Leveraging Twitter to better identify suicide risk

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ABSTRACT

While many studies have explored the use of social media and behavioral changes of individuals, few examined the utility of using social media for suicide detection and prevention. The study by Jashinsky *et al*, in particular, identified specific language patterns associated with a set of twelve suicide risk factors. We utilized their findings to assess the significance of the language used on Twitter for suicide detection. We quantified the use of Twitter to express suicide related language and its potential to detect users at high risk of suicide. First, we evaluated the presence of language related to twelve different suicide risk factors on Twitter using a list of terms/statements published by Jashinsky *et al* and searched Twitter for tweets indicative of 12 suicide risk factors. Using network analysis, for each suicide risk factor we established a subnetwork of users and their tweets related to that suicide risk factor. We computed the density of each subnetwork to estimate the presence of the language of that suicide risk factor. Second, we investigated relationships between suicide risk factors, using associated language patterns, In two groups "high risk" and "at risk". We divided Twitter users into "high risk" and "at risk" based on two of the risk factors ("self-harm" and "prior suicide attempts") and examined language patterns by computing co-occurrences of terms in tweets. We identified relationships between suicide risk factors in both groups using co-occurrences. We found that users within a subnetwork used similar language to express their feeling/thoughts. Stratifying users into "high-risk" and "at-risk", we found stronger relationships between pairs of risk factors such as ("depressive feelings", "drug abuse"), ("suicide around individual", "self-harm"), and ("suicide ideation", "drug abuse") in the "high-risk" group relative to the "at-risk" group. In addition, the presence of social-related suicide risk factors including "gun ownership", "suicide around individual", "family violence", and "prior suicide attempts" was more pronounced in the "high-risk" group.

Keywords

Twitter, social media, suicide risk factor, subnetwork, categorization, medical informatics, mental health.

1. INTRODUCTION

Suicide ranks as the second leading cause of death among individuals 25–34 years old and the third leading cause of death among 15–25 years old [26]. Preventing suicide is inherently complicated by the heterogeneity of individuals who commit suicide and the lack of strong, reliable predictors of suicide. Less than 50% of suicide victims contact a mental health or primary care provider within one month of their suicide attempt [18]. As such, there is more interest in leveraging social media platforms to detect suicidality and intervene in high risk cases outside the healthcare delivery system [23]. To better detect suicide risk, previous research manually analyzed the contents of suicide notes/letters as they include thoughts and feelings of completers that may be indicative of their emotional and mental state directly before they die [3][7][11][15].

Recently, researchers investigated the utility of applying automated and computational methods to suicide notes to find patterns of behaviors or alarming language associated with suicide. Ultimately, the objective is to describe patterns that would guide early interventions that would prevent active suicide. For example, in [20][21], natural language processing approaches were applied to distinguish between classes of suicide notes (of completers versus not). In a different study [17], a self-administered risk assessment tool has shown that adolescents with previous suicide attempts have many psychological risk factors (i.e. history of past attempt, current suicidal ideation and depression, recent attempt by a friend, low self-esteem, and having been born to a teenage mother) in common. Although these studies are important, the reported results were based on small scale data; therefore, conclusions need to be further investigated with larger and other samples, perhaps using big data, before generalization. Social media, a big data resource, has been recently utilized for promoting positive behaviors such as help seeking for depression management [9], surveying social needs [12] and preferences on receiving mental health services using technology [14]. Social media has also been used to identify users with high suicide probabilities [16].

In this paper, we leverage Twitter to better identify high risk suicide behavior. Twitter is a social media forum by which users (tweeters) socialize and tweet through the network. Users on Twitter interact through tweeting new thoughts, retweeting and replying to other tweets. Previous research has utilized Twitter as a source of information for suicide prevention and learning more about suicidal behaviors and ideations [2][10][13][28]. Jashinsky *et al* [13] tracked suicide risk factors through Twitter knowing that a recent live Twitter feed of a pending suicide demonstrate that at risk tweets about suicide can foretell suicidal behavior [19]. They identified a list of terms and language associated with suicide risk factors. Tweets that include this language were considered risky. We extended their study to quantify the presence of high risk language of suicide risk factors. We divided Twitter users into two groups: "high risk" and "at risk" based on two of the risk factors ("self-harm" and "prior suicide attempts") and examined language patterns by computing co-occurrences of terms in tweets which helped identify relationships between suicide risk factors in both groups. Our overall aim is to leverage Twitter to better detect high risk suicide behavior. The contributions of this study are two-fold: (1) evaluating the presence and density of language related to twelve suicide risk factors on Twitter, (2) analyzing the relationships between suicide risk factors.

