Fat-Burning Or Fat-Shaming? Theme And Community Overlap Between Online Weight-Stigmatizing And Exercise-Promoting Networks.

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Abstract

Purpose: This study aimed to determine if networks of users consistently posting about exercise and fat exist and overlap on social media sites.

Method: We collected 1,971,207 English-language posts from 1,446,630 Twitter users that included the words “fat” and “exercise”. Using network structure methods, we identified communities of interconnected users and overlaps between those tweeting “fat” and those tweeting “exercise”.

Results: Common word pairings were identified using Natural Language Processing (NLP). Networks of users consistently talking about exercise (n=3,573) and fat (n=2,007) were found on Twitter. An increased mean total-degree and reduced average path length indicate that the fitness-talk network serves as a connecting bridge between highly scattered communities of the weight-talk network.

Conclusion: We identified groups on Twitter that consistently produce weight stigmatizing content and promote exercise with weight-loss messages. These groups partially overlap with pro-health groups which could lead to users looking for exercise advice in Twitter to find themselves immersed in a stigmatizing network.

Level of evidence:

What Is Already Known On This Subject?

Current research has shown that weight stigmatizing content is pervasive in social networking sites with negative consequences to their users. Most of the content revolves around weight loss and personal contributors to weight.

What does this study add?

This study adds to existing knowledge in three important ways: (1) it determined the existence of a community that consistently produces weight stigmatizing content within the weight-talk network, (2) it showed partial overlap between fitness-talk and weight-talk communities on Twitter, and (3) it confirmed previous findings regarding the content of communications within and between these communities.

Introduction

Posts and messages concerning weight, obesity and higher weight individuals are common in social networking sites (SNS). The words “fat” and “obesity” appear most commonly on Twitter [1]. In those posts the word “fat” is by far the most common [1], with a particularly negative connotation. For example, one study found that 56% of the messages containing the word “fat” were explicitly negative towards higher weight individuals [2]. This suggests the presence of weight stigma, the pervasive social devaluation and denigration of higher-weight people, on SNS which may be problematic given that weight stigma is related to unhealthy behaviors, such as high calorie intake, binge eating, and physical inactivity [3].

Communities promoting weight loss online do so while overlapping with those promoting fitness [4, 5], which means that users looking for information related to healthy exercise habits might inadvertently end up receiving stigmatizing content. This could happen because weight loss messages are common within Twitter stigmatizing communications [2]. Alternatively, the word “fat” works both as an adjective with a negative connotation (i.e., fat person), and as a noun that is commonly associated with exercise (i.e., burn fat), which could result in a bundling together of both concepts by Twitter’s recommendation algorithm. Finally, there is large body of research suggesting that individuals have an inaccurate understanding of physical activity, mainly reducing it to weight loss and appearance change [6], which could result in an overlap between stigmatizing and fitness promoting content.

The focus on weight when promoting exercise could be particularly prejudicial if higher weight users are the ones searching for exercise-related information. Indeed, these users could be exposed to stigmatizing content if there is an overlap in themes and users. Departing from previous research that has thus far mostly focused on the content of social media posts. This study aimed to determine if networks of users consistently talking about exercise and fat exist on Twitter (objective 1). Assuming they do, we hypothesized that they overlap (objective 2), and that, in accordance with previous findings, the content of their communications will be negative, or weight loss-related (objective 3).

Methods

Data collection

Data were collected using Twitter’s Application Programming Interface (API), a web-based program that allows users to interact with Twitter’s data (i.e., tweets and metadata). This allowed for keyword searches of all tweets containing the words “exercise” and/or “fat”. These searches were implemented daily over a period of 3 months (November 2017 to February 2018). Each daily search provided the most recent tweets of the day (up-to 50,000).

Community structure and overlap

In order to determine if networks of users consistently talking about exercise and fat exist on Twitter (objective 1) users who tweeted at least once a week about “fat” or “exercise” were assigned to a core group, while those who only tweeted once in three months about “fat” or “exercise” were assigned to the visiting group, a threshold similar to previous studies looking at core and visiting communities [7]. To identify users who consistently talk about weight or exercise, only users who tweeted at least once a week for the duration of data collection were included in the study.

