

A Sentiment and Content Analysis of Twitter Content Regarding the use of Antibiotics in Livestock

On January 1, 2017, the final rule of the Veterinary Feed Directive (VFD) was put into place which required the use of antibiotics approved for both humans and animals to be discontinued for the use of growth promotion (Food and Drug Administration, 2015). Additionally, the final rule stipulated that all antibiotics of medical importance to human medicine must be prescribed and overseen by a veterinarian if used in animals (FDA, 2015).

The VFD was passed due to empirical research indicating the significant role of antibiotic use as a growth promoter in livestock production plays in the development of antibiotic resistance (FDA, 2015). Antibiotic resistance is the decreased ability for antibiotics to effectively treat the adverse effects resulting from bacterial infection (World Health Organization, 2017). The use of antibiotics in livestock production has long been debated, particularly the practice of providing antibiotics at sub-therapeutic levels for growth promotion. Antibiotic use as growth promoters has been disputed because of concerns that it encourages the development of antibiotic-resistant bacterial strains, thus making it harder to treat bacterial infections (Lappe, 1982).

Every year, at least two million people in the United States become infected and at least 23,000 die from infections with bacteria that are resistant to antibiotics (CDC, 2013). Although antibiotic-resistant infections can happen anywhere, most deaths happen in health care settings such as hospitals or long-term care facilities such as nursing homes (CDC, 2013). Antibiotic resistance increases the costs associated with health care by increasing the length of stays in the hospital and requiring more intensive medical care for patients (World Health Organization, 2017). Furthermore, the development of new antibiotics to treat these resistant bacteria is stagnant among pharmaceutical companies (McKenna, 2017). These companies are often unable to have new products on the market long enough to make back their investment in developing the products before the antibiotics ultimately begin showing signs of resistance. Thus, the financial motivation to develop new antibiotics is low (McKenna, 2017). The manner in which both human medicine and livestock production uses antibiotics has been found to contribute to the expedited development of resistance to newly developed antibiotics (McKenna, 2017).

Scientists continue to discover new information regarding the role both humans and livestock play in the development of antibiotic-resistant bacteria with the livestock industry contributing to antibiotic resistance by using antibiotics for growth promotion and humans contributing by demanding antibiotics from their doctors or not taking their full prescriptions (Runge et al., 2013). Additionally, increased access to and use of the internet as a source of information has created an urgency for scientists to place more attention on communicating science to the world (Brossard & Scheufele, 2013). Social media are often the first sources of information the public have regarding a topic or issue of controversy (Gil de Zuniga, Jung, & Valenzuela, 2012). Opinion leaders on these social media platforms can have a significant impact on shaping what the public knows about topics based on how the opinion leaders perceive and understand the topic (Park, 2013). The public's reliance on the internet as a source for information is important for scientists as researchers have found a positive relationship between time spent on the internet and a more positive attitude toward science (Dudo et al., 2011).

As new scientific information regarding both antibiotic use in livestock and antibiotic resistance is discovered, one way these findings are being shared with the public is through online media platforms via social media (Runge et al., 2013). Thus, as a platform for distributing and

debating scientific information, social media tools are an important piece of the puzzle with regard to understanding how the public learns about the role antibiotic use in livestock plays in the development of antibiotic-resistant bacteria (Runge et al., 2013).

Considering the amount of scientific information being communicated via social media, it is important to understand the audience who receives the information and discusses scientific issues through online media (Anderson, Brossard, & Scheufele, 2010). Consumers of online science news tend to be different than the general population. In 2010, 54.9% of science-seeking internet users had a college degree and nearly all had completed high school (Anderson et al., 2010). This stands in stark contrast to the education level of general internet users. In 2016, 98% of college graduates used the internet while 68% of those with less than a high school diploma used the internet (Pew, 2017a)

The use of the internet in the search for science news often times occurs through the use of social media (Anderson et al., 2010). According to the Pew Research Center (2017b), 69% of Americans used some type of social media. Of those using social media, the most popular social media platforms include Facebook, Instagram, Pinterest, LinkedIn and Twitter (Pew, 2017b).

