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

Marika Tiggemann [a,*], Owen Churches [a], Lewis Mitchell [b], Zoe Brown [a]

[a] School of Psychology, Flinders University, Australia
[b] School of Mathematical Sciences, University of Adelaide, Australia

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.

© 2018 Elsevier Ltd. All rights reserved.

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

---

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
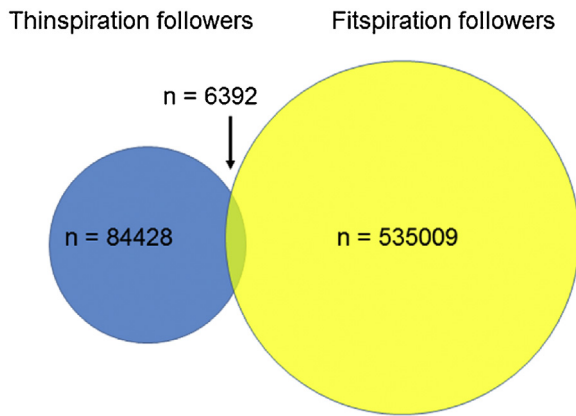
Fig. 1. Venn diagram of followers of accounts with thinspiration and fitspiration tweets.

evaluation by 50 different raters and have demonstrated robustness (Dodds et al., 2011). We removed the words "lose", "loss", "losing", "like" ("look like"), and "weight" due to their specific meaning in this context. The mean sentiment for each tweet was calculated, and the relative sentiment of thinspiration and fitspiration tweets compared.

3. Results

3.1. Nature of the communities

The 3289 tweets collected during the collection window came from a set of 841 accounts. More accounts tweeted tweets containing fitspiration hashtags ($n = 647$) than thinspiration hashtags ($n = 189$). Interestingly, there was minimal overlap between the communities with just five accounts tweeting tweets related to both thinspiration and fitspiration.

To understand the reach of the information propagated by the 841 accounts described above, the number of followers of each account was accessed. Because some tweets had been deleted in the interim, the new sample contained 800 accounts. These accounts had a total of 625,829 followers. The accounts tweeting thinspiration had a comparable number of followers ($M = 928.18$, $SD = 1705.62$) to the accounts tweeting fitspiration ($M = 966.75$, $SD = 1498.48$), $t(151) = 0.03$, $p = .97$. However, because there were more fitspiration-tweeting accounts, there were many more (more than six times as many) followers in total of accounts tweeting fitspiration than accounts tweeting thinspiration. Again, as can be seen in Fig. 1, there was minimal overlap between the communities with only 7.04% of followers of thinspiration accounts also following fitspiration accounts and 1.18% of followers of fitspiration accounts also following thinspiration accounts.

