Presence and Patterns of Suicide-related language on Twitter

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**ABSTRACT**

**Background:** 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. The study by Jashinsky et al, in particular, identified specific language terms associated with a set of twelve suicide risk factors. We utilized their findings to identify language patterns, on Twitter, related to the twelve potential suicide risk factors as these patterns maybe useful for characterizing users with higher risk behaviors of suicide.

**Objective**: We aim to identify patterns of suicide related language and its potential to detect users at high risk of suicide. Specifically, we evaluated the presence of language related to twelve different potential suicide risk factors on Twitter, investigated co-occurrences of words related to suicide risk factors to identify patterns and computed relationships between suicide risk factors based on the identified language patterns.

**Methods:** Using a list of terms/statements published by Jashinsky et al, we searched Twitter for tweets indicative of twelve suicide risk factors. We collected a sample of tweets using this language and computed the presence of each risk factor in our sample. 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 of each group. We identified patterns of words associated with the twelve suicide risk factors using network analysis. We computed co-occurrences of the words in the tweets. We computed relationships between suicide risk factors by aggregating the co-occurrences of the respective words.

**Results:** A total of 571,995 tweets were retrieved using suicide-related search terms. We found that “depressive\_feelings”, “drug\_abuse” and “bullying” were the most present risk factors in the sample of tweets. Stratifying users into “high-risk” and “at-risk”, we found that users in the “high-risk” group exhibit more focused patterns of language use as compared to their counterparts in the “at-risk” group. In general, “high-risk” users mostly tweet about “bullying”, “depressive\_symptoms”, and “depressive\_feelings. In particular, “self-harm” users mostly tweeted (“depressive feelings” and/or “depressive\_symptoms”), “Prior\_suicide\_attempts” users also tweeted (“self\_harm”, “depressive\_feelings”, “depressive\_symptoms”.) Other obvious tweeting patterns of the “high-risk” group include: (“suicide\_ideation”, “depressive\_feelings”), (“gun\_ownership”, “depressive\_feelings”).

**Conclusion**: Twitter could be potentially useful to characterize those who might be at higher risk of suicide. Mapping word co-occurrences using network analysis provides a distinct pattern of “high-risk” users that may be further developed to help detect people at higher risk for suicide.

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**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 [1]. 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 [2]. 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 [3]. To better detect suicide risk, previous research manually analyzed the contents of suicide notes/letters as they express the thoughts and feelings of completers that may be reflective of their emotional and mental state directly before they die [4-7].

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 to guide early interventions that would prevent active suicide. For example, in [8-9], natural language processing approaches were applied to distinguish between classes of suicide notes (of completers versus not). In a different study [10], a self-administered risk assessment tool has shown that adolescents with previous suicide attempts have many risk factors in common (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). Social media has been recently utilized for promoting positive behaviors such as help seeking for depression management [11], surveying social needs [12] and preferences on receiving mental health services using technology [13]. Social media has also been used to identify users with high suicide probabilities [14].

**Aim of Study**

In this study, we leverage Twitter to identify patterns of language associated with risk factors for suicide. 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. We harness tweets to extract written thoughts, feelings and behaviors indicative of suicide risk factors. Previous research has utilized Twitter as a source of information for suicide prevention and learning more about suicidal behaviors and ideations [15-18]. Jashinsky et al [15] tracked suicide risk factors through Twitter, knowing of a recent live Twitter feed of a pending suicide, to 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. We extended their study to identify patterns of language used on Twitter by examining co-occurrences of language terms and risk factors. We divided Twitter users into two groups: “high risk” and “at risk”. High risk groups are defined by tweets that allude to suicide related behavior (“self-harm” and “prior suicide attempts”) while at risk tweets are related to general depression or suicide risk factors. We examined language patterns by computing co-occurrences of terms in tweets which helped identify relationships between suicide risk factors in both groups. These patterns could be used as markers that could potentially inform interventions such as sending inquiry or alert tweets to those individuals. The contributions of this study are two-fold: (1) show the presence of high risk language related to twelve suicide risk factors on Twitter, (2) identify markers of language patterns associated with users in the “high-risk” group.

