Representations of Health and Wellness on Instagram:
An Analysis of 285,000 Posts

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Abstract

Image-based social media is undergoing a significant increase in popularity among adolescents and young adults (Pew Research Center, 2018). On Instagram, Health Influencers share magazine-ready images that communicate health and wellness to millions of followers. These images have been criticized by academics and the public alike as self-promotional, lacking a scientific basis, and promoting Western beauty standards and thin-ideals. Given Health Influencers' considerable social reach, and mounting concern that certain types of Instagram content can negatively affect young people's mental health and body image, it is important to assess the social costs of their posting habits. While empirical research has identified types of posts that contribute to body image issues (e.g., selfies exhibiting naked body parts), research on the prevalence of these posts in health messages on Instagram is more limited. To this end, we analyzed the most frequently used hashtags of 784 Health Influencers with ten-thousand or more followers and fit an unsupervised topic model to over 285,000 of their posts. This analysis revealed that a majority of health and wellness content on Instagram is related to four themes: *Cosmetics and Appearance, Self-promotion, Fitness,* and *General Wellness.* Furthermore, while many posts appear to promote health habits (e.g., vegan food recipes or posts of inspiration and encouragement), a substantial number of images contain content previous research has suggested can lead to body-image and self-esteem issues (e.g., photos promoting thin-body ideals). Future work will package this model as a web application that informs users of their own potentially harmful posting behaviors.

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Image-based social media is experiencing a significant increase in popularity among adolescents and young adults (Pew Research Center, 2018). However, a large body of research suggests that increased exposure to visual social media is correlated with mental health issues (Nesi & Prinstein, 2015; Feinstein, Hershenberg, Bhatia, Latack, Meuwly, & Davila, 2013; Jeri-Yabar, Sanchez-Carbonel, Tito, Ramirez-delCastillo, Torres-Alcantara, Denegri, & Carreazo, 2019; Shensa, Escobar-Viera, Sidani, Bowman, Marshal, & Primack, 2017; Balta, Emirtekin, Kircaburun, & Griffiths, 2020), which primarily affects adolescents (e.g., Frison & Eggermont, 2017) and women (e.g., Tiggermann, Hayden, Brown, & Veldhuis, 2018; Sherlock & Wagstaff, 2019). Indeed, frequent Instagram use is positively correlated with appearance-related anxiety (Fardouly, Willburger, & Vartanian, 2018), dysmorphia (Bue, 2020), depressive symptoms (Donnelly & Kuss, 2016), and low self-esteem (Sherlock & Wagstaff, 2019). Strikingly, some adolescent Instagram users have even reported developing eating disorders in order to take photos that get more likes (Carrotte, Vella, & Lim, 2015).

A likely reason for these trends is that many images on Instagram promote Western beauty and thin-body ideals, which are known to induce body-image disturbances (Grabe, Ward, & Hyde, 2008). *Instagram Influencers*, a class of Instagram user with the largest social reach on the platform, often promote a curated, stylized aesthetic which rarely represent a diverse range of physical appearances (Marengo, Longobardi, Fabris, & Settanni, 2018), abilities (Aziz, 2017), lifestyles (Marcella-Hood, 2020), cultural identities (Yang, Hauff, Houben, & Bolivar, 2016), and races (Brandt, Buckingham, Buntain, Anderson, Ray, Pool, & Ferrari, 2020). As a result, Instagram has become a medium composed largely of Western bodies (Hendrickse, Arpan, Clayton, & Ridgway, 2017) promoting Western ideals of beauty (Anixiadis, Wertheim, Rodgers, & Caruana, 2019), in turn inducing negative self-perceptions in the many people not seeing themselves represented in their image feeds (Feltman & Szymanski, 2018). This mechanism is analogous to the effects of more traditional forms of popular Western media on mental health (e.g., printed images, Benton & Karazsia, 2015; television, Cattarin, Thompson, Thomas, & Williams, 2000; Hargreaves & Tiggemann, 2003; visual advertising, Tiggermann & McGill, 2004), which extensive research has indicated promotes thin-body ideals that lead to negative self-perceptions (Agliata & Tantleff-Dunn, 2004; Grabe, Ward, & Hyde, 2008). Because millions of people, particularly adolescents and young adults, now use Instagram daily, it is important to understand the sources of toxic content on the platform and to develop approaches that can reduce it.