In terms of information flow, despite there being fewer thinspiration-tweeting accounts, there were significantly more thinspiration re-tweeted tweets ($n = 572$; 48.7%) than fitspiration re-tweets ($n = 173$; 6.7%), $\chi^2(1) = 213.69$, $p < .001$, indicating that accounts associated with thinspiration-related content are more engaged in spreading information. The network graphs of communication for thinspiration and fitspiration related accounts are shown in Fig. 2. It can be seen that thinspiration accounts not only re-tweet more, but re-tweet from a greater diversity of other accounts, creating a more complete network, as predicted. Mean node degree, an index of the ability for information to flow through a network defined by the average number of edges per node (Vinson & Dale, 2016), was substantially higher for thinspiration-related accounts ($M = 4.45$, $SD = 1.27$) than fitspiration-related accounts ($M = 1.42$, $SD = 9.18$), $t(497) = 5.07$, $p < .001$. The bottom panel of Fig. 2 shows the degree distributions for the two networks, which visualises the spread of retweeting levels for accounts in the two networks. We observe the characteristic non-normal "skewed" distributions common in social networks (Hanneman & Riddle, 2005), with most accounts in both networks having a small number of retweets, and a small number being highly retweeted.
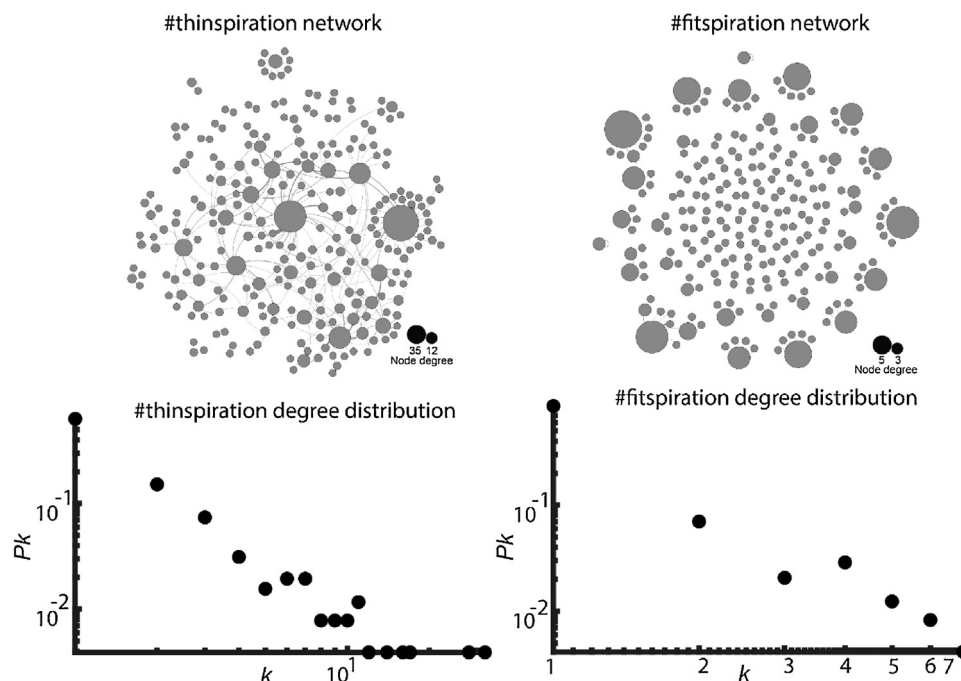

Fig. 2. Network graphs of connections between thinspiration and fitspiration accounts. Thicker lines represent more retweets between the connecting accounts. Larger circles represent more retweets of that account. The lower panels show the degree distributions for the networks, representing the proportion (Pk) of accounts that were retweeted k times.

(a) Thinspiration

(b) Fitspiration

Fig. 3. Word clouds depicting unigrams for (a) thinspiration and (b) fitspiration tweets. Words are sized by frequency.

The large and unconnected nodes in the fitspiration network graph (Fig. 2) raise the possibility that these "users" represent brands or other forms of advertising. An automatic bot-detection system (Varol, Ferrara, Davis, Menczer, & Flammini, 2017) was used to compute bot scores (probability of being a "bot", i.e., non-human) for each account. The mean bot score for fitspiration-related accounts ($M = 0.39$, $SD = 0.16$) was significantly higher than for thinspiration-related accounts ($M = 0.31$, $SD = 0.14$), $t(450) = 8.00$, $p < .0001$. This difference indicates that fitspiration accounts are on average 25% more likely than thinspiration accounts to be automated ("bots").

3.2. Topic and sentiment analysis

The topics and constructs contained in tweets with thinspiration and fitspiration hashtags were investigated by counting the number of different unigrams/words used (excluding articles and prepositions). Tweets were pre-processed by removing the string "RT" ("retweet"), URLs, and the hash (#) and @-symbols. Fig. 3 provides a graphical representation of the resulting word frequencies. The most frequent individual unigrams appearing in the thinspiration tweets were "bonespo" and "skinny", followed by "askanamia", "hourly", "thin", and "prettygirl". The most frequent bigram was

"prettygirl slim". For the fitspiration tweets, the most frequent words were "fitness", "weight", "fitfam", and "fit". The most frequent bigrams were "weight loss" and "favorite mo". Nevertheless, as can be seen in the figure and as predicted, the most frequently covered topics by both sets of tweets related to body appearance and weight.

