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What Do People Like to "Share" About Obesity? A Content Analysis of Frequent Retweets About Obesity on Twitter

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Twitter has been recognized as a useful channel for the sharing and dissemination of health information, owing in part to its "retweet" function. This study reports findings from a content analysis of frequently retweeted obesity-related tweets to identify the prevalent beliefs and attitudes about obesity on Twitter, as well as key message features that prompt retweeting behavior conducive to maximizing the reach of health messages on Twitter. The findings show that tweets that are emotionally evocative, humorous, and concern individual-level causes for obesity were more frequently retweeted than their counterparts. Specifically, tweets that evoke amusement were retweeted most frequently, followed by tweets evoking contentment, surprise, and anger. In regard to humor, derogatory jokes were more frequently retweeted than nonderogatory ones, and in terms of specific types of humor, weight-related puns, repartee, and parody were shared frequently. Consistent with extant literature about obesity, the findings demonstrated the predominance of the individual-level (e.g., problematic diet, lack of exercise) over social-level causes for obesity (e.g., availability of cheap and unhealthy food). Implications for designing social-media-based health campaign messages are discussed.

"Based on U.S. obesity rates, soon candidates will just walk for president." Although this frequently retweeted message may have been intended to be a joke, it nonetheless reflects the escalating obesity rate. In fact, obesity has become a national epidemic, with 34.9% of adults being obese (Ogden, Carroll, Kit, & Flegal, 2014). This epidemic must be addressed, as obesity is a major contributor to numerous leading causes of death in the United States, including heart disease, diabetes, and several types of cancer (Flegal, Carroll, Ogden, & Johnson, 2002). Obesity is also linked

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to depression and psychological stress (Strauss & Pollack, 2003), in part caused by prevalent social stigmatization (Puhl & Heuer, 2009).

A considerable body of behavioral science has provided a foundation to understand the public's attitudes and beliefs about obesity, which are crucial components in the development of effective public health interventions. Recently, another fruitful way to learn about public attitudes toward a health issue has emerged: to unobtrusively examine them through analyses of social media content (Chou, Prestin, & Kunath, 2014; Neiger et al., 2012). Scholars have begun to appreciate the utility of social media as an ongoing record of public sentiment about health and other issues (Salathé & Khandelwal, 2011) and to extend their investigation into social media interactions. For example, Scanfeld and colleagues (2010) performed a content analysis on tweets about antibiotics and found that the most commonly held misunderstanding concerned the use of antibiotics as a treatment for viral infections, followed by the belief that sharing leftover antibiotics with others is acceptable. These types of social media analyses can enhance our understanding on the public's genuine attitudes and beliefs about obesity through an unobtrusive method.

The ease of sharing information in social media makes these platforms a potentially valuable context for research examining the public's attitudes and beliefs about health issues. In particular, Twitter has gained scholarly interest due to its unique features including the "retweet" function, which allows the users to conveniently share tweets with others. Examinations of widely shared retweets about obesity would allow us to identify the types of obesity-related messages that people frequently endorse and publicly share, thus shedding light on the attitudes or beliefs that are widely accepted by the public. Moreover, investigating the obesity-related messages that prompted social sharing on Twitter has an important implication for designing health campaign messages that aim at maximizing their reach via Twitter and other social media outlets. In fact, the latter point gains greater importance when considering the fact that one of the biggest challenges to the effectiveness of public health campaigns is their limited reach (Hornik, 2002).

To this end, this research offers a content analysis of obesity-related messages on Twitter that were frequently shared or "retweeted." The specific aims of this study are twofold: First, this article provides an understanding of frequently shared attitudes and beliefs about obesity expressed in a naturalistic online setting. Second, by examining the common characteristics or elements of Twitter messages (or "tweets") that generate engagement and prompt sharing (or "retweets"), this research offers insight into designing social media-based health campaign messages that can maximize their reach to the public.

Twitter possesses a number of distinctive features that allow it to be well suited for these inquiries. First, unlike other social media outlets such as Facebook, Twitter users do not need to post personal information about themselves to find "friends" and make connections with others (Hughes, Rowe, Batey, & Lee, 2012). This feature offers a potential for anonymity, which may encourage Twitter users to be relatively less concerned about the social desirability of their posts and more honest about what they have to say (Huberman, Romero, & Wu, 2009). Thus, an unobtrusive analysis of tweets may present a relatively more truthful account of the public's attitudes and beliefs about obesity compared to surveys or other self-reported data. Second, Twitter tends to focus on the sharing of opinions and information rather than on reciprocal social interaction as Facebook does (Hughes et al., 2012). Thus, it is better suited for instantaneous sharing among loosely connected individuals (Kwak, Lee, Park, & Moon, 2010), making it an effective source of news and information (Lee & Oh, 2013), as well as a potential tool for health promotion and campaigns (Lee & Sundar, 2013). Given the potential utility of Twitter in health information dissemination, understanding the characteristics of tweets that are frequently shared will be informative in designing Twitter-based health communication messages.

Thus, with an eye toward understanding features of widely shared tweets about obesity, the overarching questions that guided this study are as follows: What do people endorse and share widely on Twitter when it comes to obesity-related topics? What are the prominent message features of frequently retweeted messages about obesity? What are the implications of these findings on health campaigns utilizing Twitter?

RETWEETS AND DISSEMINATION OF HEALTH INFORMATION

Twitter is a popular social media outlet that has been recognized as a promising communication channel for disseminating health information. It is a microblogging platform where users can post messages (i.e., "tweets") within a 140-character limit. Created in 2006, Twitter has grown in popularity as of March 2013 to 200 million active users, who produce more than 400 million tweets each day (Twitter, 2013). Twitter allows users to post tweets to their own profile pages, subscribe to other users' tweets by "following" them, and share messages from other users with their own followers by "retweeting" them. The retweet function makes content sharing easy and efficient, and also gives Twitter the potential to magnify the reach of health-related messages. In fact, Twitter users are already producing and sharing health information. For example, Paul and Dredze (2011) found that out of 2 billion messages posted in a 17-month period, 1.5 million tweets were health-related messages. Reflecting such prevalence, 18% of Americans reported that they rely on Twitter to receive health-related information (National Research Corporation, 2011). Recognizing the potential of Twitter as a convenient and cost-effective way to reach large audiences (Neiger et al., 2012), health organizations such as the National Institutes of Health (NIH), the Centers for Disease Control and Prevention (CDC), and the World Health Organization (WHO) utilize Twitter as a dissemination tool for health information (Park, Rodgers, & Stemmle, 2013).