**Method**

**Data**

As of 2015, Twitter has more than 305 million active monthly users and more than 500 million tweets per day [20]. Using Twitter developer APIs [21], we retrieved (571,995) 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 limited the sample to tweets that contained terms/key words associated with the 12 suicide risk factors identified in [15] as shown in **Table 1.**

**Table 1: search terms and statements as reported by Jashinsky et al**

|  |  |
| --- | --- |
| **Search Terms and statements** | **Suicide risk factor** |
| “Me abused depressed”, “Me hurt depressed”, "Feel alone depressed", "I feel helpless", "I feel sad", "I feel empty" | Depressive feelings |
| "Sleeping a lot lately", "I feel irritable", ”I feel restless” | 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 |
| 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 “I want to commit suicide” | Suicide ideation |
| "Stop cutting myself" | Self-harm |
| I’m being bullied, I’ve been cyber bullied, feel bullied I’m, stop bullying me, keeps bullying me, always getting bullied | Bullying |
| "Gun suicide" | Gun ownership |
| 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 | Psychological disorders |
| "Dad fight again", "Parents fight again" | Family violence/discord |
| "I impulsive", "I’m impulsive" | Impulsivity |

**Presence of language terms associated with suicide risk factors on Twitter**

Using the tweets and the users’ identification codes (which we also retrieved during the search process), we computed counts of users tweeting terms of a particular risk factor and counts of tweets posted for that risk factor. We first built the user-term matrix which associates the authors with their tweets wherein rows represent users and columns denote terms or statements of suicide risk factors (see ***Table 1***). Figure 1 depicts the structure of the matrix; where is the number of tweets that were initiated by user *i* and includes the search term *j*. To calculate counts of tweets of a risk factor, we aggregated columns corresponding to terms/statements of that risk factor by adding the number of tweets in each column.

users

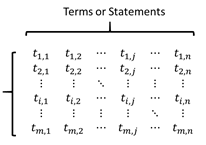


Figure 1: user-term matrix

**Grouping Twitter users into “high-risk” vs “at-risk”**

Because our goal is to identify language patterns associated with high-risk behaviors, we stratified twitter users into two groups: “high-risk” and “at-risk”. Users in the “high-risk” group are those with tweets containing language pertaining to suicide related behavior such as “prior suicide attempts” and “self-harm”. We suggest that this group is at higher risk of future suicide attempts because they insinuate suicide related behavior, whereas the other terms do not directly describe suicide attempts or self-harm. 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”.

We computed ratios of tweeting about “self-harm” and “prior suicide attempts” across the two groups to show differences. First, we computed the following two quantities for both risk factors in each group:

(1) *Average of tweets within risk factor*: the total number of tweets for a given risk factor normalized by the total number of users tweeting about that risk factor. For example, the average of tweets within “self-harm” in the “high-risk” group is the total number of tweets about “self-harm” divided by the total number of users who tweeted about “self-harm” in the “high-risk” group.)

(2) *Average of tweets across all risk factors*: the total number of tweets for a given risk factor normalized by the total number of users in a group. For example, the average of tweeting of “self-harm” across all risk factors in the “high-risk” group is the total number of tweets about “self-harm” divided by the total number of users in the “high-risk” group).

We divided the average of tweets within a risk factor of the “high-risk” group by that of the “at-risk” group to get the ratio. The same was done for the average of tweets across all risk factors.

**Patterns of risk factor language used on Twitter**

We focused on key “words” in the list of search statements/terms (see ***Table 1***) to build a network of risk factor language used on Twitter. However, many of the tweets we collected contain one key word indicative of the feeling/behavior in combination with a descriptor to complete the meaning. For example, the tweets including “Me abused depressed”, “Me hurt depressed” has one key word “depressed”. So, to build a meaningful network we pooled these tweets under the word “depression” and added up the corresponding frequencies. Similarly, pronouns such as “me”, “I”, “myself” were dropped and the tweets were pooled under the key word in these tweets. For example, “me helpless”, “I feel helpless”. This yielded a matrix of the frequencies of words per user. The list of words we had are included in ***Table 2***. We generated two matrices for “high-risk” and “at-risk” groups.