Analysis of the sentiment of each tweet showed that on average both thinspiration and fitspiration tweets were mildly positive in sentiment, consistent with the observed universal positivity of language (Dodds et al., 2015). We tested the difference between groups in two ways: by using individual tweets as the sample and testing for difference in average tweet sentiment; and by using all words posted by a single individual as the sample and testing for difference in average user sentiment. At the tweet level, the words in fitspiration-related tweets were found to be significantly more positive ($M = 5.48$, $SD = 0.90$) than those in thinspiration-related tweets ($M = 5.24$, $SD = 0.77$), $t(13644) = 21.92$, $p < .001$. This was also the case at the user level; fitspiration users had significantly higher level of expressed happiness ($M = 5.56$, $SD = 0.34$) than thinspiration users ($M = 5.16$, $SD = 0.29$), $t(845) = 21.87$, $p < .001$.

To visualise the differential effect of individual words, we created a "word shift" diagram (Dodds et al., 2011) that ranks words in order of contribution to the difference in scores between groups (interactive word shift available at http://maths.adelaide.edu.au/lewis.mitchell/share/spiration/spiration_shift.html). Word shifts have been used previously to characterise regional variation in expressed happiness (Mitchell et al., 2013) as well as estimated caloric balance (Alajajian et al., 2017). Here we found that increased usage of the positive words "fitness", "healthy", and "health", and decreased usage of the negative words "kill", "wait", and "gone", made the most highly-ranked contributions to the difference in positivity between thinspiration and fitspiration tweets.

4. Discussion

To the best of our knowledge, the present study is only the third to address similarities and differences between thinspiration and fitspiration material on the Internet. In contrast to the methodology of the previous studies (Boepple & Thompson, 2016; Talbot et al., 2017), we used a big data approach that enabled an analysis of users and content in a way not previously attempted. We chose the social media platform of Twitter, rather than general websites, because the inherent interactivity provides a means of analysing the nature of the communities and their respective information flow. The major findings are clear. First, as predicted, the thinspiration community on Twitter is smaller but more cohesive than the fitspiration community. Second, although the specific most frequently-used words are different, concepts contained in both thinspiration and fitspiration tweets largely relate to body appearance and weight loss. Finally, the content of fitspiration is more positive in sentiment. Thus, our analysis of Twitter thinspiration and fitspiration users and tweets suggests that there are both similarities and important differences between the two.

Our first finding points to the existence of two quite distinct communities, with minimal overlap between them. Further, the communities are very differently structured. The thinspiration community is smaller, tighter, and more cohesive – they have a more complete network with greater information flow and fewer non-human ("bot") contributors. Thus, the community is not characterised by casual visitors to sites and occasional comments. Rather, thinspiration tweeters likely represent a genuine on-line community. This tighter network is consistent with views of the pro-ana community as somewhat secretive and exclusive (Arseniev-Koehler et al., 2016), attributes likely strengthened by the banning of thinspiration content by a number of social media

platforms (Casilli, Pailler, & Tubaro, 2013; Judkis, 2012). Undoubtedly, such on-line communities provide a sense of community, social support and opportunity to interact with like-minded others (Norris et al., 2006). However, as pointed out by Rouleau and von Ranson (2011), the support provided in on-line communities is often superficial and conditional upon active participation and conformity to group norms. The observed much greater information flow is also potentially dangerous if this information constitutes the "tips and tricks" about weight loss or how to conceal eating disorder symptoms from family, friends, and health professionals suggested by other research (Harshbarger, Ahlers-Schmidt, Mayans, Mayans, & Hawkins, 2009; Rouleau & von Ranson, 2011). In the present case, participation in a tightly knit on-line thinspiration community may reinforce idealization of the extreme thin ideal and serve to normalize associated negative body image and disordered eating attitudes, behaviours, and identity. Accordingly, clinicians might be particularly mindful of their clients' use of social networking sites in general, and engagement in thinspiration on-line communities in particular.