This paper analyzes the content of one of the most common types of Instagram Influencers, *Health Influencers*—users who promote physical health and mental wellbeing by posting stylized photos of themselves engaged in activities such as working out at the gym and cooking healthy food. Recent research suggests Health Influencers post content with negative health effects (Hooper, 2020; Safarnejad, Xu, Ge, Krishnan, Bagarvathi, & Chen, 2020), such as promoting thin-body ideals (Fardouly, Willburger, & Vartanian, 2018; Turner & Lefevre, 2017) and health cures that lack scientific basis (Pilgrim & Bohnet-Joschko, 2019). While extensive work has detailed *which* content is likely to induce mental health effects, research on *how* prevalent that content is (at least among Health Influencers) remains to be done. To this end, we report a large-scale computational analysis of over 285,000 Instagram posts from 742 highly influential Health Influencers to provide the first comprehensive assessment of their posting behaviors. Specifically, we analyze the most commonly used hashtags to group images into larger semantic categories (Study 1). We then fit an unsupervised topic model to the post descriptions (Study 2), which uncovered many of the same semantic categories as Study 1. Future work will package the model as a web-application that acts as a scorecard for Health Influencer's posting habits, informing them if their post content correlates with mental health harms, and acting as an intervention for this behavior (cf Eshleman, Jha, & Singh, 2017).

The paper continues as follows: We first detail the process employed to curate a list of Health Influencers and extract their posting history. Next, we report the results of two studies. Study 1 reports a qualitative assessment of the thematic content associated with hashtags Health Influencers most commonly use. This analysis provides a benchmark for assessing the results of a topic model fit to the descriptions of the posts in Study 2. These two studies suggest that Health Influencers, while operating under the guise of promoters of physical health and mental well-being, post a substantial amount of toxic content promoting themselves as well as Western beauty and thin-ideals. This content is well-known to harm the self-esteem and mental health of its viewers. We conclude with a discussion of the application of our resulting topic model as a scalable intervention that can flag-and-reduce the future posting of toxic content on Instagram.

Data Collection

Data collection occurred in two phases. First, a collection of Health Influencer profiles were mined from a website online personalities utilize to promote their online presence. Second, posts from the influencers in our collection were extracted using the CrowdTangle platform (Sehl, Cornia, & Nielsen, 2018).

Part I: Health Influencer Selection

We curated a list of Health Influencers for analysis by mining the user profiles of 10,000 self-identified Health Influencers from the website influence.co, a website designed for social media influencers to promote their online profiles to a broader audience (the data mining script can be found on this project's GitHub). Because we sought to analyze the content posted by Health Influencers with considerable social reach, we decided to exclude any user with less than 10,000 followers from analysis. This selection cut-off was informed by social media expert opinion that influencers with 10,000 or more followers are "top-ranked" (eMarketer, 2017). This selection criteria resulted in a total of 742 top-ranked Health Influencers whose post history was collected in the next data collection phase.

Data Availability

The list of all users mined from influence.co can be found on the project's GitHub.

Part II: Mining Instagram Content

Using the CrowdTangle platform, we mined every available post from the 742 top-ranked Health Influencers in our curated list. This resulted in 285,400 Instagram posts and associated metadata (e.g., username, number of followers, number of likes post received). The present analyses, however, only focused on extracting thematic content from posts' descriptions, because previous research indicates that computer vision-based analyses of post images provide less insight (Hosseini, Xiao, Jaiswal, & Poovendran, 2017).

Data Availability

Due to CrowdTangle's data confidentiality policy, we are prohibited from making the dataset of posts publicly available for replication and extension. However, we make the list of users scraped from Influence.co publicly available (see above), and any researcher with access to the CrowdTangle platform can extract the same dataset using this list of profiles to replicate and extend our reported results.