In twitter users can follow another user, creating a link (e.g., A à B). In A à B, user A has an out-degree of 1 (because it follows B) and user B has an in-degree of 1 (because it is followed by A). In social networks, the direction of the arrow typically represents information flow, but in the case of Twitter the relationship is inversed because users follow other users to see the content they publicly post, not to send direct information. In short, if user A follows user B (A à B), user A is seeing information posted by user B.

Users with a large following within the network have a high in-degree, while users following a large number of users within the network have a high out-degree, with the sum of both hereby rereferred to as total-degree. Additionally, within the social network, communities can emerge [8]. These communities are composed of users with more connections among them but fewer connections to users outside the community which may themselves be part of different communities.

Relationships between users were mapped to allow for social network analysis and to determine network structure. The relationships were then filtered to only include relationships within the core group. Using these relationships, a core weight-talk network and a fitness-talk network were mapped. Additionally, to determine if there is an overlap between weight-talk and fitness-talk communities, a combined network was mapped, and the metrics of this network compared to the previous ones.

To answer questions regarding structure and overlap (objective 2), four standard network metrics were used: density, average path length, mean total-degree, and clustering coefficient. Density measures how many connections exist in the network and ranges from zero (no connections) to one (all possible connections exist). Average path length refers to the average shortest paths between two users and is important because it indicates how far in average, information has to travel to reach from one user to another. Mean total-degree refers to the average number of connections per user and is useful for determining how well connected a network is. Finally, clustering coefficient is a measure of the extent to which users in a network tend to cluster together, which allows us to understand the network structure in reference to its communities.

Additionally, modularity was calculated within the network. This is the identification of communities within a network based on the similarities between their connections. It was done using the fast unfolding of communities in large networks algorithm [8]. This algorithm decomposes the networks into sub-units or communities, which are sets of highly inter-connected users. Four main communities per network were extracted. Hubs were found by ranking the users based on their in-degree. This allowed for a linguistic corpus analysis based on the communities of each network.

Linguistic corpus

The linguistic corpus is the whole set of text data (tweets) to be analyzed. Simple Natural Language Processing (NLP) techniques like the division of sentences into individual words (tokenization) and their subsequent analyses in duos or triplets (n-grams) were used to analyze these data. Latent Dirichlet Allocation (LDA), which allows for the grouping of observations (words) to be explained by unobserved groups (themes), was also used. A total of 3,772,507 tweets were collected, however out of those, non-English-language tweets (n=510,145) and tweets from people that were not in the core or visiting categories (n=1,291,155) were removed. As a result, the total corpus was reduced to 1,971,207 English-language tweets.

Linguistic n-grams

In order to confirm that the communicational content of the weight-talk and fitness-talk network is explicitly negative, or weight loss related (objective 3) the tweets were divided into the four main communities of each core social network. Finally, a Latent Dirichlet Allocation (LDA) model was applied to differentiate individual unobserved clusters of words, which allowed for a qualitative lexical text analysis and extraction of common themes within the communities.

Results

Network characteristics

The weight-talk and fitness-talk networks were similar in size, both in its core (N_{fat}=2,007; $N_{exercise}$=3,573) and visiting forms (N_{fat}=737,102; $N_{exercise}$=703,948). The number of tweets, however, was smaller in the core weight-talk network. A total of 3,573 users consistently use their accounts as a way to communicate about exercise, while 2,007 use them for “fat” related communication, indicating the existence of communities that consistently produce thematic content within the networks. The number of users and tweets in the visiting and core networks, as well as the four main communities, are described in Table 1.

Network structure

The mean total-degree is larger in the fitness-talk network (13.40) than in the weight-talk one (5.54) indicating that the fitness-talk network users are more connected overall, which makes the average path length smaller (3.79 for the fitness-talk, and 6.02 for the weight-talk network). Despite of this inter-user connectivity, communities within the weight-talk network are scattered, this means that users cluster together into well connected communities that appear to have well defined themes of conversation that don't have much contact with other communities through friends or followers. The communities within the networks, however, seem to be more clustered together in the weight-talk network (0.17) than in the fitness-talk one (0.093), creating a divided network with a larger diameter (24 compared to 16).