2. METHODOLOGY

2.1 Data

As of 2015, Twitter has more than 305 million active monthly users and more than 500 million tweets per day [27]. Using Twitter developer APIs [1], we retrieved (571,995) risky tweets that were initiated by 396,574 Twitter users between (1/1/2014) and (4/15/2015) and included an additional 500 of the most recent publicly available tweets for each user using The Twitter REST API.) We obtained the risky tweets via search queries containing terms/key words associated with the 12 suicide risk factors identified in [13] such as “depressive feelings”, “drug abuse”, “self-harm”, “suicide ideation”, “bullying” and “prior suicide attempts”. Table 1 shows the list of suicide risk factors and the associated statements/terms.

Table1: search terms and statements as reported by Jashinsky *et al*

Search Terms and statements	**Suicide risk factor**
"Feel alone depressed", "I feel helpless", "I feel sad", "I feel empty"	Depressive feelings
"Sleeping a lot lately", "I feel irritable"	Depression symptoms
"Depressed alcohol", "sertraline", "Zoloft", "Prozac", "Pills depressed"	Drug abuse
"Suicide once more", "Pain suicide"	Prior suicide attempts
"Mom suicide tried", "Sister suicide tried", "Brother suicide tried", "Friend suicide", "Suicide attempted sister"	Suicide around individual
"Thought suicide before", "Had thoughts suicide", "Had thoughts killing myself", “I want to commit suicide”	Suicide ideation
"Stop cutting myself"	Self-harm
"I’m being bullied", "Feel bullied I’m", "Stop bullying me", "Always getting bullied"	Bullying
"Gun suicide"	Gun ownership
"Been diagnosed anorexia", "I diagnosed OCD", "I diagnosed bipolar"	Psychological disorders
"Dad fight again", "Parents fight again"	Family violence/discord
"I impulsive", "I’m impulsive"	Impulsivity

We searched Twitter for the language indicative of suicide risk factors. The retrieved tweets are considered “risky” because of their contents. The terms and statements used for the search are listed in Table 1 along with the associated suicide risk factors. We used network analysis to analyze patterns between and among risky tweets. Using the risky tweets and the users’ identification codes (which we also retrieved) we built the author-term matrix. The matrix associates the authors with their risky tweets wherein rows represent authors and columns denote terms or statements of suicide risk factors used to search for risky tweets.

2.2 Presence of Language Pattern of Suicide Risk Factors

We examined the presence of the language associated with suicide risk factors using network analysis. For each suicide risk factor, we generated a subnetwork to capture the presence of statements/terms associated with the risk factor. We defined the nodes of the subnetwork as the authors and the edges between nodes as the number of terms/statements (of a certain suicide factor) authors tweeted about. It is important to emphasize that an edge between two nodes in the subnetwork does not mean that the corresponding authors exchanged tweets, rather, authors use same language to write their tweets. Each subnetwork is represented by a matrix called author-author matrix, which is established using information from the author-term matrix (described in the previous section). Each element in the author-author matrix encodes the number of common terms and statements tweeted by authors. The cell, c(i,j), in the matrix is the frequency of tweeting same terms/statements by author i and author j. For example, users in the “depressive symptoms” suicide factor subnetwork can express their symptoms by tweeting the statements: "sleeping a lot lately" or "I feel irritable" as shown in Table 1. If authors i and j had tweets that include these statements, then they are connected in the subnetwork and c(i,j)=2. We used network density to measure the presence of the language associated with the risks. We define density of a subnetwork as the total number of tweets containing terms/statements of a risk factor divided by the number of pairs of users tweeting about that risk factor.

Density of a risk factor subnetwork = $\sum_{i=1,m} \sum_{j=1,m} C_{i,j} /(m(m-1))$

where m is the total number of authors tweeting in the suicide risk factor subnetwork.

Suicide subnetworks were generated to measure the presence of the language patterns of suicide risk factors used by Twitter users. If users use same terms to tweet a particular risk factor, then the connectivity is higher in the subnetwork and stronger presence of a risk factor will be captured using the density measure.

