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ORIGINAL RESEARCH

Weight loss support seeking on twitter: the impact of weight on follow back rates and interactions

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Abstract

People seek weight loss support on online social networks, but little is known about how to build a supportive community. We created four Twitter accounts portraying women interested in weight loss (two obese, two normal weight/overweight) and followed health care professional and peer accounts for 2–5 weeks. We examined follow back rates, interactions, and organic follows from professionals and peers by weight status. Follow back rates did not differ by weight status when following professionals (6.8 % normal weight/overweight vs 11.0 % for obese; $p = 0.4167$) or peers (6.7 % for normal weight/overweight vs 10.8 % for obese; $p = 0.1548$). Number of interactions and organic followers also did not differ by weight status. Peers interacted with study accounts significantly more than professionals ($p = 0.0138$), but interactions were infrequent. Women seeking weight loss support on Twitter may need to be present for more than 5 weeks to build an interactive weight loss community.

Keywords

Obesity, Social media, Peer-to-peer healthcare, Twitter

Implications

Practice: Twitter is a viable platform through which individuals seeking help with weight loss can garner support.

Policy: Weight bias that is seen in in-person interactions does not appear on Twitter and Twitter can help patients who want to lose weight find non-judgmental support.

Research: Future research is needed to examine how patients can find and participate in online communities for weight loss support.

Introduction

People are increasingly using online social networks to learn about health and interact with healthcare professionals and other peers [1, 2]. In 2012, Pew's Associate Director of Digital Strategy, Susannah Fox, labeled this emerging trend as "peer-to-peer health-care" [2]. While social media provides an opportunity for people to connect with health professionals and peers with similar health concerns, little is known about how to help people use online social networks to build a community that supports their health endeavors.

Users of weight loss-specific online social networks report receiving strong social support for their weight loss [3, 4]. General social media sites like Twitter are also being used to garner social support for weight management [5]. One study surveyed Twitter users who use it to discuss their weight loss journey and found that they rated their Twitter connections to be a greater source of weight loss social support than their in-person friends and family [5]. Information sharing and social support were the two most commonly cited benefits of using Twitter during a weight loss attempt [5]. The advantage of using general online social networks to find support for a health behavior change is that such networks can be used for a wide variety of social networking activities (e.g., socializing, following news, and other interests) which can reinforce a user's online presence even when motivation for health behavior change wanes.

People trying to lose weight may want to follow and interact with both peers and health care professionals on Twitter for health information and support. Health care professionals are increasingly using Twitter as a way to educate the public about their science and to network with colleagues [6]. In one study, 42 % of practicing physicians and 79 % of resident physicians say they use social media for professional purposes [7]. A 2015 Pew survey found that scientists are using Twitter more often to disseminate health information to the lay public (37 %) than to other scientists (16 %) [8]. Given Twitter is a public network, and more health care professionals use Twitter to disseminate health information to the public, as opposed to use it as a platform to advise or counsel patients [9]. Despite the increased use of social media among professionals to communicate with the public, little data exists on the extent to which they follow and interact with members of the public who are seeking health information on Twitter.

In clinical settings, health care and fitness professionals have been shown to exhibit weight bias [10–12] toward patients with obesity [13]. Weight bias undermines quality of care [14] and creates barriers to treatment utilization for people with obesity [15, 16]. It is unknown if implicit weight bias is conveyed by health care professionals and/or peers on Twitter toward people with obesity, as evidenced by lower rates of follow backs (i.e., getting followed back by accounts you follow) and interactions (i.e., mentions and "likes") for users with obesity compared to users who are not obese. This type of weight bias could discourage engagement in social media for weight management.

Discussing weight loss in an online social network may also lead to negative experiences, given the potential for negativity and stigmatizing language [17, 18]. The quality of the user's connections is important. One study showed that people trying to lose weight felt their Facebook friends were less supportive relative to their Twitter connections, were more judgmental about their weight, and more likely to perceive accomplishments as bragging [5]. Twitter may provide more opportunities to find supportive connections for weight loss specifically given that connections on Twitter are typically made based on shared interests. Facebook connections, on the other hand, are based on a previously existing relationship, and depending on the nature of the connection, they may or may not welcome being exposed to frequent posts about a friend's weight loss journey [5]. For this reason, patient communities appear to be flourishing on "interest-based" social networks like Twitter. The Healthcare Hashtag Project has curated 1.4 billion tweets on over 17,500 health-related topics on Twitter [19]. However, little is known about how difficult it is for a newcomer to a social media platform like Twitter to find a supportive community to support her weight loss attempt.

