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Tweet Now, See You In the ED Later?: Examining the Association Between Alcohol-Related Tweets and Emergency Care Visits

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Abstract

Background—Alcohol use is a major and unpredictable driver of ED visits. Regional Twitter activity correlates ecologically with behavioral outcomes. No such correlation has been established in real time.

Objectives—To examine the correlation between real-time, alcohol-related tweets and alcohol-related ED visits.

Methods—We developed and piloted a set of 11 keywords that identified tweets related to alcohol use. In-state tweets were identified using self-declared profile information or geographic coordinates. Using Datasift, a 3rd-party vendor, a random sample of 1% of eligible Tweets containing the keywords and originating in-state were downloaded (including tweet date/time) over 3 discrete weeks in 3 different months. In the same timeframe, we examined visits to an urban, high-volume, level I trauma center that receives >25% of the emergency care volume in the state. Alcohol-related ED visits were defined as visits with a chief complaint of alcohol use, positive blood alcohol, or alcohol-related ICD-9 code. Spearman's correlation coefficient was used to examine the hourly correlation between alcohol-related tweets, alcohol-related ED visits, and all ED visits.

Results—A total of 7,820 tweets (representing 782,000 in-state alcohol-related tweets during the 3 weeks) were identified. Concurrently, 404 ED visits met criteria for being alcohol-related versus 2939 non-alcohol-related ED visits. There was a statistically significant relationship between

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hourly alcohol-related tweet volume and number of alcohol-related ED visits (r_s =0.31, p<0.00001), but not between hourly alcohol-related tweet volume and number of non-alcohol-related ED visits (r_s = −0.07, p=0.11).

Conclusion—In a single state, a statistically significant relationship was observed between the hourly number of alcohol-related tweets and the hourly number of alcohol-related ED visits. Real-time Twitter monitoring may help predict alcohol-related surges in ED visits. Future studies should include larger numbers of EDs and natural language processing.

Introduction

Twitter is an online social networking platform used by approximately one-quarter of online adult Americans and approximately 320 million people world-wide.[1,2] Through Twitter, short 140 character messages called "tweets" can be composed, sent, and publicly read via computer, smartphone application, or text message. The public nature of Twitter makes it ideal for public health and disaster surveillance. Indeed, regional Twitter content has been shown to correlate with a variety of disease-related states, including heart disease, suicide, asthma, and substance use.[3–6]

Alcohol use is a common risky behavior that impacts emergency department (ED) volume and staffing needs: alcohol-related ED visits are associated with increased length of stay and increased boarding.[7,8] Increases in alcohol-related ED visits are often unpredictable, varying widely from day to day.[9] Being able to predict increases in alcohol-related ED visits through automated monitoring of publicly available data could assist EDs in staffing and other crowding-related actions.

To our knowledge, no studies have correlated risk-behavior-related tweets with real-time risk-behavior-related ED visits. Examining this association may support a role for public health monitoring of Twitter or other social media modalities. The objective of this pilot study, therefore, was to examine the real-time association between alcohol-related tweets in a single state and alcohol-related visits to that state's largest ED.

Methods

Study Design, Setting, and Population

This cross-sectional study examined the association between alcohol-related tweets in a small Northeast state and alcohol-related visits to the ED of an urban, high volume, level I trauma center and tertiary care hospital which sees approximately 25% of the emergency care volume in the state. The study was deemed exempt by the investigators' hospital Institutional Review Board.

Study Protocol and Measurements

Categorization of Alcohol-Related Tweets—Prior to data collection, we developed a list of keywords that would identify tweets related to alcohol consumption, in accordance with prior studies' process for developing Twitter queries.[6,10] First, the team created an inclusive list of approximately 30 formal and colloquial words used to describe social drinking, drawn from a review of a random sample of tweets as well as web posts. Next, Twitter was queried at multiple distinct time points using each potential keyword; a randomly selected 10% of tweets containing that keyword were hand-reviewed for relevance to alcohol consumption; additional alcohol-related words used in those tweets were noted; and the keyword list was iteratively refined by three authors (MLR, EKC, BC). The remaining keywords were piloted over a four-day period via the Twitter streaming application program interface (API), with review of a random selection of tweets by the same authors for apparent alcohol-related content. For example, a tweet identified by the search term "booze" that was deemed to be alcohol-consumption related was "@[TwitterHandle] this party is all wine booze and ganja." The term "bar," however, was too nonspecific, eliciting tweets the reviewers agreed were not alcohol-related, such as "how did those granola bars treat you this morning? #lolz." Words for which <25% of randomly sampled tweets containing these words actually described alcohol use, based on agreement by all three reviewers, were deleted in order to minimize over-estimation of alcohol consumption-related tweets. Based on this process, 11 alcohol keyword stems were chosen for the study: alcohol, beer, wine, cocktail, booze, drunk, partying, clubbing, wasted, plastered, and tipsy. This process mirrors that used by other published analyses of healthcare-related Twitter content.[6,10–12]