**Table 2: Words used to build the network**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Abused | Sertraline | suicide\_brother | Schizophrenia | fight\_mom |
| Depressed | Zoloft | suicide\_friend | Anorexia | fight\_parents |
| Hopeless | Prozac | suicide\_thought | Bulimia | fight\_sister |
| Worthless | Pills | suicide\_kill | Ocd | fight\_brother |
| Empty | suicide\_abused | suicide\_think | Bipolar | argue\_dad |
| Anxious | suicide\_pain | Cut | Ptsd | argue\_mom |
| Sleeping | suicide\_tried | Bully | borderline\_personality | argue\_parents |
| Irritable | suicide\_before | Bullied | panic\_disorder | impulsive |
| Restless | suicide\_mom | suicide\_gun | social\_anxiety |  |
| Alcohol | suicide\_sister | suicide\_shoot | fight\_dad |  |

Using these matrices, we generated the words’ co-occurrence matrices to capture language patterns. Each cell *c(i,j)* in the co-occurrence matrix denotes the number of users who had tweets including the word *i* and the word *j*. Using this co-occurrence matrix, we formed a network where the nodes are the words and the edges are the users who tweeted bot words. The size of a node is dependent on the degree of that node (i.e. the number of nodes/words connected to this node). The width of the edge between two nodes is proportional to the number of users who tweeted both words of these nodes. We established these networks for both “high-risk” and “at-risk” groups. We used the “igraph” package from R to visualize “at-risk” and “high-risk” networks via the Fruchterman-Reingold layout. Words of one risk factor share the same color and the edges between nodes were colored based on the source.

**Results**

**Presence of language terms associated with suicide risk factors on Twitter**

Statistics relevant to the presence of twelve suicide risk factors’ is reported in Table 3. In general, the table shows that a substantial number of users discuss different suicide matters on Twitter. “Drug abuse”, “depressive feelings”, and “bullying” are the top three risk factors in terms of presence on Twitter, with the largest percentages of tweets 50%, 33%, and 13% tweeted by 157,117, 161,413, and 63,457 users, respectively. Despite the large gap, in terms of number of users and tweets, between the three highest risk factors and the rest, thousands of users tweeted about “depression symptoms”, “impulsivity”, “suicide ideation”, “suicide around individual”, “self-harm” and “gun ownership”. “Prior suicide attempts”, “family violence and psychological disorder” exhibited least presence with the least number of users and tweets.

**Table 3: Presence of suicide risk factors**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Suicide Risk Factors** | **#Users** | **# Risky Tweets** | **% of tweets** | **Avg. tweet/user** |
| Drug Abuse | 157117 | 285954 | 50% | 1.82 |
| Depressive feelings | 161413 | 188060 | 33% | 1.16 |
| Bullying | 63457 | 75383 | 13% | 1.18 |
| Depression symptoms | 7139 | 7642 | 1% | 1.07 |
| Impulsivity | 4435 | 4677 | .8% | 1.05 |
| Suicide around individual | 3164 | 4327 | .8% | 1.36 |
| Suicide ideation | 3443 | 3955 | .7% | 1.14 |
| Self-harm | 2012 | 3122 | .5% | 1.55 |
| Gun ownership | 1097 | 1574 | .3% | 1.43 |
| Prior suicide attempts | 144 | 148 | .03% | 1.02 |
| Family violence | 122 | 127 | .02% | 1.04 |
| Psychological disorder | 6 | 10 | .002% | 1.66 |

**Grouping Twitter users into “high risk” vs “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 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. Each of these tweets were then parsed for every suicide related search term and statement [15]. All users who had zero tweets containing any of the risk factor phrases for any risk-factor were dropped. 505 “high-risk” users and 1,857 “at-risk” users were retained.