The present study was designed to mimic the experience of new users joining Twitter for the purpose of seeking weight loss support. The primary aim was to examine and compare the extent to which new Twitter users of different weight statuses whose profiles reveal an interest in weight loss receive follow backs and interactions from health care professionals and peers. Given that some health care professionals express concern about engaging with nonprofessional users in online social networks [20], the research team hypothesized that health care professionals would be less likely to follow back and interact with users relative to peers. Our secondary aim was to examine whether listing an obese weight in the user's profile is associated with a lower rate of follow backs and interactions than when the weight listed was not obese. Third, we examined whether following back organic followers preserved the followership of the study accounts.

Methods

Procedures

The research team created four Twitter profiles of women who each mentioned their current weight and an interest in losing weight in their bios (Fig. 1). All profiles depicted women because women are more likely to use online social networks for weight-related support [5] and they are more often the recipients of weight stigma [21]. Profile pictures were either of a pet or a woman with characteristics of a typical of individuals who reported tweeting about their weight loss in a previous study (e.g., white woman in her 30s) [5]. Women also identified as moms, given their high social media use [22] and many challenges they face to in-person participation in lifestyle interventions [23–26]. Study accounts varied by weight category: normal weight/overweight for women of most heights (i.e., between 5′1″ and 6′4″: 155 and 158 lbs) versus obese for women of most heights (i.e., under 6′5″; 257 and 263 lbs). Weights were varied to avoid identical profile content which may raise suspicions among other Twitter users that these were spam accounts. Spam accounts commonly have numerous identical accounts that have automated content that is often used for marketing [27]. The username for the profiles included a term related to a weight loss journey (@Amyloseit, @clarabfit, @startingover39, @fit_laurie). The University of Massachusetts Medical School Institutional Review Board approved this study.

In phase 1, each of the four study accounts were to follow 60 health care professional accounts and in phase 2, each followed 60 peer accounts. In each phase, the study accounts followed professional/peer accounts in a staggered rather than simultaneous fashion in order to minimize being perceived as spam. Each study account started following professional or peer accounts (depending on the phase) 4 weeks apart and followed 20 accounts per week until 60 accounts were followed, a process that took 3 weeks. Study accounts were active for a total of 5 weeks and followed the professional or peer accounts for an average of 4 weeks (range 3–5 weeks). Each study account followed the professional or peer accounts in a different order as determined via the random order function in SPSS (Version 21.0, Armonk, NY). On Twitter, when a user follows another account, tweets from that account will appear in his/her home feed. Users may follow back other users if they find their tweets of interest [28]. The research team collected data on interactions including "mentions" (tweets that include a reference to a user and are used to interact with an individual user directly; either replies or retweets of the user's content) and "likes" (public acknowledgments of "liking" the user's tweet).

Accounts followed

Professionals–The professional accounts followed included nutrition and/or fitness professionals with an interest in weight management. Eligibility criteria for the professional accounts included the following: (1) accounts publicly viewable, (2) following at least 200 others to insure they are experienced and engaged users, (3) following no more than 7000 users because

Fig. 1 | Study account Twitter profile pictures and bios

this user would have a highly populated feed and thus less likely to see our account's tweets, (4) have a follower to following ratio of no greater than 2:1 to insure a fair chance of a follow back and exclude users who do not tend to follow many others back (a follower to following ratio of 2 indicates that twice as many accounts follow the health care professional than the number of accounts the health care professional follows), (5) tweets at least 5 out of 7 days over the last week to insure accounts were likely to be active during the study period, (6) and at least 7 of the last 10 tweets related to weight or health in general to insure relevance. Eligible professional accounts had to indicate in their profile bio that they were health care professionals with a background in obesity, nutrition, and/or exercise. Specifically, the professional Twitter accounts were nutrition ($N = 37$; dietitians and nutritionists) or exercise professionals ($N = 23$; exercise physiologists, and Certified Strength and Conditioning Specialists). Searches for professionals were performed in January 2014 via the Twitter search bar and selecting the option for "people" results. Search keywords for professional accounts included the following: "dietitian," "nutritionist," "RD" (registered dietitian), "personal trainer," "exercise physiologist," "CSCS" (Certified Strength and Conditioning Specialist), "psychologist and obesity," "obesity and physician," and "obesity specialist."

