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Research and Applications

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Using social media to monitor mental health discussions – evidence from Twitter

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ABSTRACT

Objectives: Given the public health importance of communicating about mental illness and the growing use of social media to convey information, our goal was to develop an empirical model to identify periods of heightened interest in mental health topics on Twitter.

Materials and Methods: We collected data on 176 million tweets from 2011 to 2014 with content related to depression or suicide. Using an autoregressive integrated moving average (ARIMA) data analysis, we identified deviations from predicted trends in communication about depression and suicide.

Results: Two types of heightened Twitter activity regarding depression or suicide were identified in 2014: expected increases in response to planned behavioral health events, and unexpected increases in response to unanticipated events. Tweet volume following expected increases went back to the predicted level more rapidly than the volume following unexpected events.

Discussion: Although ARIMA models have been used extensively in other fields, they have not been used widely in public health. Our findings indicate that our ARIMA model is valid for identifying periods of heightened activity on Twitter related to behavioral health. The model offers an objective and empirically based measure to identify periods of greater interest for timing the dissemination of credible information related to mental health.

Conclusion: Spikes in tweet volume following a behavioral health event often last for less than 2 days. Individuals and organizations that want to disseminate behavioral health messages on Twitter in response to heightened periods of interest need to take this limited time frame into account.

Key words: social media, mental health, Twitter, ARIMA, health communication

BACKGROUND AND SIGNIFICANCE

The use of social media has expanded in recent years, and it is increasingly seen as an essential tool for public health communication.[1] Social media not only could complement traditional broadcast sources (eg, radio, TV, newspaper) in spreading public health messages, but might also be necessary to reach the growing percentage of the population who are abandoning traditional broadcast media as adoption of Internet technologies increases.[2] Twitter use is higher among certain populations (eg, youths, African Americans, and Hispanics) who can be harder to reach using traditional media sources.[3] If the goal of public health communication is to spread information as broadly as possible to ensure that those who need the information as well as those who can further influence those who need the

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information get the message, then social media will play an increasingly important role. Although there has been widespread adoption of social media as a health communication tool, few studies have examined its effectiveness in promoting public health messages,[3] especially in relation to mental health issues such as depression and suicide.[4]

Mental health disorders affect a substantial portion of the US population. It is estimated that nearly half of all Americans will experience a mental illness during their lifetime.[5] One study estimated that nearly 4% of individuals 18 or older in 2013 had serious thoughts about committing suicide and nearly 7% experienced symptoms that were consistent with major depression in the past year.[6] The economic and social costs associated with mental illness are significant, and are a major cause of limitations in daily living and participation in social activities.[7,8] In addition, individuals with mental health conditions are more likely than those without such conditions to live in poverty and have lower educational attainment.[9] These social and economic impacts, along with treatment costs, have placed mental illness among the 5 most costly medical conditions in the nation.[10]

Twitter is a free, widely used social media platform, and an estimated 18% of US adults have an account.[11] The service allows users to post brief messages, or "tweets," up to 140 characters in length. Although the Twitter population comprises only a moderate fraction of the adult population, the reach of tweets has far broader impact through social multiplier effects. Unless Twitter users mark their tweets as private, they are public, allowing people to read and respond to other users' tweets. Twitter enables additional communication between users through retweeting (ie, reposting other users' tweets to one's own feed), responding to tweets, and following other users' Twitter feeds. Twitter uses hashtags – labels preceded by "#" (e.g., "#depression") that are included in tweets – to enable other users to view posts on a related subject. The public nature of most tweets also makes Twitter a potentially valuable source of information about the views of individuals and organizations on a variety of subjects, including mental health.[12]

A number of studies have analyzed Twitter content on health-related topics, including an influenza outbreak,[13] problem drinking,[14] dental pain,[15] physical activity,[16] vaccination,[17] breast cancer,[18] and childhood obesity.[3] However, no studies to date have analyzed communication on Twitter about mental health, particularly depression and suicide. The patterns of Twitter use revealed by our data analysis suggest that social media could become a very important avenue to get mental health–related information to a wide audience. A significant portion of the US population with mental illness does not get any treatment.[19] In addition, negative perceptions and discrimination toward persons with mental illness are substantial and widespread.[20] Thus, in the context of the evolving mental health–related policy environment, targeted and effective messaging could have a significant impact on how people view mental illness, as well as on the need for and sources of mental health prevention and treatment.

To better understand patterns of communication related to mental illness on Twitter, we collected and analyzed tweets (including retweets) identified with hashtags and terms relating to depression and suicide. In particular, we analyzed the number of tweets about depression and suicide from 2011 to 2014 to develop an empirical model to predict trends in communication about depression and suicide. This model could allow public health agencies and organizations to identify deviations from the predicted trend in real time during periods of heightened interest about mental health on Twitter. Although the literature has identified several factors that help messages successfully resonate and spread on Twitter,[21] our study is one of the first to use an analytic approach to empirically identify periods of heightened interest around a particular topic, because most health-related Twitter studies with an analytic component have focused on content analysis.[22] Timely dissemination of public health messages could help them resonate widely on Twitter and influence health behaviors.[23] The results of our study could assist efforts to disseminate behavioral health information on Twitter.

METHODS

Data source

Crimson Hexagon's ForSight software provides access to public social media activity from a variety of social media sources, including Twitter. In this study, ForSight was used to collect data on 176 million tweets from 2011 to 2014 for terms related to depression and suicide. Because the social media data for analysis were limited to publicly available data, the Institutional Review Board at RTI International determined that the study did not constitute human subjects research and was exempt from review.

Crimson Hexagon provides more comprehensive data compared to other tools that have been used in previous studies, such as the free Twitter application interface. The application interface currently provides access to only a sample of publicly available tweets, but Crimson Hexagon has partnered with Twitter to collect and index a full census of public tweets since 2010. However, only data since 2011 were used in our analyses, because Crimson Hexagon did not collect and index the full census of tweets until July 2010. (See the supplementary technical appendix for further details on data selection.)

The website http://hashtagify.me/ was used as the starting point for identifying hashtags related to depression or suicide. The hashtags informed the selection of other relevant search terms, and an initial query of tweets was performed. Based on the initial results in Crimson Hexagon, such as word frequencies and a list of the most tweeted hashtags, we iteratively refined our search terms related to depression and suicide to ensure that the tweets to be analyzed were as comprehensive as possible and were, with a high level of precision, all directly related to mental health. For example, the search terms "depression" and "suicide" returned some tweets related to the Great Depression and suicide bombers, respectively. Therefore, these and similar terms were added to the query as exclusion criteria. Table A in the supplementary technical appendix shows the final search terms, as well as terms that were excluded.

Analyses

We analyzed tweet frequency with an autoregressive integrated moving average (ARIMA) model. First developed as an econometric tool, the ARIMA model is widely used to forecast time series data, such as stock prices and gross domestic product, and often predicts future values of these data better than more complex models.[24] We performed a natural log transformation of trends in the volume of tweets related to depression or suicide to standardize the variance of the time series.[24] Figure A in the supplementary technical appendix shows the raw number of tweets per day. As the number of tweets grows, the size of deviations from the trend increases. This increase in volatility can pose analytical problems, because time series modeling and forecasting rely on an assumption of standard variance throughout the time series.

Following well-established modeling procedures,[24,25] we determined that the appropriate model for mentions of depression and

