on Twitter, which was a similar finding to the "antibiotic" dataset (56% male/44% female).

We also analyzed our dataset by location. The countries that participated the most in this conversation were from the United States and the United Kingdom. Approximately 29% of users were from the United States and 23% were from the United Kingdom. The remaining percentages were from countries in the "other" category (27%), India (5%), Canada (5%), Australia (4%), and Italy (2%). Similar to the "antibiotic" dataset, this country breakdown is not surprising given our filtering parameters and exclusion of languages outside of English.

Hashtags

We also analyzed the most popular hashtags associated with "antimicrobial resistance" on Twitter. The top 10 hashtags were as follows: #amr, #antimicrobial, #unga, #antibioticresistance, #health, #antibiotics, #unfao, #abresistance, #phehealthmatters, and #wha69 (Figure 7).

These popular hashtags indicate that conversations as a whole are centered around AMR, health, and antibiotics. Several of the hashtags in this dataset are easily identifiable, such as #amr, #antimicrobial, #abresistance, and #antibioticresistance. The uses of #unga and #unfao refer the General Assembly of the United Nations and the Food and Agriculture Organization of the United Nations' involvement in AMR research and their recent updates.

The use of #phehealthmatters is a popular hashtag employed by Public Health England (PHE). This hashtag was most popular in December 2015 when PHE gave a presentation on the importance of studying AMR. Lastly, #wha69 was a part of the World Health Assembly's discussion on AMR. Overall, these hashtags imply that conversations in the "antimicrobial resistance" dataset revolve around antibiotics and health research

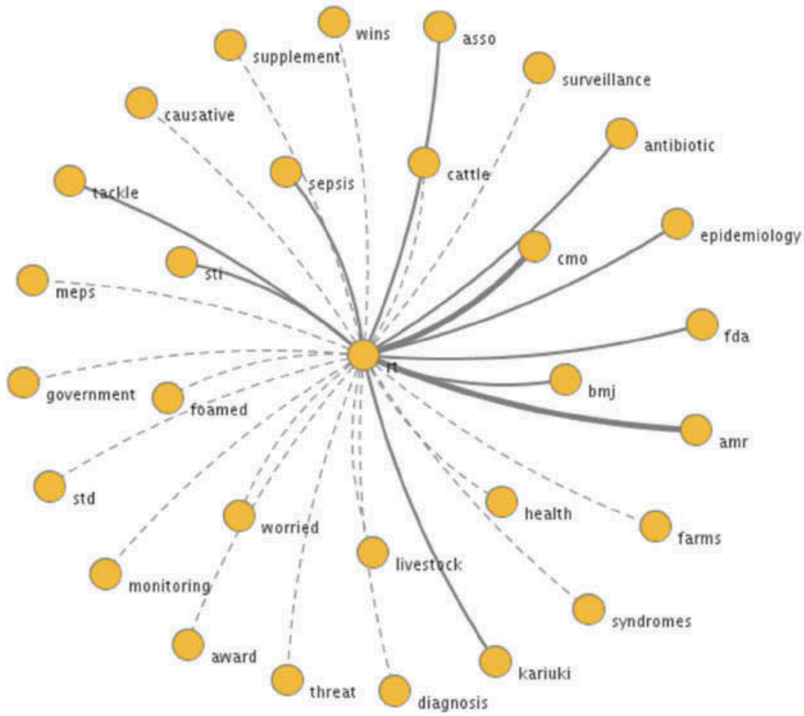

Figure 6. BuzzGraph for search term "antimicrobial resistance" on March 11, 2016.