Present Studies

In two studies, we perform a large-scale analysis of the content Health Influencers post to Instagram. Study 1 reports a qualitative assessment of the thematic content of hashtags most commonly used by Health Influencers. Study 2 reports the results of an unsupervised topic model (i.e., latent Dirichlet allocation, Blei, et al., 2003) fit to the text descriptions of each post. Both studies indicate that Health Influencers post potentially harmful content.

Study 1: Thematic Analysis of Common Hashtags

Analyzing hashtag use on social media can provide rich insight into the thematic content of the posts (Ferragina, Piccinno, & Santoro, 2015). For instance, researchers can leverage hashtag statistics to structure large corpora of social media data (Nazir, Ghazanfar, Maqsood, Aadil, Rho, & Mehmood, 2019), because hashtags can be treated as data annotations produced by the author of the post (Argyrou, Giannoulakis, & Tsapatsoulis, 2018). Furthermore, because topic models don't have clear metrics for assessing overall fit and interpretability (Hosseini, Xiao, Jaiswal, & Poovendran, 2017), analysis of commonly used hashtags can be useful in assessing topic modeling results (e.g., by comparing topic model results to the groupings induced by clustering commonly used hashtags).

Methods

We extracted the 500 most frequently used hashtags in our dataset and manually grouped them into categories based on their thematic content. Grouping hashtags into semantic groups was an iterative process between two coders (i.e., the first two authors of this paper) to mitigate annotation bias. The process used to manually label hashtags follows:

First, both coders independently annotated each hashtag with respect to its thematic category. This process required searching Instagram for recent posts not in our dataset that were also labeled with the hashtag. These out-of-sample posts were used to inform us of the typical content associated with each hashtag, and guided the labels provided to them. For instance, if a search for hashtag #cardio returned photos of people engaged in fitness activities, #cardio would be labeled as a part of the *fitness* category. After independently annotating each hashtag, the two coders consulted and discussed the labels until an agreed upon set of labels was decided for each hashtag. Because some hashtags pertained to multiple categories, we provided multiple labels for hashtags when necessary (e.g., #nike relates to both *fitness* and *fashion*).

Results

Our two-step coding process of hashtags revealed posts fell into eighteen higher-level categories (see Table 1) roughly composing four broad themes: *Fitness, Wellness,* *Self-promotion,* and *Cosmetics and Appearance.* Suggesting that while there is a large portion of content related to health and wellness (i.e., *Fitness* and *Food* themes), there is also a large body of content related to other factors as well (see Table 1). Indeed, the prevalence of hashtags related to self-promotion indicates that a large body of content is devoted to promoting the Influencer's online personality (N_{posts} = 54,905). Because research indicates that Influencer identities do not represent the diversity of Instagram users (e.g., Abidin, 2016), self-promotional content is likely to distort many users' understanding of health and well-being, increasing the likelihood they engage in self comparison. However, future empirical research is needed to confirm this connection.

The prevalence of hashtags related to fashion, which indicates Health Influencers' proclivity for sharing posts that promote their style and aesthetic, also raises concern. Well-known fashion brands such as Adidas (N_{posts} = 721) and Nike ($\mathrm{N}_{\text{posts}}$ = 1167) are prevalent hashtags, suggesting that product promotion is central to health content on Instagram. As product promotion is common among Instagram Influencers in general (Pilgrim & Bohnet-Joschko, 2019), it undermines Health Influencers role as authorities on health and well-being. Notably, these brands promote Western Educated Industrial Rich and Democratic (WEIRD) representations, which may suggest that WEIRD identities and Western-beauty norms are represented as health and defined well-being. This is particularly problematic considering the diversity of Instagram users (Brandt, Buckingham, Buntain, Anderson, Ray, Pool, & Ferrari, 2020). Because previous research indicates that these aesthetics and styles are often not representative of everyday Instagram users (e.g., Fardouly, Willburger, & Vartanian, 2018), these posts raise concern for the effects on users' body images.