***Table 4*** shows the average tweets within a risk factor and across all risk factors for the “high-risk” and the “at-risk” groups. 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”, they will tweet on average 2.5 tweets about “self-harm”, while an “at-risk” individual who tweets about “self-harm” will only tweet on average 1.2 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 (.68 compared to .04, respectively).

**Table 4: Tweeting ratios of “high-risk” versus “at-risk” groups in terms of “self-harm” and “prioir suicide attempts”**

|  |  |  |
| --- | --- | --- |
| **Description** | **Prior-suicide-attempts** | **Self-harm** |
| High-risk users | | |
| Total tweets | 27 | 345 |
| Total users | 23 | 140 |
| Average of tweets within risk factor | 1.2 | 2.5 |
| Average of tweets across all risk factors | 0.05 | 0.68 |
| At-risk users | | |
| Total tweets | 51 | 81 |
| Total users | 36 | 69 |
| Average of tweets within risk factor | 1.4 | 1.2 |
| Average of tweets across all risk factors | 0.03 | 0.04 |
| Ratio of high-risk to at-risk | | |
| Ratio of tweets within risk factor | 0.83 | 2.09 |
| Ratio of tweets across all risk factors | 1.94 | 15.66 |

For “Prior suicide attempts”, a “high-risk” user will tweet on average 1.2 tweets compared to 1.4 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, .05 compared to .03, respectively. With this analysis, we have shown that there are differences in the frequency of tweeting between both groups. This distinction would potentially result in different patterns of tweeting as we show in the next analysis.

**Patterns of risk factor language used on Twitter**

Figure 1 and Figure 2show graphs of suicide-related words’ use on Twitter depicting the co-occurrences of the words for the “high-risk” and “at-risk” groups, respectively.A pair of words are connected in the graph if at least one user tweeted both words. The connectivity in the graph reflects the tweeting behavior of users in the graph. While Figure 2 shows highly connected network of words, Figure 1 shows more specific patterns of connected words characterizing those who are at high risk. The high connectivity of the “at-risk” group in Figure 2 is represented by the large size of many nodes in the graph and the large size of edges connecting these nodes. The dense connectivity could be attributed to the fact that the tweets we are analyzing are by definition risky; meaning that each tweet at least contains one of the risky words of the suicide risk factors (see ***Table 1***). We show from the connectivity in the "at-risk" graph the tendency of users in this group to use risk factor words in multiple contexts. For example, users tweeting the word “cut” (which belongs to the self-harm risk factor and has the largest node size) also heavily tweeted words of other risk factors such as “panic\_disorder”, “bi\_polar”, “bully”, “empty”, “alcohol”, “worthless”, “anxious”, “depressed”, and “sleeping”. In addition, the edges’ width (the frequency of tweeting a pair of words) between “cut” and these nodes are noticeably large implying that “cut” is more frequently tweeted with these words. Among these words, “Empty”, “worthless”, “alcohol”, “bully” that belong to “drug\_abuse”, “depressive\_feelings” and “bullying” risk factors are in the center of the graph and mutually connected, an observation that supports previous findings about the correlation between these risk factors in the literature [25-27].

The centrality of the word “cut” is shown in both Figures 1 and 2. In the “high-risk” graph, however, an explicit and centered pattern of tweeting “cut” with “panic\_disorder”, “sleeping”, “depressed”, “alcohol” and “bully”. Furthermore, in the high risk group “cut” is relatively more central than the other terms as indicated because of the relatively larger size of the circle. In contrast, the size of all the nodes in the at-risk group are relatively similar. In the “high-risk” graph, the word “panic\_disorder” is the most tweeted word of the “psychological disorder” risk factor) as opposed to what is captured in the “at-risk” graph, all “psychological disorder” words have been frequently tweeted in the context of words of the same risk factor or other factors. Similarly, the words “pill” and “alcohol” of “drug\_abuse” risk factor are more frequently used by users in the “high-risk” group compared to Figure 2 wherein an explicit mention of drug names is present. While words of the “suicide\_ideation” risk factor including “suicide\_think”, “suicide\_thought” and “suicide\_kill” were connected to the words “cut” and “sleeping” in the at-risk group, only the word “suicide\_think” appeared in the “high\_risk” graph connected to “cut” and “sleeping”.