With the increasing prevalence of available platforms and the development of stronger connections, a user can gain influence and authority on any platform (Dubois & Gaffney, 2014). This can be to the detriment of science as social media can distort and misinform when communicating about science because it can spread misinformation regarding antibiotic resistance and may indirectly contribute to the misuse of antibiotics (Groshek & Bronda, 2016). Thus, it is important for agricultural and science communicators to identify the key influencers who are sharing information regarding antibiotic use in livestock and antibiotic resistance as well as the characteristics of the messages they are sharing.

Literature Review

With more than 328 million users, Twitter is one of the most popular social media platforms in the world (Forbes, 2017). Although Twitter now allows 240 characters, at the time of data collection for this study, Twitter allowed users to send and receive micro-blogs with 140 characters or less (Twitter.com, 2017). These micro-blogs are called tweets (Kwak, Lee, Park, & Moon, 2010). Twitter has gained popularity as a tool for communicating scientific information (You, 2014). Twitter can allow for scholarly discussion, the rapid dissemination of research to the public, and the scope of the audience to be expanded (Bombaci et al., 2015).

Scientists have cautioned that Twitter might not accurately convey science accurately due to the limited space for content, thus resulting in misinformation for those consumers using social media to locate scientific information (Bombaci et al., 2015). Thus, the use of communication tools such as hyperlinks and hashtags can be useful in communicating science with the public on social media platforms, especially Twitter (Su, Scheufele, Bell, Brossard, & Xenos, 2017). Hyperlinks can direct a user's followers as well as other Twitter users to more online information regarding the topic content of the tweet (Hughes & Palen, 2009). Therefore, hyperlinks can allow Twitter users to provide more content to the reader without being limited by the character limits of Twitter (Hughes & Palen, 2009). Hashtags, a key feature in Twitter, are a tool for linking similar content on Twitter (Su et al., 2017). Hashtags are represented by the “#” symbol and allow users to search for and follow specific topics (Su et al., 2017). Su and colleagues (2017) found that using communication tools such as hyperlinks and hashtags can empower science public relations practitioners to foster greater engagement and relations with the public.

One method of determining how science is discussed in an online platform such as Twitter is through the use of social media monitoring and sentiment analysis (Munro, Hartt, & Pohlkamp, 2015). Social media monitoring is the collecting of social media content shared openly on social media platforms (Liu, 2012). Sentiment analysis is the textual analysis of the content to determine the tone or valence in which the content was shared. Valence is the intrinsic attractiveness or averseness of an event, object, or situation (Frijda, 2986). Content is generally categorized as having a positive, negative, or neutral tone (Liu, 2012). Sentiment analysis software programs use textual analysis to determine how words, word combinations, and phrases communicate about a topic in a generally positive, generally negative, or neutral manner (Liu, 2012). By communicating about topics positively, negatively, or neutrally, the communicator can influence how the receiver interprets information (Liu, 2012).

Netlytic, a social media monitoring and sentiment analysis program housed at Dalhousie University, has previously been used to monitor Twitter content regarding genetically modified organisms (Munro et al., 2015). Findings from this study indicated a 6:1 ratio of positive to negative sentiment, meaning for every tweet negatively discussing genetic modification, there were six tweets positively discussing genetic modification (Munro et al., 2015). While several social media monitoring programs exist and provide information in a variety of manners, most generally provide information beyond that of sentiment including total mentions of the key search terms, reach, trending hashtags, trending URLs, and key influencers. Information such as this can be used to better understand the contents of the messages being communicated regarding the topic and who the key influencers, or opinion leaders, are discussing the topic (Munro et al., 2015).

Previous research has evaluated the accuracy of information provided on social media platforms such as Twitter. Park and colleagues (2016) evaluated colorectal cancer information on Twitter and found 65.2% of the information contained in the tweets were medically relevant to the topic of colorectal cancer and 86.1% of the information contained in the tweet was medically correct. Medical professionals and medical institutions tweeted less than 3% of the tweets analyzed whereas 85.2% of the tweets originated from organizations. Finally, this study analyzed the frequently shared URLs on Twitter and found links to news/magazine articles and general information websites were the domain types most shared regarding information about colorectal cancer (Park et al., 2016).