Table 1. *Themes and semantic categories of 500 most frequently used hashtags.*

Theme	Category	Example Hashtags
Cosmetics and Appearance	Appearance	#blondevibe, #balletbody
	Fashion	#bikini, #streetstyle
	Beauty	#wakeupandmakeup, #organicbeauty
Self-promotion	Promotional	#ad, #slave2beauty
	Brand	#reebokwomen, #adidas
	Blog	#beautyblogger, #lifestyleblogger
	Trend	#instacool, #instafit
	Travel	#travelfit, #wanderlust
	Place	#lasvegas, #paris
Fitness	Fitness	#bodybuilding, #fitnessmotivation
	Spirituality	#yoga
	Motivation	#transformation, #boldliving
Wellness	Food	#foodporn, #youarewhatyoueat
	Emotion	#selflove #lawofattraction
	Wellness	#healthylifestyle, #thenewhealthy
	Family	#partner, #twins
	Gender	#runlikeagirl, #womensbest

Some categories of posts, such as posts about physical appearance and beauty (N_{posts}= 16,668**)**, warrant closer investigation. For example, posts related to physical attributes (e.g., #blonde) and cosmetics (e.g., #wakeupandmakeup) suggest that Health Influencers promote specific appearances unrelated to health and wellbeing. Beyond the presence of certain hashtags advocating for makeup use and promoting specific Western characteristics (i.e., blonde hair), it remains unclear the extent to which these physical appearance and beauty posts specifically promote Western beauty and thin-ideals. Future work should directly analyze posts categorized with these hashtags to better assess the semantic content associated with each hashtag. In addition, future analyses should look at what types of emotional states are discussed in posts associated with emotion groups. Because discussions of mental health on social media are known to have real-life mental health effects (Fergie, Hunt, & Hilton, 2016), understanding how mental health and emotion is discussed among Health Influencers is an important route of empirical study.

Analyzing hashtag use is a reliable method for understanding the thematic dimensions of social media posts. By analyzing the 500 most frequently used hashtags in our dataset, we found that content posted by Health Influencers fit into roughly eighteen distinct categories belonging to four broad themes. In Study 2, we sought to confirm and extend these analyses by using an unsupervised topic modeling algorithm. However, follow-up work should (1) further confirm that posts tagged by hashtags related to the *Cosmetic and Appearance* theme promote Western-beauty and thin-ideals and (2) look closer at how mental health is discussed by Health Influencers.