Capture of Tweets—Per IRB protocol, only publicly available tweets (representing ~90% of Twitter accounts) were eligible for capture. Among these, tweets were considered to originate in the state if either (a) self-declared profile information indicated the user was from the state (e.g. any part of location field contained the state name or abbreviation), or (b) geographic coordinates identified it as originating in the state. Approximately 34% of tweets are either geo-located or contain location-identifying profile information.[13]

Eligible tweets (publicly available, originating in the state, and containing one of the 11 keywords or its stems) were then collected via Datasift, a licensed third party vendor of Twitter data that, at the time of the study, was able to apply search algorithms to real-time Twitter feeds. The Datasift algorithm automatically selected a random sample of 1% of tweets, according to their standard protocol and in accordance with others' scholarly work on Twitter.[6,10] Tweets were collected over three discrete time periods (December 19 to December 25, 2013; January 9 to January 15, 2014; and March 13 to March 20, 2014) that were selected to include weekdays and weekends, holiday periods and non-holiday periods. In accordance with others' work, tweets that were "retweets" (a re-posting of someone else's tweet) or promotional tweets (e.g., tweets that advertise a particular restaurant or bar) were filtered out, as these tweets were not considered representative of individuals' behavior.[10] Demographic characteristics are not routinely available from Twitter handles, and thus were not included in the analysis.

Identification of ED Visits—ED visits were operationalized as any presentation to the ED by a patient age 18+ during one of the three time periods during which tweets were collected. Additional inclusion criteria for alcohol-related ED visits were a chief complaint of alcohol, a positive blood alcohol content, or a discharge diagnosis of an alcohol-related ICD-9 code (see Online Appendix for a list of these codes). Data extracted included day of the week and time of presentation to triage by hour. Visits were identified through an automated query of the institution's data warehouse.

Data Analysis

We graphed counts of relevant tweets and alcohol-related ED visits against time (in hours). We evaluated the linear relationship between tweets and ED visits (alcohol-related, and non-alcohol related) using the Spearman correlation coefficient. Demographic characteristics of ED visits were examined using descriptive statistics.

Results

Within the three study weeks, a total of 7,820 eligible tweets (e.g., related to alcohol consumption and within the geographic parameters defined) were identified, representing a random sample of 1% of 782,000 total eligible tweets. Over the same time period, 404 ED visits met criteria for being alcohol-related, versus 2939 non-alcohol-related ED visits. Mean age of alcohol-related ED visits was 44.7 (SD 13.1), with patient demographics being recorded as 60% (n=244) White, 13% (n=54) Hispanic, and 77% (n=312) male. A moderate, statistically significant correlation between the raw number of hourly alcohol-related tweets and alcohol-related ED visits was observed ($r_s = 0.31$, $p<0.001$); a non-significant negative correlation between hourly alcohol-related tweets and non-alcohol-related ED visits was observed ($r_s = -0.07$, $p=0.11$). (See Figure 1)

Discussion

This study demonstrates a direct positive relationship between hourly tweets about alcohol use and number of ED visits for alcohol-related complaints. No such relationship was found between alcohol-related tweets and non-alcohol-related ED visits, suggesting that our observations were not simply due to diurnal variations in overall tweeting volume. The study is novel in that prior work has not examined real-time associations between risk behaviors and ED visits. Predicting surges in patient volume is highly desirable from the standpoint of EDs. ED patients regularly use Twitter and other forms of social media.[14,15] It has been demonstrated that combining data from a number of information streams (including Twitter, Google, and environmental data), ED asthma visits can be predicted with reasonable accuracy.[6] Our study, in contrast, showed that Twitter *alone* associates with alcohol-related ED visits. We also note that the observed patterns of alcohol-related tweets differ from circadian rhythms of Twitter in general, in which the highest volume of tweets is observed in the early afternoon.[16]

Our study's population-level findings make intuitive sense. Individuals have been shown to feel comfortable posting – and even to find affirmation – about their substance use on social media.[11] Compared to drugs, alcohol is legal and widely socially accepted. As such, few barriers likely exist to posting about alcohol use online, and because drinking often occurs in groups, such posts are likely to reflect not only the behavior of the individual tweeting but those around them. Individual patients who end up in the ED for alcohol-related complaints may not themselves tweet; nevertheless, an increase in tweeting volume related to alcohol consumption may predict a surge in alcohol-related visits by reflecting the behavior of the general population.