The research team reviewed 316 professional accounts to identify 60 eligible professional accounts to follow. Accounts were ineligible because content of tweets was not relevant ($N = 131$; 51 %), the ratio of followers to following was greater than 2 to 1 ($N = 123$; 48 %), not tweeting at least 5 of the past 7 days ($N = 122$; 47 %), had too many followers ($N = 28$; 11 %), had too few followers ($N = 18$; 7 %), the tweets were not in English ($N = 5$; 2 %), or the account was private ($N = 1$; 0.3 %); 52.8 % ($n = 133$) accounts were ineligible for more than one reason. Professional accounts meeting inclusion criteria had a median followers to following ratio of 1.1 (interquartile range 0.8–1.5; Table 1). Across professional accounts, a median 9 out of their 10 previous tweets were related to health or weight (interquartile range 8–10; range 7–10). The professional Twitter accounts included 61.7 % nutrition ($N = 37$; dietitians/nutritionists) and/or 38.3 % exercise professionals ($N = 23$; exercise physiologists, Certified Clinical Exercise Specialist, and Certified Strength and Conditioning Specialists). Two professional Twitter accounts were deactivated during the study period, resulting in two of our study accounts following 59 professional accounts and the other two study accounts following 58 professional accounts.

Peers–Eligibility criteria for the peer accounts included the following: (1) accounts publicly viewable, (2) following at least 200 others to insure they are

Table 1 | Characteristics of professional and peer Twitter accounts followed by the study accounts, median (interquartile range); range

	Professional accounts ($N = 60$)	Peer accounts ($N = 60$)
Number of followers	1236 (573–2748); 142–6954	621.5 (403–1327.5); 217–6640
Number of following	1293 (642.5–2003); 234–4158	899.5 (554–1674.5); 157–6803
Ratio of followers to following	1.1 (0.8–1.5); 0.4–2.0	0.9 (0.5–1.2); 0.2–2.0

experienced and engaged users, (3) following no more than 7000 users because this would create a highly populated feed for the user who might then not see our account's tweets, (4) have a follower to following ratio of no greater than 2:1 to insure a fair chance of a follow back and exclude users who do not tend to follow many others back, and (5) tweets at least 5 out of 7 days over the last week to insure accounts were likely to be active during the study period. Anyone listing health care professional backgrounds in nutrition and/or exercise or being fitness blogger was excluded for the peer accounts because they may have a level of professionalism above what a typical peer would have. Searches were performed in September 2014 via the Twitter search bar and selecting the option for "people" results. Search keywords for the peer accounts included the following: "battling with weight," "determined to lose weight," "dropping pounds," "eat right exercise," "exercise and diet," "getting healthy," "lbs lost," "lbs to lose," "lose weight," "losing pounds," "must lose weight," "need to lose weight," "too fat," "trying to diet," "trying to eat healthy," "trying to get fit," "trying to get in shape," "trying to lose weight," "weight loss goal," "weight battle," "weight loss," "weight loss adventure," "weight loss attempt," "weight loss blogger," "weight loss journey," and "Weight Watchers." Some search terms originated from eligible profiles (e.g., "battling with weight") and then used to find similar profiles.

The research team reviewed 190 accounts in January 2015 to identify 60 eligible peer accounts to follow. Accounts were ineligible because they did not tweet 5 out of the last 7 days ($N = 98$; 76 %), the ratio of followers to following was greater than 2:1 ($N = 32$; 25 %), had too few followers ($N = 18$; 14 %), had too many followers ($N = 12$; 9 %), was a fitness blogger or professional account ($N = 6$; 5 %); 28 % ($n = 36$) were ineligible for more than one reason. Peer accounts meeting inclusion criteria had a median followers to following ratio of 0.9 (interquartile range 0.5–1.2; Table 1). Many of the 60 eligible peer accounts were found using the search terms "weight loss journey" ($N = 14$; 23 %) or "Weight Watchers" ($N = 14$; 23 %). The remaining eligible accounts ($N = 32$; 53.3 %) came from other search terms including "weight loss," "lose weight," "weight battle," "weight loss blogger," "trying to lose weight," "lbs to lose," "lbs lost," "getting healthy," "trying to get fit," "trying to get in shape," "trying to diet," "weight loss attempt," and "battling with weight." Each of the aforementioned search terms yielded few accounts (5 for less) per search.