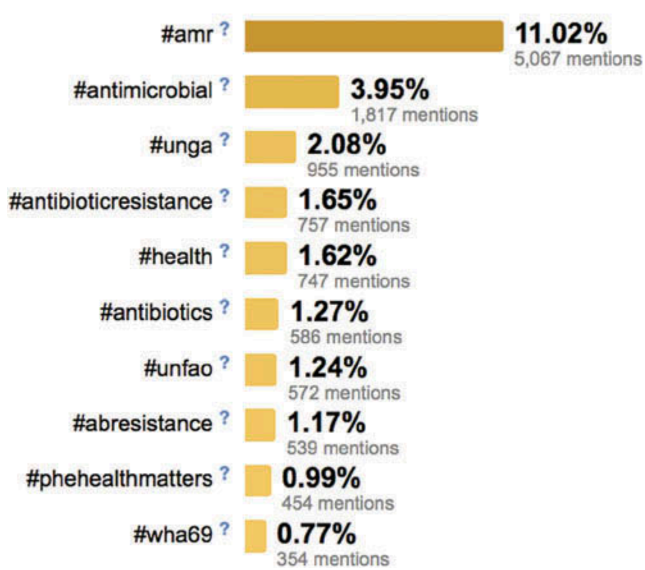

Figure 7. Commonly used hashtags associated with "antimicrobial resistance."

updates, specifically governmental research. Much like the "antibiotic" dataset, these conversations stem from reputable news sources and facts regarding AMR and antibiotics.

Influential users

The top 5 influencers within the dataset are @bmj_latest, @CDCgov, @PHE_uk, @NPR, and @EU_Health. The top influencer in this dataset is @bmj_latest, an organization that leads debates on health in efforts to improve patient outcomes. The BMJ has 231k followers on Twitter. The second influencer is @CDCgov, Center for Disease Control and Prevention, with 706k followers on Twitter. @CDCgov posts regularly about new health research and safety. The third influencer is @PHE_uk, Public Health England, a source that covers updates in the public health fields, with an emphasis on diseases. @PHE_uk has 108k followers.

The next influencer is @NPR, a popular source for news. NPR posted about AMR in September 2016, which is why the account is in the "antimicrobial resistance" dataset. @NPR account has over 6.3 million followers. The fifth influencer in this list is @EU_Health, the official account for European Union health and food safety. This account provides updates in the health field and innovative drug treatments. @EU_Health has 29k followers. From this list of users, we can see that the most influential users in the "antimicrobial resistance" conversation are governmental health organizations and popular news sources. Similar to the "antibiotic" dataset, Tweets regarding AMR originate from reputable sources with insight into the field.

Identical tweets (retweets)

We then looked at the most retweeted content within the "antimicrobial resistance" dataset. The top 5 most retweeted posts are outlined in Table 2.

As seen in Table 2, the most retweeted items were news updates pertaining to AMR. All of the tweets were from academic or general news sources. This indicates that many users are retweeting links to reputable AMR research and updates.

Network analysis (BuzzGraph)

We then examined the most frequently used words associated with AMR (Figure 8).

The most common word linkages are "amr," "global," and "threat." This implies that users are discussing the health threats associated with AMR and that it is a global phenomenon, not limited to the United States alone. Users also

Figure 8. BuzzGraph for search term "antimicrobial resistance" during the 1-year period.

Table 2. Most common retweeted content for search term "antimicrobial resistance."

Original tweet	Username	Date tweeted	Number of retweets
How farms can help tackle antimicrobial resistance - http://ln.is/allscienceglobe.com/nmM7r	@MoreScienceNews	March 11, 2016	2,813
Antimicrobial resistance is one of the greatest threats to global health. 5 things to know: http://cnn.it/2dim2dH	@CNN	September 21, 2016	374
On the cover this week: Superbugs rising. Inadequate sanitation promotes transmission of antimicrobial resistance: https://pbs.twimg.com/media/CiQV4QuWUAEPSZc.jpg	@nature	May 12, 2016	267
World leaders say antimicrobial resistance is now the biggest health threat facing the world today. http://nbcnews.to/2d9qMSb @NBCNightlyNews	@NBCNewsHealth	September 22, 2016	193
Review of Antimicrobial Resistance by Tony Fauci and colleagues http://ja.ma/2drAqTX	@JAMA_current	September 24, 2016	141

incorporate words such as "combat" and "tackle," implying AMR is an issue that needs to be addressed and fought.