In contrast to the thinspiration community, the fitspiration community on Twitter is larger and more diverse, likely contained more advertising, and had lower information flow. This suggests a loosely connected collection of individuals with a similar interest, rather than a genuine community. This structure reflects the fact that fitspiration is much more widespread across a range of individuals, for most of whom it is not necessarily a core identity. Nor is there any need for secrecy. Fitspiration (as the pursuit of health and fitness) is both socially acceptable and viewed positively. This does not mean that participation is benign, but rather that there is less investment in a community of practice.

In terms of content, although the specific individual words were different, both thinspiration and fitspiration had a focus on appearance and weight loss. This finding is consistent with Boepple and Thompson's (2016) analysis of general websites. Thus, although fitspiration is positioned as a healthy alternative to thinspiration, it contains some of the same problematic features. This echoes Holland and Tiggemann's (2016) finding that the posters of fitspiration material on Instagram were at greater risk of eating disorder diagnosis than the posters of other (control) material. In terms of sentiment, fitspiration tweets were significantly more positive than thinspiration tweets (although both were mildly positive). This is consistent with the finding that much of the text on fitspiration Instagram imagery is positive and the suggestion that the text may be the source of the inspiration that people feel (Tiggemann & Zaccardo, 2017).

The use of a big data approach carries a number of advantages. It offers an objective methodology that uses computational power to investigate larger data sets than can be handled manually. As a consequence, there is no need for elaborate code books or coding systems with their inherent subjectivity and concerns about reliability. Of particular importance, a big data approach also enables the analysis of patterns of communication and information flow between communities of users, in addition to analysis of individual postings. Of course, there are also limitations to the methodology. We were unable to delve more deeply into the characteristics and motivations of individual users. We examined only individual unigrams (and bigrams), but not their meaning in the surrounding context. Likewise, we did not investigate the content of any images, which would require the development of a coding system. Smaller in-depth studies using different methodologies are necessary for a richer description than the 'big picture' we offer here. In addition, we investigated only publicly available postings on Twitter. We chose this platform because it is a popular site that is textually-based and has not banned thinspiration material. Nevertheless, the communities under investigation may display different characteristics on other social media platforms. It also needs to be noted that

the results (like any concerning the Internet) offer a snapshot at a particular point in time. Websites open and close and individuals move in and out of social media platforms and on-line communities. Thus, the latter can change in composition very rapidly.

Despite the above limitations, the present study has offered a novel big data approach to the comparison of thinspiration and fitspiration communities on Twitter. In particular, the thinspiration community was identified as a more cohesive community enabling the ready transmission of both attitudes and information. The findings contribute to a greater understanding of these communities, thereby providing valuable information for researchers, parents, educators, and for health professionals who deal with members of these communities.

References

Abena. (2013). From thinspo to fitspiration: How social media could be affecting your body image. [Blog post]. *College Fashion*,. Available at. http://www.collegefashion.net/college-life/from-thinspo-to-fitspiration-how-social-media-could-be-affecting-your-body-image/

Alajajian, S. E., Williams, J. R., Reagan, A. J., Alajajian, S. C., Frank, M. R., Mitchell, L., . . . & Dodds, P. S. (2017). The lexicocalorimeter: Gauging public health through caloric input and output on social media. *PLoS ONE*, 12(2), 1–25. http://dx.doi.org/10.1371/journal.pone.0168893

Arseniev-Koehler, A., Lee, H., McCormick, T., & Moreno, M. A. (2016). #Proana: Pro-eating disorder socialization on Twitter. *Journal of Adolescent Health*, 58, 659–664. http://dx.doi.org/10.1016/j.jadohealth.2016.02.012