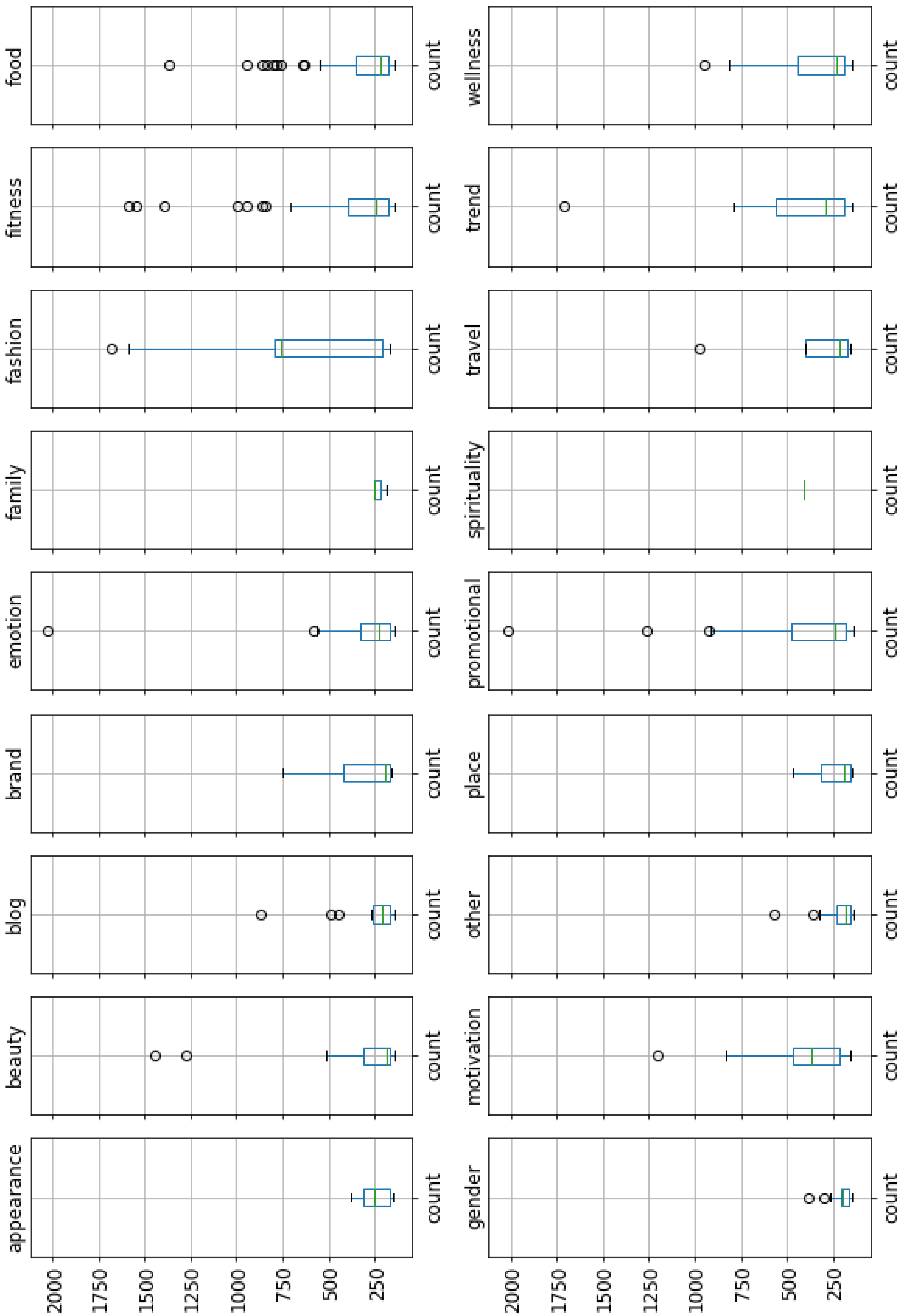

Figure 1. *Boxplots of number of posts containing each hashtag belonging to a semantic category.*

Study 2: Topic Modeling Instagram Posts

Study 2 sought to confirm and extend the results of Study 1 which suggests that Health Influencers post content related to four broad themes. Because analyses in Study 1 relied heavily on human coding, we sought to use a more data-driven approach in Study 2. Additionally, we are interested in which lower-level topics may be present within each of these four themes. To this end, we used the unsupervised topic modeling algorithm latent Dirichlet allocation (Blei, et al., 2003) to assess which topics are most prevalent in the dataset.

Topic Modeling with LDA

LDA assigns documents (here, the description of a post on Instagram) to k predefined topics, where each topic is defined by a set of terms that best describe the documents in that topic. More generally, LDA assigns a k-lengthed probability vector to each document where each element i represents the probability that the given document belongs to topic i. Loosely speaking, the probability values for a given document are determined by how many of topic k's "representative" terms appear in the document.

Because LDA requires a predefined number of topics before fitting the model, we fit models with a number of topics in the neighborhood of $k = 14$, the number of semantic categories resulting from our analysis of commonly used hashtags in Study 1. Additionally, we used the Python package Gensim (Rehurek & Sojka, 2010) to fit our topic models to preprocessed post descriptions.

Preprocessing Text Descriptions

We preprocessed text descriptions using the Python package spaCy (Honnibal & Montani, 2017). First, we lemmatized each word in the description and removed punctuation, whitespace, and stop-words. We also only kept terms whose part-of-speech was a noun, adjective, adverb, and verb. With these preprocessed strings in hand, we then calculated *term-frequency inverse-document frequency* (cf Aizawa, 2003) representations of the bigrams and trigrams of each description. We used this final representation of the text descriptions to fit our topic models.

Topic Model Evaluation

Visual interpretations of a fitted topic model have been proposed to guide model selection (e.g., Chaney and Blei, 2012). Here, we used interactive visualization software (Sievert & Shirley, 2014) to interpret the fit of our topic model and to label the resulting topics (i.e., dimensions in a lower-dimensional embedding) with relevant semantic labels. Specifically, we used the Python package pyLDAvis (Maybe, 2019), to transform our Gensim model into an interactive visualization (this visualization is available on the project's GitHub here) to guide model selection and assign labels to the learned topics. Furthermore, the final topic model reported provided the most semantically distinct, yet interpretable topics. However, other models (not reported) predefined with similar-but-different values of *k* returned similar topics, suggesting that our results are not specific to the value of *k* we chose.

Topic Model Results

Our reported topic model was fit with eleven topics. Topic labels were assigned by the first two authors after evaluating each topic's keywords using the pyLDAvis software (see above). Topics and their associated keywords are in Table 2 and the proportion of the corpus categorized as each topic is shown in Figure 3. Topic modeling revealed Health Influencers post a mixture of content related to health and wellness as well as other—potentially problematic—topics. Specifically, Study 2 confirmed the results of Study 1 suggesting that Health Influencers post content varying along four thematic dimensions: *Cosmetics and Appearance, Self-promotion, Fitness,* and *General Wellness*. Furthermore, the topic model provided greater detail into the semantic content of these broad themes as well as the rates at which the themes are discussed in the corpus. Both of these findings are discussed in more detail below.

First, topic modeling confirms that Health Influencers are prone to post promotional content: over one-quarter of the posts belong to a promotion-related topic. And while Study 1 indicated that promotional content was common, the topic model shed further light on what types of promotional content is present in the corpus. Specifically, promotional content is composed of three distinct types of posts: promotion of the Influencer's online profile (i.e., the *Online* topic), their business and brand (*Business*), and fashion brands or styles (*Fashion*). These results are particularly informative because while some forms of promotion are likely not problematic (e.g., promoting one's business), some may be. For instance, the promotion of certain fashion trends and styles, which are known to promote body dissatisfaction (Tiggemann & Anderberg, 2020), may be problematic for many users and require intervention. Topic modeling also indicates that content related to cosmetics is common among Health Influencers, confirming the finding that *Cosmetics and Appearance* is a common theme in health messages on Instagram. Future empirical work is needed to better understand how fashion-related and cosmetic content shapes Instagram users' perceptions of health and well-being.

Table 2. *Topics and associated keywords returned by LDA model*

Topic Label	Keywords
Family + Relationships	love, family, baby, birthday, mom, kid
Mental Health (Spirituality)	change, yoga, mind, positive, life, matter
Promotional	
Business	comment, link, code, shop, box, order
Fashion	beauty, style, fashion, model, ootd, dress
Online	friend, tag, free, country, care, industry
Cosmetics	skin, hair, product, natural, face, essential
Motivation	inspiration, motivation, dream, follow, success, passion
Routine (Workouts)	day, week, morning, today, time, weekend
Ingredients	
Meal	fresh, salad, dinner, pepper, potato, veggie
Dessert	protein, chocolate, milk, coconut, cream, butter

Note. Topic Labels were assigned after interpreting the keywords defining the topic using interactive visualization software pyLDAvis.

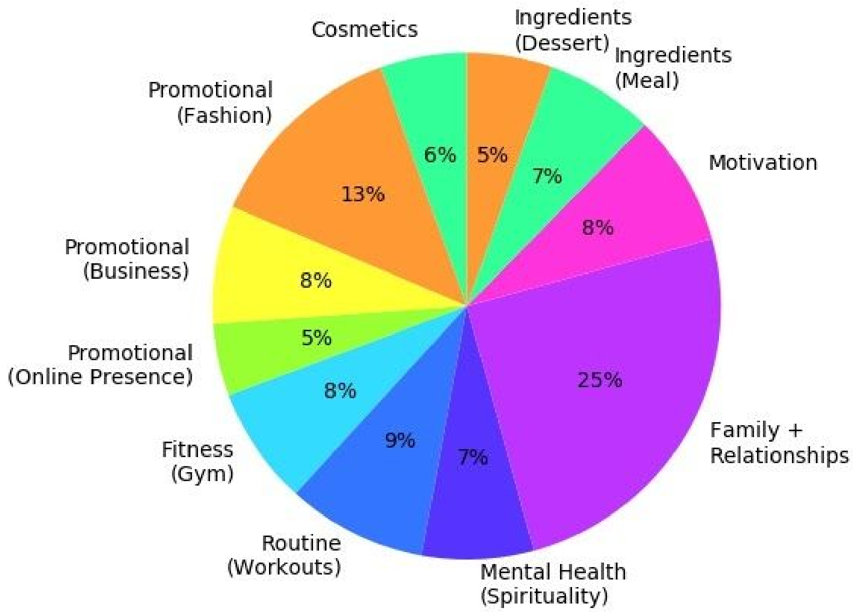

Figure 2. Proportion of posts belonging to each topic. While a large portion of posts contain content related to health and wellness (e.g., *Family + Relationships, Mental Health (Spirituality), Motivation*) much content is unrelated to health, such as *Cosmetics* and self-promotional topics: *Promotionional (Fashion), (Business),* and *(Online Presence)*.

While a large portion of content is related to topics not related to health (e.g., approximately one-fourth of content is promotional) and some content is likely harmful to some users (e.g., about one-fifth of the content is about fashion promotion and cosmetics), a majority of content pertains directly to health (e.g., the *Fitness* topic) and wellbeing (e.g., *Family + Relationships*). However, future work is needed to better assess how these topics are communicated. For instance, research suggests that fitness images containing a Health Influencer's bare chest can lead to lower body satisfaction in men (Tiggemann & Anderberg, 2020). Human coders should analyze the content of a random sample of posts belonging to each topic and code the visual cues present in the images. This analysis will shed further light on how these topics are communicated to Instagram users as well as their effects on users' mental health.

Furthermore, this study presents a bird-eye view of how health is communicated on Instagram. Because this dataset is inherently rich (as is the case with all social media data), future computational analysis is needed to better understand its structure. For instance, what remains unclear is how the production of harmful content, such as promoting a specific fashion brand or associating cosmetic products with being healthy, varies across the Health Influencers in our dataset. For instance, some users may be particularly prone to posting harmful content while others are not. As will be proposed in the Discussion of this paper, Author Topic Models (Rosen-Zvi, Griffiths, Steyvers, & Smyth, 2004) are a suitable computational model for such analyses with the dual-benefit of setting the stage for a scalable intervention that informs users of their potentially harmful posting behaviors.

Discussion

Here, we performed a large-scale analysis of health-related content on Instagram. By focusing on content produced by Health Influencers (Instagram users promoting health content with the most social influence on the platform), we took a first glimpse at how health and wellness are represented in millions of Instagram user's image feeds. Because there is considerable evidence that specific types of content can induce body dissatisfaction and other related issues among Instagram users, we sought to understand if similar factors (e.g., promotion of a thin body or other Western ideals of beauty) were present in health-related content on Instagram. Two computational studies suggests that a large portion of content produced by Health Influencers likely contain these factors. Indeed, we found that messages communicated by Health Influencers often relate to four themes: *Cosmetics and Appearance, Self-promotion, Fitness,* and *General Wellness.* While this finding is preliminary, it warrants a closer investigation of how health is communicated by Health Influencers on Instagram. Specifically, future work should empirically establish the effects of different types of health-related content on (1) people's understanding of health and well-being and (2) the resulting real-life health effects from these conceptualizations. Along this line, future work is needed to develop strategies to reduce this behavior if we wish to make positive change in how millions of people view health and themselves.

While these studies provided a high-level perspective on what factors are present in health messages on Instagram, many questions remain about the structure of this corpus. For instance, future computational work will investigate how the production of problematic content differs across different users in the dataset. Specifically, such work will fit an Author Topic Model to the corpus of posts to assess how topic distributions vary among different Influencers.

