TBM

ORIGINAL RESEARCH

# Obesity in social media: a mixed methods analysis

Wen-ying Sylvia Chou, PhD, MPH,[1] Abby Prestin, PhD,[2] Stephen Kunath, MS,[3]

[1]Health Communication and Informatics Research Branch, Behavioral Research Program, Division of Cancer Control and Population Sciences, National Cancer Institute, National Institutes of Health, 9609 Medical Center Dr. 3E614, Rockville, MD 20892, USA

[2]Health Communication and Informatics Research Branch, Behavioral Research Program, Division of Cancer Control and Population Sciences, National Cancer Institute, National Institutes of Health, 9609 Medical Center Dr., Rockville, MD 20892, USA

[3]Department of Linguistics, Georgetown University, 9609 Medical Center Dr. 3E614, Rockville, MD 20892, USA

Correspondence to: W Chou
chouws@mail.nih.gov

Cite this as: *TBM* 2014;4:314–323
doi: 10.1007/s13142-014-0256-1

## Abstract

The escalating obesity rate in the USA has made obesity prevention a top public health priority. Recent interventions have tapped into the social media (SM) landscape. To leverage SM in obesity prevention, we must understand user-generated discourse surrounding the topic. This study was conducted to describe SM interactions about weight through a mixed methods analysis. Data were collected across 60 days through SM monitoring services, yielding 2.2 million posts. Data were cleaned and coded through Natural Language Processing (NLP) techniques, yielding popular themes and the most retweeted content. Qualitative analyses of selected posts add insight into the nature of the public dialogue and motivations for participation. Twitter represented the most common channel. Twitter and Facebook were dominated by derogatory and misogynist sentiment, pointing to weight stigmatization, whereas blogs and forums contained more nuanced comments. Other themes included humor, education, and positive sentiment countering weight-based stereotypes. This study documented weight-related attitudes and perceptions. This knowledge will inform public health/obesity prevention practice.

## Keywords

Obesity, Weight stigma, Cyber aggression, Social media, Health communication, Mixed methods, Online social support

**Implications**

**Practice**: Public health practitioners and health-care providers must be aware of the nature of authentic online conversations surrounding obesity, including negative sentiment that could drown out health messages as well as positive, health-promoting sentiment, and consider ways to leverage ongoing conversations to counter weight-based stigma.

**Policy**: Broader efforts can be implemented to curb online weight stigma, by partnering with existing anti-cyberbullying efforts and online "influencers" such as celebrity figures to affect the dialogue over time.

**Research**: This work offers insights into the lived experience of obesity. It will inform research investigating the efficacy and effectiveness of health promotion and weight control interventions using social media.

## INTRODUCTION

Obesity control and prevention is an urgent public health priority facing the USA today, as an estimated 69 % of US adults were overweight in 2011 [26]. In order for programs at multiple levels (from individual education to environmental and policy changes) to be effective, it is important to understand popular attitudes toward weight and obesity. Recent behavioral science research has documented widespread stigmatization and negative stereotyping of overweight individuals in media and in public discourse, and such stigma is found to be detrimental to those struggling with weight issues [23, 33]. The growth of social media offers another way to document public attitudes about obesity, posing the question of whether or not weight stigma may be exacerbated in user-generated online interactions. A systematic examination of social media interactions surrounding obesity-related topics will facilitate an understanding of how public attitudes inform obesity prevention efforts.

### Weight stigma in the media

Despite the fact that being overweight has become the norm in many regions of the USA, weight stigmatization has persisted [30, 31, 50]. Negative weight-based characterizations in the media have been consistently documented, whereby obese individuals are portrayed as unintelligent and undisciplined architects of their own condition [1]. Furthermore, overweight people are underrepresented in entertainment programs, but those who do appear are portrayed as unattractive, shown engaging in stereotypical eating behavior, and the target of ridicule and derision [8, 10, 19]. The news media also contribute to weight bias by portraying overweight individuals in stigmatizing ways [35, 36] and by focusing primarily on individual-level causes (e.g., diet) and solutions rather than on social or genetic factors [18, 25]. Even in some obesity prevention campaigns, "fat shaming" continues to be a theme [35, 36].

These negative media portrayals have reinforcing effects. For instance, competitive weight loss reality programs have been shown to promote individual blame beliefs and contribute to weight stigma [6, 44, 49], and children exposed to greater amounts of media express greater stigmatization toward overweight individuals [11, 21]. These stereotypes are internalized by some overweight individuals and can result in serious health consequences [47]. For instance, whereas members of other stigmatized groups engage in favorable ingroup bias that buffers them against prejudice [37], overweight or obese individuals commonly hold negative ingroup attitudes that indicate internalization of weight stigma [47]. Victims of weight-based prejudice are at higher risk for mental health comorbidities, including depression, body dissatisfaction, loneliness, anxiety, and low self-esteem [23, 41]. Weight-based teasing and peer victimization can also contribute to unhealthy behaviors such as disordered eating [42] and decreased physical activity [41].

### The role of social media in shaping attitudes about obesity

Over the past decade, social media have allowed Internet users to interact with one another on unlimited topics, including health and weight [2, 3]. Recent studies have noted the presence of weight stigma in social media dialogue. On YouTube, for example, personal causes of and responsibility for obesity were dominant themes, and individual-level behavioral changes were recommended most often [50]. The user-generated videos frequently contained weight-based teasing and ridicule, and videos with a derogatory stance toward overweight individuals received more views, ratings, and user comments than those without a teasing tone. Indeed, stigmatization in both the video content and user comments has been repeatedly documented [13]. On the other hand, social media platforms can provide safe havens against weight bias. There exist supportive online communities that provide compassionate, nonjudgmental spaces for individuals to share weight-related experiences and efforts. Over time, these interactions may improve self-esteem and resilience to stigma [5, 15, 22].