We zoomed out and rolled the co-occurrence matrices from the word level to the risk factor level that contain counts of users tweeting about pairs of risk factors. Figure 3 and Figure 4 depicts the connectivity between the risk factors of the “high-risk” and “at-risk” groups. For a risk factor, we used the same colors of its corresponding words in Figures 1 and 2. The size of a node in the figure is equivalent to the number of users who tweeted about the corresponding risk factor. About 24%, 15%, 7% of the users in the “high-risk” tweeted about “depressive\_feelings”, “depressive\_symptoms” and “bullying”, respectively, compared to 15%, 7%, 6% users in the “at-risk” as sown in Figures 3 and 4. Although “self-harm” has its largest connectivity with the same risk factors in both graphs, (including “depressive\_symptoms”, “depressive-feelings”, “psychological\_disorders”, “drug\_abuse”, and “bullying”), there are discrepancies in the widths of the edges implying different patterns of tweeting behavior across both groups. For example, in the “high-risk” group (Figure 3), 18% and 13% of the “self-harm” connections where with “depressive\_feelings” and “depressive\_symptoms” which is larger than self-harm connections with the same nodes 16% and 9%, respectively, in the “at-risk” group (Figure 4).

This variation in edges weights most likely pushed “self\_harm” to the center of Figure 3 for the “high\_risk” users. In the “high\_risk” group, about 28% of the users who tweeted about “suicide\_ideation”, had tweets of “depressive\_feelings” compared to 14% only in the “at\_risk” group. Significantly more than the “at-risk” users, tweeters of “gun\_ownership” had 45%, 9% of their tweets about “depressive\_feelings” and “drug\_abuse” compared to 11%, 6%, respectively, in the “at\_risk” group. Of those “high\_risk” users with “prior\_suicide\_attempts” tweets, 18%, 12%, 6%, 22%, 9% tweeted about “depressive\_feelings”, “depressive\_symptoms”, “drug\_abuse”, “self\_harm”, and “bullying”, respectively compared to lower percentages of users in the “at\_risk” group 10%, 3%, 5%, 16%, 8% in the same respective order. In the “high\_risk” group, once more, “depressive\_feelings”, “depressive\_symptoms”, “drug\_abuse”, and “self\_harm” have more prevalence about 20%, 10%, 10%, 22% for users tweeting “psychological\_disorders” compared to 10%, 3%, 5%, and 16%, respectively in the “at\_risk” group. These differences are useful to draw a line between “high\_risk” and other users.

**Table 5** shows examples of users’ tweeting about several risk factors (column 1 titled #RF indicates how many risk factors a user tweeted about). We include example tweets of three users and enlist the actual risk factors as well as the search keywords used to retrieve the corresponding tweets. We gave each user a sequence number “ID” in the second column in the table to help the discussion. User 1 tweeted about multiple risk factors including: bullying, impulsivity, drug abuse and depressive feelings. User 2 is a sixteen year old explicitly seeking advice on how to harm himself as evident from the question he posted ”Any advice on how to stop cutting myself?”. In another tweet, he expressed his intention to commit suicide “I want to commit suicide” indicating