Taken together, health organizations and health communication researchers alike recognize the utility of Twitter to engage in health communication. Now the question is how to utilize Twitter to its fullest capacity and connect health communication efforts to the widest range of people. As an initial step in understanding the diffusion of health information on Twitter, we discuss factors that may motivate people to retweet messages and how the extant literature can help us predict what type of obesity-related tweets might reach a wider audience.

WHY DO WE RETWEET?

Retweeting is a key mechanism for information diffusion that allows tweets to reach a new set of audiences beyond their initial reach (Boyd, Golder, & Lotan, 2010). As such, this feature has spurred research in a number of areas, including reasons for retweeting. According to Boyd and her colleagues (2010), for example, some of the major motivations for retweeting include the desire to entertain or inform followers as an act of curation, to publicly agree with or validate someone, and to comment on a tweet by retweeting with new information added. Narrowing down the investigation to specific message features that motivate retweeting, Naveed and his colleagues (2011) found that frequently retweeted messages were more likely to concern broader public interests such as the economy and public events, rather than more narrow topics or personal tweets. This pattern was replicated in a content analysis of retweets about H1N1 flu (Chew & Eysenbach, 2010). It can be inferred from these studies that enthusiasm for utilizing Twitter as an effective communication channel for disseminating information about public health concerns is well grounded. Despite the growing interest in retweeting behavior, however, extant research aimed at understanding motivations for retweeting and features of retweeted content is still limited. In addition, a vast majority of extant studies on this topic are not grounded in theory and are exploratory in nature. Thus, we turn to a larger body of research that delves into a more fundamental psychology of social sharing to shed more light on this "social sharing" phenomenon on Twitter.

Emotion and Social Sharing

A useful theoretical framework that can help us understand the fundamental psychology behind retweeting behavior is the social sharing of emotions (Rimé, 1995). According to Rimé (1995), emotion is an important motivator of social sharing. A considerable body of literature on the social sharing of emotions has widely documented the instinctive need people have to disclose to others when they experience emotionally charged events (e.g., Christophe & Rimé, 1997). Generally, the more intense the emotional experience, the more likely it is to be socially shared (Rimé, Mesquita, Boca, & Philippot, 1991). For example, a review of eight studies, in which participants were asked to recall a recent experience that evoked a specified emotion (e.g., joy, fear, or sadness) and then describe the extent to which they shared this experience (e.g., when and how often), found that more than 90% of the emotional episodes were shared on average (Rimé, Philippot, Boca, & Mesquita, 1992). As predicted, the extent of sharing (i.e., number of repetitions and recipients) was positively correlated with the intensity of the emotional arousal.

There is also evidence that emotionally evocative events shared with one set of individuals can be further shared by those individuals, a process called secondary social sharing. Evidence of this phenomenon emerged from two studies by Christophe and Rimé (1997) in which participants were asked to reflect on a time when someone had shared an emotional experience with them and indicate whether they had shared the story they heard with anyone. These shared episodes were able to evoke emotional responses in the listeners, and, on average across two studies, more than 70% of the stories were secondarily shared. Again, the intensity of the emotional response was an important predictor of secondary social sharing. Secondary social sharing of emotions is a particularly relevant phenomenon for the present study, as it is very similar to retweeting behaviors in that the individuals are motivated to share the information they initially received from someone else. Taken together, if we can consider retweeting behavior as a form of social sharing, then research on social sharing of emotions suggests that emotionally arousing tweets will provoke social sharing, specifically retweeting behavior.

In line with research on social sharing of emotions, research on viral marketing (Dobele, Lindgreen, Beverland, Vanhamme, & van Wijk, 2007; Lindgreen & Vanhamme, 2005) and online social sharing (Shamma, Yew, Kennedy, & Churchill, 2011) also positions emotion as an important ingredient in the success of online ads that have gone "viral," or gained heightened prominence and viewership from social transmission. Indeed, empirical research shows that online content that sparks strong emotional responses is more likely to be passed along to others. For instance, Bardzell and colleagues (2009) found that greater emotional arousal measured by elevated heart rate was a significant predictor of greater intention to share Internet videos with others. Drawing from the foregoing discussion on the centrality of emotion in social sharing, the following hypothesis is advanced:

H1: Tweets drawing emotional responses will be more frequently retweeted than non-emotional messages.

Given the influence of emotionality on the likelihood of sharing social media content, scholars have begun to investigate the types of emotion that would have the greatest potential to motivate sharing. In terms of valence of emotions, the literature is mixed: Some studies found that messages provoking positive emotions are more widely shared (e.g., Eckler & Bolls, 2011), while other studies found evidence substantiating the power of negative emotions (e.g., Heath, Bell, & Sternberg, 2001). Given these mixed findings, Berger and Milkman (2012) investigated the role of extent of arousal (or intensity) as opposed to valence of emotions in social transmission as suggested by the literature on social sharing of emotion (Rimé et al., 1991). Specifically, they proposed that high-arousal emotions (e.g., awe, surprise, and anger) would increase the likelihood of social sharing compared to low-arousal emotions (e.g., sadness) regardless of valence. As predicted, they found that online *New York Times* articles evoking high-arousal emotions were more frequently forwarded to others via e-mail than articles evoking low-arousal emotions.

Though the literature investigating the influence of specific types of emotions on social sharing is growing, it is not yet mature enough to allow us to make specific predictions about the role of discrete emotions in social sharing. However, identification of discrete emotions that likely induce retweeting would be informative in guiding the design of campaign messages utilizing emotional appeals. Thus, we propose this follow-up research question:

RQ1: Which discrete emotions are conveyed frequently in retweets about obesity?

Humor

Humor is one of the most widely recognized message features of online content that facilitates social transmission and sharing (Masland, 2001). For example, Phelps and his colleagues (2004) found that almost half of all pass-along e-mails participants received were jokes. Similarly, Dobele and her colleagues (2007) found that humor and amusement were key mechanisms for the success of online viral marketing campaign messages. This argument was substantiated in an experiment that demonstrated that humorous advertisements that are also high in violence were significantly more likely to be forwarded to others (Brown, Bhadury, & Pope, 2010). Moreover, a content analysis comparing traditional media advertisements and Internet advertisement that has "gone viral" gave humor the position of a universal appeal that was used almost unanimously in viral advertisements (Porter & Golan, 2006). Given the emphasis numerous scholars have placed on the role of humor in facilitating social transmission of online content, it is not surprising that empirical research shows amusement or exhilaration, a typical emotional reaction to humorous stimuli (Ruch, 1993), is one of the most frequently experienced emotions individuals expressed when consuming viral online content.

Popularity of humorous content is also evident in social media research. For instance, Holton and Lewis (2011) content analyzed tweets generated by the 430 most-followed journalists active in Twitter and found that humorous tweets were significantly more retweeted. More relevant to the current study, Yoo and Kim (2012) found that about 20% of the sampled YouTube videos about obesity portrayed an obese individual as an object of humor (i.e., weight-based teasing theme). More interestingly, they found that these videos with weight-based humor were viewed more than six times more frequently than videos without weight-based teasing. Thus, we predict that tweets about obesity that contain humorous elements will be more frequently retweeted and spread more widely than nonhumorous tweets.

H2: Twitter messages containing humor will be more frequently retweeted than those without humor.

Though much research has considered humor as a key ingredient in motivating sharing behavior, little is known about the specific types of humor that individuals like to share online. There is some evidence regarding the thematic types of humor that are frequently shared. For instance, of the humorous pass-along e-mails participants received in a month, more than 20% were general (or topic-diffuse) jokes, followed by sexual humor (14.5%), gender issues, and work- or computer-related jokes (Phelps et al., 2004). In this study, we utilized a theory-grounded humor typology developed by Buijzen and Valkenburg (2004) to examine the types of humor that are frequently retweeted. Thus, we ask:

RQ2: What types of humor are used frequently in retweets about obesity?

Attributions of Causal Claim in Obesity

Obesity is a complex health condition caused by behavioral, genetic, environmental, and psychosocial factors (Agurs-Collins & Bouchard, 2008). Despite the multifaceted nature of the causes of obesity, the society has placed a much greater emphasis on individual factors such as excessive food intake, lack of physical exercise, and, more recently, genetics, than on societal factors such as the marketing of low-cost unhealthy food (Kim & Willis, 2007). Consistent with this pervasive attitude, a survey of a nationally representative sample of U.S. adults showed that respondents viewed obesity as a consequence of individual-level factors more than of environmental factors (Oliver & Lee, 2005). Attribution of cause for obesity is an important issue to address as it accompanies behavioral implications that likely influence the prevalence of obesity. For instance, publics must recognize the existence of systematic, societal-level influence on obesity in order for policy changes to reduce obesity rates to take place (Blendon, Hunt, Benson, Fleischfresser, & Buhr, 2006). Similarly, if individuals believe that obesity is primarily caused by genetic factors, which are out of one's control, they will not engage in behavioral changes that are conducive to maintaining a healthy weight (Wang & Coups, 2010).

The unbalanced emphasis on individual factors also prevails in the mass media. Numerous content analytic studies of news articles have documented the tilted perspective (e.g., Boero, 2007; Jeong & Hwang, 2007). For example, Kim and Willis (2007) found that for a 10-year period from 1995 through 2004, six major national and local newspapers mentioned individual-level causes for obesity significantly more frequently than societal-level causes. More recently, Yoo and Kim (2012) extended this line of research to the social media context and found that, similar to traditional mass media, a significantly greater volume of YouTube videos endorsed individual-level causes than systematic or societal-level causes for obesity.

Thus, it is speculated that a pattern similar to that in the Yoo and Kim (2012) study will be observed in obesity-related tweets as well. Since this study focuses on frequently retweeted tweets as opposed to original tweets, however, a slightly different approach using the cognitive dissonance theory (Festinger, 1957) is employed to make a prediction. In essence, the cognitive dissonance theory posits that we experience psychological discomfort when we are exposed to beliefs or attitudes that are inconsistent with our own. The theory further predicts that in an effort to reduce this discomfort, we try to selectively expose ourselves to information that helps us avoid or resolve the cognitive conflict. For instance, Knobloch-Westerwick and Meng (2009) found that subjects in an experiment spent significantly more time reading attitude-consistent news. Drawing from this line of research, we anticipate that Twitter users will be more motivated to expose themselves to, endorse, and retweet messages that are congruent with their preexisting beliefs. Given that individual-level factors are much more widely recognized as the primary cause of obesity, we predict that tweets endorsing individual-level causes will be retweeted more frequently than those concerning societal-level causes. A follow-up research question examining the specific types of causes that are frequently retweeted is advanced as well.

H3: Tweets endorsing individual-level causes for obesity will be more frequently retweeted than those endorsing societal-level causes for obesity.

RQ3: What are the types of specific causes that are most frequently retweeted?

METHOD

Data Collection and Sample

Twitter data were collected as a part of a larger-scale research project concerning obesity-related contents in social media in general (for broad-level findings from the larger corpus see Chou et al., 2014). Social media data were initially extracted through a commercially available Web-crawling search service, which offers a data-monitoring product to help marketing companies track and analyze social media conversations about their brands. A profile, a collection of predetermined keywords used for data mining, was established, including the following four search terms: obese, obesity, overweight, and fat. Data were downloaded from the server at 12-hour intervals in a 2-month period between January 23, 2012, and March 23, 2012, each time extracting the first 20,000 pieces of data. Approximately 200,000 posts containing at least one of the keywords were collected on a given day. Once the initial data were collected, a machine-learning, decision-tree classifier based on the human-coded training data was constructed and used to automatically exclude irrelevant posts.[1] Of the data collected across different social media platforms, 1.25 million pieces (about 91%) were from Twitter. With the cleaned data set, an additional procedure took place in order to select the most frequently retweeted tweets in all four keywords. Because Twitter users often make minor modifications to the tweets before retweeting, an algorithm that utilizes a similarity metric was designed. Specifically, the designed algorithm considered tweets with 65% or greater similarity to be retweets of the original message and counted the frequency at which the message was shared. The algorithm generated a rank-ordered list of tweets with the frequency at which each message was retweeted.

Purposive sampling was used to select the most frequently retweeted tweets. Specifically, as this study aimed at examining the common features of frequent retweets, the 30 most retweeted tweets for each keyword were sampled, resulting in a total of 120 tweets. The decision to examine the 30 most frequent retweets was based on the fact that the retweet frequency dropped significantly after the 30th most retweeted messages for most keywords.[2] In sum, the total

[1]Two independent coders evaluated the relevance of each piece of data in a randomly selected sample of dat a to create human-coded training data for a machine-learning classifier.

[2]For example, the frequency of the 31st most frequently retweeted message for "obese" dropped to 24 times, while the first ranked message for the same keyword was retweeted 7,188 times. "Fat" keyword was an exception to this pattern as it maintained a high retweet frequency after the first 30 most retweeted messages: The 31st most retweeted tweet under the keyword "fat" was retweeted 1,523 times.

retweet frequency of the sampled 120 tweets was accumulated to be 121,268, which represents approximately 12.13% of all Twitter data collected.

Coding Procedure

Each tweet served as the unit of analysis for coding.[3] There were in total seven coding tasks that needed to be performed to test the hypotheses and answer research questions advanced in this study. For each task, two independent coders discussed the coding rules and agreed on the conceptual and operational differences among the coding categories before initiating the tasks. After establishing coding rules and specifying them in a codebook, the two coders independently coded approximately 20% of the tweets and reconvened to examine whether the coding rules were adequate and sufficient to code the complete sample of tweets. Instances that were difficult or ambiguous to code with the previously agreed-upon coding rules were discussed. After the discussion, the codebook was modified by the inclusion of additional rules and the further specification of existing rules. Then the two coders independently coded the entire sample of tweets using the modified codebook.

Upon the completion of coding, the two coders reconvened and intercoder reliability was computed. This study utilized Krippendorff's alpha as a reliability coefficient. As suggested by Krippendorff (2004), a reliability coefficient greater than or equal to .80 was considered ideal and a coefficient between .667 and .80 was deemed acceptable for drawing tentative conclusions. Disagreement was resolved through discussion between the two coders.

Content Analysis Variables

General Theme

The lead author studied the entire sample of tweets to identify prevalent themes conveyed in the tweets. In total, eight major thematic categories emerged from the preliminary examination: derogatory jokes, nonderogatory jokes, advocating societal change, causal factors for obesity, factoids, sarcastic comments, obesity prevalence, and nonscientific weight loss tips. Prior to coding, the coders discussed the operational definitions of each theme category. For instance, utilizing the definitions offered by the *Merriam-Webster Dictionary* (2014), "derogatory jokes" were operationalized as messages containing humor "expressing a low opinion of someone or something; showing a lack of respect for someone or something" (e.g., Just saw a fat ginger girl buying a rape whistle . . . gotta admire her optimism), and "factoids" were operationalized as "a briefly stated and usually trivial fact" related to obesity (e.g., Researchers in Australia have completed a study that shows weight loss may result in better sex for overweight diabetics). When tweets contained information about factors and/or behaviors that contribute to obesity, they were categorized as "causal factors for obesity" (e.g., One soda a day increases kid's risk of being obese by 60%). Tweets containing critical comments about obesity issues with arguments for a change or action in the society were categorized as "advocating societal change" (e.g., Obesity figures are troubling; new trends need to be countered in some way). All categories were mutually exclusive to allow for statistical inference (Krippendorff's $\alpha = .87$; see Table 1 for other examples of each category).

When a given tweet did not fall into one of the eight themes in the codebook, the coders were instructed to mark them as miscellaneous and were asked to identify possible coherent themes among these cases. Of the 10 Tweets that were classified as miscellaneous, six were categorized as forming a coherent category of "personal experience or anecdote" after discussion (e.g., I hate when someone skinnier than you says "I'm fat" and it makes you feel obese).

Emotion

Since H1 was based on research on the social sharing of emotion (Rimé, 1995), which assumes that the emotional state of the sharer motivates social sharing, the emotion coding focused on the coders' interpretation of what the message sharer likely felt when retweeting. First, the coders identified whether or not each tweet was deemed to have been retweeted due to an emotional response to reading the tweet (Krippendorff's $\alpha = .84$). The tweets that were coded as being retweeted due to an emotional response were again coded for discrete emotion. In other words, the coders put themselves in the perspective of the "social sharer" and identified the emotion that would have motivated social sharing. The list of emotion words offered by Shaver, Schwartz, Kirson, and O'Connor (1987) was utilized to identify the emotion. Consistent with the previous content analysis studies (e.g., Freimuth, Hammond, Edgar, & Monahan, 1990), the tweets were coded for one predominant emotion (Krippendorff's $\alpha = .77$). For example, when the tweets were thought to generate the feeling of being pleased after encountering a statement that one strongly agrees with or approves, the coders coded them as evoking "contentment," a low-arousal, positive emotion (Fredrickson, 1998) evoked by satisfaction experienced after the fulfillment of one's need (Berenbaum, 2002). As "disappointment" refers to an emotion experienced by nonfulfilment of desired expectation (Frijda, 1986), a tweet

[3] In a few instances where the tweet contained a link, the two coders discussed and decided on whether the tweet itself contained enough information to be coded and to assist the Twitter users' decision to retweet the message. When the message was deemed to provide insufficient information, it was marked and coders were instructed to visit the link contained in the tweet and code for the dominant theme of the information provided in the link. When doing so, the coders were reminded to put themselves in the position of a typical Twitter user and read the content casually without overanalyzing the content.

TABLE 1
Common Themes of the Frequent Retweets About Obesity

	Example Tweet	*Top Tweets*	*Retweet Frequency*
Derogatory jokes	Apparently, "I can't believe it's not butter" is not an appropriate comment to make when your obese neighbors show you their newborn baby.	25%	49.7%
Nonderogatory jokes	Dear Food, either stop being delicious or stop making me fat.	30.8%	32.8%
Personal experience or anecdote	If it wasn't for softball, I would be obese. #softballprobz	5.8%	6.5%
Advocating societal change	77% of girls think they're ugly. 52% of girls think they're fat. 100% of society should stop insulting girls for their appearance.	6.7%	4.5%
Causal factors for obesity	Not eating breakfast increases your risk of becoming obese by 450%, according to a UMass study.	13.3%	3.0%
Factoids	When you hear eating disorder you automatically think of skinny instead of obese.	6.7%	2.5%
Sarcastic comments	Americans spend $77 billion a year treating obesity solving the worlds water crisis would cost just $30 billion.	4.2%	0.4%
Obesity prevalence	Obesity kills 300,000 Americans a year.	3.3%	0.4%
Nonscientific weight loss tip	Tired of being overweight? This program will turn your body into a fat burning machine! [URL OMITTED]	1.7%	0.1%
Miscellaneous	Today we wish a happy second anniversary and an early #FF to @LetsMove, @MichelleObama's initiative to fight childhood obesity.	2.5%	6.7%

Note. The actual URLs included in the tweets are omitted to preserve anonymity of the posters.

TABLE 2
Discrete Emotions Evoked by Retweets

Emotion	*Example Tweet*	*Top Tweets*	*Retweet Frequency*
Amusement	Based on US obesity rates, soon candidates will just walk for president.	56.9%	78.8%
Contentment	The only "overweight" thing about Adele is her paycheck.	7.8%	11.5%
Surprise	The difference between overweight & normal-weight Americans? Only 100 calories a day! Burn it off: Go for a brisk 23-minute walk, vacuum for 30 minutes, or swim for 17 minutes.	15.7%	4.9%
Anger	Camera Crew Discreetly Trails Overweight Woman For Obesity Segment [URL OMITTED]	9.8%	3.7%
Sympathy	Overweight guy asks for help [URL OMITTED] via @youtube	2.0%	0.4%
Disappointment	I turn on @CNN looking for an update on the Syrian massacre. I get a story about "Pet Obesity on the Rise". Yay, America!	2.0%	0.3%
Sadness	60 percent of all Americans are either overweight or obese while 30,000 people starve to death each day.	2.0%	0.2%
Worry	Learn About Health Problems Associated With Being Overweight [URL OMITTED]	2.0%	0.1%
Hope	Lettuce. Carrots. I don't care what you say, these boys are bringing an end to teenage obesity.	1.0%	0.1%

Note. The actual URLs included in the tweets are omitted to preserve anonymity of the posters.

was coded as reflecting "disappointment" when the expectation of what the society should be primarily concerned about (e.g., "Syrian massacre" as opposed to "pet obesity on the rise") was violated or unmet. Using these operational definitions, the following nine discrete emotions were identified: amusement, contentment, surprise, anger, sympathy, disappointment, sadness, worry, and hope (see Table 2).

Humor

The coders determined whether each tweet contained humorous content and could therefore be classified as jokes (Krippendorff's $\alpha = .80$). Once the humorous tweets were identified, the coders classified them into different types of humor utilizing the categorization scheme offered by Buijzen and Valkenburg (2004). As this humor taxonomy was originally specific to audiovisual humor content, only the types that could be applied to textual humor were utilized as coding categories in this study (Krippendorff's $\alpha = .80$). Of the original 27 humor types from the Buijzen and Valkenburg (2004) taxonomy that are relevant to textual humor, in total 16 humor types were identified (see Table 3).

Attribution of Causes of Obesity. The coders determined whether or not each tweet contained information about causes of obesity. Tweets that did not explicitly state

TABLE 3
Frequently Retweeted Humor Types

Humor Types	*Example Tweet*	*Top Tweets*	*Retweet Frequency*
Puns	Do drug dealers sell 'Diet Coke' to their overweight customers??	25.8%	22.2%
Repartee	"what do we want?!" . . . "a cure for obesity" . . . "when do we want it?" . . . "after dinner!".	12.1%	18.1%
Parody	Life is like a box of chocolates. It doesn't last long if you're morbidly obese.	4.5%	12.1%
Sarcasm	Happy Chocolate Day. But in these obese United States, every day is Chocolate Day	9.1%	9.1%
Ridicule	Apparently clumsy people are more likely to be obese. That's because they keep walking into things . . . like McDonald's.	4.5%	8.9%
Outwitting	"Does this dress make me look fat?" No, I'm pretty sure your fat makes you look fat.	6.1%	7.5%
Absurdity	I love my six pack so much, I protect it with a layer of fat.	10.6%	6.6%
Conceptual surprise	Everybody thinks a Girl's Dream is to find the Perfect Guy. Lol no, our dream is to eat without getting fat.	12.1%	6.4%
Anthropomorphism	Dear Food, Either stop being delicious or stop making me fat.	1.5%	3.3%
Stereotype	We all have that one skinny friend that eats more than fat person:P:D	1.5%	2.7%
Irony	Dear Chubby kids chasing me, this is my way of helping cure Obesity . . . Sincerely, the Ice Cream Truck Driver. =) #TeamGuilty	4.5%	1.1%
Embarrassment	An obese guy was in the elevator with me. He caught me staring at the weight limit sign. Awkward.	1.5%	1.0%
Irreverent behavior	Dear obese gym teacher, We will run the mile once we see you do it first. Sincerely, your students.	1.5%	0.5%
Disappointment	I turn on @CNN looking for an update on the Syrian massacre. I get a story about "Pet Obesity on the Rise". Yay, America!	1.5%	0.2%
Ignorance	It's not fair that all those kids in Africa and Asia get to play hunger games while American kids are stuck playing childhood obesity games.	1.5%	0.1%
Malicious pleasure	90% of the BAD females you went to high school with are now either A: overweight B: have kids or C: both A & B	1.5%	0.1%

Note. The actual URLs included in the tweets are omitted to preserve anonymity of the posters.

but rather implied causal factors of obesity were also categorized as conveying such information (e.g., "You know why America is obese? Because the only running they do is on temple run"; Krippendorff's $\alpha = .78$). Coders then engaged in a secondary level of coding this data for specific causal factors related to obesity. Drawing from extant research on obesity, tweets implying a cause for obesity were specified into one of the four categories: societal-level cause, (individual-level) dietary cause, (individual-level) exercise cause, and (individual-level) genetic cause (Krippendorff's $\alpha = .90$). Following the coding method employed for thematic coding, if the tweet did not fall into one of the four categories, the coders were instructed to mark it as miscellaneous and asked to construct a cohesive category among these miscellaneous cases, if possible. There were two tweets that were marked as miscellaneous: One concerned a personality factor ("People who remain calm in stressful situations have higher rates of depression and obesity, a study finds") and the other concerned lack of sleep as a cause ("Lack of sleep increases your risk for heart disease, diabetes and obesity"). Since they did not form a cohesive category together, they remained in the category of their own (see Table 4).

RESULTS

Overview of the Data: Two Possible Approaches to Data Analysis

Since the data contained both the rank-ordered, 30 most frequently retweeted tweets for each of the four keywords, and the actual frequency with which each tweet was retweeted, there were two ways to analyze the data. First, quite simply, each of the 120 tweets in the data without reflecting the actual frequency of sharing could serve as a unit of analysis. In this type of analysis, each sampled tweet is given the same weight regardless of whether it was ranked as the first or the 30th most frequently shared tweet. This approach is useful in gaining understanding of the general landscape of the tweets sampled in this study. The second approach involves an analysis of weighted data, in which the actual number of retweets, or retweeted frequency of each tweet, is reflected in the analysis. As this study was primarily motivated by the question "What causes an obesity-related tweet to be retweeted?" the second approach, which takes retweet frequency into account, aligns more closely with the research questions and hypotheses advanced in this article. Thus, the primary analysis testing the hypotheses was conducted using

TABLE 4
Attribution of Causes of Obesity

Attribution of Causes	*Specific Causes*	*Example Tweet*	*Top Tweets*	*Retweet Frequency*
Societal level	Cheap and unhealthy food	Here is why we have an obesity problem in America: Because Burgers are $.99, & Salads are $4.99.	3.28%	11.94%
	School system	Excess homework has been linked as a cause to childhood obesity.	1.64%	1.0%
	Portion size	Very important #infographic on portion sizes and the #obesity epidemic [URL OMITTED] #health #diet #food	1.64%	0.48%
	Broken food system	For the sake of our country &economy, it's time to see obesity/ diabetes/ allergies/ cancer for what they are: symptoms of a broken food system	1.64%	0.08%
Individual level	Diet	Don't pick on fat people. They have enough on their plates.	57.4%	60.8%
	Exercise	Relationships are like fat people, most of them don't work out.	26.2%	22%
	Personality	People who remain calm in stressful situations have higher rates of depression and obesity, a study finds.	1.6%	3.2%
	Genetic	Is being overweight in the genes? [URL OMITTED]	4.9%	0.3%
	Lack of sleep	Lack of sleep increases your risk for heart disease, diabetes and obesity.	1.6%	0.2%

Note. The actual URLs included in the tweets are omitted to preserve anonymity of the posters.

the weighted data set. Nonetheless, the findings from the first analytic approach are also included briefly for information purposes.[4]

Overall Thematic Analysis

Prior to discussing the findings related to the aforementioned hypotheses and research questions, the prevalent themes of the frequently retweeted messages about obesity is presented to provide an overall idea of the thematic landscape of this content. The results of descriptive analysis of the themes of each tweet indicate that the majority (55.8%) of the collected tweets were jokes about obesity or weight (see Table 1). The jokes were further categorized as either derogatory or nonderogatory in tone. A slightly greater number of jokes were nonderogatory (30.8%) and the rest were derogatory (25%). Causal factors for obesity comprised the third most frequently appearing theme among the top retweets (13.3%), followed by advocating societal change (6.7%) and factoids (6.7%).

A slightly different pattern emerged when retweet frequency was taken into consideration. Descriptive analysis of data weighted by retweet frequency revealed that derogatory jokes were by far most frequently retweeted (49.7%), followed by nonderogatory jokes (32.8%). These two joke categories together made up the vast majority of retweets (82.5%). In sum, not only were jokes the prevalent theme among the 120 tweets but they were also very frequently retweeted. Tweets concerning personal experience or anecdotes about obesity (6.5%) were also retweeted quite frequently and were followed by tweets advocating societal change (4.5%), tweets concerning causal factors for obesity (3.0%), and factoids (2.5%; see Table 1).

Emotion

H1 predicted that messages drawing emotional responses will be retweeted more frequently than nonemotional messages. A chi-squared test of goodness of fit indicated that a significantly greater number of tweets drew emotional responses (85%), $\chi^2(1, N = 120) = 58.80$, $p < .001$. The finding was replicated with the analyses involving the data weighted by retweet frequency: Messages drawing emotions (99%) were significantly more frequently retweeted than those not drawing emotions (1%), $\chi^2(1, N = 121{,}268) = 116{,}425.34$, $p < .001$. Thus, H1 was supported. In addition, a cross tabulation analysis showed that the predicted tendency was maintained across the four obesity keywords (see Table 5).

RQ1 asked what the prevalent discrete emotions identified in the frequent retweets were. Perhaps due to the fact that the majority of retweets were humor based, amusement was

[4]We anticipated some degree of inconsistency between the results yielded by the two approaches since it was evident that there were significant differences in the retweet frequency between not only the top retweets and the 30th retweets but also across the four keywords. For instance, the keyword "fat" generated most retweets (79.93%), followed by "obese" (9.5%), "obesity" (7.6%), and "overweight" (3.01%). The difference in the retweet frequency across the four keywords was significant, $\chi^2(3, N = 121{,}268) = 196{,}221.36$, $p < .001$. Thus, if the study only employed the first analytic approach, the findings might be misleading because they do not take into consideration the actual frequency with which the tweets were shared.

TABLE 5
Test of Hypotheses Through Comparison

	Top Tweets	Retweet Frequency	*Retweet Frequency by Keywords*			
			Overweight	*Obese*	*Obesity*	*Fat*
H1						
Emotion	$85\%_a$	$99\%_a$	74.3%	98.3%	99.1%	100%
Nonemotion	$15\%_b$	$1\%_b$	25.7%	1.7%	0.9%	0%
H2						
Humor	55%	$82.2\%_a$	35.2%	88.3%	59.1%	85.4%
Nonhumor	45%	$17.8\%_b$	64.8%	11.7%	40.9%	14.6%
H3						
Individual cause	$91.7\%_a$	$86.5\%_a$	100%	24.2%	83.8%	100%
Societal cause	$8.3\%_b$	$13.5\%_b$	0%	75.8%	16.2%	0%

Note. Within the test of each hypothesis, percentages in the same column that do not share subscripts differ at $p < .001$.

identified as the most prevalent discrete emotion (78.8%), followed by contentment (11.5%), surprise (4.9%), and anger (3.7%; see Table 2).

Humor

H2 predicted that humorous tweets would be retweeted more frequently than the ones without humorous content. The results of a chi-squared test of goodness of fit showed that a slightly greater number of tweets contained humor ($n = 66$) than not ($n = 54$) but the difference was not statistically significant, $\chi^2(1, N = 120) = 1.20, p =$ ns. When using weighted data, however, humorous tweets (82.2%) were significantly more frequently retweeted than non-humorous tweets (17.8%), $\chi^2(1, N = 121{,}268) = 50{,}319.21, p < .001$, as predicted by H2 (see Table 5). Thus, H2 was supported. In addition, a cross-tabulation analysis showed that the prediction held for obese, obesity, and fat keywords but not for overweight. With the overweight keyword, non-humorous tweets were retweeted more frequently (see Table 5).

RQ2 asked what types of humor were most frequently retweeted. Tweets with puns, or humorous use of words that are alike or nearly alike in sound but different in meaning, were most frequently retweeted (22.2%). Next, repartee (18.1%), or verbal banter usually in a witty dialogue, was found to be frequently shared, followed by parody (12.1%), and sarcasm (9.1%). As expected with the high volume of derogatory jokes, ridicule (8.9%) was another frequently shared humor type, followed by outwitting (7.5%), outsmarting someone by a retort, response, or punch line that makes the former statement seem inferior. Absurdity (6.6%) and conceptual surprise (6.4%), a humor tactic that misleads the reader by means of a sudden unexpected change of concept, were also found (see Table 3).

Attribution of Causes of Obesity

Prior to examining the specific types of causes of obesity mentioned or implied in the frequently retweeted tweets, we examined how many of the messages were, in fact, either containing or implying any types of cause of obesity at all. The results show that exactly half of the tweets (50%) either contained information about causes of obesity or implied it in a more subtle way, $\chi^2(1, N = 120) = 0.00, p =$ ns. The same pattern was observed with the weighted data: 50.6% of retweets contained information about causes of obesity, $\chi^2(1, \mathrm{N} = 121{,}268) = 17.92, p < .001$.[5]

H3 predicted that tweets emphasizing individual-level causes for obesity would be retweeted more frequently than those implying societal-level causes for obesity. Of the 60 tweets that either mentioned or implied causal factors, a vast majority (91.7%) stated or implied individual-level causes, and the rest concerned societal-level causes (8.3%), $\chi^2(1, N = 60) = 41.67, p < .001$. The same pattern was observed with the weighted data: Tweets concerning individual-level causes were more frequently retweeted (86.4%) than those concerning societal-level causes (13.6%), $\chi^2(1, N = 61{,}371) = 32{,}602.73, p < .001$. Thus, H3 was supported. A cross-tabulation analysis indicated that the predicted pattern was observed in data for the overweight, obesity, and fat keywords but not in data for the obese keyword. Tweets containing obese keyword were more frequently retweeted when they concerned societal-level causes (75.8%) than when they concerned individual-level causes (24.2%), which was a direct opposite to the patterns observed in the overall data and data for the other three keywords (see Table 5).

RQ3 asked what types of specific causes were most frequently retweeted. Of the retweets concerning individual-level causes, problematic diet was the most frequently retweeted cause (60.8%), followed by lack of exercise (22%), personality issues (3.2%), genetic predisposition to obesity (0.3%), and sleep deprivation (0.2%). Of the retweets

[5] Although the chi-squared statistic showed a statistically significant difference, it is likely to be due to the large sample size, not an actual difference, as indicated by descriptive statistics (50.6% versus 49.4%).

concerning societal-level causes, the availability of cheap and unhealthy food was the most prevalently retweeted cause (11.94%), followed by the current school system (1.05%), portion size offered at restaurants (0.48%), and a broken food system (0.08%; see Table 4).

DISCUSSION

This study presents findings from a content analysis of frequently retweeted obesity-related messages on Twitter, a popular social media outlet often utilized for sharing health-related information. As predicted, the results of the content analysis indicate that obesity-related tweets that are emotionally evocative, humorous, and concern individual-level cause for obesity were more frequently retweeted and shared than their counterparts.

Consistent with research on the social sharing of emotions and viral online content that emphasizes the role of emotion in social transmission, emotionally arousing tweets were much more likely to be retweeted than nonemotional ones. Specifically, a vast majority of tweets were found to draw positive emotions such as amusement (78.8%) and contentment (11.5%). This finding resonates with research on viral online media content, which demonstrates that people are more inclined to share media content that is expected to evoke positive emotions in the recipients. From a self-presentation perspective, Berger and Milkman (2012) explain that this is because people prefer to share messages that will generate positive emotion in the receivers rather than upset them, thus potentially reflecting positively on themselves.

In contrast, in health communication campaigns, the most widely utilized emotional appeal involves fear and its family emotions such as worry and anxiety (Freimuth et al., 1990; Job, 1988). However, only 0.1% of the frequent retweets about obesity reflected such emotions in this study. The stark contrast between this finding and the type of emotional appeal health campaigns utilize the most presents an important implication for designing social-media based obesity-related messages: If the message focuses on evoking negative emotions such as fear and anxiety as in a traditional health campaign context, it may not be shared as widely as messages utilizing other positive emotional appeals, thus possibly defeating the purpose of utilizing such social networking sites. In other words, if social media is to be utilized to maximize its reach to public, the message may need to be different from traditional health campaign messages that very often employ negative emotional appeals (e.g., fear, guilt).

The third most pervasive emotion in the analysis was surprise. This finding lines up well with the finding that tweets containing health information, interesting facts, and statistical information that likely have surprise or novelty value were retweeted quite frequently. This finding also resonates with extant research on risk perception that suggests novelty value as an arousing aspect of perceived risk (Fischhoff, Slovic, Lichtenstein, Read, & Combs, 1978). Thus, surprise may be another viable candidate for emotional appeals when using social media to transmit health-related information.

Although, on the whole, tweets that evoked negative emotions were less likely to be shared, anger (3.7%) was found to be shared quite frequently. Tweets that potentially made users angry were far more likely to be retweeted than those that concerned other negative emotions such as disappointment, sadness, and worry (all falling below 1.0%). A closer look into the data reveals that a vast majority of the tweets that seemed to have been shared due to anger concerned issues related to the widespread stigmatization against overweight and obese individuals. Thus, the observed prevalence of anger may be specific to health issues that are linked to social stigmatization. It also suggests that publics are, to some degree, not only aware of the social injustice issues associated with weight-related stigmatization but also motivated to share their "anger" with others on social media.

As can be predicted from the finding that highlights the dominant role of amusement in motivating retweeting behaviors, humorous tweets were significantly more likely to be retweeted than nonhumorous ones. In terms of tone, derogatory jokes about obesity were more likely to be retweeted (60.64%) than nonderogatory ones (39.54%; percentage within humorous tweets). This finding is similar to what Yoo and Kim (2012) found in their content analysis of obesity-related YouTube videos; it provides yet another piece of empirical evidence demonstrating the omnipresence of weight stigma in social media. Moreover, the fact that these derogatory jokes were widely shared on Twitter shows that a great number of Twitter users do not see a problem in publicly discriminating against overweight people. However, it should also be noted that roughly half of the humorous tweets about obesity studied here were not derogatory in tone.

Investigation into the different types of humor appeals shows that Twitter users found various humor appeals, including those that could be used in a health communication context, to be amusing enough to share with others. Specifically, tweets using "puns," humorous use of words that sound alike but have different meanings, were retweeted most frequently, closely followed by "repartee," a verbal banter in a witty dialogue. As these types of humor can be more easily delivered in brief statements compared to other types of humor (e.g., conceptual surprise), they seem to be particularly well suited for tweets. For obvious reasons, some of the humor techniques identified in this study that are inherently derogating in tone, such as ridicule, stereotype, irreverent behavior, and malicious pleasure, cannot and should not be considered in public health campaigns aiming at reducing obesity. This is particularly important to note since some health communication practitioners and designers of antiobesity public service advertisements (PSAs) seem to hold an unfounded assumption that provoking shame in overweight and obese individuals will motivate them to manage their weight (Puhl & Brownell, 2003).

One implication of this finding is to incorporate humor in social-media-based health messages to maximize exposure. The use of humor in a public health communication context is not new. For instance, owing to humor's potential to ameliorate denial and resistance toward serious health issues, humor-based HIV/AIDS prevention messages have been shown to be quite effective (Peterson, 1992). The use of humor is also prevalent in antismoking PSAs. In a content analysis of televised anti-smoking PSAs, humor was one of the most prevalent appeals used along with informational appeals (Cohen, Shumate, & Gold, 2007). Despite its popularity, however, some studies report adverse effects of humor (e.g., Fishbein, Hall-Jamieson, Zimmer, Haeften, & Nabi, 2002). Given the mixed findings, the utility of humor in health communication needs to be examined further. In sum, though the use of some of the humor techniques observed in this study (e.g., puns) is feasible and likely to generate wider dissemination than others, caution should be practiced when using humor in communicating about obesity.

The final hypothesis concerned the prevalence of retweets concerning individual- versus societal-level causes of obesity. As predicted, the majority of popular retweets concerned a variety of individual causes of obesity, including individual dietary practices and lack of physical activity. This finding resembles the results of previous content analytic studies that showed predominance of the individual frame in the traditional mass media. In other words, the data show that, as much as public health agencies and health communication researchers acknowledge that the issue is complex and multilevel solutions are necessary, the public's day-to-day conversations on Twitter indicate predominant discussions about individual factors. As obesity is a multifactorial health issue that is also profoundly affected by societal or environmental factors, efforts to promote a more balanced view of attribution are warranted.

Although it was not a central component of the study, this study also showed that the predictions held across the four different obesity keywords, with two exceptions: When tweets contained the word "overweight," nonhumorous tweets were more frequently retweeted than humorous ones. In addition, when tweets contained the word "obese," tweets concerning societal-level causes were significantly more frequently retweeted than those concerning individual-level causes. We speculate that these exceptions were in part caused by technical and scientific connotations attached to the words "overweight" and "obese." However, due to the paucity of research in this area, this finding awaits more scholarly attention from future research.

This study has several limitations. First, though this study involved an examination of a large set of data, the data were collected over a 2-month period. Moreover, based on the fact that retweet frequency dropped significantly after the top 30 retweets (see footnote 2 for details), the 30 most frequently shared tweets for each of the four keywords were sampled in this study, resulting in 120 pieces of tweets. Thus, the findings are by no means representative of the obesity-related content on Twitter as a whole. In terms of coding, the method we used to code for a predominant emotion that likely motivated social sharing warrants a note. Due to the nature of the data set that only allowed for a secondary analysis, we cannot ascertain that these are the emotional responses that actually motivated the Twitter users to retweet the messages. However, it should be also noted that this type of interpretive coding is often employed in secondary analyses (e.g., Berger & Milkman, 2012), particularly those studying the contents of social media. Future survey-based, diary-based, and qualitative studies employing interviews would provide invaluable insight into understanding the actual emotional processes that take place when retweeting and effectively complement the findings from the current study. Lastly, although this study has identified some active ingredients in tweets that likely lead to social sharing, it is important to note that the message itself is not the only factor influencing social sharing. In particular, in the context of social media, whether or not you are connected to an individual disseminating the health message is of utmost importance because it determines whether or not you are exposed to the message at all. However, examination of the networking aspect of Twitter is beyond the scope of the current study. Therefore, in order to fully understand the social transmission of health-related information on Twitter, future research should also investigate what influences one's decision to be connected to other Twitter users, thus presenting a more complete picture of the process of social transmission and potentially aiding public health agencies to build a widespread social network in social media.

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