Who is sharing information regarding issues related to science on social media is also notable. Wickstrom and Specht (2016) examined opinion leaders on Twitter discussing a water crisis in Toledo, Ohio. Findings indicated individuals involved in activist-type organizations or groups tended to be the most outspoken against agriculture and were more likely to share information placing the blame on agriculture. By identifying these opinion leaders, practitioners are then better suited to identify social media accounts to monitor using social media monitoring programs as issues arise (Wickstrom & Specht, 2016).

Finally, in a study of Chinese scientists' use of social media, researchers found scientists believe social media can help them bypass legacy media and reach a wider audience while allowing for more interdisciplinary collaboration opportunities (Jia, Wang, Mao, & Zhu, 2017). Although Twitter is blocked in China, the microblogging program Weibo serves a similar purpose (Jia et al., 2017). Findings from this study additionally indicated scientists believe using social media allows them to encounter the public actively and gain more social recognition (Jia, et al., 2017). While the literature gives us some indication of the use of social media for communicating science, additional research is needed regarding the communication of agricultural science information, specifically in relation to antibiotic use in livestock.

Conceptual Framework

Opinion leadership served as the conceptual framework for this study. For this study, opinion leaders were identified by the “key influencers” Nuvi identified. Opinion leaders, in both online and interpersonal settings, serve as a primary means through which ideas are spread, information is disseminated, and innovations are adopted (Rogers, 2003). Opinion leaders exert influence over the members of the social system in which they exist (Rogers, 2003), with the online environment, specifically Twitter, serving as the social system for this study. Traditionally, the opinion leader pays close attention to issues reported in the media, discusses these issues, and views themselves as more inclined to persuade others to adopt an opinion or make an action (Lazersfeld, Katz, & Gaudet, 1948). Although opinion leadership was conceptualized as the two-step flow of communication from the media to the opinion leaders and then the opinion leaders to their acquaintances generally through face-to-face interaction, the social media landscape is now a platform for opinion leaders to transfer information and opinions to their audiences (Winter & Neubaum, 2016).

Opinion leaders earn and maintain their status as an opinion leader through competence, social accessibility, and the conformity to the norms of a system. Those who are more interested in or invested in an issue are more likely to emerge as opinion leaders than their peers (Rogers, 2003). “Opinion leaders can contribute to a comprehensive understanding of the development trend of public opinion,” (Zhang, Li, He, & Wang, 2014, p. 1). Park (2013) found opinion leadership on Twitter plays an important role in moving individuals who are motivated to discuss a specific issue to actively use Twitter.

Two key differences between opinion leaders on Twitter and their followers are relevant for this study. Accessibility is one key difference between opinion leaders and their followers, meaning the opinion leader has more access to the public through their interpersonal network (Rogers, 2003). In the case of the current study, this network includes the Twitter followers of the opinion leaders. Next is the innovativeness of the opinion leader (Rogers, 2003). The opinion leader is recognized by their peers as being a competent and trustworthy source regarding the information the followers are seeking (Rogers, 2003). As the followers seek information regarding a topic from those whom they deem as competent and trustworthy, the opinions, knowledge, and beliefs of the opinion leaders are communicated to the followers and ultimately influence the opinion of the followers (Rogers, 2003).

Winter and Neubaum (2016) found individuals on social media with high personality strength and high levels of political interest were the ones who try to influence others on social media. This study also found the number of friends on Facebook could significantly predict opinion leadership. That is, individuals with a greater number of Facebook friends were more likely to share their opinion regarding a topic (Winter & Neubaum, 2016). The same can be said for Twitter. Hwang (2015) found the higher degree of self-esteem of a Twitter user influenced the user to seek out more followers and reaching more individuals with his/ her opinion (Hwang, 2015). Thus, opinion leaders on Twitter have the opportunity to share their opinions with a larger audience, giving them the opportunity to share information with more individuals (Winter & Neubaum, 2016). Although the traditional view of opinion leaders is that of one individual, opinion leaders can also be groups or organizations (Dur & De Bievre, 2007). Special interest groups can serve as opinion leaders and can play a major role in allowing citizens to express their opinions to decision makers (Dur & De Bievre, 2007). By understanding the role of opinion leaders on social media, agricultural and science communicators can better develop and present information to opinion leaders regarding the role antibiotic use in livestock plays in the development of antibiotic resistance.

