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ORIGINAL RESEARCH

Tweet for health: using an online social network to examine temporal trends in weight loss-related posts

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Abstract

Few studies have used social networking sites to track temporal trends in health-related posts, particularly around weight loss. To examine the temporal relationship of Twitter messages about weight loss over 1 year (2012). Temporal trends in #weightloss mentions and #fitness, #diet, and #health tweets which also had the word "weight" in them were examined using three a priori time periods: (1) holidays: pre-winter holidays, holidays, and post-holidays; (2) Season: winter and summer; and (3) New Year's: pre-New Year's and post-New Year's. Regarding #weightloss, there were 145 (95 % CI 79, 211) more posts/day during holidays and 143 (95 % CI 76, 209) more posts/day after holidays as compared to 480 pre-holiday posts/day; 232 (95 % CI 178, 286) more posts/day during the winter versus summer (441 posts/day); there was no difference in posts around New Year's. Examining social networks for trends in health-related posts may aid in timing interventions when individuals are more likely to be discussing weight loss.

Keywords

Social support, Informatics, Weight loss, Exercise, Social networks

Implications

Practice: Using online social networks to track mentions of health behaviors may allow for the timing of interventions when discussions around behavior change are high.

Policy: Broader reach for weight loss interventions may be achieved by using social media to understand when to time interventions and by using hashtags to attract users to weight loss programs.

Research: Researchers can monitor social media data to detect when interest in health is high so as to effectively time interventions.

INTRODUCTION

Online social media sites, such as Twitter, have grown over the past decade [1]. As compared to other social network sites, Twitter users are more likely to have public accounts, allowing anyone to read and access posts [2]. This open access allows a unique opportunity to use Twitter as a data collection tool. Studies have used Twitter to predict the outcomes of the stock market [3], assess scientific impact of journal articles [4], and track influenza outbreaks [5, 6]. Also, unique to Twitter is the use of symbols to emphasize particular words. Words that a user may wish to highlight are often preceded by a hashtag ("#"), which allows other users to follow relevant topics of interest [7]. Recent studies have used Twitter to develop a classification model to categorize posts with hashtags related to physical activity (PA) [8] and examine posts to Twitter with the hashtag #childhoodobesity [9]. Twitter, which has been in existence since 2006 [10], also presents a unique opportunity to examine trends over time. Previous studies have examined temporal differences in posts related to cardiac arrest [11] and happiness [12]. However, very few studies have examined temporal trends in health-related posts to Twitter, particularly in the area of weight loss.

In free-living adults, certain measured health-related behaviors have shown temporal trends depending on time of the year. This may be particularly evident for weight loss and relevant weight loss behaviors related to eating and PA. Research among U.S. adults has shown that weight gain tends to occur over holiday periods (between Thanksgiving and New Year's) [13–15], with a renewed interest in losing weight around New Year's Day [16]. In addition, studies have found PA levels among adults to be higher in the summer versus the winter [17–20]. To date, no study has used Twitter to explore the relationship of these temporal trends by examining discussions related to weight loss over time. Therefore, the primary goal of this study is to examine posts related to weight loss over the course of 1 year.

METHODS

The present study was conducted in 2013 and examined posts to Twitter over the course of 2012. PeopleBroswr (http://www.peoplebrowsr.com), which provided access to the Twitter "firehose" (full stream of Twitter data) and allows users to examine the number of posts related to search queries, was used for data collection. The primary interest of this paper is to assess Twitter posts related to weight loss. Because