Discussion

As concerns over the unchecked surge of AMR grow, so do calls for multidisciplinary approaches to help address the problem, particularly as it relates to antibiotic misuse and the general population's understanding of antibiotic use. In addition, as health information seekers increasingly turn to the Internet and social networking sites in particular, understanding information networks related to medical discussions online is crucial to helping address potential problems. In this study, we examined information networks on Twitter using two search terms, "antibiotic" and "antimicrobial resistance," identifying user demographics, key nodes in the network, and terms most commonly used in conjunction with the search terms examined in this study. Our main goal was to determine whether there were instances of misinformation and false information being spread about AMR and antibiotic use, as part of a greater client project.

A few key insights emerge from the results of this study. First, we identified users on Twitter who are key nodes in the information network related to AMR. For both search terms, we identified the top five influential users, as they have the highest influence and reach, and also provided our team with identification of the types of users disseminating and reaching the largest audience on Twitter. These types of users were shown to be health news sources and those working within the medical and pharmaceutical fields. This identification of influential users provides a key piece of information for any AMR-related informational campaign on Twitter. Following Budak et al.'s (2011) argument for the importance of decontaminating influential nodes in a network, we contend that these influential users may be key to the dissemination of corrective information to combat any AMR-related misinformation. The results of this study also present the argument for scholars to engage with practice, specifically with these news sources in order to promote informative content regarding AMR and even collaborate with the users within the medical and pharmaceutical fields to create and disseminate AMR and antibiotic-related posts on social media.

In addition, the BuzzGraphs generated by the Sysomos system help provide insight regarding key topics in Twitter conversations about AMR and antibiotics in general. Although the BuzzGraphs for the two days on which frequencies of the respective search terms peaked related specifically to the event that caused the peak (e.g., colistin for May 27, 2016), the general BuzzGraphs over the 1-year period indicate that users do associate the terms "superbug," "resistant," and "diseases" with "antibiotics," "threat," "global," "infectious," and "antimicrobial resistance." These associated terms may provide insight for future research into semantic networks related to AMR, such as the larger research project of which this study is a part, as well as future efforts to monitor user conversations related to AMR on Twitter and directly intervene if necessary, which is another phase of our ongoing larger project.

These results also help confirm Scanfeld et al.'s (2010) discussion of Twitter being a space for individuals to seek and share health-related information, and as a venue to identify potential indicators of misinformation. Both the "antibiotic" and "antimicrobial resistance" datasets showed users were sharing information from reputable sources including online news sites and those working within the medical and pharmaceutical fields. These findings support prior research that found a limited amount of health-related tweets contain misinformation (Chew & Eysenbach, 2010; Love et al., 2013). The data demonstrates an observable pattern that tweets in both datasets originated from sources generally regarded by information-seeking users as credible, such as news outlets and government health accounts. Past research indicates that users prioritize display names when evaluating tweet credibility (Morris, Counts, Roseway, Hoff, & Schwarz, 2012; Shariff, Zhang, & Sanderson, 2014), and that they rank the tweets of recognizable organization names, such as news outlets, as more credible than those of nonverified individual or anonymous users (Pal & Counts, 2011). In addition to generally credible organizations, tweets also originated from specialized sources of AMR knowledge, such as a pharmacologist with real-world expertise and authority in the field. Our results ultimately show that Twitter conversations regarding AMR and antibiotic use were informative and factual.

When considering the type of tweets about AMR, informative and reliable content was prevalent in the dataset. However, this overall pattern does not hold for the popular category of retweets in the "antibiotics" dataset, which featured jokes about antibiotic misuse. The popularity of jokes within this otherwise informative atmosphere could be cause for concern for health policy makers. While retweeting a joke may not indicate actual antibiotic misuse, exposure to jokes about harmful behaviors has been associated with the enactment of such behaviors (e.g., Ford, Boxer, Armstrong, & Edel, 2008). The high number of retweets suggests the need for Twitter interventions to clarify the implications of the content of such jokes, and encourage the correct use of antibiotics.

