Body Image 25 (2018) 133–138

Contents lists available at ScienceDirect

Body Image

journal homepage: www.elsevier.com/locate/bodyimage

Tweeting weight loss: A comparison of #thinspiration and #fitspiration communities on Twitter

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ARTICLE INFO

Article history:
Received 21 December 2017
Received in revised form 12 March 2018
Accepted 13 March 2018

Keywords:
Thinspiration
Fitspiration
Body image
Disordered eating
Social networks
Twitter

ABSTRACT

Thinspiration and fitspiration represent contemporary online trends designed to inspire viewers towards the thin ideal or towards health and fitness respectively. The aim of the present study was to compare thinspiration and fitspiration communities on Twitter. A total of 3289 English-language tweets with hashtags related to thinspiration ($n = 1181$) and fitspiration ($n = 2578$) were collected over a two-week period. Network analysis showed minimal overlap between the communities on Twitter, with the thinspiration community more closely-connected and having greater information flow than the fitspiration community. Frequency counts and sentiment analysis showed that although the tweets from both types of accounts focused on appearance and weight loss, fitspiration tweets were significantly more positive in sentiment. It was concluded that the thinspiration tweeters, unlike the fitspiration tweeters, represent a genuine on-line community on Twitter. Such a community of support may have negative consequences for collective body image and disordered eating identity.

1. Introduction

Recent research evidence has demonstrated a link between the time spent on the Internet by adult and adolescent women and body dissatisfaction and disordered eating symptomatology (Bair, Kelly, Serdar, & Mazzeo, 2012; Tiggemann & Miller, 2010; Tiggemann & Slater, 2013, 2014). One particular form of Internet engagement that has been implicated is the increasingly popular use of social network sites, such as Facebook, Instagram, and Twitter. Australian statistics suggest that approximately 79% of adults use social networking sites, with 59% doing so on a daily basis (Sensis, 2017). These sites allow users to create online profiles, to share information, and to form relationships and interact with other users of the same website. Users can choose when and how much they wish to participate, they can search for like-minded others, and they can comment on, reply to, or re-send other users' posts. It is this interactivity that most clearly distinguishes social media from traditional forms of mass media (Perloff, 2014).

A small but growing body of research has addressed the impact of social networking sites, most commonly Facebook, on body image and disordered eating outcomes. In their recent systematic review of this research, Holland and Tiggemann (2016) concluded that across a number of different measures and methodologies (correlational, experimental, and longitudinal), general social networking use is linked to body image and eating concerns. The review focused on studies that investigated unselected content, rather than sites dedicated to specific content.

The Internet offers one particular appearance-based trend which has proven damaging to body image, known as "thinspiration" (an amalgamation of the words *thin* and *inspiration*). Thinspiration consists of text and images designed to inspire and give users tips on how to lose weight in order to achieve an extremely thin and skeletal appearance (Borzekowski, Schenk, Wilson, & Peebles, 2010; Ghaznavi & Taylor, 2015). Thinspiration is typically found on pro-eating disorder (pro-ana) websites dedicated to promoting eating disorders as a lifestyle choice and offering a community of support for individuals with anorexia nervosa (Arseniev-Koehler, Lee, McCormick, & Moreno, 2016; Norris, Boydell, Pinhas, & Katzman, 2006; Rouleau & von Ranson, 2011). Exposure to such websites has been found to be damaging to body image and self-esteem in both correlational (Harper, Sperry, & Thompson, 2008) and experimental studies (Bardone-Cone & Cass, 2007). Fortunately, thinspiration is limited to a relatively small number of pro-eating disorder websites. A number of social media platforms, including Instagram, Tumblr, and Pinterest, have made

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https://doi.org/10.1016/j.bodyim.2018.03.002
1740-1445/

the move to ban all thinspiration content (Casilli, Pailler, & Tubaro, 2013; Judkis, 2012).

A much more widely promulgated trend offered by the Internet across a range of websites is "fitspiration". Fitspiration (amalgamation of the words *fitness* and *inspiration*) consists of text and images that are designed to motivate people to pursue a healthier lifestyle through exercise and good eating (Abena, 2013). Fitspiration has been positioned as a healthy alternative to thinspiration because it promotes health and fitness, rather than thinness and weight loss, as illustrated in the popular slogan "Strong is the new skinny" (Boepple, Ata, Rum, & Thompson, 2016: Tiggemann & Zaccardo, 2016). Despite its avowedly positive and empowering intention, however, there are several aspects of fitspiration that are concerning. Content analyses of fitspiration suggest that a thin and toned body is idealized, that appearance-based motives for exercise are emphasised, and that extreme and excessive behaviours are sometimes encouraged (Boepple et al., 2016; Tiggemann & Zaccardo, 2016). In addition, Holland and Tiggemann (2017) found that women who post fitspiration content on Instagram are at increased risk for diagnosis of a clinical eating disorder and more likely to engage in compulsive exercise. Finally, one experimental study has shown that exposure to fitspiration imagery resulted in increased negative mood and body dissatisfaction (Tiggemann & Zaccardo, 2015).

