Tracking Suicide Risk Factors Through Twitter in the US

Jared Jashinsky[1], Scott H. Burton[2], Carl L. Hanson[1], Josh West[1], Christophe Giraud-Carrier[3], Michael D. Barnes[1], and Trenton Argyle[1]

[1]Department of Health Science, Brigham Young University, Provo, UT, USA, [2]Department of Computer Science and Electrical Engineering, Brigham Young University Idaho, Rexburg, ID, USA, [3]Department of Computer Science, Brigham Young University, Provo, UT, USA

Abstract. *Background:* Suicide is a leading cause of death in the United States. Social media such as Twitter is an emerging surveillance tool that may assist researchers in tracking suicide risk factors in real time. *Aims:* To identify suicide-related risk factors through Twitter conversations by matching on geographic suicide rates from vital statistics data. *Method:* At-risk tweets were filtered from the Twitter stream using keywords and phrases created from suicide risk factors. Tweets were grouped by state and departures from expectation were calculated. The values for suicide tweeters were compared against national data of actual suicide rates from the Centers for Disease Control and Prevention. *Results:* A total of 1,659,274 tweets were analyzed over a 3-month period with 37,717 identified as at-risk for suicide. Midwestern and western states had a higher proportion of suicide-related tweeters than expected, while the reverse was true for southern and eastern states. A strong correlation was observed between state Twitter-derived data and actual state age-adjusted suicide data. *Conclusion:* Twitter may be a viable tool for real-time monitoring of suicide risk factors on a large scale. This study demonstrates that individuals who are at risk for suicide may be detected through social media.

Keywords: Twitter, suicide, social media

Suicide is a leading public health concern in the United States. As the tenth leading cause of death in 2009, the most recently compiled year for national suicide statistics, suicide resulted in 36,909 deaths (Kochanek, Jiaquan, Murphy, Minino, & Hsiang-Ching, 2011). When accounting for the age at death, suicide becomes the fifth leading cause of years of potential life lost in the US (Centers for Disease Control and Prevention [CDC], 2013). Nonfatal forms of self-inflicted violence further burden the nation with mounting emergency department visits; 472,000 visits were seen in 2007 alone (Niska, Bhuiya, & Xu, 2010). Furthermore, surviving family and friends who have to endure the outcomes of fatal or nonfatal self-directed violent behavior also shoulder the burden of suicide.

While suicide poses a major community health risk, research in this area remains difficult. Several barriers in regard to suicide studies include the lack of organized surveillance (specifically concerning suicide attempts), a relatively low base-rate of suicide, issues concerning ethics and safety, and the difficulty of ascertaining information after the death of an individual (who may not have shared pertinent information with those around him or her). Each of these barriers complicates the gathering of suicide data, thereby slowing the pace of understanding suicide through research (Goldsmith, Pellmar, Kleinman, & Bunney, 2002).

To aid in suicide prevention, public health and mental health officials need data that are collected in real time in order to intervene before people actually take their own lives. Crosby, Han, Ortega, Parks, and Gfroerer (2011) stated: “Public health surveillance with timely and consistent exchange of data between data collectors and prevention program implementers allows prevention program practitioners to implement effective prevention and control activities” (p. 1).

Social media is an emerging tool that may assist research in this area, as there exists the possibility of passively surveying and then subsequently influencing large groups of people in real time. Recent studies have shown “that social media feeds can be effective indicators of real-world performance” (Asur & Huberman, 2010, p. 1), box office predictions (Asur & Huberman, 2010), and stock market forecasts (Zhang, Fuehres, & Gloor, 2011). Twitter has also been used to “estimate disease activity in real time, i.e., 1–2 weeks faster than current practice allows” in a study tracking the spread of influenza A H1N1 in 2009 (Signorini, Segre, & Polgreen, 2011, p. 7). Furthermore, Ruder, Hatch, Ampanozi, Thali, and Fischer (2011) have shown that some Facebook users do, in fact, post suicide notes on their profiles, exposing the potential for suicide research in social media.