Study account activity

In each phase, each study account made two tweets per day about their weight loss journey so that the account would appear to be a real woman trying to lose weight. These tweets provided content to elicit interaction. The content and number of tweets were the same for each account but delivered in random order. The content of the tweets was based on the content in tweets posted by Twitter users who tweet about their weight loss in our previous research, 80 % of whom were female [5]. Examples of the study accounts' tweets included the following: "Back pain! No exercise today," "Hiked today. Felt great!," "Ugh! Husband brought home doughnuts!" Tweets were programmed using a software program called Hootsuite, which schedules and posts content for a preset time [29]. The tweets were modified to adjust for seasons, holidays, and location. Specific details in a tweet were varied for each study account (e.g., one account reported walking 8010 steps while another account reported walking 9838 steps) to avoid identical tweet content again to avoid suspicions that these were spam accounts. In both phases, the study accounts kept the same bios, used the same tweets, and tweets were posted in the same order according to the same schedule.

In phase one, each study account acknowledged interactions initiated by professional accounts by "liking" the tweets and tweeted "thanks for the follow!" to those who followed back. Study accounts also followed back organic followers (i.e., Twitter users who spontaneously followed the study accounts), and tweeted "thanks for the follow!" to these followers. In phase two, each study account acknowledged interactions initiated by peer accounts by "liking" the tweets and tweeted "thanks for the follow!" to those who followed back. However, study accounts did not follow back organic followers in phase two. However, the study accounts did tweet "thanks for the follow!" to these organic followers. In neither phase did study accounts initiate interactions with any of the followed accounts.

Measures

Research staff checked each study account daily for the 5 weeks; each study account was active and logged all account activity. An archive of tweets was kept for each account. Once the data collection period ended, the accounts were permanently deleted.

Follow backs

The research team logged into each of the study accounts daily and recorded "follow backs," i.e., the accounts that followed the study accounts. We calculated the percentage of professional and peer accounts that followed back each study account.

Interactions

The research team logged into each of the study accounts daily and tracked tweets that mentioned the study account (i.e., mentions), and any time an account liked one of study account's tweets (i.e., likes). We recorded mentions and likes by followed professional and peer accounts versus other Twitter users. In each phase of the study and for each study account, we summed the number of mentions and likes to obtain the number of interactions, both overall and for type of account (followed professionals or peers versus other Twitter users).

Organic follows

The research team recorded when other Twitter accounts followed the study accounts (i.e., organic follows), and when any of these organic followers subsequently stopped following (i.e., unfollowed) the study accounts. We calculated the percentage of organic followers who subsequently unfollowed the study accounts.

Statistical analyses

Characteristics of professional and peer accounts followed by the study accounts were summarized by their median, interquartile range (IQR), and range. Follow back rates were calculated as the number of accounts (professionals or peers, depending on the phase of the study) that followed back the study accounts divided by the total number of test accounts followed. Paired t tests were used to compare follow back rates and number of interactions by study phase (professional versus peer). We also compared the percent of organic followers who subsequently unfollowed the study accounts by study phase (professional versus peer) using paired t tests. Independent sample t tests were used to compare the follow back rates, number of interactions, and number of organic followers by weight category (normal/overweight versus obese), within each phase of the study. Statistical analyses were conducted using SAS 9.3 (SAS Institute, Cary, NC).

Results

Professional vs peer accounts

Follow back rates from professional accounts (M[SD] 8.9 % [4.1 %]) were not different from peer accounts (M[SD] 8.8 % [2.8 %], $t(3) = 0.06$, $p = 0.9568$; Table 2). When the study accounts followed health care professionals, they experienced an average of 6.0 (SD 3.2) interactions from these followed accounts or others on Twitter, and when the study accounts followed peers, they experienced an average of 13.0 (SD 5.8) interactions from these followed accounts or others on Twitter ($t(3) = -3.93$, $p = 0.0293$; Table 2). Specifically, study accounts received more interactions from peers they followed (M[SD] 8.5[3.0]) than from professionals they followed (M[SD] 4.0 [2.4]; $t(3) = -5.20$, $p = 0.0138$). The number of interactions from others on Twitter (i.e., accounts other than those peers or professionals followed) did not differ (M[SD] 4.5 [3.3] interactions when study accounts followed peers vs 2.0 [1.4] when they followed professionals; $t(3) = -1.61$, $p = 0.2062$).

Study accounts did not attract more organic followers when they followed health care professionals compared to when they followed peers (M[SD] 4.5 [2.6] organic followers in professional phase vs 7.3 [3.0] organic followers in peer phase, $t(3) = -1.10$, $p = 0.3510$; Table 2). However, a higher proportion of organic followers subsequently unfollowed the study accounts when study accounts followed peers (M[SD] 63.0 % [9.6 %]), when study accounts did not routinely follow back organic followers, compared to when study accounts followed professionals and did follow back organic followers (M[SD] 15.6 % [23.7 %]; $t(3) = -3.75$, $p = 0.0331$; Table 2).

Weight status

The proportion of professional accounts who followed back the study accounts did not differ by weight status (M[SD] 11.0 % [3.3 %] for study accounts with obesity vs 6.8 % [1.2 %] for study accounts who were normal weight/overweight; $t(2) = 1.02$, $p = 0.4167$; Table 2). Similarly, the proportion of peer accounts who followed back the study accounts did not differ by weight status (M[SD] 10.8 % [1.2 %] for accounts with obesity vs 6.7 % [2.4 %] for accounts who were normal weight/overweight, $t(2) = 2.24$, $p = 0.1548$). The number of interactions experienced by study accounts did not differ by weight status when they followed professional accounts (M[SD] 7.0 [4.2] for accounts with obesity vs 5.0 [2.8] for accounts who were normal weight/overweight, $t(2) = 0.55$, $p = 0.6349$) or when they followed peer accounts (M[SD] 16.5 [3.5] for accounts with obesity vs 9.5 [6.4] for accounts who were normal weight/overweight, $t(2) = 1.36$, $p = 0.3069$).

The number of organic followers did not differ by weight status in either study phase. When following health care professionals, study accounts with obesity had an average of 5.5 (SD 3.5) organic followers compared to an average of 3.5 (SD 2.1) for accounts who were normal weight/overweight, $t(2) = 0.69$, $p = 0.5636$. When following peers, study accounts with obesity had an average of 8.5 (SD 3.5) organic followers compared to an average of 6.0 (SD 2.8) organic followers for accounts who were normal weight/overweight ($t(2) = 0.78$, $p = 0.5166$).

Discussion

In this study, less than 10 % of health care professional and peer accounts followed back the study accounts,

Table 2 | Follow backs, organic followers, and interactions when following professional and peer Twitter accounts, by weight category of study accounts

	Amy (obese)	Rachel (obese)	Clara (normal weight/ overweight)	Laurie (normal weight/ overweight)
Professional accounts				
Follow backs, *n* (%)	8 (13)	5 (9)	6 (10)	2 (3)
Organic followers, *n*	8	3	2	5
Organic followers who subsequently unfollowed the study account, *n* (%)	1 (13)	0 (0)	1 (50)	0 (0)
Total interactions, *n*	10	4	7	3
Mentions	5	1	4	0
Likes	5	3	3	3
Peer accounts				
Follow backs, *n* (%)	6 (10)	7 (12)	3 (5)	5 (8)
Organic followers, *n*	6	11	8	4
Organic followers who subsequently unfollowed the study account, *n* (%)	4 (67)	8 (73)	5 (63)	2 (50)
Total interactions, *n*	19	14	14	5
Mentions	11	9	10	3
Likes	8	5	4	2

with no differences between professional and peer accounts. Study accounts experienced more interactions when they followed peers compared to when they followed health care professionals. We did not observe a difference in follow backs rates, interactions, or organic followers by study accounts' weight status. Organic followers did not differ when study accounts followed health care professionals versus peers, although a significantly higher percent of organic followers subsequently unfollowed the study accounts when study accounts did not routinely follow them back.

While both health care professional and peer accounts were selected because they were followed by no more than twice as many accounts as they were following, the majority did not follow back. One possible reason is that the study accounts did not initiate interactions with the professionals or peers they followed. It may be that women seeking weight loss support on Twitter would attract more followers by initiating interactions with the people they follow. Interaction may beget interaction, thus future studies should explore what level of interaction is necessary to quickly build a community on Twitter. Greater interaction about weight loss may also lead to more weight loss. One study found that for every ten posts in a Twitter weight loss group, participants lost approximately 0.5 % of their bodyweight [30]. Moreover, people who tweeted about their weight loss attempt rated their Twitter connections to be a greater source of positive social influence than their offline friends and family [5].