Crucially, an Author Topic Model can be leveraged to build a scalable intervention that can inform specific users if they post problematic content. As will be discussed, such an intervention may prove to be an effective tactic for reducing problematic content on the platform.

Reducing Problematic Social Media

Social media enables the sharing of an unprecedented amount of health information (Huang & Su, 2018). Developing approaches that limit the spread of information with negative health effects—from curbing the spread of misinformation designed to undermine people's trust in vaccines (Mitra, Counts, & Pennebaker, 2016) to decreasing the amount of instagram content harming users' mental health (Instagram, 2019)—is therefore important to making positive social change in the digital age.

Conventional approaches used to reduce problematic content on social media platforms have largely centered around developing machine learning systems that can tag content believed to be misinformation (Farajtabar, Yang, Ye, Xu, Trivedi, Khalil, ..., & Zha, 2017). Due to the vastness and quantity of information shared on social media, computational approaches like these are essential for reducing problematic content on the internet because they can scale to the demands required by social media sites (Lazer, et al., 2018; Sayyadiharikandeh, Varol, Yang, Flammini, & Menczer, 2020; Nwankwo & Ukurebor, 2020). Another approach which has shown promise is to train individuals to discern the quality of information and their sources (Pennycook and Rand, 2019; Pennycook, McPhetres, Zhang, Lu, & Rand, 2020). Simple information about the quality of source can lead to people being less likely to share misinformation (Pennycook & Rand, 2019).

Effective intervention strategies for reducing problematic content of the type discussed in the present paper are likely to be guided by the two aforementioned perspectives. This is because production of this style of content, while having well-established effects on the health of its consumers, doesn't violate user agreements and isn't classifiable as misinformation. As a result, education strategies are required that can inform users who produce the most problematic content of the effects of their behaviors. While requiring empirical validation of the positive effects of such an approach, scalable education campaigns are one promising route for reducing toxic content on Instagram.

To this end, future work will focus on building a web application that utilizes an Author Topic Model to inform users of their potentially harmful posting behaviors. At a general level, the web application will take an Instagram user's username as input. Then a web scraping script will collect recent posts from the user. The Author Topic Model will then predict a topic distribution vector for the user given these posts. Then, by leveraging a simple connectionist network, features of the posts' content (such as their topics and hashtags) will be mapped to established mental health risks. To complete this process, the application will then inform the user of the potential risks known to be associated with their posting behavior. See Figure 3 for a wireframe of this application.

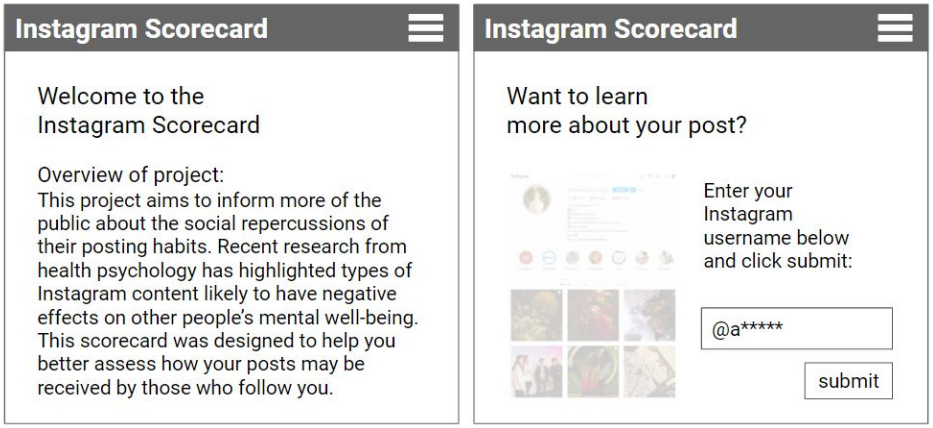

Figure 3. Wireframe of the *Instagram Scorecard*, a scalable intervention that will use an Author Topic Model to inform users of their potentially harmful posts. Future work will focus on implementing this intervention.

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