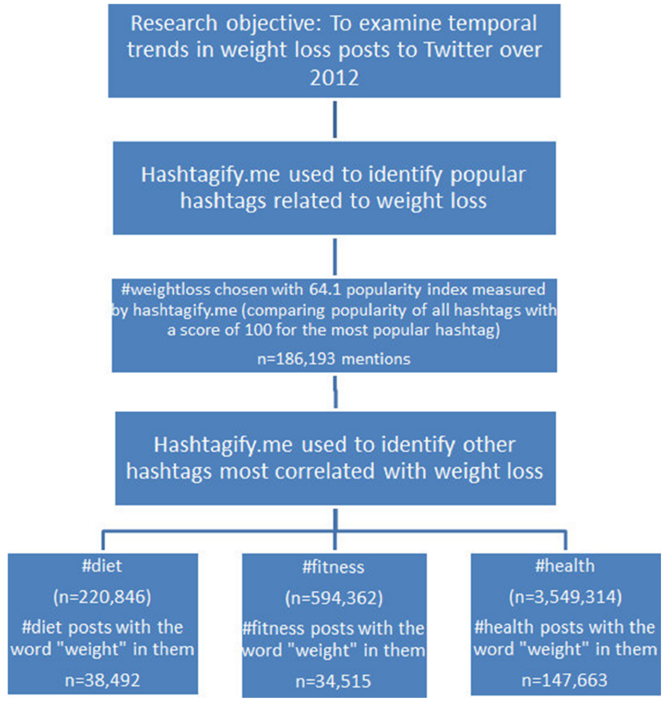

Fig. 1 | Schematic overview of the flow of data collection of posts to Twitter used for data analysis

Twitter hashtags are a common way that Twitter users categorize messages, promote ideas, and follow topics [21], hashtags were chosen as the tracking method for weight loss-related posts. Figure 1 provides a schematic overview of the flow of data collection. In order to determine which hashtags were most commonly used for weight loss-related topics, the visual hashtag explorer Hashtagify.me (www.hashtagify.me) was used. This method was employed by another study that examined mentions of childhood obesity on Twitter (#childhoodobesity) over the course of a 1 month [22]. Hashtagify.me is a website that collects posts to Twitter and examines hashtag usage patterns. This tool allows the users to examine common hashtags used around topics, in addition to exploring which hashtags are most closely related to a hashtag of interest. In order to capture additional posts that could be related to weight loss, Hashtagify.me was also used to identify hashtags most commonly related to #weightloss which identified #fitness, #diet, and #health. Posts to Twitter using these hashtags were only included in analysis if they included the word “weight” in them (e.g., “I can’t believe how much weight I’ve gained. Need to go on a #diet!”). Because data collected only revealed frequency of posts that contained selected hashtags, we were not able to determine number of users or if the posts were from accounts from commercial entities or from individuals. The time period was limited to all posts in 2012 to collect data over the course of a 1-year period.

The primary goal of this study was to examine temporal trends in Twitter posts about weight loss by tracking mentions of the four key words (#weightloss and #fitness, #diet, and #health with “weight” in the posts) over a 1-year period. This was achieved by examining three a priori time periods based on the literature demonstrating differential weight gain and PA occurrences by holiday and season. The first period examined three 61-day time frames related to holidays: (1) pre-winter holiday season (September 16–November 15), (2) holiday season (November 16 to January 15), and (3) post-holiday season (January 16–March 16). The second period examined two 88-day time frames related to season: (1) winter (December 21–March 17) and (2) summer (June 21–September 16). The third time period examined the effects of New Year’s resolutions by examining two 31-day time frames: (1) pre-New Year’s (December 1–31) and (2) post-New Year’s (January 1–31). We hypothesized that examined posts related to weight loss would be higher after holidays than before, lower during the winter, and higher after New Year’s.

Statistical analysis

For the Twitter mentions of weight loss, diet, fitness, and health, mixed model regressions accounting for the serial dependencies among days were estimated. Three models were estimated for each keyword term for the following comparisons: (1) during and post-holiday mentions compared to pre-holiday; (2) winter mentions compared to summer; and (3) after New Year’s mentions compared to pre-New Year’s. For each model, dummy variables were created for each