Overlap between networks

A small percentage (7.6%) of users are in both networks. The mean total-degree of the combined network (12.91) is larger than the averaging of the means of the individual networks (9.71). The average path length (4.31), and the clustering coefficient (0.107) for the combined network drop below the averages of both individual networks, while the diameter is widely reduced from the weight-talk network. This could indicate that the users in the fitness-talk network serve as a connecting bridge between highly scattered communities of the weight-talk network. Table 1 shows descriptions of the networks.

Content of communications

To understand the overall content of each group, the tweets were divided into individual words (tokenization), pairs of words (bigrams) or triplets of words (trigrams). Table 2 provides a comparison of the bigrams found in the tweets of the four larges communities of each network. The lists that the main themes of the three largest communities of the fitness-talk network are fitness and health-related. The fourth community uses the word "exercise" in other contexts. The weight-talk network on the other hand, has different themes within each community. The largest one mainly tweets about fat in the context of exercise and weight loss, the second community is mainly concerned with insults, the third one appears to be related to eating and self-directed stigmatization, and the fourth community describes porn. Further analysis of the tweets with full examples can be found in the supplementary materials.

Discussion

The belief that health can be achieved through weight loss reduction behaviors such as physical activity seems to be common [6]. This study aimed to test this overlap within Twitter communities that mainly shared and produced content relating to weight and fitness by posing three important questions: Are there communities of users consistently discussing "fat" and "exercise" online? If so, do this communities overlap? and what are the themes of these communities? Results corroborated the existence of a large core network of users tweeting about fitness or weight at least once per week. Dense and highly clustered communities were found within the individual networks with the communities in the weight-talk network mainly focusing on weight loss, stigmatization, and internalized stigma, and communities in the fitness-talk network focusing on exercise for health and exercise for fitness. While the geodesic distance in the fitness-talk network was higher than that of the weight-talk network, the clustering coefficient was not. This corroborates previous findings that weight-loss promoting communities are more closely knitted together than pro-health ones [4]. It is also in line with research that has found that health-promoting tweets focus on nutrition and exercise, while pro-thinness ones focus on thinness and disordered eating behaviors [5]. The combination of both networks showed a mild overlap between them. This is consistent with previous studies showing the prevalence of pro-thin type communications among weight-talk networks in Twitter [1, 2]. Given that the Twitter algorithm recommends people whom the user is most likely to interact with, this could create an ever-growing community of bias. On the other hand, there could be an ingrained association between exercise and weight loss, through concepts like "fat-burning" [6]. This, in turn, might lead to people looking for pro-health advice to find themselves within a stigmatizing network. Finally, this study examined what people were tweeting and sharing about fat and exercise. We found that the networks were not only divided as a function of their interconnectivity, but also by their topics. In the case of the fitness-talk network, fitness and health-related exercise tweets were found to be the most common reasons for practicing physical activity. Other topics were more generic and unrelated to physical activity, like English learning and politics. In the weight-talk network, on the other hand, the most popular topics were weight loss-related tweets. This resembled previous findings where weight loss was a common theme of Twitter [2]. The second most common category of tweets in the weight-talk network was explicit weight stigmatization, confirming previous findings [1, 2]. Internalized stigma tweets, which is to say tweets making explicit self-directed stigmatizing comments, were found in a specific sub-cluster that also happens to house pro-anorexia accounts. Apart from the direct descriptive implications of the study, the results can be framed within the broader theoretical framework of Group Norms Theory [9], which states that intergroup attitudes and behaviors are strongly influenced by representatives of psychologically valued "reference" groups. The weight-talk network in particular is shown to have clustered communities within it. These communities have explicitly stigmatizing messages and pro-thinness communications that could arise contagion of these sorts of attitudes. This has a wide array of public health implications. Understanding the transfer and propagation of stigma could help in the design of campaigns directed at prevention (i.e., via information), inoculation (i.e., coping mechanisms), and intervention of stigmatizing attitudes in a large-scale fashion. Specifically, individual targeting to the hubs that are shared in both networks could result in a reframing of the health and exercise promotion communications [10]. Another important alternative to consider is the targeting of subcommunities, like the pro-thinness one in the weight-talk network or the pro-health one in the