Although not unexpected, our population-level findings are important. Alcohol has such a close relationship with harmful outcomes that healthcare visits are inevitable with a rise in use in the community. Our study suggests that Twitter-gathered information about population-level surges in alcohol use in the community may help EDs anticipate visits due to intoxication alone, as well as due to motor vehicle collisions and other injury mechanisms, and prepare both human and physical resources (e.g., trauma bays or space in sobering observation beds) for these types of patients. Likewise, a lack of alcohol-related tweets might signify a quieter-than-usual weekend evening, enabling the ED to avoid wasted resources.

Our study had several limitations. First, because many tweets are not geocoded, and many users do not provide location information, we sampled from a limited subgroup of tweets generated in the state during the study periods. Further, users with state information in their profile may have been outside of the state while tweeting, meaning we may have included some people who were actually outside the state while tweeting. Importantly, our keywords may have missed some tweets referring to alcohol use and may have included some that were not related to alcohol. Improved natural language processing may improve the accuracy of identifying specific content among the millions of tweets generated each day, and may alter the strength of the observed relationship between tweets and visits. Identification of alcohol-related ED visits depends on clinician identification, charting and coding; as such, some intoxicated patient visits may have been missed. As stated above, this study did not determine whether individual tweets correlated with individual ED visits, nor whether people who tweeted about alcohol use were the same people who visit the ED for alcohol use. Additionally, we were unable to compare the volume of alcohol-related tweets to overall tweets in the state, as this information was not part of our initial data query; nor were we able to examine the relative demographics of tweeters versus ED patients, as demographic information (including age) is not included in Twitter profiles. However, these analyses were not the purpose of the study, which aimed to examine whether population-level tweets correlated with overall ED visits for a specific complaint. Finally, as a pilot study, we examined correlation between tweets and ED visits for alcohol intoxication for only a handful of weeks over the year, some of which included holidays, in a single state. A larger, more diverse sample would affirm the correlations we found here and provide more information about validity and reliability of using tweets to predict ED surge in alcohol-related visits.

In conclusion, in a single state, a statistically significant relationship was observed between the hourly number of alcohol-related tweets and the hourly number of alcohol-related ED visits. Real-time Twitter monitoring may help predict alcohol-related surges in ED visits. Future studies should include larger numbers of EDs, natural language processing, and consider other measurable factors that may contribute to ED visits related to alcohol. This pilot study supports the need for future work including larger numbers of ED visits and natural language processing to improve accuracy of identifying relevant tweets. If the relationship between tweets and ED visits holds true, future research may examine how social media can be used to guide utilization of limited hospital resources.

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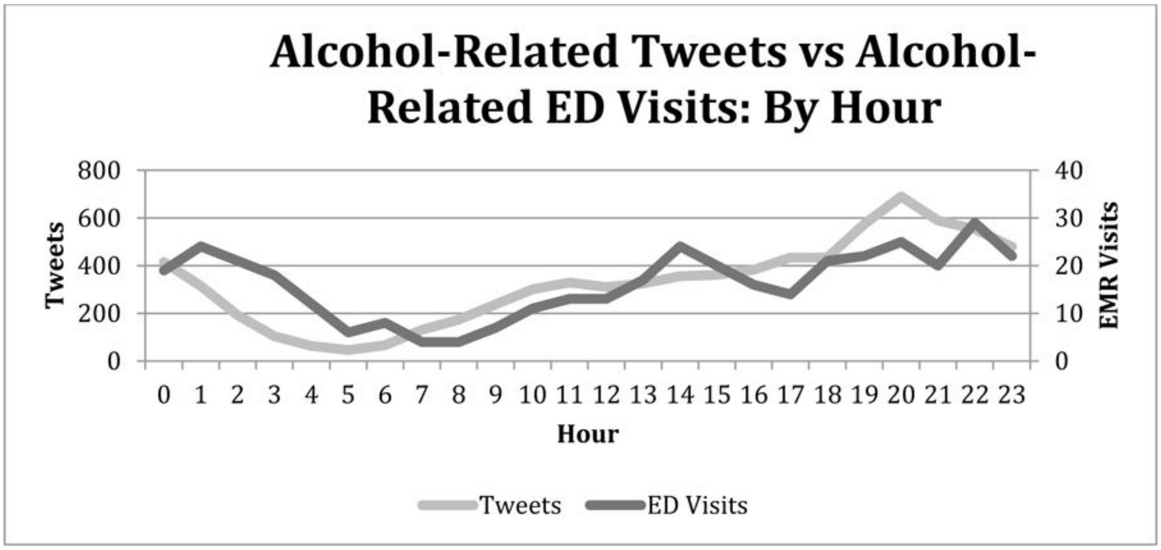

Figure 1.

Hour-to-hour number of alcohol-related tweets and alcohol-related ED visits over a 24-hour period