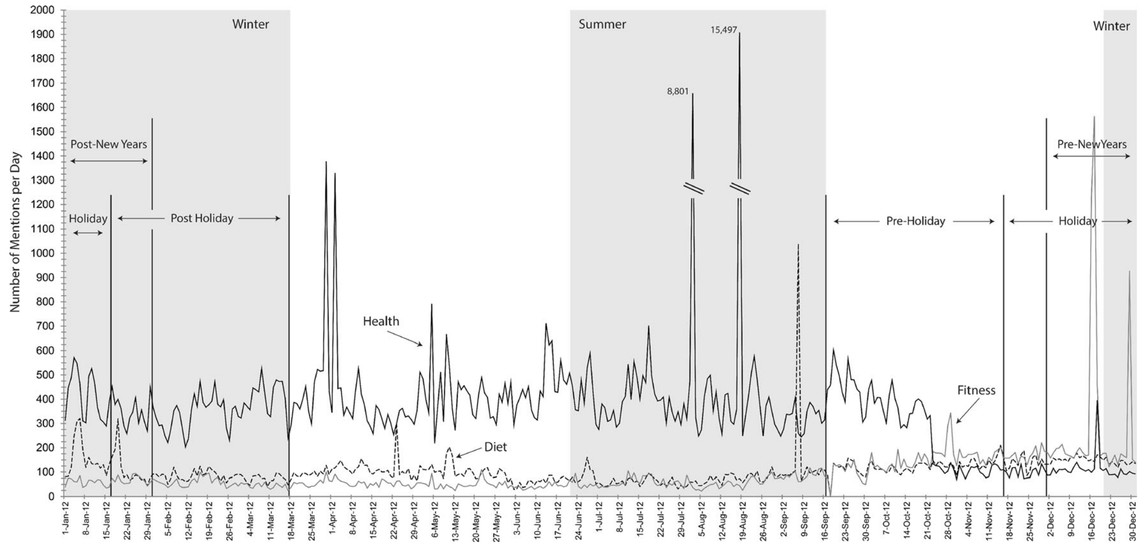

Fig. 2 | Frequency of posts to Twitter related to #weightloss, #diet, #fitness, and #health in 2012

contrast, with the reference group being pre-holiday, summer, and pre-New Year's, respectively. Comparisons for the three holiday time periods were estimated using analogous mixed models as described above. All analyses were conducted using STATA (v.12.0, College Station, TX).

RESULTS

Example Twitter posts for each of the four keyword searches as well as the top 15 most common words in Twitter posts that contained #weightloss, #health, #diet, or #fitness are presented in Table 1. Figure 2 presents the frequency of posts for all four key words over the course of 2012, and Table 2 presents the temporal trends in the four key words examined by three different time periods. Regarding weight loss, there were 145 (95 % CI 79 to 211) more posts/day during holidays and 143 (95 % CI 76 to 209) more posts/day after holidays as compared to 480 pre-holiday posts/day; 232 (95 % CI 178 to 286) more posts/day during the winter versus summer (441 posts/day); there was no difference in posts before or after New Year's.

Other hashtags related to #weightloss were also examined. For #diet, there were fewer mentions (−33 posts/day fewer) post-holiday (95 % CI −46 to −20) and more mentions (27 posts/day more) during the holiday (95 % CI 14, 40) than pre-holiday (122 posts/day). There were no differences by New Year's for #diet related posts. There were 86 (95 % CI −138 to 33) fewer mentions of #fitness per day post-holiday and 56 (95 % CI 3, 109) more posts/day compared to pre-holiday (143 posts/day). There were 161 (95 % CI −240 to −82) fewer #fitness posts/day after-New Year's versus pre-New Year's (224 posts/day). There were 103 (95 % CI −149 to −56) fewer #health posts/day during the holidays and 75 (95 % CI −30, 122) more #health posts/day post-holiday than pre-holiday (286 posts). There were 288 (95 % CI 237 to 338) more #health posts/day after New Year's than pre-New Year's (95 posts/day). No difference was observed between winter and summer posts/day for #diet, #fitness, or #health.

In summary, #weightloss, #diet, and #fitness posts all showed increases during the holidays as compared to pre-holidays with #weightloss posts also showing a continued increased post-holiday as well. Only #weightloss posts differed by season with more posts in the winter versus summer. While #weightloss and #diet posts did not differ by pre- and post-New Year's, #fitness posts were lower after New Year's and #health posts were higher.

DISCUSSION

Twitter, which is one of the most diverse social networks [23], has the potential to provide a great deal of both quantitative and qualitative data, with over 200 million users worldwide and over 400 million tweets each day [24]. The present study sought to examine the frequency and temporal relationship of posts around weight loss to understand when people may be discussing weight loss the most. This study found that more posts about weight loss (as reflected in #weightloss and weight-related #diet and #fitness posts) were occurring during the holidays, at a time when weight gain is commonly occurring. In addition, there were more #weightloss posts in winter than summer and post-holiday compared to pre-holidays.

The present study also identified common words that appeared in Twitter posts with each of the four keywords. Despite #health having the potential to be related to any area of health (smoking, cancer, colds and flu, etc.), half the words most commonly occurring with #health posts were related to diet, exercise, or

Table 1 | Examples for the four keyword Twitter searches and top 15 most common words which appear in each Twitter post with #weightloss, #diet, #fitness, or #health in 2012