With the continued growth of social media and its expanding impact, it is important to understand how social media interactions reflect and shape the public discourse. Key questions requiring empirical evidence from authentic social media discourse include: Does the social media dialogue perpetuate or curb weight stigmatization? How is obesity (and affected individuals) portrayed in social media? Do conversations about obesity or weight differ across channels such as blogs, Twitter, and Facebook?

A comprehensive mixed methods investigation of obesity-related communication across multiple social media channels will begin to answer these questions. The present project capitalizes on the accessibility of this dialogue while protecting confidentiality and anonymity. Incorporating innovative Natural Language Processing (NLP) analytic techniques and qualitative sociolinguistic analysis, this study presents one of the first attempts to document social media discourse surrounding obesity.

## METHOD

### Linguistic corpus

Social media data were extracted through a commercial web-crawling search service that utilized a combination of data feeds and comment crawlers to index publicly available data across blogs, Twitter, Facebook, forums, Flickr, YouTube, and comments (defined as user-generated responses to content on all channels except Twitter). A set of predetermined keywords was used for data mining, including "obese/obesity," "overweight," and "fat." Data were mined at 12-h intervals between January 23, 2012, and March 23, 2012, and each extraction pulled the first 20,000 pieces of data available on the server. For context, in March 2012, Twitter reported that users made 340 million Tweets per day [45], and on a given day, roughly 200,000 posts containing our keywords were available on the server. Data files containing a total of approximately 2.2 million initial posts were retrieved, deduplicated, and saved into a shared file repository. Individual records were de-serialized, moved to a relational database (MySQL) for organization and verification, and deposited in a searchable cloud-based web service.

Data cleaning was performed on the initial posts by doing the following: (1) excluding excluded data from Flickr and YouTube (which only captured text comments on photos and videos, respectively), leaving the following five channels: Twitter, Facebook, blogposts, forums, and website comments; (2) excluding non-English posts and posts without a keyword; and (3) excluding irrelevant posts through NLP-assisted machine-learning techniques. In this step, two trained human coders evaluated a subsample for relevance. Irrelevance was identified through the co-occurrence of keywords with modifiers indicating reference to topics other than human body weight (e.g., fat blunt, Gong Hay Fat Choy, Fat Joe). A machine-learning, naïve Bayes classifier was constructed to automatically exclude irrelevant posts based on human-coded training data. We spot-checked within the cleaned data to confirm exclusion. The data-cleaning process was iterative with classifiers modified and reapplied on the corpus as additional exclusion terms were uncovered. The final corpus contained approximately 1.37 million posts.

### Mixed methods data analysis

We applied a mixed methods approach to capture a broad sense of the data and also to delve into specific findings. In the initial exploratory phase, we

generated descriptive statistics on relative distributions of each keyword and the distribution of posts across channels. Team members also individually reviewed the corpus and selected illustrative posts, and convened multiple times to discuss noticeable trends and themes. Subsequently, we generated lists of linguistic bigrams and content/lexical words (e.g., excluding prepositions, conjunctions, and linguistic fillers) adjacent to each keyword. Bigrams are typically used in computational linguistics to build language models and identify frequencies of the occurrence of linguistic elements (e.g., alphabets, lexical items). Additionally, since Twitter data represented the majority of the corpus, the top 25 most retweeted posts were identified and analyzed for each keyword.

Next, we performed discourse analysis (an approach commonly used in sociolinguistics to interpret the meaning and context of naturally occurring interactions) on a small portion of data excerpts representing themes highlighted in quantitative findings. Two simultaneous procedures guided the selection of *paradigmatic* data excerpts: (1) quantitative discoveries from bigram data (e.g., frequent co-occurrence of "fat" and "girl" prompted the selection of a post containing those two adjacent terms) and top retweets and (2) purposeful selection by the study team through a consensus process. Note that to preserve the anonymity of posters, in our presentation of excerpts and phrases, some exact wording is modified, links to URLs are replaced with "[URL included]," and users' Twitter handles are replaced with "@USERNAME." All typos, misspellings, and slang are retained to illustrate authentic exchanges, while expletives are censored with the first letter of the word followed by asterisks for each additional letter.

## RESULTS

Study findings are presented in the following order: overall prevalence of keywords across social media channels, linguistic bigrams (list of most commonly appearing content words associated with each keyword), content of the top five retweeted posts (a small number due to space constraint) for each keyword, and finally, qualitative illustrations of selected posts.

### Distribution of keywords across media channels

Among the keywords, "fat" was most commonly used both overall and across different channels (92 % of the entire corpus). By comparison, "obese/obesity" appeared in 6 % of the data, followed by "overweight" (2 %). Table 1 presents post count by keyword and by channel.

Across three keywords, the majority of the dialogue took place on Twitter (approximately 1.25 million posts or 91 % of the corpus). In comparison, the keywords were more evenly distributed on blogs, forums, and comments. For instance, "obese/obesity" appears in 24 % of forum posts, and "overweight" appears in 6 % of forum posts, suggesting more varying themes in these channels as compared to Twitter and Facebook.

### Linguistic bigrams and top retweeted posts: toward emerging themes

To glean the overall sentiment surrounding our keywords, NLP techniques helped produce linguistic bigrams on the content words most commonly adjacent to the keywords (Table 2). The lists of words reveal a few striking patterns: firstly, compared to "obesity" and "overweight," "fat" is most closely associated with words with negative connotations, including derogatory and misogynist terms. Secondly, and not surprisingly, "fat" is more likely to be found in colloquial conversations compared to the other two keywords. For example, notice that the word "children" is more frequently associated with "obesity" and "overweight," whereas "kid" is associated with "fat." Finally, dialogues containing the terms "obesity" and "overweight" often include more information, such as hyperlinks to news articles or health-care agency websites (e.g., "http" appears in the bigrams for both keywords).

Twitter provides over 90 % of all interactions about obesity in this corpus; as such, its use pattern deserves special attention. Of note, Twitter's "retweet" feature is a unique aspect of this channel that provides insight into the common sentiments in the corpus. When users retweet a message, they share it with their followers and promote it as content of interest. To understand how Twitter stimulates conversation, we identified the most frequently shared tweets, noting their retweet count (Table 3).

**Table 1** | Distribution of each term (count and proportion within each channel) by social media channel

| SM channel | Search term | | | |
|---|---|---|---|---|
| | Fat (*N*=1,252,648) | Obese/obesity (*N*=88,204) | Overweight (*N*=32,295) | Total posts[a] (*N*=1,373,147) |
| Twitter | 1,156,338 (92 %) | 74,797 (6 %) | 25,580 (2 %) | 1,256,715 |
| Facebook | 51,090 (90 %) | 3,595 (6 %) | 2,220 (4 %) | 56,905 |
| Blogs | 25,438 (79 %) | 3,957 (12 %) | 2,684 (8 %) | 32,079 |
| Forums | 13,616 (69 %) | 4,754 (24 %) | 1,262 (6 %) | 19,632 |
| Comments | 6,166 (79 %) | 1,101 (14 %) | 549 (7 %) | 7,816 |

[a] Twitter posts make up roughly 91 % of total posts, followed by Facebook (4 %), blogs (2 %), and forums (1 %) and comments (<1 %)

**Table 2** | Table of top 20 words co-occurring with keywords: linguistic word bigrams

| Fat (total $N$=1,156,338) | | | Obese/obesity (total $N$=74,797) | | | Overweight (total $N$=25,580) | | |
|---|---|---|---|---|---|---|---|---|
| Content word | Count | % | Content word | Count | % | Content word | Count | % |
| Fat a** | 100,632 | 0.08 | Childhood obesity | 6,348 | 0.08 | Overweight people | 1,121 | 0.04 |
| Fat people | 61,724 | 0.05 | Obese maybe | 5,443 | 0.07 | Overweight http | 789 | 0.03 |
| Fat girl | 74,168 | 0.06 | Kids obese | 5,242 | 0.07 | Only overweight | 532 | 0.02 |
| Fat so | 51,233 | 0.04 | Obesity http | 3,878 | 0.05 | Overweight thing | 513 | 0.02 |
| Fat b****** | 39,897 | 0.03 | Morbidly obese | 3,397 | 0.05 | System overweight | 474 | 0.02 |
| Fat kid | 36,371 | 0.03 | Obesity epidemic | 3,217 | 0.04 | Overweight women | 449 | 0.02 |
| Big fat | 27,861 | 0.02 | Obese people | 2,740 | 0.04 | Becoming overweight | 314 | 0.01 |
| Fat city | 26,915 | 0.02 | Obesity runs | 2,243 | 0.03 | Overweight guy | 314 | 0.01 |
| Fat b**** | 24,037 | 0.02 | Children obese | 2,139 | 0.03 | Overweight children | 272 | 0.01 |
| Getting fat | 18,455 | 0.02 | Obesity online | 1,820 | 0.02 | Just overweight | 271 | 0.01 |
| Look fat | 18,244 | 0.02 | Obese probably | 1,152 | 0.02 | Pounds overweight | 265 | 0.01 |
| Fat fat | 17,358 | 0.02 | Obese guy | 1,149 | 0.02 | Overweight bodies | 251 | 0.01 |
| Fat person | 16,923 | 0.01 | Child obesity | 1,131 | 0.02 | Stands overweight | 250 | 0.01 |
| Fat boy | 15,910 | 0.01 | Obesity rates | 1,116 | 0.02 | Overweight person | 247 | 0.01 |
| Fat loss | 14,269 | 0.01 | Anti obesity | 1,006 | 0.01 | Overweight man | 224 | 0.01 |
| Fat guy | 13,097 | 0.01 | Except obesity | 930 | 0.01 | Slightly overweight | 223 | 0.01 |
| Fat lady | 12,180 | 0.01 | Obese by | 894 | 0.01 | Very overweight | 211 | 0.01 |
| Fat chick | 11,968 | 0.01 | Being obese | 813 | 0.01 | Overweight Barbie | 207 | 0.01 |
| Like fat | 10,968 | 0.01 | Becoming obese | 773 | 0.01 | Overweight obese | 200 | 0.01 |

**Table 3** | Top five most retweeted posts by keyword

| Retweet count | Retweeted content |
|---|---|
| Keyword: fat | |
| 6,994 | RT @USERNAME: *Fat* City B****. Fat Fat City B****Ten Ten Doughnuts and a Twinky B****. VIP Micky D's No Guest List. |
| 6,328 | RT @USERNAME: That awkward moment when someone skinnier than you calls themself *fat*... So what I am then, a pig? |
| 6,165 | RT @USERNAME: *Fat* b****** on Twitter calling themselves Barbies: B****, you ain't no damn Barbie you a care bear |
| 6,039 | RT @USERNAME: I said to a *fat* girl today, You're a big girl! She replied, Tell me something I don't know. I said, Salad tastes good. |
| 5,728 | RT @USERNAME: #NeverTellAGirl she is ugly or *fat*. This is what happens. [URL omitted] |
| Keyword: obese/obesity | |
| 4,658 | RT @USERNAME: Why are kids *obese*? Maybe because burgers are $0.99 & salads are $4.99. |
| 1,611 | RT @USERNAME: It's a recipe for disaster when your country has an *obesity* epidemic & a skinny jeans fad. |
| 1,462 | RT @USERNAME: People who remain calm in stressful situations have higher rates of depression and *obesity*, a study finds. |
| 533 | RT @USERNAME: My brother died from childhood *obesity*. a fat kid ate him. |
| 445 | RT @USERNAME: Not eating breakfast increases your risk of becoming *obese* by 450 % according to a UMass study! #JumpstartYourDay |
| Keyword: overweight | |
| 295 | RT @USERNAME: The only "*overweight*" thing about Adele is her paycheck |
| 163 | RT @USERNAME: I think they should create an *overweight* Barbie to prove all shapes and sizes are beautiful. |
| 137 | RT @USERNAME: You should probably stop trash talking the *overweight* dancer because she's better than you and has more passion. #DancerProbz |
| 72 | RT @USERNAME: Eating quickly doubles your likelihood of becoming *overweight*. Slow down when you chew & other quick tips: [URL omitted] |
| 36 | RT @USERNAME: Difference between *overweight* & normal-weight Americans? Only 100 cal/day! Burn it off: Go for a brisk walk [URL omitted] |

Over one third of the top retweets across three keywords suggest the popularity of "fat jokes/teases," including lyrics parodying a rap song ("Rack City") that celebrates the rapper's affluent lifestyle and objectification of women. The lyrics promote the stereotype that overweight women eat junk food and cast them as outgroup members relegated to "Fat City." On the other hand, popular retweets also contain positive information about weight management, links to photos and information about disorders, and comments about healthy eating, stress, and exercise. Finally, the top retweeted content containing the keyword "overweight" refuted weight stigma or promoted healthy behavior.

### Qualitative data illustrations and analysis

The following examples illustrate discourse across social media platforms and explicate key findings. Particular excerpts are selected from the major themes noted in the lists of bigrams or retweets.

*Negative weight stigmatization*–The most prevalent theme in the corpus, as confirmed by bigrams and top retweets, is derogation and stigma against overweight individuals.

Example 1: Ewwwwww *fat* people disgust me!!! [Twitter]

Example 2: I hate when your on the bus or train and a *fat* person tries to squeeze in a seat that they have no business squeezing into. *Fat* people should only get one seat like everyone else. [Facebook]

Example 3: *Fat* person: "The problem is, *obesity* runs in our family." Doctor: "No, the problem is, no one runs in your family." [Twitter]

In addition to the mean-spirited attack on one's physical appearance, these examples show overweight individuals ("fat people/person") as outgroup members. Moreover, these posts are characterized by negative emotion. The expression of the disgust in ex 1 denotes a sense of moral repugnance toward overweight people [46], and irritation or anger is indicated in ex 2, where the poster is annoyed by the inconvenience he believes overweight people cause him. Ex 3 displays a "fat joke" playing on stereotype that overweight people do not exercise.

*Personal attacks*–Another form of weight stigma is directed toward specific individuals through weight-related insults and verbal attacks.

Example 4: @USERNAME, you're an ugly *fat* b****. kill yourself. [Twitter]

These more extreme cases of stigmatization take the form of weight-based flaming, aggressive online interactions [40], and cyberbullying. Defined as willful and repeated harm inflicted via the use of information technology, cyberbullying includes harassing messages, derogatory comments, physical threat, or intimidation [12]. Tweets such as ex 4, where aggressors directly and publicly attack other users with weight-related insults, are unfortunately common.

*Sexism and misogyny*–Misogyny represents a strong undercurrent in the corpus [7]. Indeed, as Table 2 indicates, many of the words associated with "fat" reference women (e.g., girl, chick, lady), including a number of derogatory terms (e.g., "b****").

Example 5: ATTENTION *FAT* B*****S: Stop wearing tight a** pants and leggings, that s*** is nasty! Wear baggy jeans or overalls… [Twitter]

Example 6: I hate when a *FAT* chick can't cook.... Umm ok b**** you just **fat** for no reason at all [Twitter]

Both examples strongly reinforce gender and weight stereotypes. The ridicule and criticism of women's clothing choices are accompanied by prescribing sartorial "do's" and "don'ts" for overweight women.

*Self-derogation*–Many derogatory posts are self-referential, especially with respect to diet and perception of one's own weight.

Example 6: I just ate McDonalds. full as hell! coca cola, 2 cheeseburgers and of course medium fries…what a *fat* a** i m! [Facebook]

Example 7: I'm Not *Fat*! My Stomach Is Just 3D. [Twitter]

Ex 6 shows a "confessional" where the poster discloses regretted dietary choices. Such "coming out as fat" is particularly common on Facebook in our observation. Ex 7 illustrates a self-deprecating joke–common and frequently retweeted–indicating that this lighthearted self-disclosure resonates with others, potentially serving to build camaraderie with followers who are also dissatisfied with their weight.

*Informational content*–There was frequent provision of information related to weight and obesity, primarily with regard to the keywords "obese/obesity" and "overweight."

*Nexus of responsibility for obesity*–The question of "who/what is to blame for obesity" is commonly discussed, and posts range from the individual level to societal factors.

Example 8: Two thirds of the country are *overweight* or *obese* and 30,0000 people will die this year from the complications of *obesity*,…. The main causes of *obesity* are increased consumption of high calorie foods, lack of exercise, genetics, medical treatments and psychological problems. [Blog]

Example 9: Very important #infographic on portion sizes and the #*obesity* epidemic [URL included] #health #diet #food [Twitter]

In contrast to the negative sentiment found in the bigram data for "fat," the top content words associated with "obese/obesity" in the bigrams have clinical or scientific connotations (e.g., "obesity epidemic," "obesity rates"). These examples demonstrate the type of information related to obesity that is found on social media platforms. Such posts typically point to the consequences and causes of obesity, as well as efforts to address the problem. As shown in ex 9, informational Tweets often contain links out to other sources, as well as hashtagged terms (e.g., #health, #diet, and #food) that include the post in the larger stream of conversation on Twitter.

Example 10: Should Happy Meals be blamed for rising *obesity* among US children? http:… [Twitter]

Example 11: I started dieting a week before Christmas and have dropped 21 lb went shopping yesterday to buy all my healthy goodies and end up spending $250 dollars. I understand why there are *overweight* people, because everything that is good and healthy for you is so damn expensive. [Facebook]

As these examples illustrate, in contrast to individual-blaming attitudes and perceptions associated with "fat," posts containing "obesity" tend to place more emphasis on macro-level factors. Opinions expressed run the gamut from stressing the role of parenting, to debunking the impact of policies such as menu labeling and food pricing, to blaming the fast food industry.

*Countering weight-based stereotypes*–Another theme directly contrasting the pervasive negative sentiment is seen in posts that counter weight stigma and advocate acceptance of overweight individuals.

Example 12: Some people are so cruel and shallow. Just because I'm *overweight* doesn't mean I'm less of a person. I'm beautiful the way I am and I don't care what some loser on facebook has to say about it. [Facebook]

Example 13: I think they should create an *overweight* barbie. To prove all shapes and sizes are beautiful. [Twitter]

Ex 12 shows the poster challenging the common weight stigmatization and stereotypes, particularly against women. This Facebook user, who self-identifies as overweight, asserts her belief in her own beauty and her disregard of strangers' criticisms. Moreover, there are pockets of positivity and

self-acceptance among the most retweeted content, particularly surrounding the term "overweight." In ex 13, for instance, the poster expresses an appreciative and protective attitude toward overweight individuals. Typically, other attributes not related to weight (e.g., talent, intelligence) are highlighted to downplay weight and validate a nuanced identity.

*Help/advice seeking and provision*–Finally, personal weight management experiences are frequently shared coupled with advice-seeking and supportive sentiment.

> Example 14: I'm on a diet. I'm still *overweight* but I've gone from 230 lb to 210. Its going well–I feel tremendous, but I'm not so sure I look it?… I'm afraid I will always see my self as fat (like I do now). is there any advice? Suggestions. anything ps. [Forum post]
>
> Example 15: I started dieting a week before Christmas and have dropped 21 lb went shopping yesterday to buy all my healthy goodies and end up spending $250 dollars. I understand why there are *overweight* people, because everything that is good and healthy for you is so damn expensive. [Facebook]

In ex 14, the poster shares her self-doubt about body image and weight loss effort and asks the forum members for advice. Whereas self-disclosure is also a prevalent theme in posts containing "fat," we do not observe the same humorous, self-deprecating undertone in dialogues surrounding "overweight." Instead, those on social media use blogs and forums to share their weight loss struggles, seek support, and express personal opinions. Ex 15 shows frustrations about the challenges of eating healthy economically. The poster identifies the high cost of healthy foods as a barrier to weight loss and a contributing factor to the obesity epidemic.

## DISCUSSION

The study identifies pervasive negative stereotypes, jokes, and alienation of overweight people, as well as self-deprecating humor. Contrary to individual-oriented blame or responsibility, there are also abundant socially oriented discussions. In the following section, we highlight a few emerging key points from this mixed methods inquiry.

### Weight stigmatization on social media

An abundance of stream-of-consciousness observations about overweight people is observed across authentic social media channels, marked with sentiments of anger, disgust, and alienation. Of note, this derogatory content is often reflected in "fat jokes"; though perhaps intended to entertain, these jokes position overweight individuals as targets of ridicule and as members of an outgroup. In fact, fat jokes were among the most frequently retweeted content. This is consistent with a recent study that confirmed the prevalence and popularity of weight-based teasing on YouTube [50]. Taken together, user-generated content on social media reflects and reinforces weight stigma.

Even more alarmingly, this negative sentiment extends to verbal aggression, with unchecked instances of flaming and cyberbullying against overweight individuals, particularly women. This aggression is rampant on Twitter, where users can obscure their identities, and this anonymity and reduced social cues (e.g., eye contact) may increase aggressive responses both offline [51] and online [4, 48], leading to more acts of "toxic disinhibition" [20, 40, 43]. It is notable that in this study, the determination of tone of posts is based upon the authors' perspective as observers and not participants with access to shared message meaning. Future studies should incorporate the perspectives and interpretations of social media participants to ascertain the impact of such sentiment on psychological and physical well-being [27]. To understand weight-based cyberbullying, it is imperative that we carefully examine unsupervised peer victimization in online communities.

### Positive sentiment

Our data also reveal discourse of encouragement and acceptance for individuals with excess body weight on social media. Forums and blogs are particularly common channels for the exchange of social support in weight loss efforts [16], echoing research on weight loss and physical activity communities on social media channels where participation is associated with encouragement for healthy behaviors [14, 17, 28] and receipt of social support can buffer against weight stigma [32].

Our data also document a theme of "fat acceptance" on social media. These pockets of acceptance counteract the prevailing negative sentiment and may help overweight individuals to resist and respond proactively to weight stigma. Support-oriented blogs and forums are health-promoting communities that offer a safe place where members' bodies are accepted, and allow participants to understand, negotiate, and, at times, reject the marginalized identity ascribed to them in their offline environment [38]. This type of supportive dialogue can be empowering [5]. As such, social media must not be viewed simply as breeding grounds for weight stigma, but also environments that can insulate overweight individuals from stigma.

### Not all social media are equal

This study represents one of the first social media analyses to examine multiple social media channels. These observed differences in frequency and types of conversation across social media channels suggest

that discrete channels may facilitate dissimilar types of discussions surrounding weight issues. It is possible that channels with predefined audience networks and implicit or explicit limitations on length (e.g., Facebook's typically brief status update and Twitter's 140-character limit), and those that are more amenable to "stream-of-consciousness" sharing, encourage discourse about "fat," presumably because of its more casual and *quotidian* nature. On the other hand, social media channels with no length limits (e.g., forums and blogs) that typically support ongoing conversation among a smaller number of participants may better enable discussions related to weight management and healthy lifestyle choices. Compared side by side, channels carry very different conversations. Twitter and Facebook attract a much larger volume of participation and contain the most negative sentiments regarding obesity; in comparison, blogs and forums produce a smaller volume of posts but support in-depth, sustained exchanges surrounding weight-related topics.

Moreover, many Facebook posts are self-referential, in that users update and comment on their own diet and exercise activities. In contrast, Twitter appears to be a unique channel that potentially perpetuates and enables terse and insensitive flaming or aggressive cyberbullying. Our analysis suggests the importance of considering the uniqueness of each social media channel in future research and intervention design.

### Emerging analytic methods for social media interactions

This study combines quantitative (computational linguistics/NLP tools) with qualitative (discourse analysis) approaches to address a set of research questions. The NLP-assisted, broader scan allows a data-driven approach not limited by a priori assumptions. On the other hand, the qualitative analysis of examples allowed us to dig into actual communicative exchanges to examine the posters' intent and meaning-making in these conversations.

With the massive amount of available public discourse and the rapid and constant evolution of social media, innovative scientific methods are urgently needed to study perceptions and attitudes as well as behavioral ramifications of health-related conversations online. Even within our corpus, we see the potential for numerous next steps integrating cutting-edge NLP techniques, including network analysis of the diffusion of content, sentiment analysis, coding of prevalent themes, mapping of ecologic models of obesity control to discourse, and analysis of conversations along the energy balance continuum (e.g., mentions of diet vs. physical activity).

Finally, this methodology presents a novel way to look at issues related to obesity prevention and weight stigma, which has traditionally been explored through surveys, implicit association tests, and interviews. In many ways, this type of direct observation allows us to examine authentic perspectives on the issue and observe communication in action, thus circumventing weaknesses inherent in self-report measures, such as social desirability bias.

### Implications for public health and behavioral medicine

These findings have implications for obesity prevention practice and research. First, it is crucial for public health practitioners to acknowledge the true nature of authentic online conversations about obesity. The social media landscape is cluttered with messages and opinions about weight issues. The negative sentiment that dominates this communication may drown out public health messages intended to alter obesogenic behaviors. This hostile online environment also promotes weight stigmatization, which has been shown to have serious public health consequences [34]. Health-care providers will also be better poised to support patients when they have a better understanding of the potentially damaging effect of social media discourse on overweight individuals' psychosocial well-being.

Broader efforts may be implemented to curb weight stigma online. Communication science can help in reframing the public discourse, raising awareness of cyberbullying, and countering weight-based stereotypes and misogyny. As we have witnessed, "grassroots" conversations are occurring to criticize and counter stigmatization. These posters may be agents for sociocultural change as opinion leaders and "influencers" [29], and recent research has documented personality characteristics (e.g., empathy, extroversion) associated with anti-bullying intervention behavior on social media [9].

It is also possible for public health and behavioral medicine to leverage public figures and celebrities to affect the dialogue. Pop stars such as Lady Gaga–who had more than 40 million Twitter followers as of December 2013–already use social media to oppose bullying and promote self-acceptance. Specific moments in popular culture may also spark interaction that promotes positive sentiment. To illustrate, the singer Adele won six Grammy awards in 2012, igniting positive dialogue on Twitter about her talent and beauty. When some users insulted her weight, others refuted these attacks ("The only thing overweight about Adele is her paycheck!") and shamed the original posters. These cultural figures and events offer opportunities to provide a more positive dialogue with regard to weight and obesity. Public health practitioners may partner with "influencers" and leverage ongoing conversations to counter weight-based stigma. Gradually changing the pervasive negative attitudes about obesity is an important step to improving public health.

This research also offers insight into the lived experience of obesity, from individual-oriented causes and solutions to supportive communities, and reflects on the individual, social, and environ-

mental factors contributing to obesity. Interventions could build upon existing sentiment and peer support and strategically highlight causes and solutions without victimizing or blaming individuals. Furthermore, they may help to enhance body satisfaction, which has been linked to self-efficacy and sustained healthy behavior [39]. Any social media-based obesity prevention efforts require careful presentation of the issue in a balance that avoids individual-oriented stigma and blame while still enabling individuals to maintain the locus of control. After all, obesity prevention efforts at the individual level must focus on *empowering* those endeavoring to make behavioral change.

### Study limitations

This study describes conversations about obesity and weight on social media. While contributing broadly to our understanding of weight-related public dialogue, it consequently sacrifices some depth of understanding in any particular area of inquiry beyond interpretations of selected posts. Subsequent in-depth analyses based on this corpus will examine specific issues, such as the assignment of responsibility and blame for obesity on multiple levels (based on a multilevel ecological framework), emotional themes, humor, and the link between obesity and other chronic conditions.

We were also limited by the inability to systematically compare across social media channels, given differential privacy settings and drivers of engagement. The fact that only publicly accessible posts were mined means a significant portion of online activities were left out of the corpus. For instance, a recent survey of Facebook users found that 58 % restricted access to their profiles [24]. Not only did we not include restricted posts, we also do not capture any information about message posters in order to protect privacy and anonymity. The lack of poster information limits our ability to address some pertinent research questions (i.e., Were the majority of posts containing sexist language posted by males or females? How does the follower base of individual posters affect what's being retweeted?). Finally, this work does not analyze social media conversations, only initial posts and comments; yet, interactivity is a hallmark of social media. Future studies can explore complete interactions between users to gain further insight into the construction of weight-related communication in digital spaces.

## CONCLUSION

The study complements existing knowledge of obesity by identifying the nature and scope of user-generated social media conversations on this topic. The mixed methods analysis addresses a key issue facing behavioral medicine and obesity prevention, namely the nature of public attitudes and perceptions about the issue as expressed on social media channels. The analysis confirms hostility and stigmatization toward overweight individuals (particularly women). Yet, pockets of acceptance and discussion about societal and environmental contributors are present as well, although they generate less volume of content. Our analysis also noted the distinct ways in which social media channels function, pointing to the need for those designing health interventions to consider the accessibility and feasibility of particular channels.

**Acknowledgments:** Data collection for this project was enabled through the support of the National Institute on Minority Health and Health Disparities and the National Cancer Institute.

1. Ata RN, Thompson JK. Weight bias in the media: a review of recent research. *Obes Facts*. 2010; 3: 41-46. doi:10.1016/j.bodyim.2010.10.003.
2. Chou WY, Hunt YM, Beckjord EB, Moser RP, Hesse BW. Social media use in the United States: implications for health communication. *J Med Internet Res*. 2009; 11: e48. doi:10.2196/jmir.1249.
3. Chou WS, Prestin A, Lyons C, Wen K. Web 2.0 for health promotion: reviewing the current evidence. *Am J Public Health*. 2013; 103(1): e9-e18. doi:10.2105/AJPH.2012.301071.
4. Christopherson KM. The positive and negative implications of anonymity in Internet social interactions: "On the Internet, Nobody Knows You're a Dog. *Computers and Human Behavior*. 2007; 23(6): 3038-3056. doi:10.1016/j.chb.2006.09.001.
5. Dickins M, Thomas SL, King B, Lewis S, Holland K. The role of the fatosphere in fat adults' responses to obesity stigma: a model of empowerment without a focus on weight loss. *Qual Health Res*. 2011; 21(12): 1679-1691. doi:10.1177/1049732311417728.
6. Domoff SE, Hinman NG, Koball AM, et al. The effects of reality television on weight bias: an examination of *The Biggest Loser*. *Obesity*. 2012; 20: 993-998. doi:10.1038/oby.2011.378.
7. Fikkan JL, Rothblum ED. Is fat a feminist issue? Exploring the gendered nature of weight bias. *Sex Roles*. 2011; 66: 575-592. doi:10.1007/s11199-011-0022-5.
8. Fouts G, Burggraf K. Television situation comedies: female weight, male negative comments, and audience reactions. *Sex Roles*. 2000; 42: 925-932. doi:10.1023/a:1007054618340.
9. Freis SD, Gurung RAR. A Facebook analysis of helping behavior in online bullying. *Psychology of Popular Media Culture*. 2013; 2: 11-19. doi:10.1037/a0030239.
10. Greenberg BS, Eastin M, Hofschire L, Lachlan K, Brownell KD. Portrayals of overweight and obese individuals on commercial television. *Am J Public Health*. 2003; 93: 1342-1348.
11. Harrison K. Television viewing, fat stereotyping, body shape standards, and eating disorder symptomatology in grade school children. *Commun Res*. 2000; 27: 617-640. doi:10.1177/009365000027005003.
12. Hinduja S, Patchin JW. Bullying, cyberbullying, and suicide. *Arch Suicide Res*. 2010; 14: 206-221. doi:10.1080/13811118.2010.494133.
13. Hussin M, Frazier S, Thompson JK. Fat stigmatization on YouTube: a content analysis. *Body Image*. 2011; 8: 90-92. doi:10.1016/j.bodyim.2010.10.003.
14. Hwang KO, Etchegaray JM, Sciamanna CN, Bernstam EV, Thomas EJ. Structural social support predicts functional social support in an online weight loss programme. *Health Expect*. 2011. doi:10.1111/j.1369-7625.2011.00759.x.
15. Hwang KO, Ning J, Trickey AW, Sciamanna CN. Website usage and weight loss in a free commercial online weight loss program: retrospective cohort study. *J Med Internet Res*. 2013; 15: e11. doi:10.2196/jmir.2195.
16. Hwang KO, Ottenbacher AJ, Green AP, et al. Social support in an Internet weight loss community. *International Journal of Medical Information*. 2010; 79: 5-13. doi:10.1016/j.ijmedinf.2009.10.003.
17. Hwang KO, Ottenbacher AJ, Lucke JF, et al. Measuring social support for weight loss in an internet weight loss community. *J Health Commun*. 2011; 16: 198-211. doi:10.1080/10810730.2010.535106.
18. Kim S-H, Anne Willis L. Talking about obesity: news framing of who is responsible for causing and fixing the problem. *J Health Commun*. 2007; 12: 359-376. doi:10.1080/10810730701326051.

19. Klein H, Shiffman KS. Thin is "in" and stout is "out": what animated cartoons tell viewers about body weight. *Eat Weight Disord*. 2005; 10: 107-116. doi:10.1007/BF03327532.
20. Lapidot-Lefler N, Barak A. Effects of anonymity, invisibility, and lack of eye-contact on toxic online disinhibition. *Computers and Human Behavior*. 2012; 28: 434-443. doi:10.1016/j.chb.2011.10.014.
21. Latner JD, Rosewall JK, Simmonds MB. Childhood obesity stigma: association with television, videogame, and magazine exposure. *Body Image*. 2007; 4: 147-155. doi:10.1016/j.bodyim.2007.03.002.
22. Lewis S, Thomas SL, Blood RW, Castle D, Hyde J, Komesaroff PA. 'I'm searching for solutions': why are obese individuals turning to the Internet for help and support with 'being fat'? *Health Expect*. 2011; 14: 339-350. doi:10.1111/j.1369-7625.2010.00644.x.
23. Libbey HP, Story MT, Neumark-Sztainer DR, Boutelle KN. Teasing, disordered eating behaviors, and psychological morbidities among overweight adolescents. *Obesity*. 2008; 16(S2): S24-S29. doi:10.1038/oby.2008.455.
24. Madden M (2012) Privacy management on social media sites. Washington, DC: Pew Research Center; 2012. Available at: http://pewinternet.org/Reports/2012/Privacy-management-on-social-media.aspx. Accessed July 1, 2013.
25. Major LH. Break it to me harshly: the effects of intersecting news frames in lung cancer and obesity coverage. *J Health Commun*. 2009; 14: 174-188. doi:10.1080/10810730802659939.
26. National Center for Health Statistics (2011) Health, United States, 2011: with special feature on socioeconomic status and health. Hyattsville (MD): National Center for Health Statistics (US); 2012. Available at: http://www.ncbi.nlm.nih.gov/books/NBK98752/. Accessed July 5, 2013.
27. O'Sullivan PB, Flanagin AJ. Reconceptualizing "flaming" and other problematic messages. *New Media & Society*. 2003; 5: 69-94. doi:10.1177/1461444803005001908.
28. Pagoto SL, Schneider KL, Oleski J, Smith B, Bauman M (2013) The adoption and spread of a core-strengthening exercise through an online social network. *Journal of Physical Activity and Health*, (online ahead of print).
29. Poirier J, Cobb NK. Social influence as a driver of engagement in a web-based health intervention. *J Med Internet Res*. 2012; 14(1): e36. doi:10.2196/jmir.1957.
30. Puhl R, Brownell KD. Bias, discrimination, and obesity. *Obes Res*. 2001; 9: 788-805. doi:10.1038/oby.2001.108.
31. Puhl RM, Brownell KD. Psychosocial origins of obesity stigma: toward changing a powerful and pervasive bias. *Obes Rev*. 2003; 4: 213-227. doi:10.1046/j.1467-789X.2003.00122.x.
32. Puhl RM, Brownell KD. Confronting and coping with weight stigma: an investigation of overweight and obese adults. *Obesity*. 2006; 14(10): 1802-1815. doi:10.1038/oby.2006.208.
33. Puhl RM, Heuer CA. The stigma of obesity: a review and update. *Obesity*. 2009; 17(5): 941-964. doi:10.1038/oby.2008.636.
34. Puhl RM, Heuer CA. Obesity stigma: important considerations for public health. *Am J Public Health*. 2010; 100(6): 1019-1028. doi:10.2105/AJPH.2009.159491.
35. Puhl RM, Luedicke J, Peterson LJ. Public reactions to obesity-related health campaigns. *Am J Prev Med*. 2013; 45: 36-48. doi:10.1016/j.amepre.2013.02.010.
36. Puhl RM, Peterson JL, DePierre JA, Luedicke J. Headless, hungry, and unhealthy: a video content analysis of obese persons portrayed in online news. *J Health Commun*. 2013; 18: 686-702. doi:10.1080/10810730.2012.743631.
37. Rudman LA, Feinberg J, Fairchild K. Minority members' implicit attitudes: automatic ingroup bias as a function of group status. *Soc Cogn*. 2002; 20: 294-320. doi:10.1521/soco.20.4.294.19908.
38. Smith N, Wickes R, Underwood M. Managing a marginalised identity in pro-anorexia and fat acceptance cybercommunities. *J Sociol*. 2013. doi:10.1177/1440783313486220.
39. Sonneville KR, Calzo JP, Horton NJ, Haines J, Austin SB, Field AE. Body satisfaction, weight gain and binge eating among overweight adolescent girls. *Int J Obes (Lond)*. 2012; 36(7): 944-949. doi:10.1038/ijo.2012.68.
40. Sproull L, Kiesler S. *Connections: New Ways of Working in the Networked Organization*. Cambridge, MA: MIT Press; 1992.
41. Storch E, Larson M, Ehrenreich-May J, Jones AE, Renno A, et al. Peer victimization in youth with autism spectrum disorders and co-occurring anxiety: relations with psychopathology and loneliness. *J Dev Phys Disabil*. 2012. doi:10.1007/s10882-012-9290-4.
42. Suisman JL, Slane JD, Burt SA, Klump KL. Negative affect as a mediator of the relationship between weight-based teasing and binge eating in adolescent girls. *Eat Behav*. 2008; 9(4): 493-496. doi:10.1016/j.eatbeh.2008.04.001.
43. Suler J. The online disinhibition effect. *Cyberpsychology and Behavior*. 2004; 7: 321-326. doi:10.1089/1094931041291295.
44. Thomas S, Hyde J, Komesaroff P. "Cheapening the struggle": obese people's attitudes toward *The Biggest Loser*. *Obes Manag*. 2007; 3: 210-215. doi:10.1089/obe.2007.0065.
45. Twitter (2012) Twitter turns six. *Twitter Blog*. Available at: https://blog.twitter.com/2012/twitter-turns-six. Accessed July 5, 2012.
46. Vartanian LR. Disgust and perceived control in attitudes toward obese people. *Int J Obes (Lond)*. 2010; 34: 1302-1307. doi:10.1038/ijo.2010.45.
47. Wang SS, Brownell KD, Wadden TA. The influence of the stigma of obesity on overweight individuals. *International Journal of Obesity Related Metabolic Disorders*. 2004; 28(10): 1333-1337.
48. Ybarra ML, Mitchell KJ. Youth engaging in online harassment: associations with caregiver–child relationships, Internet use, and personal characteristics. *J Adolesc*. 2004; 27: 319-336. doi:10.1016/j.adolescence.2004.03.007.
49. Yoo JH. No clear winner: effects of *The Biggest Loser* on the stigmatization of obese persons. *Health Commun*. 2013; 28: 294-303. doi:10.1080/10410236.2012.684143.
50. Yoo JH, Kim J. Obesity in the new media: a content analysis of obesity videos on YouTube. *Health Commun*. 2012; 27: 86-97. doi:10.1080/10410236.2011.569003.
51. Zimbardo PG. The human choice: individuation, reason, and order versus deindividuation, impulse, and chaos. *Nebr Symp Motiv*. 1969; 17: 237-307.