The amount of publicly available information spread across the realm of social media is extensive. Twitter is of interest because of its greater public availability of data, larger user base, and it being a platform of personal expression. Twitter is a social media platform wherein users (“tweeters”) post status updates, or “tweets,” that are dis-

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tributed to others that "follow" them, and are also made available to the public. Emerging from its beginning in 2006 (Arrington, 2006), "Twitter is now playing a major role in our society, with over 200 million users already and estimates of 500,000 new accounts being added each day" (Griggs, 2011). Together these users generate 400 million tweets per day (Bennett, 2012). This large reservoir of information regarding people's daily lives and behaviors, if handled correctly, can be used to study suicide and possibly intervene.

The recent live Twitter feed of a pending suicide demonstrates that at-risk tweets about suicide can lead to suicidal behavior – in this case fatal (Markman, 2013). While suicidal risk factors may or may not be a direct cause, they are important characteristics associated with suicide and can be observed through conversation. Research regarding these risk factors is well established and provides a framework for further research and intervention (McLean, Maxwell, Platt, Harris & Jepson, 2008; US Public Health Services, 1999).

The purpose of this study was to determine whether at-risk suicide Twitter conversations are related to actual suicide rates. If so, Twitter could serve as an important portal for future research and a potential platform for public health interventions to prevent suicide.

Method

Twitter Data

Twitter offers an application-programming interface (API) that enables programmatic consumption of the data. The Twitter Streaming API provides means of obtaining tweets as they occur, filtered by specific criteria, such as a list of keywords. While some tweets/accounts are marked private, most are openly available to the public and authored without expectation of privacy, making them an accessible data source for researchers. We received an exemption from the university's internal review board to monitor these publicly available tweets.

To identify potential suicide-related tweets, a list of search terms was created based on various risk factors and warning signs linked to suicide. These risk factors and warning signs included depression and other psychological disorders (Lewinsohn, Rohde, & Seely, 1994), prior suicide attempts (Lewinsohn et al., 1994), family violence, family history of drug abuse, firearms in the home, and exposure to the suicidal behavior of others (National Institute of Mental Health, 2012). Other search terms included common antidepressants, as well as phrases that indicated suicide (Hawton, Zahl, & Weaterall, 2003), ideation (American Foundation for Suicide Prevention, 2012a), deliberate self-harm (Zahl & Hawton, 2004), bullying (Klomek, Sourander, & Gould, 2011), feelings of isolation (CDC, 2012), and impulsiveness (American Foundation for Suicide Prevention, 2012b).

The researchers employed a two-part process to identify keywords, or search terms, that represented each risk factor. First, the researchers jointly generated multiple search terms for each risk factor by simply identifying phrases or keywords that appeared to be related to the risk factor. Second, the researchers' pilot tested each search term. Those terms that appeared in tweets, accompanied by the expected suicide risk context, were retained. Search terms that did not appear in the initial search were deleted from the list. These terms are listed in Table 1.

Using the Twitter Streaming API filtering by terms listed in Table 1, tweets were collected and stored in a database categorized as potential at-risk tweets, or tweets that seemed

Table 1. Twitter search terms and statements for suicide risk factors

Suicide risk factor	Search terms and statements
Depressive feelings	Me abused depressed, me hurt depressed, feel hopeless depressed, feel alone depressed, I feel helpless, I feel worthless, I feel sad, I feel empty, I feel anxious
Depression symptoms	Sleeping "a lot" lately, I feel irritable, I feel restless
Drug abuse	Depressed alcohol, sertraline, Zoloft, Prozac, pills depressed
Prior suicide attempts	Suicide once more, me abused suicide, pain suicide, I've tried suicide before
Suicide around individual	Mom suicide tried, sister suicide tried, brother suicide tried, friend suicide, suicide attempted sister
Suicide ideation	Suicide thought about before, thought suicide before, had thoughts suicide, had thoughts killing myself, used thoughts suicide, once thought suicide, past thoughts suicide, multiple thought suicide
Self-harm	Stop cutting myself
Bullying	I'm being bullied, I've been cyber bullied, feel bullied I'm, stop bullying me, keeps bullying me, always getting bullied
Gun ownership	Gun suicide, shooting range went, gun range my
Psychological disorders	I was diagnosed schizophrenia, been diagnosed anorexia, diagnosed bulimia, I diagnosed OCD, I diagnosed bipolar, I diagnosed PTSD, diagnosed borderline personality disorder, diagnosed panic disorder, diagnosed social anxiety disorder
Family violence/discord	Dad fight again, parents fight again
Impulsivity	I impulsive, I'm impulsive