	Weight loss		Diet		Fitness		Health	
Example Twittter posts of each examined hashtag and keyword search	I'm cutting out soda… Will keep you posted on my #weightloss.		Time to lose weight! (link to blog post) #Diet		Be determined and you really can lose the weight. It's a daily fight, but it's so worth it! #fitness (link to photo of user)		How much can body weight fluctuate in a day or week? #health #Fitness #running	
	This was so good, I want to cry nectarines, mango and raspberries #fruit #weightloss #fitfam		Keep on improving myself, lost weight and fitness has got 100× better #healthy #diet #changes		Workout Day! Weight Training and 8 miles on the bike! 136 lbs gone in 15 months and 65 lbs to go!! #fitnessmotivation #fitness		Quiet your Busy Brain with Mindfulness Meditation and get healthy, happy and lose weight—(link to blog) #health	
	Fat Burning Grocery List #FatBurning #WeightLoss #HealthyEating #fit (link to website)		Make weight loss fun with these seven #diet sites (link to website)		Lost nearly 14 lbs! 2 more pounds until my goal weight. #fitness #countingcalories #hardworkpaysoff		I'm determined to lose weight this summer. At least 20 lbs. If I do I will be so proud of myself! #WeightLossTime #Health #ICanDoIt #Support	
	Love seeing this going down!!! #myfitnesspal #graph #weightloss #love #slim4summer #slimforsummer (link to picture of weight chart)		I'm going to start dieting again today! Need to lose some weight I gained the last weeks because of those horrible exams #diet #summer		Goal achieved!!! Weight less than 200 pounds! #workout #fitness		Got 1 month to drop some serious weight. Proportioned snacks and meals for the week. #health #food	
	#weightloss common words	N	#diet common words	N	#fitness common words	N	#health common words	N
Top 15 most common words which appear in posts to Twitter with #weightloss, #diet, #fitness, or #health	**weight**	53,981	health	46,966	#health	98,245	fitness	434,460
	health	47,142	#health	44,083	workout	64,922	#fitness	409,933
	#health	45,427	**weight**	38,492	#ptwall	64,199	care	202,555
	#fitness	44,009	food	30,511	personal	60,292	#diet	191,577
	fitness	43,563	loss	28,304	training	57,968	tips	182,144
	diet	43,151	#weightloss	27,433	exercise	49,859	#news	164,634
	loss	37,865	#fitness	26,570	#weightloss	43,965	**weight**	147,663
	#diet	27,381	nutrition	21,817	trainer	39,748	#wellness	141,433
	update	25,128	#food	20,765	#workout	35,133	#food	125,600
	hr's[1]	24,689	healthy	15,898	#exercise	34,615	#nutrition	125,051
	lose	15,929	fat	15,593	**weight**	34,515	healthy	116,389
	tips	13,758	#pregnancy	14,205	#nutrition	27,564	#weightloss	116,016
	fat	9950	#nutrition	14,150	#diet	26,575	cancer	108,984
	exercise	9653	lose	13,387	free	26,013	free	106,864
	#nutrition	8505	update	12,171	day	19,770	loss	83,935

[1] Refers to Twitter account @HealthRockStar

Table 2 | Number of #weightloss posts and posts with hashtags #diet, #fitness, and #health and the word "weight" by holiday, season, and New Year's in 2012

	Twitter mention keyword terms (number of mentions/day)							
	Weight Loss		Diet		Fitness		Health	
	b	(95 % CI)	b	(95 % CI)	b	(95 % CI)	b	(95 % CI)
Holiday								
During Holiday	*+145*	*(79, 211)*	*+27*	*(14, 40)*	*+56*	*(3, 109)*	*−103*	*(−149, −56)*
Post-Holiday	*+143*	*(76, 209)*	*−33*	*(−46, −20)*	*−86*	*(−138, −33)*	*+75*	*(−30, 122)*
Pre-Holiday (reference)	480	(433, 527)	122	(113, 131)	143	(106, 180)	286	(254, 319)
Season								
Winter	*+232*	*(178, 286)*	+22	(−3, 47)	+16	(−5, 37)	−310	(−692, −73)
Summer (reference)	441	(403, 480)	85	(67, 102)	62	(47, 77)	646	(375, 916)
New Year's								
After New Year's	+80	(−93, 253)	−5	(−49, 39)	*−161*	*(−240, −82)*	+288	*(237, 338)*
Pre-New Year's (reference)	693	(544, 841)	138	(100, 176)	224	(156, 292)	95	(51, 139)

Significant findings are in italics.

weight loss, demonstrating that weight loss is a frequent health-related topic discussed on Twitter. In addition, examining temporal changes in common key words for each hashtag is potentially another way to examine trends in health-related issues. For example, the hashtags #paleo and #gluten did not appear as common words associated with #diet until December 2012, which coincided with the increasing popularity of Paleo and Gluten-free diets around that time [25]. In addition, our study also found that the word "meningitis" appeared as a popular keyword for #health only in the month of October 2012, the same time when a viral meningitis outbreak was occurring [26].

U.S. studies have observed temporal weight gain differences related to holidays and season [14, 15, 27]. Winter holidays are a time when people are faced with several opportunities to increase energy consumption, such as parties with high caloric food [28]. Studies have shown a pattern of average weight gain during winter holidays of around 0.5 kg [14, 15], which is not subsequently lost in the spring [15]. Overweight and obese individuals may gain more weight during holiday periods than normal weight individuals [15]. Our present study observed an increase in #weightloss and weight-related #diet and #fitness Twitter posts during holidays (when weight gain commonly occurs) and in #weightloss and #health posts after holidays (when interest in weight loss is presumed to be greater). #Weightloss posts were also higher in the winter; a time when weight gain may be greater due to decreases in PA and increases in energy intake [27]. Contrary to what was hypothesized, there was no effect for New Year's on #weightloss or #diet and there were fewer weight-related #fitness posts after New Year's. This is surprising as losing weight is one of the most popular New Year's resolutions [29]. Only weight-related #health posts saw a significant increase post-New Year's. It is possible that individuals are more interested in weight loss for health-related reasons after the New Year's than before or during the holiday, when weight gain is commonly occurring. Future qualitative research should use Twitter to explore weight loss motivation over time. Overall, it appears that people are actively discussing weight loss during the holidays and winter when weight gain has been shown to be commonly occurring.

Social media has played a powerful role in providing interaction and support among people with similar health needs and concerns [30–32] as well as an intervention tool [33, 34]. Online social networks also allow the users to share information with one another [30] and spread exercise behaviors [35]. Social media is widely used to discuss weight loss and other health-related topics [30] and has the ability to be a useful source of data for examining frequency of discussions around health-related topics.

The findings of the present study have several implications for future weight loss intervention work. Assuming mentions of #weightloss indicate interest in either losing weight or current weight loss efforts, it appears that people are interested in or engaging in weight loss during and after holidays and during the winter when weight gain has been shown to be commonly occurring. Knowing this may help to time interventions to when weight loss readiness or motivation is higher. Secondly, it may be useful to identify popular hashtags related to weight loss that can help promote public health weight loss efforts or help users identify community-based weight loss programs. Lastly, if interventions are delivered via Twitter or other social media platforms, it may be beneficial to utilize hashtags in posts as a way to allow participants to engage with other users and resources related to weight loss beyond the study setting.

The present study has several strengths. It is one of the first studies to use objective social networking data to examine temporal trends of posts related to weight loss and included a very large number of posts for analysis. The study used an objective method for identifying key hashtag words related to weight loss. In addition, the study provided examples of common words appearing with Twitter posts which contain #weightloss, #diet, #fitness, or #health. There are also some limitations. Posts could have been overlapping if they included multiple tags (e.g., #weightloss and #fitness in the same post) and therefore, would be counted twice (once under #fitness–if weight was mentioned–and once under #weightloss). Also, we limited our searches only to hashtag keywords and, therefore, did not collect posts without one of the four examined hashtags that may have been discussing weight loss. While an objective method was chosen to identify hashtags related to weight loss, use of these hashtags limited the ability to identify all possible Twitter posts related to weight loss. In addition, membership to Twitter continues to grow so the number of users on Twitter may have increased (with an increase in types of posts) over the course of 2012; however, this would have resulted in an increase in the number of posts of all four keyword searches. Lastly, the content of the posts were not assessed and therefore it cannot be confirmed that the posts were actually about the keyword. Sample posts were examined, however, (as presented in Table 1) which revealed relevant posts to weight loss. Future research should conduct qualitative analysis of weight loss-related posts to assess content of posts.

CONCLUSION

In conclusion, examining posts to social networks, such as Twitter, may be an effective way to track frequency of discussion around certain health behaviors. This approach of using social networking data to examine trends in health-related keyword mentions has the potential to support findings of studies which measure health-related outcomes, such as PA or weight loss. Future studies using social media to deliver weight loss interventions may aim to deliver behavioral messages during and after holidays, as well as during winter months, to target individuals when discussion of these topics is greater.

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Conflict of interest and adherence to ethical principles statement: GTM and MWB have no conflicts of interest to declare. All procedures, including the informed consent process, were conducted in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000.

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