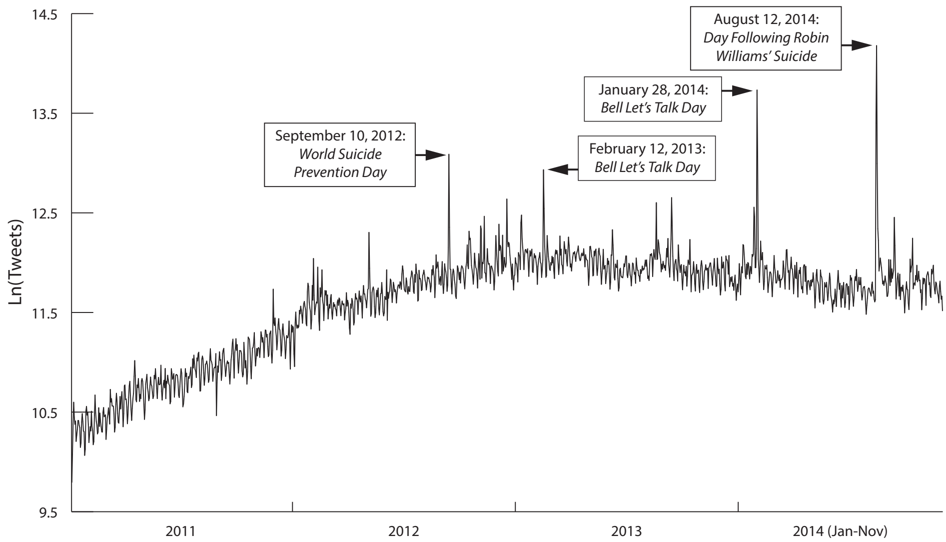

Figure 1. Natural log transformation of tweets mentioning suicide or depression: January 1, 2011, to November 28, 2014

suicide on Twitter is an ARIMA model of the order (1,1,2) × (1,1,1) 7. This model consists of 1 regular autoregressive order, first differenced, and 2 regular moving average orders, with a multiplicative weekday variation component consisting of 1 "seasonal" autoregressive order, 1 "seasonal" difference, and 1 "seasonal" moving average order at the weekly period. The model was estimated with the Twitter data from 2011 to 2013 and was tested on data from 2014. Details of the modeling process and model diagnostics are included in the supplementary technical appendix.

Two types of forecasts were run using the model. The first was a "day-ahead" forecast using the full 2014 test data. The day-ahead forecast incorporates all previous realized values of the time series and offers the most precise forecast based on full information. When monitoring Twitter for potential "shocks" (ie, deviations from the forecast) in real time, day-ahead forecasts are preferable because they include all available information. However, when studying the nature of a shock, day-ahead forecasts are less useful, because when there is a shock, the expected forecast for future periods includes the shock.

For shocks that were identified from the day-ahead forecast, therefore, a 30-day forecast was estimated from the period just prior to the shock. The 30-day forecast becomes less precise for days that fall at the end of the forecast period, because forecasts for those days are based on information up to 30 days prior. From an analytical standpoint, however, examining shocks with a 30-day forecast is preferable, because the 30-day forecast provides a stable baseline estimate of tweet volume and does not "update" to include the effects of the shock. All analyses and forecasts were conducted with R version 3.1.0, using the "forecast" package. Data and programming files are available upon request from the authors. The supplementary technical appendix offers a more detailed discussion of model selection and estimation. There, Table B presents the final model's estimates and fit statistics, and Table C reports additional measures of the model's accuracy.

RESULTS

Figure 1 shows the natural log transformed trend in tweets mentioning terms related to depression and suicide on Twitter from January 1, 2011, to November 28, 2014. Visual inspection strongly suggests that there were 4 particularly large spikes in tweets evident in the transformed series. These almost certainly indicate temporary heightened interest in behavioral health corresponding to the following national or international events: World Suicide Prevention Day (WSPD) in 2012, Bell's Let's Talk campaigns in Canada in 2013 and early 2014, and the actor/comedian Robin Williams's suicide in the summer of 2014. There are also several smaller spikes, which are particularly apparent when compared with the immediate time window surrounding each observation. They also may correspond to greater interest in mental health. For example, around September 2013, 2 relatively large spikes occurred that could merit attention. However, they are less obvious when visually compared to the 4 big spikes previously identified.

This figure also shows that after each large spike, the time series returns to its previous levels, and during other periods, the fluctuations are fairly uniform around the trend. The trend in the logarithmic series is approximately linear in the first part of the period but levels off after 2013. This trend is most likely due to the general growth of Twitter instead of any particular growth in numbers of individuals with a vested interest in behavioral health joining Twitter or more general interest in tweeting about depression and suicide.

Day-ahead forecasts for the latter half of the 2014 test data are shown in Figure 2. The first half of 2014 was omitted to allow for closer inspection of the details of the time series and forecasts. However, the forecast pattern was not substantially different in the first half of the test data.

Actual values are represented by the solid line in Figure 2. The dotted line represents the day-ahead forecast from the ARIMA model, with the 95% prediction interval plotted in gray. On only 3 occasions in the latter half of 2014 did the actual values exceed the prediction interval: August 11 and 12, September 10, and October 10. These dates correspond to the suicide of Robin Williams, WSPD, and National Depression Screening Day (NDSD), respectively. These events were exogenous shocks that were unaccounted for by the model.

In the 11-month test data since January 2014, there were only 5 such shocks, all of which were upward deviations from the predicted levels, indicating periods of greater activity. These 5 shocks can be

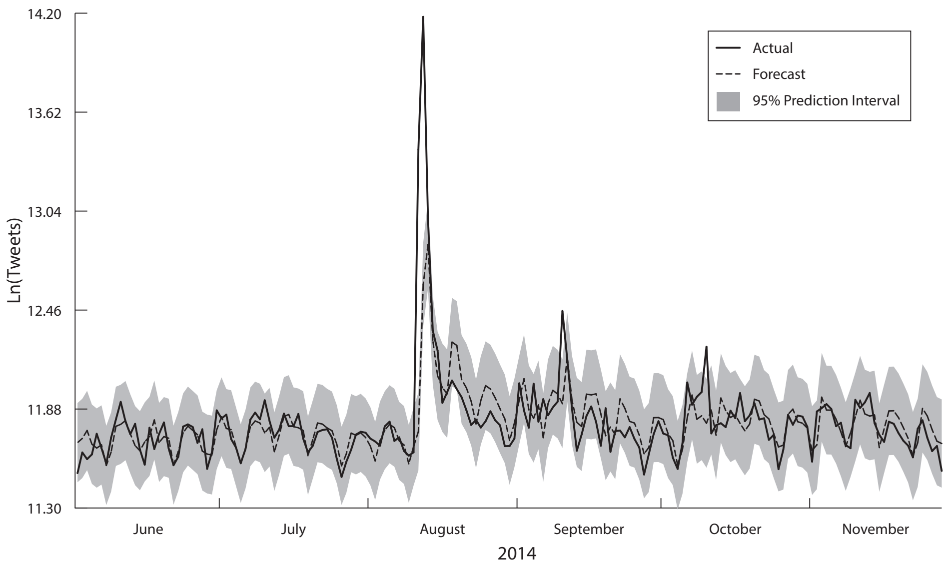

Figure 2. Actual and day-ahead forecasts of tweets mentioning depression or suicide: June 2014 to November 2014 *Notes*: The day-ahead forecast incorporated all previous tweets in the time series shown in the figure to predict the number of tweets for the next day. The day-ahead forecast and 95% prediction interval were based on an autoregressive integrated moving average (ARIMA) model using the "forecast" package in R version 3.1.0.

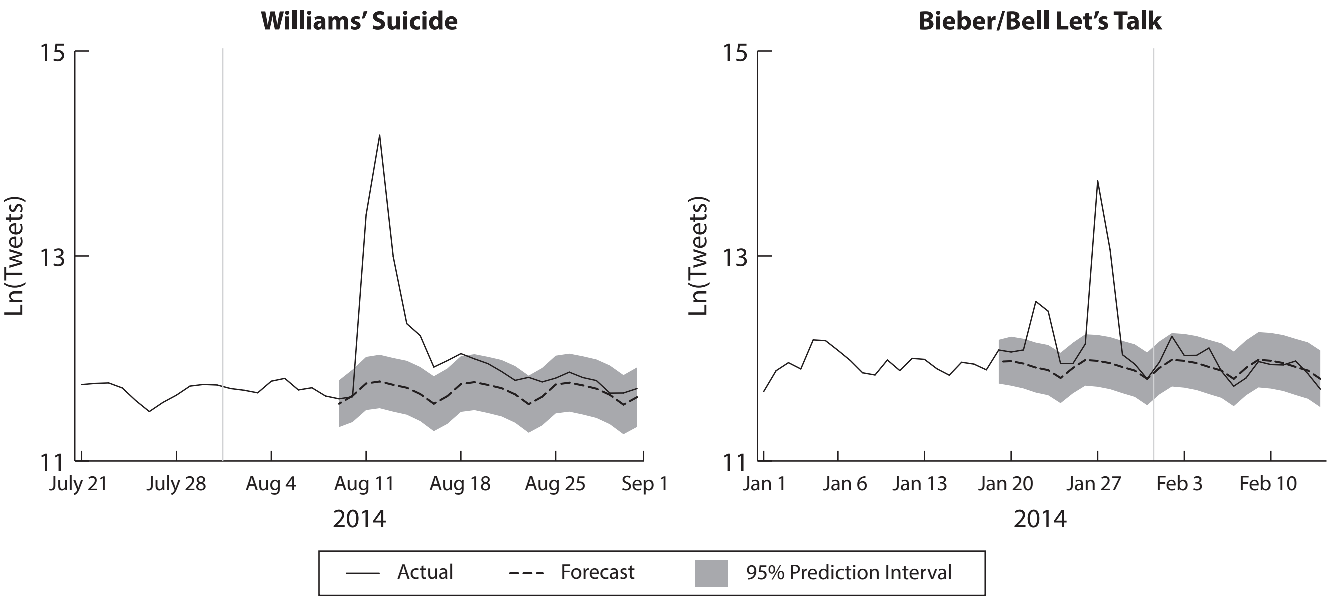

Figure 3. Unexpected shocks in 2014 and the expected Bell Let's Talk shock in January 2014 *Notes*: The 30-day forecast incorporated all previous tweets in the time series to predict the number of tweets for the next 30 days. The 30-day forecast for Robin Williams's suicide began on August 8, 2014, and the forecast for Justin Bieber's arrest and the Bell Let's Talk campaign began on January 19, 2014. Bieber's arrest occurred on January 23, 2014. The Bell Let's Talk Day occurred on January 28, 2014. Williams committed suicide on August 11, 2014. Vertical lines denote new months. The 30-day forecasts and 95% prediction intervals were based on an autoregressive integrated moving average (ARIMA) model using the "forecast" package in R version 3.1.0.

classified as 2 types: unexpected and expected. For the latter, an increase in activity is anticipated in response to a planned event. Although expected shocks exceed the prediction values specified by the model, the events were scheduled by institutions well in advance.

Figures 3 and 4 show 30-day forecasts starting shortly before each of these shocks. The largest was an unexpected shock in 2014 that occurred in response to Robin Williams's suicide (Figure 3, panel 1). In the days leading up to August 11, the day he died, the actual values fell within the model's prediction interval. Williams's death created a large increase in the number of tweets about suicide and depression that the model did not predict. The volume of tweets associated with this event continued to grow on August 12, as more people became aware of it. The shock appeared to be relatively persistent; the level of mentions exceeded the 30-day forecast's prediction interval for 8 days before slowly moving back to the trend.

The second unexpected shock occurred on January 23, 2014, and is the first spike in panel 2 of Figure 3. This deviation from the trend was associated with news of the pop star Justin Bieber's arrest

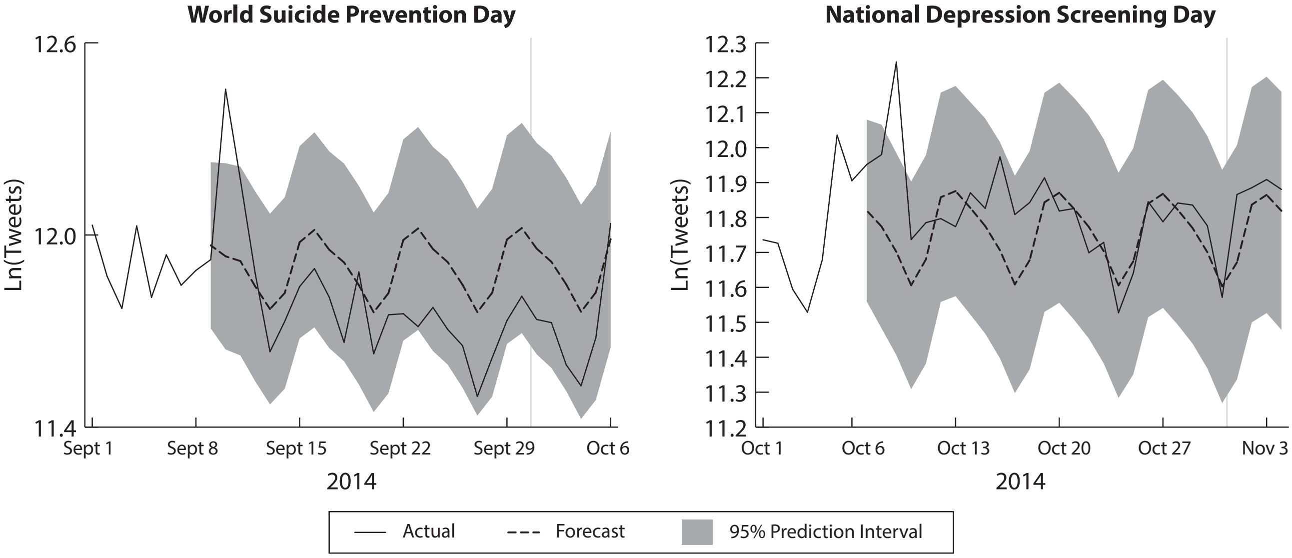

Figure 4. Predicted shocks for World Suicide Prevention Day and National Depression Screening Day in 2014 *Notes*: The 30-day forecast incorporated all previous tweets in the time series to predict the number of tweets for the next 30 days. The 30-day forecast for World Suicide Prevention Day began on September 8, 2014, and the forecast for National Depression Screening Day began on October 7, 2014. World Suicide Prevention Day was on September 10, 2014. National Depression Screening Day was on October 9, 2014. Vertical lines denote new months. The 30-day forecasts and 95% prediction intervals were based on an autoregressive integrated moving average (ARIMA) model using the "forecast" package in R version 3.1.0.

for driving under the influence, where it was reported that he had been using antidepressants recreationally prior to the arrest. Tweets exceeded forecasted levels for 2 days in this case, perhaps due to less news interest in this event. However, this shock illustrates the value of our analytic approach. Absent the model predictions, it is not readily apparent that an event related to mental health had occurred or that interest in depression (or antidepressants) on Twitter was higher than normal during this period.

The remaining 3 shocks in 2014 can be classified as expected and were associated with awareness campaigns designed to draw attention to suicide and depression. Every January, Bell, a Canadian telecommunications company, sponsors the Let's Talk campaign, in which it donates to mental health causes for each tweet about depression on the day of the fundraiser (second spike in Figure 3, panel 2). Similarly, WSPD (Figure 4, panel 1) in September and NDSD (Figure 4, panel 2) in October are intended to spread awareness about mental health. As with the Williams shock, these events drove the numbers of mentions well above the expected values based on the 30-day forecast. Unlike the unexpected shock resulting from Williams's suicide, however, Twitter volume related to these shocks diminished more rapidly, with actual mentions falling back to the 30-day forecast prediction interval within 2 days for the Let's Talk campaign and within 1 day for WSPD and NDSD.

DISCUSSION

The purpose of the study was to develop an empirical model to identify periods of heightened interest in suicide and depression topics on Twitter. Although ARIMA models have been used extensively in other fields, notably economics and finance, they have not been widely used in public health. However, our findings indicate that the ARIMA model estimated in the study is a valid tool to identify periods of heightened mental health–related activity on Twitter. Detection of any spikes by the model opens the way to increasing the large and diverse Twitter population's exposure to mental health–related public health messages. In particular, our analysis of 176 million tweets from 2011 to 2014 for search terms related to depression or suicide gives an understanding of what the number of mentions of depression and suicide "should" be. Ongoing use of this data analysis model could enable professionals to monitor these trends and quickly recognize and respond when an exogenous event has created increased interest in mental health issues.

Although many of the events detected by our model were well anticipated, unexpected events offer additional periods of greater attention that professionals can use to increase mental health awareness. As in the case of Robin Williams's suicide, some of these unexpected events and their causes may be readily apparent, but other unexpected periods of increased interest and activity may reflect lower profile events that would otherwise be overlooked by mental health professionals. Once such instance is illustrated by the Justin Bieber arrest, during which awareness of the greater interest could have enabled mental health professionals to engage in outreach about depression (or prescription drug misuse) while the issue was salient to the population of Twitter users. The model presented here offers an objective and empirically based measure to identify these opportunities of greater interest.