Purpose and Research Questions

The purpose of this study was to explore sentiment and characteristics of social media content that discussed the use of antibiotics in livestock and the development of antibiotic resistance. Additionally, this study sought to understand the characteristics of the key influencers whose opinions had the greatest amount of reach on social media. The following research questions guided the study:

RQ1: How many total mentions of livestock, antibiotic, and resistance, occurred across all social media platforms from January 1-August 31, 2017?

RQ2: What were the trending hashtags on Twitter regarding the use of antibiotics and antibiotic resistance in livestock?

RQ3: What was the social media reach regarding the use of antibiotics and antibiotic resistance in livestock?

RQ4: Who were the key influencers on Twitter regarding the use of antibiotics and antibiotic resistance in livestock and what were their characteristics?

RQ5: What was the sentiment of tweets regarding the use of antibiotics and antibiotic resistance in livestock?

Methods

This study used social media monitoring for sentiment and subsequent quantitative content analysis as the research approach. Quantitative content analysis includes statistical analysis to derive conclusions. Unfortunately, quantitative content analysis alone disregards the thoughts, feelings, intentions, and attitudes of an individual. Thus, researchers lose a deeper understanding of the topic being discussed online with quantitative content analysis alone (Munro et al., 2015). However, although social media monitoring and sentiment analysis programs can provide researchers with a great deal of information the information is mostly descriptive in nature. Content analysis of the information can allow researchers to better understand the content beyond its descriptors. Thus, the combination of both sentiment analysis and content analysis can allow for a deeper, clearer understanding of the content that cannot be attained with each method individually.

“Sentiment analysis is the application of Natural Language Processing, Computational Linguistics, and text mining to systematically analyze online expressions. It is the computational study of opinion, sentiments, and emotions expressed in text,” (Kadam & Joglekar, 2014, p. 28). Sentiment analysis allows researchers to gather a numerical ratio score of posts that are either positive, negative, or neutral in their sentiment. Sentiment analysis software allows the researcher to collect data related to total mentions, reach, spread, trending hashtags, trending URLs, and influential users. This allows researchers to draw conclusions about how particular topics are being discussed via social media platforms (Munro et al., 2015). Sentiment analysis is used in a variety of manners including gauging reactions to new products or services by companies or organizations, identifying major difficulties customers might be experiencing with a product, providing numeric inputs for marketing campaigns, and analyzing social media feeds (Kadam & Joglekar, 2013). Although practitioners in marketing and advertising widely use social media monitoring and sentiment analysis software, they have been used to a lesser degree to monitor online content regarding controversial issues such as antibiotic use in livestock and antibiotic resistance.

Social Media Monitoring

Nuvi, a social media monitoring platform, was used to collect online content regarding the use of antibiotics and antibiotic resistance in livestock. This program was available through [social media lab at university]. Within Nuvi, a monitor was established for the keywords and combinations of “antibiotic,” “resistance,” and “livestock.” Previous work guided the terms selected (Landers, Cohen, Wittum, & Larson, 2012). Nuvi identifies the presence of the search terms on all publically available social media platforms and collects those for analysis. One limitation to using these search terms is Nuvi only identifies these terms exactly, therefore if an individual used the term “resistant” instead of “resistance” or “food animals” instead of “livestock”, the content would not be collected. Because the final rule of the Veterinary Feed Directive went into effect January 1, 2017, the monitor ran for an 8-month period beginning January 1 and ending August 31, 2017. The monitor garnered $N = 3,836$ mentions during this time period.

This search returned any mentions that included these search terms on publicly available social media accounts. Nuvi provides a great deal of information for users; however, the variables of interest for this study were total mentions (total number of mentions for the search terms), reach (the number of individuals potentially reached by the messages included in the social media content), spread (the additional number of individuals potentially reached by the messages included in the social media content via retweets), trending hashtags (hashtags most commonly used within the conversation), trending URLs (the URLs most shared on the social media platforms), influential users (individual social media accounts that contribute the most to the conversation by having the a greater number of followers and shares), and sentiment (positive, negative, or neutral). Sentiment analysis allows for people’s opinions to be analyzed using an algorithm within the software program (Munro et al., 2015). The descriptive data were available in summary reports directly from Nuvi.

Quantitative Content Analysis

A quantitative content analysis was additionally conducted on the key influencers and the tweets collected during the timeframe. Nuvi provided a list of the top 10 key influencers and each individual tweet collected during the study’s timeframe. Nuvi determined the key influencers based on the number of followers and reach of the content shared or reshared by the account. A total of 199 unique tweets were collected and analyzed. The lead researcher took screenshots of the Twitter profiles of each key influencer and provided these to the coders for analysis. Individual tweets were provided to the coders in an Excel spreadsheet.

A content analysis of this content can allow for a better understanding of who is sharing the greatest amount of information regarding the topic as well as what content is being shared regarding the topic (Yi, Choi, & Kim, 2015). Because all of the top 10 influencers were Twitter accounts, variables under consideration were the username, date joined, number of followers, number of accounts the user is following, account type, verification status, location, and credentials. Additionally, coders determined if the key influencer created its own original content or simply retweeted content previously shared by another account.

Because little research has been conducted comparing the accuracy between sentiment analysis of content by computer programs and sentiment analysis of content by humans, human coders coded each tweet. Humans are better able to deal with vague, ambiguous, sarcastic, or awkwardly worded texts where computers are not (Riffe, Lacy, & Fico, 2014). Texts are made by and for humans; therefore, humans are better able to see nuances in the text that a computer program may

not (Riffe, Lacy, & Fico, 2014). The coders identified the sentiment of each individual tweet as positive, negative, or neutral and determined if each tweet contained a hashtag and link. Results from the human-coder content analysis were compared to the sentiment Nuvi assigned to each tweet to evaluate the accuracy between how Nuvi coded tweets and how a human might interpret the tweet.

Coder training was conducted using tweets collected outside of the analysis timeframe for this study and on Twitter accounts not included in the study. The lead researcher trained two independent coders who were provided 10% ($n = 20$) of the total tweets to determine intercoder reliability. Intercoder reliability was assessed using Krippendorff's alpha. The acceptable level of reliability with using Krippendorff's alpha is generally about .8, but alphas as low as .667 have been reported (Riffe et al., 2014). Because an acceptable level of intercoder reliability was not met for sentiment after the first round, coder training took place again and coders were reassigned a random sample of 10% of the total tweets for analysis. After the second round, an acceptable alpha level was reached for sentiment (.83), hashtag (1.0), and link (1.0). Coders were then equally assigned the remaining tweets to code guided by the researcher-developed codebook.

Coders additionally coded each key influencer's Twitter account using a researcher-developed codebook. Again, acceptable levels for Krippendorff's alpha were achieved for each variable including 100% agreement for account type and human coder sentiment. A Krippendorff's alpha level of .76 was achieved for credentials. To allow for analysis and description of the findings, the lead researcher met with the coders to allow them to discuss and come to a consensus regarding the three accounts where they disagreed. Descriptive statistics were reported from the content analysis of key influencers and the tweets.

Results

Descriptive data provided from the Nuvi output were used to answer research questions 1-3. Research questions 4-5 were answered using data collected from the content analysis.

RQ1: How Many Total Mentions of Livestock, Antibiotic, and Resistance, Occurred Across All Social Media Platforms from January 1-August 31, 2017?

Social mentions of the keywords "antibiotic," "resistance," and "livestock" totaled $N = 3,836$ from January 1-August 31, 2017. Of these total mentions, 2,461 came from blogs, news, and RSS feeds and 844 came from Twitter. The peak conversation occurred on June 11 with 298 mentions.

RQ2: What Were The Trending Hashtags on Twitter Regarding the Use of Antibiotics And Antibiotic Resistance in Livestock?

The majority of tweets (73.8%) included a hashtag. The top three trending hashtags during the time period were #amr (which stands for antimicrobial resistance), #antibioticresistance, and #antibiotic. While six of the top trending hashtags could clearly be identified as relevant to antibiotic use in livestock and antibiotic resistance, upon an internet search #orfc17 and #savebx were found to be used for an event or campaign. The use of #1 and #2, however, could not be identified. The top 10 trending hashtags along with the number of occurrences are reported in Table 1.

Table 1

Top 10 Trending Hashtags and Number of Occurrences

| Hashtag | Number of Occurrences* | % |
|-----------------------|------------------------|------|
| #amr | 55 | 27.6 |
| #antibioticresistance | 44 | 22.0 |
| #antibiotic | 32 | 16.1 |
| #orfc17 | 22 | 11.0 |
| #1 | 20 | 10.0 |
| #2 | 20 | 10.0 |
| #superbugs | 18 | 9.0 |
| #food | 16 | 8.0 |
| #saveabx | 16 | 8.0 |
| #livestock | 14 | 7.0 |

NOTE: *Multiple hashtags could be used in a single tweet, thus the total does not equal 100%

RQ3: What was the Social Media Reach Regarding the Use of Antibiotics and Antibiotic Resistance in Livestock?

Original mentions between January 1-August 31, 2017, had the potential to reach 1,120,906 people. Reach, as defined by Nuvi, is a potential audience reached with a single social media post (Nuvi, 2016). Spread during this time frame was 501,202. Nuvi defines spread as the number of people potentially reached by the content through retweets or reshares (Nuvi, 2016). In the same timeframe, those mentions had the potential spread to reach an additional 501,202 via re-tweets and shares. The social media account that had the greatest reach, “cowspiracy”, was found on Instagram. The remaining social media accounts with the greatest reach were Twitter accounts. The top 10 social media accounts in terms of reach are reported in Table 2.

Table 2

Top 10 Social Media Accounts with the Greatest Reach

| Social Media Platform | Account Name | Reach |
|-----------------------|-----------------|---------|
| Instagram | cowspiracy | 287,639 |
| Twitter | HamzeiAnalytics | 170,433 |
| Twitter | natalieben | 128,770 |
| Twitter | CGIAR | 60,482 |
| Twitter | statnews | 45,475 |
| Twitter | farmingfirst | 44,685 |
| Twitter | uniofleicester | 44,371 |
| Twitter | phylogenomics | 41,695 |
| Twitter | HumanityNews | 36,050 |
| Twitter | iAgribusiness | 31,830 |

RQ4: Who Were the Key Influencers on Twitter Regarding the Use of Antibiotics and Antibiotic Resistance in Livestock and What Were Their Characteristics?

All key influencers from January 1-August 31 were Twitter accounts. Nuvi determines key influencers based on the number of followers and reach of the content shared or reshared by the account. The top three key influencers were “uniofleicester,” “bfrist,” and “phylogenomics.” Six of the 10 key influencers created original content regarding the topic, while four simply retweeted content from another account. Of the key influencers who provided original content, three provided neutral content and three provided negative content – no account provided positive content. The top 10 key influencers along with their account information as determined by the content analysis are included in Table 3

Table 3

Top Ten Key Influencers and Account Information between January 1, 2017 – August 31, 2017*

| Account | Username | Date Joined | Followers | Following | Total Tweets | Location | Account Type | Credentials |
|-----------------|------------------|-------------|-----------|-----------|--------------|----------------------|-------------------------|--------------------------------------|
| @uniofleicester | Uni of Leicester | Oct. 2009 | 46,200 | 3,408 | 12,200 | Leicester, UK | Company or Organization | University or University Scientist |
| @brist | Bill Frist, M.D. | April 2007 | 13,100 | 356 | 6,080 | Nashville, TN | Personal | Human or Animal Medical Professional |
| @phylogenomics | Jonathan Eisen | June 2008 | 47,400 | 7,236 | 86,200 | Davis, CA | Personal | University or University Scientist |
| @ISGLOBALorg | ISGlobal | May 2011 | 6,400 | 680 | 20,000 | Barcelona, Spain | Company or Organization | Special Interest Group |
| @natalieben | Natalie Bennett | Oct. 2008 | 146,000 | 89,500 | 506,000 | Sheffield, UK | Personal | Politician/Governmental Individual |
| @GARREAU75 | Francois GARREAU | Nov. 2009 | 12,000 | 5,710 | 47,000 | Paris, France | Personal | Special Interest Group |
| @Laurie_Garrett | Laurie Garrett | May 2011 | 19,400 | 1,566 | 42,500 | New York, NY | Personal | Special Interest Group |
| @DrMel_T | Dr Mel Thomson | Jan. 2013 | 11,800 | 7,098 | 110,000 | Melbourne, Australia | Personal | Special Interest Group |
| @farmingfirst | Farming First | March 2009 | 49,300 | 4,975 | 10,500 | N/A | Company or Organization | Livestock Industry Organization |
| @NRDCFood | NRDC Food | Sept. 2012 | 8,014 | 933 | 11,400 | N/A | Company or Organization | Special Interest Group |

NOTE: *Key influencers are organized from highest influence to lowest influence.

RQ5: What was the sentiment of tweets regarding the use of antibiotics and antibiotic resistance in livestock?

To answer research question 5, the sentiment of each tweet as determined by Nuvi was recorded as positive, negative, or neutral. Additionally, to allow for comparison between Nuvi-coded sentiment and human-coded sentiment, human coders analyzed the sentiment of each individual tweet. Discrepancies between Nuvi and human coders were found as Nuvi coded 20 tweets as positive while the human coders coded only 10 tweets as positive. This trend was also seen within both the negative and neutral codes as well – Nuvi coded 129 tweets as negative, while the human coders determined 76 were negative. Finally, the human coders identified 113 neutral tweets while Nuvi coded only 50 as neutral. Of the 20 tweets Nuvi identified as positive, human coders agreed with Nuvi on ten (50%). Of the 129 tweets Nuvi identified as negative, human coders agreed with 66 (51%). Of the 50 tweets Nuvi identified as neutral, human coders had 100% agreement. Nuvi identified more tweets as negative than human coders, while human coders identified more tweets as neutral than Nuvi. An example of the discrepancy between human coders and Nuvi was a tweet that read “In the race to fight antibiotic resistance, the livestock industry can be a game changer <https://t.co/rEztKbV7bG>” Nuvi coded this tweet as negative while human coders coded this tweet as neutral. Results of both the Nuvi and human coded tweets are reported in Table 4.

Table 4

Sentiment of Tweets Coded by Nuvi and Human Coders (N = 199)

| Sentiment | Nuvi | | Human | |
|-----------|----------|------|----------|------|
| | <i>n</i> | % | <i>n</i> | % |
| Positive | 20 | 10.0 | 10 | 5.0 |
| Negative | 129 | 64.8 | 76 | 38.2 |
| Neutral | 50 | 25.2 | 113 | 57.0 |

Tweets with a greater reach provide information and perspective regarding the use of antibiotics in livestock. Thus, negative tweets with a greater reach provide negative information about antibiotic use in livestock to a larger audience while positive tweets with a smaller reach provide positive information regarding antibiotic use in livestock to a smaller audience. Table 5 provides positive, negative, and neutral tweets with the greatest reach.

Table 5

The Positive, Negative, and Neutral Tweet with the Greatest Reach

| Sentiment | Reach | Tweet |
|-----------|---------|--|
| Neutral | 128,770 | #orfc17 Think antibiotic resistance big? Anthelmintic resistance is huge approaching problem for livestock. Taninific forage essential |
| Negative | 57,535 | Confronting the rising threat of antibiotic resistance in livestock: https://t.co/UkPCYrCIUg @ILRI https://t.co/qqCUD6kcYb |
| Positive | 12,289 | Great step on #antibiotic resistance: https://t.co/yJIXK6ANtw |

Discussion, Conclusions, and Recommendations

Social media are often the first sources of information the public have regarding any controversial topic or issue (Gil de Zuniga et al., 2012). As the public uses social media to attain this information, it is often provided to them from individuals they view as opinion leaders (Park, 2013). Opinion leaders play an important role in shaping public knowledge and opinions about controversial issues. The purpose of this study was to explore the sentiment and characteristics of social media content that discussed one controversial issue in agriculture – the use of antibiotics in livestock and the development of antibiotic resistance.