Bair, C. E., Kelly, N. R., Serdar, K. L., & Mazzeo, S. E. (2012). Does the Internet function like magazines? An exploration of image-focused media, eating pathology, and body dissatisfaction. *Eating Behaviors*, 13, 398–401. http://dx.doi.org/10.1016/j.eatbeh.2012.06.003

Bardone-Cone, A. M., & Cass, K. M. (2007). What does viewing a pro-anorexia website do? An experimental examination of website exposure and moderating effects. *International Journal of Eating Disorders*, 40, 537–548. http://dx.doi.org/10.1002/eat.20396

Boepple, L., & Thompson, J. K. (2016). A content analytic comparison of fitspiration and thinspiration websites. *International Journal of Eating Disorders*, 49, 98–101. http://dx.doi.org/10.1002/eat.22403

Boepple, L., Ata, R. N., Rum, R., & Thompson, J. K. (2016). Strong is the new skinny: A content analysis of fitspiration websites. *Body Image*, 17, 132–135. http://dx.doi.org/10.1016/j.bodyim.2016.03.001

Borzekowski, D. L. G., Schenk, S., Wilson, J. L., & Peebles, R. (2010). e-Ana and e-Mia: A content analysis of pro–eating disorder web sites. *American Journal of Public Health*, 100, 1526–1534. http://dx.doi.org/10.2105/ajph.2009.172700

Casilli, A. A., Pailler, F., & Tubaro, P. (2013). Online networks of eating-disorder websites: Why censoring pro-ana might be a bad idea. *Perspectives in Public Health*, 133, 94–95. http://dx.doi.org/10.1177/1757913913475756

Dodds, P. S., Harris, K. D., Kloumann, I. M., Bliss, C. A., & Danforth, C. M. (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *PLoS ONE*, 6, e26752. http://dx.doi.org/10.1371/journal.pone.0026752

Dodds, P. S., Clark, E. M., Desu, S., Frank, M. R., Reagan, A. J., Williams, J. R., . . . & Danforth, C. M. (2015). Human language reveals a universal positivity bias. *Proceedings of the National Academy of Sciences*, 112, 2389–2394. http://dx.doi.org/10.1073/pnas.1411678112

Ghaznavi, J., & Taylor, L. D. (2015). Bones, body parts, and sex appeal: An analysis of #thinspiration images on popular social media. *Body Image*, 14, 54–61. http://dx.doi.org/10.1016/j.bodyim.2015.03.006

Hanneman, R. A., & Riddle, M. (2005). *Introduction to social network methods*. Riverside, CA: University of California, Riverside [Retrieved from]. http://faculty.ucr.edu/~hanneman/nettext/

Harper, K., Sperry, S., & Thompson, J. K. (2008). Viewership of pro-eating disorder websites: Association with body image and eating disturbances. *International Journal of Eating Disorders*, 41, 92–95. http://dx.doi.org/10.1002/eat.20408

Harshbarger, J. L., Ahlers-Schmidt, C. R., Mayans, L., Mayans, D., & Hawkins, J. H. (2009). Pro-anorexia websites: What a clinician should know. *International Journal of Eating Disorders*, 42, 367–370. http://dx.doi.org/10.1002/eat.20608

Holland, G., & Tiggemann, M. (2016). A systematic review of the impact of the use of social networking sites on body image and disordered eating outcomes. *Body Image*, 17, 100–110. http://dx.doi.org/10.1016/j.bodyim.2016.02.008

Holland, G., & Tiggemann, M. (2017). Strong beats skinny every time: Disordered eating and compulsive exercise in women who post fitspiration on Instagram. *International Journal of Eating Disorders*, 50, 76–79. http://dx.doi.org/10.1002/eat.22559

Judkis, M. (2012). *Instagram bans 'Thinspiration', pro-eating disorder images*. The Washington Post. Available at. https://www.washingtonpost.com/blogs/arts-post/post/instagram-bans-thinspiration-pro-eating-disorder-images/2012/04/24/gIQAXLeaeT_blog.html?utm_term=.89f76313520c