To date, there have been two studies that have offered direct comparison of thinspiration and fitspiration content. In the first, Boepple and Thompson (2016) coded 50 thinspiration and 50 fitspiration websites for eight specific messages indicative of disordered eating. They concluded that while fitspiration contained less such content than did thinspiration, both types of site contained similar potentially dangerous thematic content in terms of dietary restriction, objectification, and weight stigmatization. More recently, Talbot, Gavin, van Steen, and Morey (2017) coded a sample of 458 female images (269 thinspiration, 189 fitspiration) posted on social media for body type. They found that thinspiration contained relatively more thin and objectified bodies than did fitspiration, which contained more muscular bodies (while still containing a proportion of extremely thin bodies). Both the above studies required elaborate coding schemes of individual messages or images and did not address any aspect of the interactivity that characterises social media, as distinct from traditional and more passive forms of mass media such as fashion magazines and television (Perloff, 2014). The present study sought to complement and extend this initial research with a "big data" approach that uses objective algorithms rather than trained coders to investigate similarities and differences in topics covered and sentiment. In addition, the approach allowed extension of the investigation from analysis of individual postings (as in the previous studies) to analysis of patterns of communication between users within the thinspiration and fitspiration communities.

The social networking site Twitter was selected because, unlike other social media platforms like Instagram, there is no policy of blocking posts tagged as "thinspiration". Twitter posts, known as tweets, are brief messages of no more than 140 characters (at the time this study was conducted – the limit was raised to 280 characters in November 2017), making them ideal for a textual analysis of the words used. They can contain text, images and links to other websites. While some activity on Twitter is marked by the users as private, much of the activity is public and intended by the users for public readership through the Twitter website or mobile app. Users can post multiple tweets, "follow" other users, and transmit ("retweet") others' posts. In 2016, Twitter had 317 million users with an average of 500 million tweets being posted per day (Newberry, 2016). The platform is particularly popular with adolescents and young adults (Newberry, 2016; Sensis, 2017), although Twitter users also include corporations, brands, and celebrities (Lydecker, et al., 2016). In addition, Twitter makes all the public posts related to search criteria available for researchers through direct access to its servers.

We addressed two major research questions: (a) the extent to which there is overlap among the individuals involved in the thinspiration and fitspiration communities and whether there are differences in the structure and pattern of communication within these communities; and (b) whether there are differences in content, both in the topics covered and the sentiment of the communication. On the basis of other research suggesting that pro-eating disorder websites that promote thinspiration serve to provide a community of support for like-minded individuals (Arseniev-Koehler, Lee, McCormick, & Moreno, 2016; Norris, Boydell, Pinhas, & Katzman, 2006; Rouleau & von Ranson, 2011), we predicted that the thinspiration users would constitute a more closely linked community than the fitspiration users. On the basis of the existing comparisons of thinspiration and fitspiration content (Boepple & Thompson, 2016; Talbot et al., 2017), we expected that our textual analysis of Twitter posts would likewise produce similar themes. We had no specific prediction on the relative positivity of thinspiration and fitspiration tweets.

2. Method

2.1. Data collection

A custom written interface with the Twitter application programming interface (API) was housed at Flinders University. The API collected all tweets with hashtags related to thinspiration (#thinspiration, #thinspo, #proana) and fitspiration (#fitspiration, #fitspo) posted over a two-week period (22 September–6 October 2016), resulting in a total of 5028 tweets. When tweets written in languages other than English were excluded, the resulting set contained 3289 tweets. Of these, 1181 related to thinspiration and 2578 related to fitspiration.

2.2. Data analysis

2.2.1. User network analysis

As with the rest of Twitter's functionality, users' lists of "followers" (people who follow them) on public accounts is viewable from the Twitter web interface and is retrievable through direct access to its servers. This information allows analysis of how overlapping the communities are and how well each community is connected within itself.

To examine how information moves through the community (Lotan et al., 2011), each tweet was checked to determine if it was a new tweet or re-tweet. A network graph of communication within the communities was then built by defining a node in the network as an account, and an edge (connecting line) between nodes when one account retweets a tweet created by another account in the network. The strength of the connections to each node is the sum of the links to and from that node and indicated by the weight of the edge. This standard social network construction (Hanneman & Riddle, 2005) allowed us to investigate the relationships between individuals in the fitspiration and thinspiration communities, and in particular, the strength of their communication links.

2.2.2. Topic and sentiment analysis

The topics presented in the tweets were analysed by producing term frequency plots of the unigrams (single words or word-like elements) and bigrams (pairs of words) used in the tweets. Sentiment was analysed using the LabMT 1.0 database hedonometer (Dodds et al., 2011), which provides happiness scores (from 1 = *very negative* to 9 = *very positive*) for a set of over 10,000 frequently used English words. These scores were initially based on independent