fitness-talk network, to try and change the rhetoric of the communications [10]. While this study has described the structure and themes of weight and fitness networks on Twitter, some important questions still remain about the influence of the content posted in Twitter on in other user's levels of physical activity, as well as the predictive capacity of the textual content produced by the users over their weight stigma attitudes or physical activity habits. Future research could address these limitations by looking at egocentric networks and content produced by individuals with known levels of weight stigma (i.e. through pre-screening). This study adds to existing knowledge in three important ways: (1) it determined the existence of a community that consistently produces weight stigmatizing content within the weight-talk network, (2) it showed partial overlap between fitness-talk and weight-talk communities on Twitter, and (3) it confirmed previous findings regarding the content of communications within and between these communities. Strength and limits This study expanded the current literature by looking at structure and content within communities in social media using a large sample of both tweets and users and made use of innovative techniques like natural language processing. However it has some important limitations that need to be addressed in the future. Firstly, because of the size of the linguistic corpus, the thematic analysis was made using automated techniques and not by expert classification like previous research [2]. Another important limitation is the predictive capacity of the textual content produced by the users over their weight stigma attitudes or physical activity habits, since they could be uncorrelated. Future research could address these limitations by looking at egocentric networks and content produced by individuals with known levels of weight stigma (i.e. through pre-screening).

Declarations

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Conflicts of interest/Competing interests: The authors declase no conflict of interests.

Availability of data and material: Data is available upon request.

Code availability: Code is avialbale upon request.

References

1. Chou WS, Prestin A, Kunath S (2014) Obesity in social media: a mixed methods analysis. Transl Behav Med 4:314–323. https://doi.org/10.1007/s13142-014-0256-1
2. Lydecker JA, Cotter EW, Palmberg AA et al (2016) Does this Tweet make me look fat? A content analysis of weight stigma on Twitter. Eat Weight Disord - Stud Anorex Bulim Obes 21:229–235. https://doi.org/10.1007/s40519-016-0272-x
3. Tomiyama AJ, Carr D, Granberg EM et al (2018) How and why weight stigma drives the obesity 'epidemic' and harms health. BMC Med 16:123. https://doi.org/10.1186/s12916-018-1116-5
4. Tiggemann M, Churches O, Mitchell L, Brown Z (2018) Tweeting weight loss: A comparison of #thinspiration and #fitspiration communities on Twitter. Body Image 25:133–138. https://doi.org/10.1016/j.bodyim.2018.03.002
5. Harris JK, Duncan A, Men V et al (2018) Messengers and Messages for Tweets That Used #thinspo and #fitspo Hashtags in 2016. Prev Chronic Dis 15. https://doi.org/10.5888/pcd15.170309
6. Harris J, Cale L, Duncombe R, Musson H (2018) Young people's knowledge and understanding of health, fitness and physical activity: issues, divides and dilemmas. Sport Educ Soc 23:407–420. https://doi.org/10.1080/13573322.2016.1228047
7. Himelboim I, Han JY (2014) Cancer Talk on Twitter: Community Structure and Information Sources in Breast and Prostate Cancer Social Networks. J Health Commun 19:210–225. https://doi.org/10.1080/10810730.2013.811321
8. Blondel VD, Guillaume J-L, Lambiotte R, Lefebvre E (2008) Fast unfolding of communities in large networks. J Stat Mech Theory Exp 2008:P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008
9. Crandall CS, Eshleman A (2003) A justification-suppression model of the expression and experience of prejudice. Psychol Bull 129:414–446. https://doi.org/10.1037/0033-2909.129.3.414
10. Valente TW (2012) Network Interventions. Science 337:49–53. https://doi.org/10.1126/science.1217330

Tables

Table 1. Number of users and posts by network and community.