**Table 5: Examples of tweets**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **#RF** | **ID** | **Risk Factor (RF)** | **Search Keywords** | **Tweets** |
| 4 | 1 | Bullying | "I'm being bullied" | I'm being bullied :'( IMA STAB SOME HOEs |
| Impulsivity | "I'm impulsive" | And I'm impulsive |
| Drug abuse | "Prozac" | But don't worry, I also watched Prozac nation so I'm still on track with my emoness |
| Depressive feelings | "I feel sad" | I feel sad idk |
| 2 | Depressive feelings | "I feel helpless" | I feel helpless and alone?: i dont have any friend.No one to understand me.I feel extremely helpless hopeless |
| Drug abuse | "Zoloft" | Why is it selfish for me to kill myself?: I'm 17 and have clinical depression. I've tried Zoloft |
| Self-harm | "Stop cutting myself" | Any advice on how to stop cutting myself?: I'm a fifteen year old guy, almost sixteen |
| suicide ideation | "I want to commit suicide" | I want to commit suicide?: I had this thought since last year. I don't really have a reason to live. |
| 3 | Suicide around individual | "Friend suicide" | I'm conflicted about preventing my friend's suicide via /r/depression |
| Depressive feelings | "I feel helpless" | I can't focus. I can't do anything. I feel helpless. I never thought this would happen a |
| Drug abuse | "Prozac" | Starting Prozac, will I become a person again? |
| suicide ideation | "I want to commit suicide" | I want to commit suicide, but I just end up cutting myself at the end of the day. |
| 3 | 4 | Depressive feelings | "I feel empty" | I feel empty and dead |
| Drug abuse | "sertraline" | They're changing my antidepressants because Sertraline didn't work |
| Suicide ideation | "I want to commit suicide" | I want to commit suicide so badly but I've failed too many times idk what to do anymore |
| 5 | Depressive feelings | "I feel sad" | I feel sad inside |
| Self-harm | "Stop cutting myself" | 10k favs and I'll stop cutting myself and considering suicide |
| Bullying | "Stop bullying me" | stop bullying me jazzy |
| 6 | Bullying | "I'm being bullied" | First job and I feel like I'm being bullied by my manager, please help! I'm begging you. (wall of text): Hi al |
| drug Abuse | "Zoloft" | I've been on Zoloft for about 2.5 years for my severe anxiety and moderate dep |
| Depressive feelings | "I feel helpless" | I feel helpless, worthless, useless, brainless, .. Are there any -less left?: I'm currently a 17 year old girl |
| 2 | 7 | Depressive feelings | "I feel empty" | They say pain and sadness makes you creative but I feel empty. |
| Bullying | "Stop bullying me" | sure metre ðŸ˜‚ðŸ˜‚ you need to stop bullying me tbh ðŸ˜’ |
| 8 | Depressive feelings | "I feel empty" | even tried to force me to eat..but don't you realize, I feel like I'm not good enough and I feel empty and eating doesnt help that. |
| suicide ideation | "Pain suicide" | make them go shot them down kill the pain "suicide" |
| 9 | Self-harm | "Stop cutting myself" | Alex from target saved my life he was there when nobody was. i went through a hard time but watching him made me stop cutting myself. |
| Bullying | "Stop bullying me" | @gomezmisfits stop bullying me Jonathan ðŸ˜© |
| 1 | 10 | Depressive feelings | "I feel sad" | I feel sad for the orange team. |
| 11 | Drug abuse | "Prozac" | Over-The-Counter Weight Loss Supplement Contains Prozac |
| 12 | Drug abuse | "Prozac" | Interesting read "bellacaledonia: Prozac Nationalism |

the presence of the suicide ideation. User 3 only expressed suicide ideation “I want to commit suicide, but I just end up cutting myself at the end of the day” through his tweet but he also acted and cut himself. User 4 had a tweet about suicide: “I want to commit suicide so badly but I've failed too many times idk what to do anymore” and also posted about “depressive feelings”: “I feel empty and dead”. A seventeen years old female, User 6, expressed her depressive feelings “I feel helpless, worthless, useless, brainless, .. Are there any -less left?: I'm currently a 17 year old girl”.

**Discussion**

We found that a substantial number of users tweet about suicide and distinct language patterns distinguishes high risk from at risk users on Twitter. Using network analysis, demonstrate how high risk suicide behavior may be detected, beyond simply key words searches. We identified several language patterns and relationships between suicide risk factors that builds on previous findings in the literature [22-31].

In particular, the presence of language terms related to “depressive feelings”, “drug abuse” and “bullying” was the highest on Twitter. Our study is the first to analyze network patterns of language and relationships between suicide risk factors in social media communication. Previous studies analyzing suicide-related language on Twitter such as [15] did not examine co-occurrences of language terms. Our analyses suggest that Twitter is a rich source of information and is potentially useful for advancing suicide related research.

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 4**. We showed that “high-risk” individuals who tweet about self-harm do so by over twice as much more frequently than an “at-risk” user. Across all users (not only those who 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” users. “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 .83 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.

We identified patterns of high risk words and language (co-occurrences of words) to better characterize high risk users using network analysis to extend previous research that simply flagged high risk language on Twitter [15-18]. We characterized who might be at higher risk of suicide; however, this approach needs to be validated using clinical data and/or twitter users with known suicide related behavior. Using the network visualization (see Figures 1 and 2), we captured interesting relationships, particularly in the “high-risk” group. In Figure 1 (a) and (b), the word “cut” had a relatively larger weight as it was centered and tweeted in combination with similar words in both graphs. Nonetheless, in the “high-risk” group, that was the most obvious and explicit pattern representing a marker of behavior for this group.

Collecting word co-occurrences in matrices at the risk factor level allowed us to make more clear conclusions about word use in both groups. In general, “high-risk” users are more likely to tweet about “depressive\_feelings”, “depressive\_symptoms” and “bullying”. In particular, “high-risk” users who tweeted about “self\_harm” are more likely to tweet about “depressive\_feelings”, and/or “depressive\_symptoms” compared to their counterparts in the “at-risk” group. The odds are higher for “high-risk” users to tweet about “suicide\_ideation” and “depressive\_feelings”. “Prior\_suicide\_attempts” tweeters in the “high-risk” group are more likely to tweet about “self\_harm”, “depressive\_feelings”, or “depressive\_symptoms”. These patterns of the “high\_risk” group could be viewed as markers of its behavior. This is useful for future interventions on Twitter such as sending enquiries or tweets to those exhibiting these behaviors.

**Limitations**: One limitation of this study is related to the list of terms/statements we used to search for tweets and we do not have access to clinical data regarding actual suicide attempts or completions. As we mentioned above, Jashinsky et al [15] 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”. Nevertheless, this is an exploratory study demonstrate tools that may be useful to detect language patterns in groups of Twitter users. In future work, we plan to apply intelligent natural language processing approaches based on deep learning to better detect risk factor language on Twitter.

**Declaration**:

- Ethics approval and consent to participate

Not Applicable

- Consent to publish

Not Applicable

- Availability of data and materials

The datasets used and/or analyzed during this study available from the corresponding author

on reasonable request

- Competing interests

The author(s) declare(s) that they have no competing interests

- Funding

Not Applicable

- Authors' Contributions

Dr. Fodeh designed the study, analyzed and interpreted the data and wrote the paper. Dr. Al-

Talib assisted in data interpretation and edited the paper. Dr. Wag and Dennis downloaded

Twitter data, processed tweets and generated the data structures. Drs. Boudreaux and

Bossarte Provided insights and expertise related to suicide and assisted in the design of the

study. Dr. Brandt contributed to writing the manuscript and helped in data analysis.

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**Abbreviations:**

API: Application Programming Interface

ID: user identifier (sequence number)

**Conclusion**

Twitter is an outlet for individuals to post thoughts and feelings. Using suicide risk factors and associated language used on Twitter, we have characterized factors and patterns to help detect tweets associated with high risk of suicide behavior. Expressing “depressive feelings” and “drug abuse” and “bullying” are the most tweeted factors; however, when cutting is more centrally connected to other terms, a user may be at high risk of suicide related behavior Analyzing the co-occurrences of the terms we identified explicit language patterns such as “self\_harm” and “depressive\_feelings”. We conclude that certain language patterns pertaining to suicide risk factors may help detect potentially higher risk groups for suicide.

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