In addition to identifying periods during which to focus mental health outreach, this model offers insights into the dynamics of high-interest periods and the differences between expected and unexpected shocks. Twitter's attention to an expected shock, such as the Bell Let's Talk campaigns, fades rapidly, while attention in the wake of an unexpected shock, such as Robin Williams's suicide, is more persistent. Mental health professionals can tailor their outreach efforts accordingly, focusing on longer duration messages following unexpected shocks, for example.

For the broader health care informatics community, this analysis offers an alternative method by which to analyze data from Twitter, other social media sites, or other "big data" sources. With respect to Twitter, most prior work has focused on simple frequency analysis or content analysis, with some of the most advanced studies using machine learning approaches to classify types of tweets. Although tweet classification is an important step in understanding the implications of Twitter in health care, these investigations do not examine the full potential of the platform. This study shows that comprehensive trend analysis of social media is an important research area that can be extended to almost any health condition. Monitoring online health discussions in this manner offers valuable insights into public health conditions that are not typically available through more traditional methods.[26]

Outside of the digital domain, this analytic approach offers an important tool. The ARIMA model presented here is generalizable to any application that models and forecasts time series, such as emergency department visit rates[27] and disease surveillance.[28] Accurate forecasting allows health professionals to be prepared, whether they're ordering supplies and ensuring appropriate staffing levels or watching for bioterrorism outbreaks.[29]

Although the presented model accurately predicts behavioral health mentions on Twitter, there are limitations to this approach. We were able to filter the data to remove obvious keywords that are not related to behavioral health (eg, Great Depression, suicide bombers), but were unable to ensure that all mentions were strictly related to depression or suicide. Additionally, some tweets are clearly meant to be sarcastic or humorous and do not indicate a serious interest in behavioral health. Also, relevant tweets about these behavioral health problems may have been missed if they did not include the specified search terms. For example, a highly retweeted message in the wake of Williams's suicide was "Genie, you're free." Although clearly related to the suicide, these tweets contained none of the terms that would have been detected by our search. Better filtering of the data and techniques to further refine the sample, such as sentiment analysis, could improve the precision of the forecasts.

Another potential issue is whether these findings can be generalized to a wider population. Twitter users are not a representative random sample of the full population. As such, the population observed on Twitter may take interest in suicide and depression at times and in ways that are not synchronized with the broader population. Prior studies have shown that although 69% of US adults have access to the Internet and 23% use social media, social networking and blogging are primarily associated with younger adults.[30] This limitation is somewhat mitigated by the large number and diversity of Twitter users. Nevertheless, many messages disseminated on Twitter do reach a broader population, because Twitter users also spread these messages through their traditional social networks of family, friends, and neighbors. Future work would also seek to include the impact of expected shocks in the model and to evaluate this model when applied to other behavioral health or public health issues. In the presented model, it is not possible to distinguish expected and unexpected shocks without close inspection of the data surrounding the shocks. Incorporating expected events into the model would produce similar spikes in the forecast during the event and thus indicate that a spike in actual mentions was not unexpected. Additionally, this would improve the accuracy and precision of the model.

CONCLUSION

Applying time series analysis and forecasting techniques to new data generated by online media sources offers possibilities for new insights and opportunities to address public health concerns. By monitoring social media communications and appropriately timing dissemination of information about mental health, government agencies and public health organizations may be able to increase not only the number of tweets and retweets that incorporate credible information related to mental health, but also the number of tweets and retweets with content that is consistent with prevention and treatment initiatives.

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CONTRIBUTORS

CMcC, MMA, and RM developed the study concept and design. Initial handling and review of raw data was performed by LK and JL. CMcC analyzed the data. CMcC and MMA drafted the manuscript, and RM, LK, and JL provided critical revisions. All authors approved the final version of the manuscript for submission.

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COMPETING INTERESTS

The authors have no competing interests to declare.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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