Lotan, G., Graeff, E., Ananny, M., Gaffney, D., Pearce, I., & Boyd, D. (2011). The revolutions were tweeted: Information flows during the 2011 Tunisian and Egyptian revolutions. *International Journal of Communication, 5, 1375–1405.*

Lydecker, J. A., Cotter, E. W., Palmberg, A. A., Simpson, C., Kwitowski, M., White, K., . . . & Mazzeo, S. E. (2016). Does this Tweet make me look fat? A content analysis of weight stigma on Twitter. *Eating and Weight Disorders – Studies on Anorexia, Bulimia and Obesity*, *21*, 229–235. http://dx.doi.org/10.1007/s40519-016-0272-x

Mitchell, L., Frank, M. R., Harris, K. D., Dodds, P. S., & Danforth, C. M. (2013). The geography of happiness: Connecting Twitter sentiment and expression, demographics, and objective characteristics of place. *PLoS ONE*, *8*(5), e64417. http://dx.doi.org/10.1371/journal.pone.0064417

Newberry, C. (2016). A long list of Twitter statistics all social media marketers should know. [Blog post]. *Hootsuite*,. Available at. https://blog.hootsuite.com/twitter-statistics/

Norris, M. L., Boydell, K. M., Pinhas, L., & Katzman, D. K. (2006). Ana and the Internet: A review of pro-anorexia websites. *International Journal of Eating Disorders*, *39*, 443–447. http://dx.doi.org/10.1002/eat.20305

Perloff, R. M. (2014). Social media effects on young women's body image concerns: Theoretical perspectives and an agenda for research. *Sex Roles*, *71*, 363–377. http://dx.doi.org/10.1007/s11199-014-0384-6

Rouleau, C. R., & von Ranson, K. M. (2011). Potential risks of pro-eating disorder websites. *Clinical Psychology Review*, *31*, 525–531. http://dx.doi.org/10.1016/j.cpr.2010.12.005

Sensis. (2017). *The Sensis Social Media Report 2017.*. Available at. https://www.sensis.com.au/about/our-reports/sensis-social-media-report

Talbot, C. V., Gavin, J., van Steen, T., & Morey, Y. (2017). A content analysis of thinspiration, fitspiration, and bonespiration imagery on social media. *Journal of Eating Disorders*, *5*, 40. http://dx.doi.org/10.1186/s40337-017-0170-2

Tiggemann, M., & Miller, J. (2010). The Internet and adolescent girls' weight satisfaction and drive for thinness. *Sex Roles*, *63*, 79–90. http://dx.doi.org/10.1007/s11199-010-9789-z

Tiggemann, M., & Slater, A. (2013). NetGirls: The Internet, Facebook, and body image concern in adolescent girls. *International Journal of Eating Disorders*, *46*, 630–633. http://dx.doi.org/10.1002/eat.22141

Tiggemann, M., & Slater, A. (2014). NetTweens: The Internet and body image concerns in preteenage girls. *The Journal of Early Adolescence*, *34*, 606–620. http://dx.doi.org/10.1177/0272431613501083

Tiggemann, M., & Zaccardo, M. (2015). Exercise to be fit, not skinny: The effect of fitspiration imagery on women's body image. *Body Image*, *15*, 61–67. http://dx.doi.org/10.1016/j.bodyim.2015.06.003

Tiggemann, M., & Zaccardo, M. (2016). Strong is the new skinny: A content analysis of #fitspiration images on Instagram. *Journal of Health Psychology*, http://dx.doi.org/10.1177/1359105316639436 [Advanced online publication]

Varol, O., Ferrara, E., Davis, C. A., Menczer, F., & Flammini, A. (2017). Online human-bot interactions: Detection, estimation, and characterization. *Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM 2017) Online*, 280–289.

Vinson, D. W., & Dale, R. (2016). Social structure relates to linguistic information density. In M. N. Jones (Ed.), *Big data in cognitive science: From methods to insights*. New York, NY: Taylor & Francis.