We found that study accounts experienced more interactions when they followed peers than when they followed health care professionals, and specifically, that study accounts experienced more interactions from peers they followed than the health care professionals they followed. Greater interaction by peer accounts may be because peers share a goal of weight loss. Professionals may be hesitant to interact with the nonprofessional user population for fear of being asked for advice which could put them in an uncomfortable position [20]. Professionals have been shown to be more likely to network with their colleagues in social media rather than with nonprofessionals [9, 20]. Although health care professionals interacted less with the study accounts than peers, it does not mean following health care professionals is not useful. People interested in weight loss may benefit from following health care professionals to gain access to evidence-based health information that many professionals tweet. The study accounts may have received more interactions if they posted more weight-related posts. These types of posts have been shown to garner more interactions from other users [31].

It is encouraging that we did not observe any weight bias in follow back rates, number of interactions, or number of organic followers when study accounts followed professionals or peers. In fact, while not statistically significant, study accounts describing a woman with obesity appeared to attract more organic followers than study accounts depicting a woman of normal weight/overweight. Although we found no evidence of weight bias, this does not necessarily imply weight bias does not exist on Twitter. One study found derogatory and stigmatizing language regarding obesity was more prevalent on Twitter than blogs or forums [17]. Research is needed to explore how individuals who are obese experience or perceive weight bias on social media, identify who is the conveyer of this bias, and study how it affects participation and weight loss motivation. Women seeking weight loss support on Twitter are encouraged to review the recent tweets of potential follows before following them to identify users that may use biased or upsetting language and unfollow and/or block users who use stigmatizing language.

By design, study accounts followed back any organic followers when they followed professionals but did not follow back organic followers when they followed peers. While the number of organic followers did not differ by study phase, the proportion of organic followers who subsequently unfollowed the study accounts was significantly higher when organic followers were not routinely followed back: 63 % versus 16 %. These findings suggest that following back interesting followers may be one strategy to grow a support network on Twitter.

This study has limitations. First, the research team created only four profiles, limiting our power for statistical comparison. Creating a large number of similar profiles over a period of a few weeks could be perceived as suspicious, as this pattern of use is a characteristic of spam accounts on Twitter. While the research team attempted to make the study accounts as realistic as possible, it is impossible to know how they were perceived. Study accounts did not initiate interactions to conservatively mimic the behavior of a woman new to Twitter; as in our previous research, participants who had no experience using online social networks for weight loss support reported not being sure what to tweet about initially [32]. Initiating interactions with others may be helpful for growing a supportive community for weight loss on Twitter. We followed only professional and peer accounts with between 200 and 7000 followers who had a follower to following ratio of no greater than 2:1. Few physicians were eligible, typically due to high ratios of followers to following, and thus our results may not reflect interactions with many physicians and nurses, limiting generalizability. Finally, the bios of all four study accounts described themselves as "moms" and the two headshot profile pictures were of women appearing white. It is unknown whether a similar pattern of follow backs and interactions would be experienced by men, women without children, or of other races/ethnicities seeking weight loss support on Twitter.

Conclusion

Women interested in building a weight loss community on Twitter may initially experience low rates of follow backs and interactions by both health care professionals and peers if they do not interact with their followers. Building a supportive community may require more than a few weeks, following a large number of people, and routinely following back interesting organic follows. The effort may be worth it given the lack of cost and high rate of social support and weight loss reported by people who use Twitter to discuss their weight loss journey [5, 30]. Initiating interactions with peers and health care professionals may also be a key to establishing a supportive community for weight loss. Given research showing the benefits of using online social networks for weight loss social support [3–5], users may need guidance on how to find and build an engaging community. Research is needed to understand how patient communities form on Twitter and to explore ways to facilitate their growth.

Compliance with ethical standards

Conflict of interest: Dr. Pagoto has received speaking fees from Apple and Weight Watchers. She is on the advisory board for American Council on Exercise. The authors have no other conflicts of interest to disclose.
The findings reported have not been previously published and the manuscript is not being simultaneously submitted elsewhere. Data have not been previously reported.
Authors have full control of all primary data and agree to allow the journal to review the data if requested.

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Human and animal rights and informed consent: There were no animals used in this study.
Informed consent was not needed because all data were abstracted from a public domain, Twitter.
This work has been performed in accordance with the ethical standards laid down in the Declaration of Helsinki and its revisions.
Procedures of this study were approved and complied with the ethical standards of the institutional review board at the University of Massachusetts Medical School.

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