While the content in the two datasets was similar, it is important to note that the number of tweets mined for the search term "antibiotic" far exceeded those for "antimicrobial resistance." In the yearlong period from November 28, 2015, to November 25, 2016, 602,100 tweets using the term "antibiotics" were found, while only 45,976 tweets used the term "antimicrobial resistance." We argue that this discrepancy is indicative of the term "antimicrobial resistance" being less salient among the general population than "antibiotics." The content of the most common retweets for each search term supports this contention, in that while the top two retweets for "antibiotics" included jokes about antibiotics, all retweets for "antimicrobial resistance" were news articles.

Although our study is empirical in nature, we strongly believe these findings could be applied to a number of theoretical perspectives and frameworks including network theory (Knoke & Kublinski, 1982; Mouge & Contractor, 2003; Rogers, 1986; van Dijk, J.A.G.M, 2012) and persuasion theory (Cacioppo & Petty, 1979; Petty & Cacioppo, 1986). For network theory, we can employ our aforementioned methodology to identify social networks revolving around health conversations. Our study findings provide insight into AMR and antibiotics network by showing how these topics are discussed on social media, key users that drive conversations in these fields, user demographics, popular topics of interest to these users, and potential instances of misinformation in the network. Similarly, the methodology and findings can be applied to persuasion theory. These theories and frameworks cover the topics of how information is disseminated via online social networks and which factors affect the perceived persuasiveness of a message (i.e., credibility of source).

In addition, this data analysis methodology could be utilized in further studies to gain insight into how users perceive and evaluate different health topics. This can lend insight into facilitating health-related behavioral or attitudinal change, such as with the health belief model (Glanz, Rimer, & Lewis, 2002; McLeroy, Bibeau, Steckler, & Glanz, 1988; Stokols, Grzywacz, McMahan, & Phillips, 2003). According to the HBM, for an individual to partake in a health-related action, they must take into account the following: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cue to action, and self-efficacy (Glanz et al., 2002). In short, for individuals to engage in a health-related behavior, they must understand the severity of the condition, have knowledge of the condition, be aware of the risk levels for getting the condition, and have confidence in their ability to take action in preventative measures (Glanz et al., 2002). These HBM factors contribute to the probability of user engagement with a health-related behavior. Through analyzing user-generated content around AMR on social media, and user responses to others' postings, perceptions around AMR and the factors of HBM can be identified. In our study, we gain insight into how users discuss AMR and antibiotic use, learning of users' perceptions and baseline knowledge levels of AMR. Users retweeted news stories about the risks of AMR and current developments in the field, indicating they have a baseline knowledge of AMR, are aware of associated risks, and can identify preventative measures to help prevent AMR. By analyzing conversations on social media can provide further knowledge of how users may perceive health topics, which could be a precursor to health-related behavioral change. Although our study did not result in clear theoretical implications, the data provides additional value by enabling us to have a better understanding of how information is constructed around a global health concern in an environment that reaches billions of people, and provide a starting point for future theory-building.

This study is among the very first to monitor and track AMR-related communication in social media for an extended period of time. Our findings not only identify which types of users are influential in online discussions regarding AMR and antibiotics, but also which keywords and phrases are central to discourse on Twitter in sharing information about these topics. This work is thus an important benchmark in the study of AMR, as well as a jumping off point for future research to further diagnose and combat any instances of AMR misinformation online. The methodology employed in the study can be replicated in other health-related studies to identify potential instances of misinformation. This can ultimately lead to a broader strategy to reduce AMR itself, and other health concerns, specifically through information and awareness campaigns.

We would also like to acknowledge the limitations of our research. This study examines posts on Twitter, and there are a variety of other social media and online communities and platforms that may also provide insights about information networks related to AMR and antibiotics. Of course, there were two search terms used to identify information networks, but the variety of associated terms identified through the graphs provide researchers with a starting to point to further investigate online information networks related to AMR and other health concerns. Another limitation is that Sysomos identifies influencers primarily by users' reach and number of followers. Scholars may use other measures of centrality and power to identify influencers and add to our understanding of this network. While this analysis of the information network related to AMR is primarily descriptive, future research may use the insights from this study to develop prescriptive models of the diffusion of accurate information through these information networks.

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