Notes: OCD = obsessive compulsive disorder. *PTSD* = posttraumatic stress disorder.

Table 2. Exclusion filter terms used for search terms and statements

Search terms and statements	Exclusion filter terms
Feel alone depressed	Cockroach; 364
I feel helpless	When; without; girl
I feel sad	Episode, when, Lakers, about, game, you, sorry, for, bad, Bieber
I feel empty	Stomach, phone, hungry, food
Sleeping "a lot" lately	"Haven't been"
I feel irritable	Was
Depressed alcohol	Ronan
sertraline	"Special class"; Viagra; study; clinical; http
Zoloft	Toma; para; necesito; siempre; gracioso; desde; decirle; palabra; vida; sabor; aborto; gusta
Prozac	Toma; para; necesito; siempre; gracioso; desde; decirle; palabra; vida; sabor; aborto; gusta
Pills depressed	http
Suicide once more	Will; by; live
Pain suicide	http
Mom suicide tried	Dog; cat; fish; who
Sister suicide tried	Dog; cat; fish
Brother suicide tried	Dog; cat; fish; "big brother"
Friend suicide	"Hold still"
Suicide attempted sister	Paperback
Thought suicide before	http
Had thoughts suicide	http; never
Had thoughts killing myself	Not
Stop cutting myself	Off; shaving; hair; shave; slack; accidentally
I'm being bullied	Straightophobic
Feel bullied I'm	lol
Stop bullying me	#stop
Always getting bullied	lol
Gun suicide	Zimmerman; news; you; water; nerf
Been diagnosed anorexia	http
I diagnosed OCD	Never; CDO; check
I diagnosed bipolar	n't
Dad fight again	Food
Parents fight again	Sartan; Bradley; Pacquiao; gas
I impulsive	Clementine
I'm impulsive	Clementine

Notes: Any search terms and statements not found in this table did not undergo a filtering process because they were found to produce sufficiently positive results.

indicative of a potential risk factor of the tweeter. To focus on those tweets that were most relevant to the purpose of the study and also those tweets that were geolocated, this set was further refined in two ways. First, only those tweets where the user's state name could be easily identified were used. These states were identified by either the user-provided direct GPS information, or by parsing the user's profile "location" field for either a state name or abbreviation, or text followed by a comma and a state name or abbreviation.

The second way the at-risk dataset was filtered was through a process aimed at removing tweets that were either jokes, nonpertinent, or sarcastic in nature. A manual inspection of the sample tweets collected resulted in identified words or phrases that could be used to filter out irrelevant tweets. For example, the tweets obtained through the Twitter Streaming API included those with the words *stop*, *cutting*, and *myself* (keywords indicative of self-harm), which would seem to be related to a risk factor, but not if they also contained words such as *shaving*, *accidentally*, and *slack*. Thus, by using a list of exclusion terms in combination with each inclusion term phrase, the number of sarcastic tweets was reduced. The list of terms used as exclusion criteria can be found in Table 2. It was not feasible to manually inspect all of the at-risk tweets in this sample to determine the extent to which these exclusion terms refined the study sample. However, a review of the content of a sample of study tweets revealed that this process worked as expected.

Using the user's state information, the Twitter users that posted these at-risk tweets were grouped by state for further analysis. Rather than rely on raw numbers of tweets, which vary greatly over time, we focused on proportions. A baseline was first established using the results of Burton, Tanner, Giraud-Carrier, West, and Barnes (2012). In that study, the default random sample of 1% of all tweets provided by the Twitter API was observed during two separate weeks in October and November 2011. Unique users were identified and classified according to state using the same process as described above. The proportions of tweeters per state with respect to the total number of tweeters were then computed. These baseline values, one for each state s, are referred to here as $\alpha_b(s)$. Similarly, the proportions of at-risk tweeters per state with respect to the total number of at-risk tweeters were also computed. The resulting values, one for each state s, are referred to here as $\alpha_r(s)$. In the absence of other information, the simplest hypothesis, in a Bayesian sense, is to assume that the distributions of these quantities over states are the same, that is, for all states s, $\alpha_r(s) = \alpha_b(s)$. It is therefore possible to design a natural, unit-free measure of departure from this expectation, namely, the ratio $d_\alpha(s) = \alpha_r(s)/\alpha_b(s)$. A value of d_α greater than 1 for a given state suggested that there were proportionally more at-risk tweeters in that state than expected, whereas a value of d_α smaller than 1 suggested the opposite. We realize that the collection of at-risk tweeters lagged behind the collection of all tweets by approximately 6 months. While the raw numbers of accounts and tweets would have certainly changed over that period (see above about the estimated 500,000 accounts being added each day), there is no reason to expect the distribution of tweeters across states to have varied significantly, thus further validating our use of d_α.

Vital Statistics Data

Geographic, state-by-state, suicide rates from 2009 were based on age-adjusted data. These data were taken from the National Vital Statistics System as reported in the Center for Disease Control and Prevention report "Death: Final Statistics for 2009." This report provides the total number of deaths, the death rate, and the age-adjusted death rate for intentional self-harm (suicide) for all 50 states and the District of Columbia. Data are gathered from death certificates as completed by funeral directors, physicians, medical examiners, and coroners (Kochanek et al., 2011). As with the Twitter data, we also transformed the death data into departure from expectation values $d_\beta(s) = \beta_r(s)/\beta_b(s)$, where $\beta_r(s)$ is the ratio of the proportion of deaths by suicide per state with respect to the total number of deaths, and $\beta_b(s)$ is the proportion of the US population per state with respect to the total US population. Again, as with tweeters, variations in population distribution across states are slow so that d_β is valid.

Analysis

Using Microsoft Excel we calculated a Spearman's rank correlation coefficient between the d_αs (observations on Twitter) and the d_βs (observations in the real world), and

Table 3. Example tweets for suicide risk factors

Suicide risk factor	Example Twitter posts
Depressive feelings	I feel so worthless today.
Depression symptoms	I've been sleeping a lot lately. I take like 6 hour naps.
Drug abuse	Dear Prozac, time for a upping in your dosage!
Prior suicide attempts	I tried to commit suicide before ... Several times.
Suicide around individual	I have a friend that comitted [*sic*] suicide :'(.While hate may run deep love runs even deeper.
Suicide ideation	I have had thoughts on suicide and running away from home … and sometimes I still do.
Self-harm	People say "stop cutting! be happy with who you are." its [*sic*] so much easier to say than do... i hate myself so much..
Bullying	I'm sick of being bullied. Everyone care about there [*sic*] problems and don't even bother to check on me. I'm going to kill myself!! ?
Gun ownership	I need to get into da gun range I haven't fired my old gun in over 2 years now
Psychological disorders	… what to say but yes, I've been diagnosed with anorexia since late 2009 and early 2010.
Family violence/discord	BIGGEST fight with dad EVER. Ended in a fist fight. I've packed my bags & I'm leaving. I hold a grudge so dunno how long b4 we talk again.
Impulsivity	I'm so impulsive. I don't think before I do things. That's why I make mistakes.

Table 4. Top ten at-risk states according to d_α

Rank	State	# At-risk suicide Twitter users[a]	At-risk suicide d_α
1.	Alaska	61	1.800
2.	New Mexico	136	1.683
3.	Idaho	72	1.617
4.	South Dakota	57	1.607
5.	Montana	27	1.557
6.	Utah	195	1.551
7.	Texas	3,022	1.491
8.	Kansas	241	1.365
9.	Arizona	509	1.334
10.	Oklahoma	314	1.285

Notes: [a] Number of suicide risk factor Twitter users for a 3-month period.

Table 5. Bottom ten at-risk states according to d_α

Rank	State	# At-risk suicide Twitter users[a]	At-risk suicide d_α
42.	Vermont	26	0.814
43.	New York	1,548	0.771
44.	Hawaii	90	0.749
45.	Connecticut	280	0.729
46.	New Jersey	595	0.728
47.	District of Columbia	215	0.706
48.	Delaware	104	0.673
49.	Pennsylvania	902	0.661
50.	Maryland	606	0.606
51.	Louisiana	435	0.590

Notes: [a] Number of suicide risk factor Twitter users for a 3-month period.

a corresponding p value to verify statistical significance. Geographic maps of the d_αs and actual suicide rates were created using ESRI ArcMap 10 geographic information system software (ESRI, 2011).

Results

Using the Twitter Streaming API filtering by the inclusion terms listed in Table 1, tweets were collected from May 15, 2012, to August 13, 2012, totaling 1,659,274 tweets from 1,208,809 unique users throughout the world. Applying the exclusion terms in Table 2 resulted in a set of 733,011 tweets from 594,776 users. Sample tweets for each risk factor are listed in Table 3. Of these tweets, a specific state in the United States could be identified for 37,717 tweets from 28,088 unique users. This set of location-identified users was used for analysis and referred to as the at-risk tweeter set. Tweets indicative of suicide risk factors were varied in their seriousness and clarity. To verify the relevance of the set, we had two raters independently classify the same random sample of 1,000 tweets. They were in agreement 79.6% of the time. Cohen's κ coefficient was calculated to measure the level of agreement between the two coders (κ = .48), which is classified as moderate agreement (Landis & Koch, 1977). A third rater was then used to arbitrate those tweets that were in disagreement. Of the 1,000 tweets, 789 (78.9%) were found to be relevant, in that the keyword terms were being used to indicate the risk factor, as opposed to being out of context or in a completely sarcastic manner.

Table 4 lists the top ten states with the highest d_α values. States with the highest d_α values tended to be Alaska (1.800) and the midwestern and western states such as New

Figure 1. Risk factor tweet d_α values in the US.

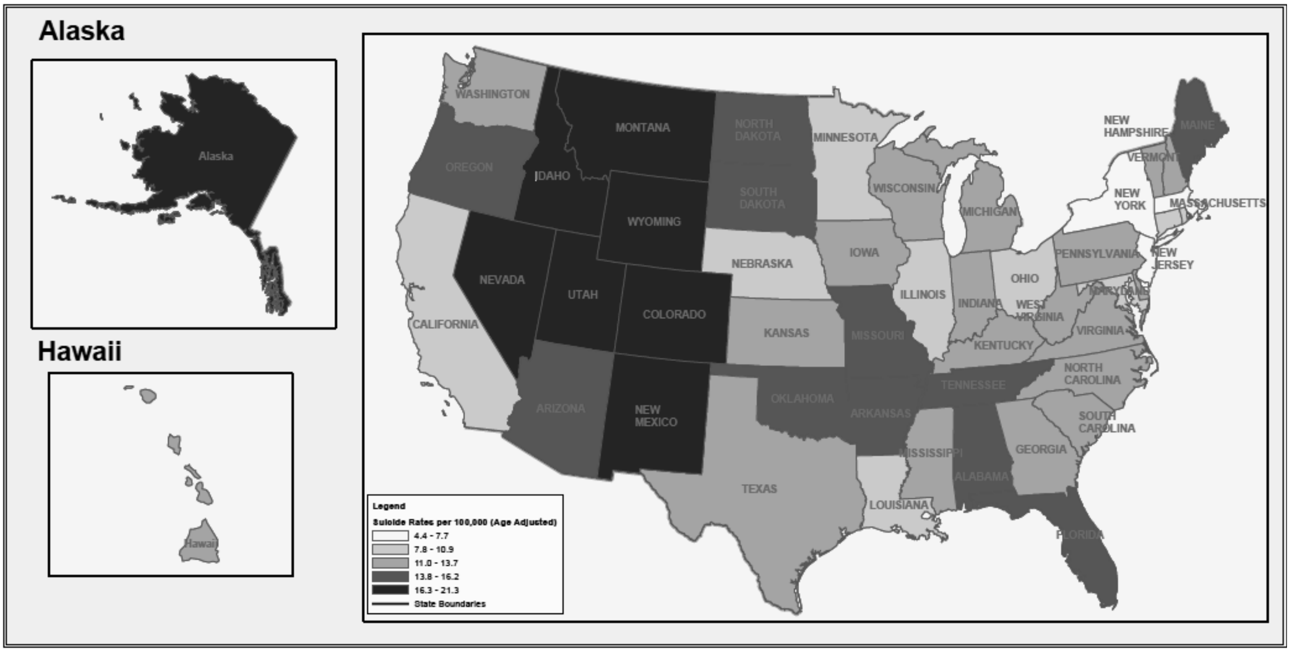

Figure 2. Age-adjusted suicide rates in the US.

Mexico (1.683), Idaho (1.617), South Dakota (1.607), and Montana (1.557). Table 5 lists the bottom ten states with the lowest d_α values. States with the lowest d_α values tended to be the southern and eastern states such as Louisiana (0.590), Maryland (0.606), Pennsylvania (0.661), Delaware (0.673), and the District of Columbia (0.706).

Results revealed a Spearman's rank correlation coefficient of $r = .53$ ($p < .001$) when comparing the Twitter-generated d_α values with the age-adjusted d_β values computed from the National Vital Statistics System, (Spearman's $r = .53$, $p < .001$). Figure 1 illustrates the d_α values for all states while Figure 2 illustrates the US age-adjusted suicide rates.

Discussion

The purpose of this study was to demonstrate that Twitter conversations indicative of suicide risk factors are related to geographic-specific suicide rates from traditional data sources. These findings provide initial validation for Twitter as a potential dataset for future suicide research and a platform for public health and social service interventions. Findings indicate that there is an association between rates of tweets by users determined to be at risk for suicide and actual suicide rates. States in the midwestern and western US region and Alaska were observed to have a higher proportion of suicide-related tweeters than expected (i.e., $d_\alpha > 1$). These states also have the highest actual rates of suicide. To our knowledge this is the first study of its kind attempting to compare tweets containing suicide-related content with actual rates of suicide. Whereas these findings do not extend our understanding of human behavior per se, this sort of validity testing of an emerging data source provides preliminary confirmation of its potential value in monitoring and understanding suicide-related risks. Had the findings from this study been inconsistent with the study hypotheses, concerns would have been raised about the utility of microblogging and social media content as a surveillance tool for social scientists.

Suicide assessment and subsequent intervention are among the most important roles of mental health professionals (McAuiliffe & Perry, 2007). With rising health-care costs and the expense associated with collecting and analyzing data for entire populations, this task of assessing patients at risk for suicide is challenging. Lamberg (2002) calls attention to the gravity of the current situation by recalling that: "It used to be that a patient talking about suicide was always hospitalized. Today the patient has to come in with a gun to his head or to your head to get hospitalized. We have to deal with suicidal patients more in the community" (p. 687). Indeed, projects like the current one that employ innovative methods may play an increasingly important role in strengthening the link between primary and secondary prevention efforts, both of which have been identified as necessary components of a comprehensive prevention effort (King, 2001). Such primary prevention efforts are underway among adolescents and have involved instructing teachers to be aware of verbal manifestations of suicide risk factors. King (2001) identifies phrases such as "my family would be better without me" and "I can't stand living anymore" as characteristic vernacular for patients at risk for suicide. For obvious reasons this is more challenging with adults. Hence, results from the current study are promising as they suggest a potential mechanism for identifying adults at risk for suicide to the extent that they tweet and make publicly available suicide-related statements. While this study is not an attempt for intervention, it may be an important surveillance tool for detecting suicidal patterns and creating a potential mechanism for a directed tweet response. Further, as identified in Table 2, a selection of qualitative statements identifies a representative listing of tweeted messages about suicide, which corroborates the phrases similarly noted above by King (2001). A systematic analysis of these qualitative data may be helpful for future research as to the severity of risk as well as the social responses that emerge from social media.

Twitter users tweet about a variety of subjects, the content of which may not be truly reflective of their feelings about a given topic. Indeed, much of Twitter content has been labeled meaningless discussion (Kelly, 2010). Despite that claim, the fact that users tweet suicide-related content likely suggests that they are at least thinking about the topic and are comfortable sharing this information with such a broad audience. Perhaps users open up in online settings more than in face-to-face settings, where research has shown individuals require a commitment to confidentiality in order to share sensitive information. Such confidentiality is antithetical to the concept of Twitter where tweets are publicly available. West et al. (2012) showed that Twitter users readily share information about their problem drinking. Another recent study of social media showed that women on blogs readily discuss challenges to breastfeeding, which is a topic of potential embarrassment (West et al., 2011). Humphreys, Gill, and Krishnamurthy (2010) found in their content analysis of Twitter messages that the majority of users do tweet about themselves; however, they overwhelmingly take care to protect privacy by not providing personal information such as phone numbers, email, or home addresses. It is unknown to what degree people tweet about their feelings related especially to suicide, and future research might focus on this question. In addition, while this study demonstrates the efficacy of Twitter for surveillance purposes, the feasibility of using this channel of communication to intervene among those at risk will likely depend on whether privacy can be ensured. That said, the current study provides promising evidence of a new way of collecting data to help advance intervention possibilities.

Provided that additional research studies corroborate the findings from the current study, public health priorities in suicide prevention should consider creating profiles of individuals that might lead to earlier detection of suicide ideation. These profiles might include characteristics such as common discussion topics, frequency of tweets, gender, etc. Users that are flagged early as at risk for suicide could be engaged in Twitter conversations with professionally trained practitioners that may be effective at convincing the tweeters to seek medical attention, or the user could simply be referred to Web-based resources. As an example, Twitcident (http://twitcident.com) is a Dutch-based system for filtering emergency-related tweets and may be used as a mode for public health. Twitcident uses Twitter data to engage emergency services personnel by monitoring tweets that discuss local emergencies. These retrospective profiles built from potential suicidal users' tweets may allow a coordinated public health and mental health response to preventing suicide. In this way, the public health response can more squarely address secondary prevention opportunities in addition to its existing primary prevention priorities.

While there have not been many applications of real-time data collection and prevention strategies within the realm of suicide research, there have been new utilizations amongst depression researchers. A new smartphone app called Mobilyze (Burns et al., 2011) has been created that uses data collected by an individual's smart phone (such as location, social contexts, and recent activities) to assess the current level of depression within that person. After installing the app, the user answers a series of surveys that the app uses to determine whether or not the owner is depressed. When the smartphone detects activities or contexts that equate with high attitudes of depression, it sends messages to select family or friends, alerting them of the individual's depression status.

A similar app could be created that measures a user's online activities, gathered in real time, to assess the level of suicide risk of the app user and alert family, friends, or a professional counselor of the elevated risk of the individual. If a patient gives consent to a counselor, that counselor can then monitor their patient's social media mood and collect important data (e.g., disrupted relationships, loss of a job, online suicide threats) within minutes and hours, rather than having to wait until their next appointment to gather such information. With these real-time data, counselors and family will be able to reach out to these at-risk individuals in the moment of need. Policy-makers and those who fund research projects should consider the next steps for studying and supporting more social media-based efforts for public health and social service interventions.

Limitations

Findings from this study should be interpreted in the context of several key limitations. First, the search filters allowed for a proportion of unrelated tweets to be coded as at-risk. Moreover, the search terms may have been insufficient to capture all instances of at-risk tweets. However, previous research was consulted to compile a list of keywords and search terms in an effort to reduce the number of false positives and false negatives. There is undoubtedly a balance that must be achieved: a sufficient number of search terms to identify risk, but not too many so as not to falsely determine risk. This balance is likely needed in face-to-face settings as well. Second, identifying tweet location in some states was challenging, which led to a smaller number of tweets. Smaller samples introduce inherent challenges related to generalizability. Notwithstanding this limitation, the trends were largely consistent with those from states with larger samples within the same general geographical region. Difficulties in ascertaining location information were not limited to this study and have been the focus of previous research (Burton et al., 2012). Efforts to detect levels of suicidal intent could not be assessed. As a result, the study findings cannot differentiate between persons who are contemplating versus those who are preparing to take immediate action. However, since the rates between actual suicides and Twitter discussion were so highly correlated, it can be presumed that the identified Twitter users are at least at risk for suicide in some regards. Third, actual suicide rates in the current study reflect 2009 values, while tweets came from 2012. The extent to which this impacted the findings of this study is unclear, especially considering that there is very little variance from year to year in suicide rates. Nevertheless, more definitive conclusions about the association between Twitter content and actual rates should be reserved for comparisons in future studies that feature data comparisons from common years. Lastly, findings from this study should be interpreted in the context of what is known about important social and cultural demographic characteristics of Twitter users. The Twitter community consists largely of young adults. In fact, 26% of Internet users aged 18–29 use Twitter compared with 14% of those aged 30–49 and 9% of those aged 50–64 (Smith & Brenner, 2012). In addition, more black Internet users use Twitter (28%) compared to Hispanics (14%) and whites (12%). Owing to the nature of the social media, Twitter provides users with a platform to engage with other users online. Engaging and associating with others is a characteristic not expected of one at risk for suicide who may be experiencing depression and its associated symptoms of social isolation and withdrawal. The degree to which social isolation and withdrawal occur within social media communities such as Twitter is less understood and warrants further research.

Conclusion

An association exists between the proportion of Twitter users determined to be at risk for suicide and actual suicide rates. States in the midwestern and western US region and Alaska were observed to have the highest d_α values (i.e., proportions of at-risk tweeters much larger than expected). These states also have the highest actual rates of suicide. Twitter may be an effective and valuable tool for gathering data in real time and on a large scale, which has not been conducted for suicide before. Suicide data gathered from Twitter are comparable to data gathered through other means and are less costly. Using social media, researchers and practitioners may be one more step toward affordably and rapidly detecting individuals with suicidal intentions and may subsequently provide a platform to improve suicide prevention strategies through timely intervention.

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About the authors

Jared Jashinsky worked as a research associate in the Department of Health Science at Brigham Young University in Provo, Utah. His research interests include mental health, social media, and gun violence. Jared is a Certified Health Education Specialist and began his MPH studies at San Diego State University in fall 2013.

Dr. Scott H. Burton recently completed his PhD in Computer Science at Brigham Young University, where his research focused on computational techniques for public health surveillance. Dr. Burton has accepted a faculty position in computer science at Brigham Young University, Idaho.

Dr. Carl Hanson is an associate professor of public health in the Department of Health Science at Brigham Young University in Provo, Utah. He is Director of the Master of Public Health Program and has research interest in computational health science.

Dr. Josh West is an assistant professor of public health in the Department of Health Science at Brigham Young University in Provo, Utah. His research interests include the use of technology to promote health, measure behavior, and achieve lasting behavior change.

Dr. Christophe Giraud-Carrier is an associate professor and director of the Data Mining Laboratory in the Department of Computer Science at Brigham Young University in Provo, Utah. His research interests include metalearning, social network analysis, computational health science, and applications of data mining.

Dr. Michael Barnes is a professor and chair of the Department of Health Science at Brigham Young University in Provo, Utah. His research interests include the use of technology to promote health and advance health communication methodologies.

Trent Argyle is a research associate in the Department of Health Science at Brigham Young University in Provo, Utah. His research interests include public health and medicine.

Carl L. Hanson

213 Richards Building
Department of Health Science
Brigham Young University
Provo, UT, 84602
USA
Tel. +1 801 422 9103
Fax +1 801 422 0273
E-mail carl_hanson@byu.edu