2.3 Grouping of Twitter users and relationships between suicide risk factors

We stratified twitter users to evaluate relationships amongst suicide risk factors. Users who had tweets pertaining to “prior suicide attempts” and/or “self-harm” were labeled as “high-risk” of future suicide. Users who did not have either of these two specific suicide risk-factors in their tweets, yet had other risk factors, were deemed “at-risk”. Of the total 396,570 users, we previously collected data on, 2,156 users were at “high-risk” of future suicide. We grouped together a maximum of 500 users from each of the remaining 10 risk factors. Some of these users had since either deleted their accounts or made their accounts private, making their tweets un-accessible to our search methods. In total 1,470 “high-risk” users and 2,761 “at-risk” users had their past tweets recovered from the previous year. Each of these tweets were then parsed for every suicide related search term and statement [13]. All users who had zero tweets containing any of the risk factor phrases for any risk-factor were dropped. 505 “high-risk” users and 1857 “at-risk” users were retained.

Using “self-harm” and “prior suicide attempts to form groups: We computed ratios of tweeting about “self-harm” and “prior suicide attempts” across the two groups to show the validity of our approach. First, we computed the following two quantities for each group:

(1) Average of tweets per user within risk factor: the total number of tweets per user for a given risk factor normalized by the total number of users tweeting about that risk factor (e.g. the total number of tweets about “depressive feelings” tweeted by the

"high-risk" group is divided by the number of users who tweeted about "depressive feelings" in the "high-risk" group.)

(2) Average of tweets per user for all risk factors: the total number of tweets per user for a given risk factor normalized by the total number of users in a group (e.g. the total number of tweets about "depressive feelings" in the "high-risk" group is divided by the total number of users in the "high-risk" group).

We then computed ratios of tweets of "high-risk" to "at-risk" using the above quantities.

Relationship between suicide risk factors: We defined a relationship between a pair of risk factors as the number of users within each group tweeting about both factors. We first computed frequencies of the collected tweets for users in each group and stored them in two different matrices; one for "high-risk" and the other for "at-risk" group. In each matrix, we had the rows represent the users and the columns are the 12 risk factors. The entry in the cell (i,j) in the frequency matrix is the number of times a user i tweeted about the risk factor j (summing up the counts of all tweeted terms/statements pertaining to that risk factor). Second, from both frequency matrices, we generated co-occurrence matrices that contain counts of users tweeting about pairs of risk factors.

To generate the co-occurrence matrices, we multiplied the transpose of this binary matrix with itself. Since each element in the matrix is the number of users who tweeted both the row and column risk factors, the diagonal of the matrix is the number of users who tweeted each individual risk factor. We used the values on the diagonal to normalize the matrix. We divided each respective column vector by each element of the diagonal vector. We used Gephi 0.9.0 to visualize "at-risk" and "high-risk" networks using the Fruchterman-Reingold layout. The nodes in the network colored by type of risk factors: green for social and (red) for psychological risk factors. The network is fully connected as we study the relationships between pairs of risk factors, however, the nodes were scaled by weighted degree of connectivity.

3. RESULTS

3.1 Presence of language patterns of suicide risk factors

The density of the 12 suicide risk factors' subnetworks is reported in Table 2. In general, the table shows that a substantial number of users discuss different suicide matters on Twitter. The densities of 7 out of 12 risk factors are above 70%, meaning that 70% of the tweets of these risk factors contain similar language patterns. That is users express their feelings using similar language patterns which makes it easier to find them.

As shown in Table 2, the language used in the "depression symptoms" subnetwork is highly similar because of the high density, above .90. Similar densities are observed in the "impulsivity", and "suicide around individual" subnetworks. Despite the large number of users and tweets of "depressive feelings", its density is low, .53, compared to other risk factors with similar volume such as "drug abuse", with a density of .76. The low presence of some suicide risk factors could be attributed to the diversity of the language used to express these risk factors on Twitter (i.e. the number of search terms, column 2 in Table 2. Recall that the edge between authors in the subnetwork is established if they have at least one search term/statement in common in their tweets. Therefore, when multiple search terms are associated with a risk factor, the likelihood of two users using the same term is smaller. If a risk factor is detected using multiple search terms (risky tweets expressed using different statements) then the subnetwork could potentially have less density. On the other hand, having one term to express a suicide risk factor as in the case of "gun-ownership" and "self-harm" results in a fully connected network with density of 1.

Table 2: Density of subnetworks of suicide risk factors

Suicide Risk Factors	# Search Terms	# Users	# Risky Tweets	Density
Depressive feelings	4	161413	188060	0.53
Depression symptoms	2	7139	7642	0.91
Drug abuse	5	157117	285954	0.76
Prior suicide attempts	2	144	148	0.81
Suicide around individual	5	3164	4327	0.99
Suicide ideation	3	3443	3955	0.00
Self-harm	1	2012	3122	0.99
Bullying	4	63457	75383	0.60
Gun ownership	1	1097	1574	1.00
Psychological disorders	3	6	10	0.33
Family violence	2	122	127	0.62
Impulsivity	2	4435	4677	0.95

3.2 Grouping of Twitter users and relationships between risk factors

Validity of using "self-harm" and "prior suicide attempts" to form groups

Table 3 shows the average tweets per user within a risk factor and across all risk factors for the "high-risk" users as well as the "at-risk" users. The ratios of tweeting both quantities in "high-risk" to "at-risk" are also shown in the table. Notice that if a high-risk individual tweets about "self-harm", he will tweet on average 2.464 tweets about "self-harm", while an "at-risk" individual who tweets about "self-harm" will only tweet on average 1.175 tweets. Similarly, and with respect to all "high-risk" users, a "high-risk" individual will still tweet on average more about "self-harm" compared to an individual from the "at-risk" group (.683 compared to .044, respectively). For "Prior suicide attempts", a "high-risk" user will tweet on average 1.174 tweets compared to 1.417 tweets of an "at-risk" user. With respect to all "high-risk" users, however, a high-risk user will tweet on average more than an at-risk user, .053 compared to .027, respectively.

Table 3: Tweeting ratios of “high-risk” versus “at-risk” groups in terms of “self-harm” and “prior suicide attempts”

Description	Prior-suicide attempts	Self-harm
High-risk users		
Total tweets	27	345
Total users	23	140
Average of tweets per user within risk factor	1.174	2.464
Average of tweets per user for all risk factors	0.053	0.683
At-risk users		
Total tweets	51	81
Total users	36	69
Average of tweets per user within risk factor	1.417	1.175
Average of tweets per user for all risk factors	0.027	0.044
Ratio of high-risk to at-risk		
Ratio of tweets per user within risk factor	82.86	209.92
Ratio of tweets per user for all risk factors	194.68	1566.23

Relationships between suicide risk factors

Figure 1 and Figure 2 show relationships and co-occurrences of language patterns of pairs of risk factors for “high-risk” and “at-risk” groups, respectively. The co-occurrence of a pair of risk factor is a result of user(s) tweeting both risk factors. In Figure 1 column 1 depicts co-occurrences of “depressive feelings” with all other risk factors (each row of that column displays the percentage of users who tweeted about “depressive feelings” and the respective risk factor.) For example, 44% of all users who tweeted at least one tweet of “depressive feelings” also tweeted at least a tweet of “depressive symptoms” as shown in row 2 for the “high-risk” group. This relationship is stronger than its respective value in the “at-risk” group, 39% (see Figure 2). Note that the relationship between “depressive feelings” and all other risk factors is higher for “high-risk” compared to “at-risk” group except for “self-harm”.

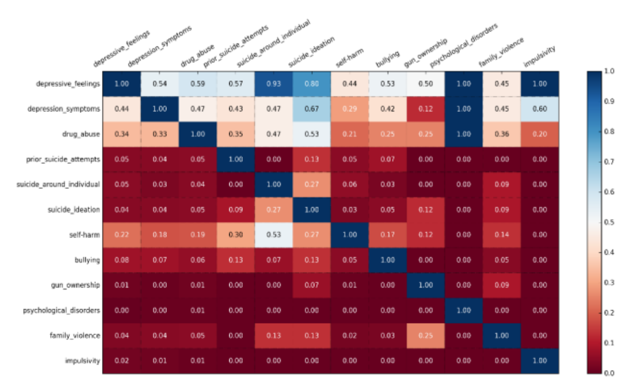

Figure 1: Co-occurrences of suicide risk factors in “high-risk” group

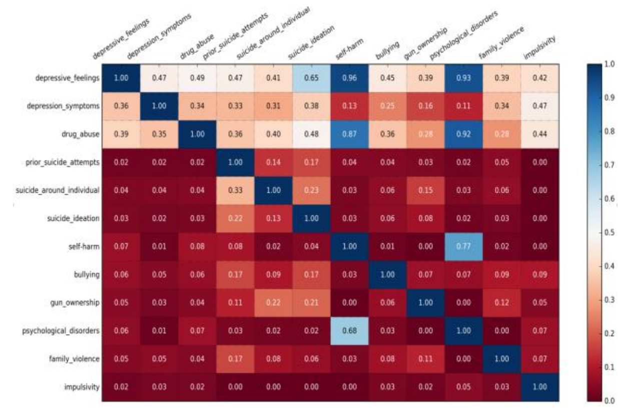

Figure 2: Co-occurrences of suicide risk factors in “at-risk” group

Relationships with lower values were observed for “self-harm” in the “high-risk” group. However, for “prior suicide attempts” 30% of users did tweet about “self-harm” in the “high-risk” group compared to 8% in the “at-risk” group. Strong relationships between “depressive symptoms” and all risk factors are observed for the “high-risk” group. In particular, “depressive symptoms” and “depressive feelings” are highly associated with “drug abuse” which supports previous findings in the literature [8][29][30]. Tweets about “prior suicide attempts”, and “self-harm” are more strongly present with “drug abuse” tweets in the “high-risk” group. In general, we observed strong language patterns and relationships of several suicide risk factors for the “high-risk”

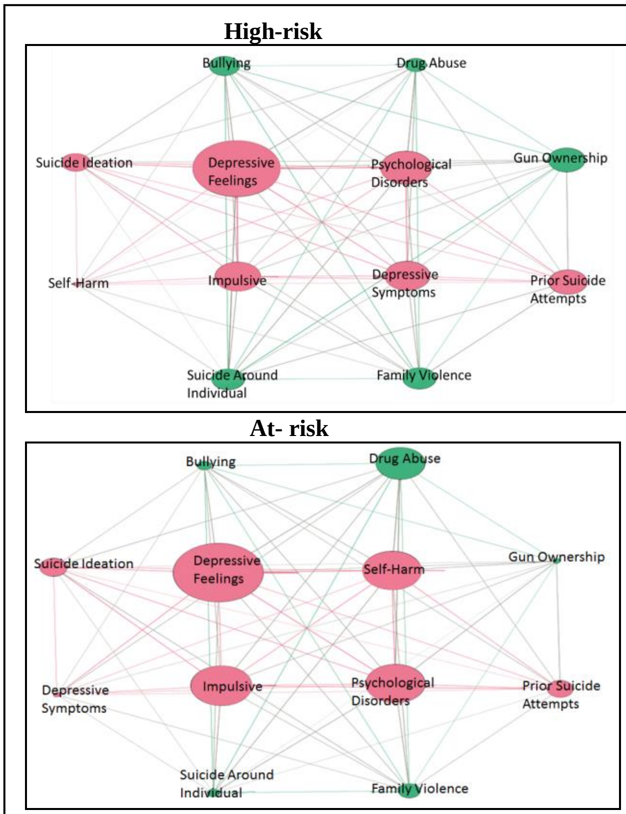

Figure 3: Relationships between risk factors in both groups

group compared to the “at-risk” group. Figure 4 is a visualization of the relationships between risk factors in the “high-risk” and “at-risk” groups. Risk factors with social themes are labeled green while psychological themes are red. The visualizations reveal new and interesting patterns in the networks, particularly for the “high-risk” group. While psychological risk factors were present strongly with slightly different weights in both networks, the presence of social risk factors including “gun ownership”, “suicide around individual”, “family violence”, and “prior suicide attempts” is more pronounced in the “high-risk” group. The role of social risk factors in the “high-risk” group underscores the additional stressors “high-risk” users experience relative to their counterparts. “Bullying” and “depressive symptoms”, two psychological risk factors, were also more pronounced in the “high-risk” group which is consistent with the strong associations we observed in Figure 3. In the “at-risk” group network, psychological factors, well-described in the literature, strongly correlated with “drug abuse”.

4. DISCUSSION

We quantified the use of Twitter to express suicide related language, and its potential to predict users at high risk of suicide. We found that a substantial number of users tweet about different suicide matters and the presence of language patterns of the different suicide risk factors varies on Twitter. Using different methods including network analysis, we investigated relationships of risk factors in groups of Twitter users. We found that relationships between tweets of social-related suicide risk factors had strong presence in the “high-risk” group as shown in the literature [4]-[6], [8], [22]-[25], [29]-[31].

We evaluated the presence of language related to twelve different suicide risk factors and found that many users openly discuss a wide variety of suicide related language on Twitter. The densities of language patterns of 7 out of 12 risk factors subnetworks are above 70%. Our study is the first to measure density of risky tweets per type (e.g. associated suicide risk factor). Previous studies analyzing suicide-related language on Twitter such as [13] did not provide deep analytical analysis of the tweets. Density computations helped estimate the presence of the different suicide factors. High density value of a risk factor suggest that it is easier to find its associated tweets as users appeared to use similar language to communicate that risk factor.

We selected “self-harm” and “prior suicide attempts” to dichotomize Twitter users into two groups “high-risk” versus “at-risk” given that these are two major factors associated with suicide [29,30]. Using Twitter data, we justified this selection by the analysis included in Table 3. We showed that “high-risk” individuals who tweet about self-harm do so by over twice as much (210) more frequently than an “at-risk” user. If we look at over all users (rather than those who only tweeted about that “self-harm” risk factor), “high-risk” users are more likely to tweet about “self-harm” 15 times more than an “at-risk” user. “Prior suicide attempts” does not have as much deviation from “high-risk” to “at-risk”. “High-risk” users who tweet about “prior-suicide-attempts” do such at only about 82.86 the rate of their “at-risk” counterparts. “High-risk” users in general, however, will tweet about twice as much more than the average “at-risk” user.

Different from previous research which simply flagged high risk language on Twitter [2][10][13][28], using network analysis, we identified patterns of high risk terms and language (co-occurrences of terms” to better detect high risk users. Specifically, we captured the differences in associations between suicide risk factors across “high-risk” and “at-risk” groups and the inner-group relationships between the risk factors. Our analysis revealed stronger relationships in the “high-risk” group as found in the literature [4]-[6], [8], [22]-[25], [29]-[31]. Although our expectation was to observe strong associations between “self-harm” and other risk factors, especially that self-harm is one criterion to form the “high-risk” group, low relationships were observed for “self-harm” in the “high-risk” group using the co-occurrence matrix approach. Perhaps, “self-harm” tweets are taken seriously by the “high-risk” group and are not frequently and purposelessly posted. The strong relationship between “psychological disorders” such as bipolar and obsessive compulsive disorder and “self-harm” in the “at-risk” group is another example. However, it is not uncommon that bipolar patients could harm themselves regardless of being at “high-risk” of suicide which would help explain the strong relationship in the “at-risk” group. Using the network visualization (see Figure 4), we captured interesting relationships, particularly in the “high-risk” group. Classifying risk factors into social and psychological, we noticed that the presence of social risk factors including “gun ownership”, “suicide around individual”, “family violence”, and “prior suicide attempts” is more pronounced in the “high-risk” group. Other risk factors such as “depressive feelings”, “psychological disorders” and “impulsivity” were present with slightly different weights in both networks. In general, we observed strong relationships between patterns of communications of several suicide risk factors for the “high-risk” group compared to the “at-risk” group.

Limitations: One limitation of this study is related to the list of terms/statements we used to search for risky tweets. As we mentioned above, Jashinsky *et al* [13] generated this list and associated 12 suicide risk factors with items in the list. We acknowledge that this list is not exhaustive and it can be improved. For instance, statements like “I’ve been too rash”, “I act to quickly”, “I have no filter” are possible ways to expressive impulsivity other than “I am impulsive”. Although, we are satisfied with our findings related to the presence of most suicide risk factors on Twitter, this issue could have contributed to the density values computations. Nevertheless, this is an exploratory study by which we convinced ourselves and hopefully the readers of the value of Twitter in detecting high risk users. In future work, we plan to apply intelligent natural language processing approaches based on deep learning to better detect risky tweets on Twitter.

5. CONCLUSION

Twitter is an outlet for individuals to potentially post stressful feelings, emotions and thoughts. In this study, we analyzed the potential use of Twitter in suicide related research. Using suicide risk factors and associated language used on Twitter, as identified in a previous study, we have shown that language patterns of the majority of suicide risk factors have strong presence on Twitter such as “depressive symptoms”, “drug abuse” and “prior suicide attempts”. We concluded that certain linguistics patterns pertaining to suicide risk factors are more frequently used by those who are at higher risk of suicide. Tweets may be highly reflective of emotional and behavioral attributes of users and could be a valuable resource for predicting suicide.

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