Regarding characteristics of social media content, 92.4% of tweets contained a link to a URL ($n = 184$) and 73.8% contained a hashtag ($n = 147$). While over 90% of all tweets contained a link, a total of only seven unique links were identified. The neutral tweet with the most reach contained a hashtag while the negative tweet contained two links and the positive tweet contained both a tweet and a link. Agricultural and science communications practitioners are advised to use these hashtags and provide links to information as they develop social media content in an effort to disseminate scientific information regarding antibiotic use in livestock to the public. Content creators should monitor social media conversations and trending hashtags regarding relevant topics. The hashtag #antibiotic was the third most trending hashtag and was included in the positive tweet with the most reach while #orfc17 was the fourth most trending hashtag during the time period and was included in the tweet receiving the greatest reach. The trending hashtags and their use as discovered in RQ2 provide more search terms for researchers as they work to discover how the topic of antibiotic use in livestock is discussed in social media.

This study also sought to understand the characteristics of the key influencers whose opinions had the greatest amount of reach on social media. Opinion leaders have a great deal of influence over the members they come into contact with (Rogers, 2003). Four of the 10 key influencers were special interest groups or representatives of a special interest group. With a specific agenda motivating the content shared by special interest groups, content is often biased toward the group's central goals and messages (Dur & De Bievre, 2007). This is an important note for agricultural communicators as special interest groups play a major role in allowing citizens to express their opinions to decision-makers (Dur & De Bievre, 2007).

Hwang (2015) found the number of followers on Twitter could significantly predict opinion leadership. The top 10 key influencers in this study had a combined Twitter followership of 359,614. These individual Twitter accounts had the ability to influence a large number of

individuals with their content. Communicators should seek out these individuals and work with them to ensure they provide credible, scientific based content to their audiences.

Although the top three key influencers were connected to a university or the medical field, it is important to note that despite antibiotic resistance is a topic of scientific and medical importance, the remaining key influencers had no defined scientific knowledge or credentials outlined in their Twitter biographies. Additionally, of the tweets by the key influencers, no account discussed antibiotic use in livestock positively. The absence of scientific information regarding the animal health and welfare benefits of antibiotic use in food animal production indicates a gap in consumer education from the opinion leaders. Because opinion leaders serve as a primary means through which ideas are spread (Rogers, 2003) agricultural communications practitioners should prioritize monitoring the content shared by key influencers to better understand the content being shared by the most influential users and mobilize key scientists to communicate the issue.

For this study, sentiment was analyzed in two ways. First, Nuvi provided sentiment for each tweet and coded 64.8% of the content ($n = 129$) as negative compared to the 38.2% ($n = 76$) humans coded as negative. The contrast between human coders and Nuvi indicates there could be discrepancies in how Nuvi codes content and how a human might interpret the content. A limitation of this finding is the total number of tweets analyzed; therefore, a blanket rejection of Nuvi's analysis of sentiment is not advised. However agricultural communicators are advised to not rely completely on the output from Nuvi to evaluate the sentiment regarding public discussions of controversial agricultural issues such as this.

Future research should include a longitudinal study to monitor the effects of the VFD and the proposals of new legislation regarding the use of antibiotics given for disease prevention. While Twitter is a microblogging platform, traditional blogs should be monitored and content analyzed to better understand how opinions are shared without a character limit. Further, additional research is also needed regarding content shared on more visual platforms such as Instagram. Finally, a content analysis of the links shared could provide insight regarding the information shared on Twitter that directs readers to a call to action.

Although understanding the sentiment and characteristics of the content is important, understanding the likelihood that someone would interact with a social media message can allow for a greater understanding of how the messages will be received. Findings from this study should inform the development of social media messages regarding antibiotic use in livestock to explore how the message characteristics and sources influence trust in the message and likelihood to interact with the content.

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