	Exercise	Fat
# Users		
Visiting	703,948	737,102
Core	3,573 (100%)	2,007 (100%)
Core (no isolates)	3,557 (99.55%)	1,827 (91.03%)
Community #1	1,363 (38.15%)	662 (36.23%)
Community #2	1,107 (30.98%)	286 (15.65%)
Community #3	491 (13.74%)	129 (7.06%)
Community #4	475 (13.27%)	125 (6.84%)
# Tweets		
Visiting	703,948	737,102
Core	399,641	130,516
Community #1	142,448(35.64%)	50,613(38.78%)
Community #2	41,220(10.31%)	4,783(3.66%)
Community #3	11,837(2.96%)	2,295(1.76%)
Community #4	12,349(3.09)	3,206(2.46%)

Table 2 *Descriptive statistics of the fitness-talk, weight-talk, and combined networks*

	Fitness-talk network	Weight-talk network	Combined network
Nodes	3,573	2,007	5,695
Edges (Links)	47,695	12,210	73,520
Semi-isolates	16	180	364
Nodes in giant component	3,557	1,827	5,331
Edges in giant component	47,677	11,955	71,627
Modularity (without isolates; Resolution 1.5)	0.24	0.53	0.20
Density (without isolates)	0.004	0.004	0.003
Communities in giant component	16	26	36
Average path length	3.79	6.02	4.31
Diameter	14	24	16
Mean total-degree	13.35	6.08	12.91
Mean total-degree (without isolates)	13.40	5.54	13.44
Mean clustering coefficient	0.093	0.17	0.107

Table 2 *Bigram comparison of the tweets produced by the four largest communities of each network.*

	Community #1 (n=142,448)			Community #2 (n=41,220)			Community #3 (n=11,837)			Community #4 (n=12,349)		
	Content	Count	%	Content	Count	%	Content	Count	%	Content	Count	%
Fitness-talk Network	exercise fitness	20,753	14.57%	exercise fitness	3,401	8.25%	exercise health	309	2.61%	exercise faith	1,157	9.37%
	exercise fit	15,670	11%	healing healingmb	1,804	4.38%	can exercise	254	2.15%	christ exercise	1,144	9.26%
	fit fitness	12,581	8.83%	practice surprising	1,377	3.34%	exercise fitness	254	2.15%	faith follow	1,139	9.22%
	training workout	9,947	6.98%	exercise healingmb	1,183	2.87%	diet exercise	207	1.75%	follow forgives	1,139	9.22%
	eatclean exercise	9,470	6.65%	healingmb health	1,166	2.83%	evidence exercise	200	1.69%	forgives god	1,139	9.22%
	fitspo getfit	9,354	6.57%	thanks transform	1,157	2.81%	effects exercise	191	1.61%	jesus repent	1,139	9.22%
	getfit gym	9,331	6.55%	exercise follow	1,141	2.77%	exercise get	165	1.39%	repent sins	1,139	9.22%
	train training	9,324	6.54%	check customer	1100	2.67%	exercise help	159	1.34%	sins standards	1,139	9.22%
	diet eatclean	9,314	6.54%	stressed stretch	1,083	2.63%	exercise great	154	1.30%	exercise force	334	2.70%
	healthy healthychoices	9,281	6.51%	transform will	1,080	2.62%	exercise good	144	1.22%	exercise forces	182	1.47%
	Community #1 (50,613)			Community #2 (4,783)			Community #3 (2,295)			Community #4 (3,206)		
	Content	Count	%	Content	Count	%	Content	Count	%	Content	Count	%
Weight-talk Network	exercise fitness	4,479	8.850	ass fat	155	3.24	fat feel	108	4.71	cock fat	332	10.36
	ways will	2,628	5.192	fat get	128	2.68	fat fucking	98	4.27	ass fat	297	9.26
	diet fat	2,578	5.094	belly fat	115	2.40	fat fuck	88	3.83	lesbian movie	254	7.92
	belly fat	2,051	4.052	fat fuck	102	2.13	even fat	78	3.40	fat full	227	7.08
	secrets success	1,924	3.801	fat girl	79	1.65	eat fat	71	3.09	fat hot	147	4.59
	burn fat	1,725	3.408	fat feat	78	1.63	eating fat	65	2.83	bbw belly	125	3.90
	belly dangerous	1,603	3.167	even fat	73	1.53	disgusting fat	63	2.75	dick fat	121	3.77
	click fat	1,507	2.977	drop fat	72	1.51	disorder eating	62	2.70	ass big	114	3.56
	fat home	1,501	2.966	bitch fat	65	1.36	fat food	62	2.70	full gallery	112	3.49
	eliminate fast	1,479	2.922	fat fool	58	1.21	fat hate	57	2.70	fatblly fatfetish	108	3.37

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementalFilesExerciseandFatonTwitter.docx