Analysis of Twitter to Identify Topics Related to Eating Disorder Symptoms

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***Abstract*—Eating disorders (EDs) are serious mental illnesses associated with physical and psychiatric problems, and premature death. Examining social media communication about ED symptoms may provide insight into how to prevent and treat these disorders. This study is to explore topics on Twitter related to EDs. We applied the Correlation Explanation (CorEx) topic model on 18,288 ED-related tweets and identified 20 topics, which were further grouped into 8 categories. The top two topic categories are body image and ED consequences. We manually evaluated the relevance of tweets to their assigned topics and average accuracy is 77.86%. Our findings are consistent with another study using content analysis, and we identified additional topics, such as ED consequences, pornography, and treatment and education from these tweets.**

Keywords*—*Eating disorder, body image, social media, Twitter, topic model

I. Introduction

The social media like Twitter and Facebook encourage the users to share their thoughts, opinions and details of their lives. The aggregation of the messages on social media could generate valuable information and knowledge about specific health topics, which could further help promote public health and encourage behavior changes [1-2]. In healthcare, data mining from Twitter has been widely applied, especially for epidemiological purposes. For instance, a study in 2010 tracked the rate of influenza in the United States and United Kingdom using Twitter. Some recent studies have begun to use Twitter to explore public mental health issues. For instance, a study in 2019 explored suicidal ideation, behaviors and risks through analyzing tweets [3]. However, few studies have examined thoughts and opinions related to eating disorders (EDs) through analysis of Twitter content.

EDs, including anorexia nervosa and bulimia nervosa, are serious mental illnesses characterized by disturbances in eating behaviors (e.g., restrictive eating, binge eating, purging through self-induced vomiting) and preoccupation with food, shape, and body weight [4]. EDs affect a substantial portion of the population [5], and are associated with significant physical and psychological morbidity [6], and elevated mortality rates [7]. Despite the severity of these illnesses, there still remain large gaps in the knowledge of the factors that promote and maintain EDs [8]. This is due in part to the secretive and self-protective nature of EDs [9], which may discourage individuals from speaking candidly about their symptoms. However, online social media communities have emerged that promote open discussion of ED thoughts and behaviors [9-10]. Thus, online language related to ED symptoms may serve as a microcosm for the ED experience, and may therefore provide researchers insight into factors that motivate these behaviors. This information could ultimately be used to better prevent and treat these disorders. Although prior content analysis research has been conducted to derive information from online ED language [9-10], these studies are limited by manual, rather than data-driven, topic clustering and short time frames. Therefore, in this study, we sought to expand beyond prior literature by using a Correlation Explanation (CorEx) algorithm to empirical detect hidden topics associated with ED social media content.

II. Method

A. Data Collection

Figure 1 shows the overall workflow of the study. The database was collected using a Twitter streaming application programing interface (API), from June 1, 2012 to January 31, 2018. A list of hashtags and keywords [10] were used to include ED related tweets in the database, e.g., 'anamia', 'edproblems', 'thinspo', *etc*. To narrow down the ED tweets in our study, we only used hashtags [10] related to EDs to extract the tweets from our random sample database. The full list of hashtags is listed in Table I.

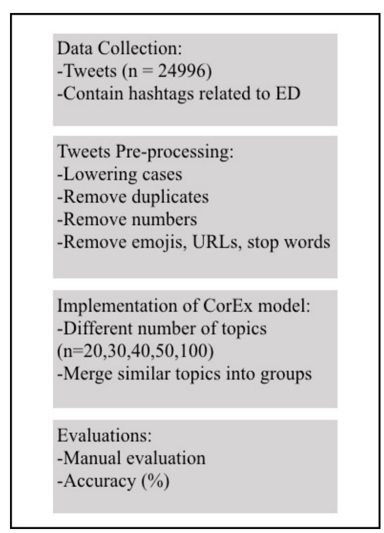

Fig. 1. Workflow of study.

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B. Data Preprocessing

A standard pipeline was implemented to clean the tweets data. All the words were transformed into lower cases, and the numbers, punctuations, emoji and URLs were removed. Also, the stemmer was applied to transform the terms to their root forms and a normal English stop word list was applied to remove the stop words. After the preprocessing, the tweets shorter than length of 5 tokens were removed. The remaining tweets were transformed into a binary document-word matrix for the further topic model implementation.

C. Exploring Topics from Eating Disorder Tweets

To understand the Twitter users' thoughts and interests about their ED, we implemented topics modeling to identify the latent topics from the tweets. There are several prevailing topic modeling methods; most of them utilize probabilistic generative models that speculate the mechanisms for how documents are generated in order to infer latent topics [11]. A representative example is the Latent Dirichlet Allocation (LDA) model [12]. Based on our preliminary studies[13], we found that the CorEx model could better discover the most coherent topics compared to the LDA. Unlike the LDA, CorEx topic modeling is discriminative and does not rely on any assumptions of LDA [14]. The CorEx discovers topics through maximizing the mutual information between words and topics. We implemented the CorEx on the Tweets with different number of topics (n = 20, 30, 40, 50, 100). The number of topics is important for identifying the latent topics from the tweets. If the number of topics is too large, there may be redundant and irrelevant topics, or unclear and insignificant [3]. To select the optimal number of topics, we calculated the distribution of total correlations for each topic to see how much correlation each additional topic contains. The model with optimal number of topics was further analyzed, the produced topics with similar meanings were grouped by domain experts into different 'categories', which represent the higher level topics. The summarized categories are based on previous studies related to ED [9-10].

D. Topics Evaluation

To evaluate the accuracy of the topic model, we extracted the top 10 ranked tweets under each topics based on their probabilities associated with the topic. The accuracy was defined as the percentage of extracted tweets that correctly aligned with the corresponding topics generated by the above topic modeling. The correctness was determined by a domain expert (AH) through manual review.

III. RESULTS

A. Twitter Data

After data pre-processing, we obtained 18,288 tweets to feed into the CorEx topic modeling. These tweets contained 11,652 unique tokens and covered 18 keywords related to the EDs. Figure 2 shows the distribution of the tweets' length. The mean length of the tweets was 14 and the max length was 54. Table I shows the keyword (hashtag) distribution among the tweets. Hashtags with the most tweets are #thinspo, #anorexia, and #EDproblems.

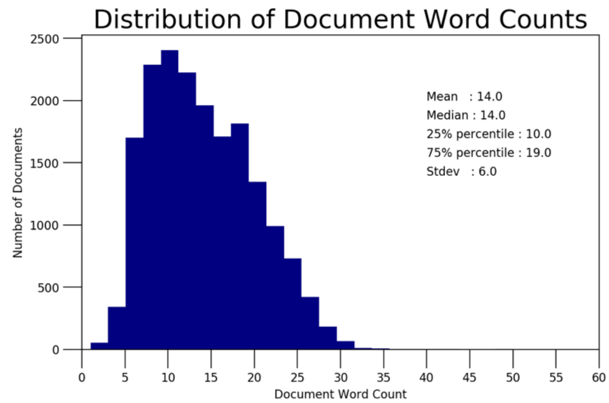

Fig. 2. Distribution of tweets length.

TABLE I. ED RELATED HASHTAGS AND COUNT OF TWEETS

Hashtags	Count	Hashtags	Count
#EDproblems	1916	#collarbones	127
#anamia	44	#edlogic	210
#anorexia	2215	#ednos	227
#anorexic	507	#edprobs	868
#bodyslip	420	#proana	509
#bonespo	27	#promia	7
#bulimia	612	#thinspiration	1266
#bulimic	35	#thinspo	9271
#chestbones	5	#thinspos	22

B. Imlementation of CorEx Topic Model

We implemented the CorEx topic models with topic numbers set to 20, 30, 40, 50 and 100. Figure 3 shows the distribution of the total correlation of each topic. When the number of topics approached 50, the new additional topics are nearly noninformative.

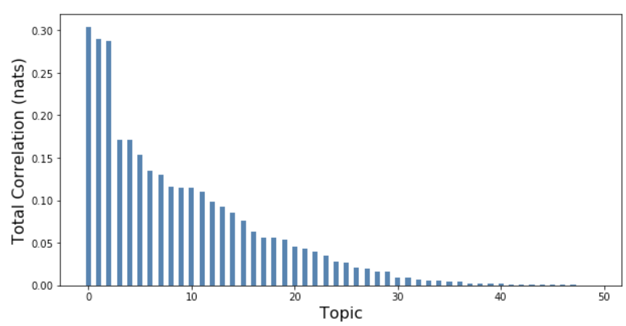

Fig. 3. Distribution of total correlation within each topic.

We also manually check the topics produced by different models, and found that when topic number equaled to 30, the produced topics were more coherent and relevant to EDs than other models.

C. Distribution and Evalution of Topics

The domain experts further analyzed the 30 topics generated by the CorEx topic model. We summarized the 30 topics into 20 unique topics and the topics with similar themes were grouped into 8 unique categories: 'body image', 'ED motivation/aspiration', 'education and treatment', 'media', 'ED symptoms', 'ED consequences', 'promoting or discouraging ED' and 'food and drink'. The topics in each category are shown in Figure 4. Table II lists all the explored topics, associated keywords and summarized categories. We manually evaluated the top 10 relevant tweets for all the topics, and the accuracy for each topic are also reported in Table II.

TABLE II. EVALUATION OF TOPICS AND ACCORDING CATEGOTY.

Topic Categories	Topics	Representative Topic Keywords	Accuracy
Body Image	Thinness	calorie, amazing, slim	92%
	Fitness	fit, workout, gym	50%
	Emaciation	bone, chest, hip	70%
	Legs/thighs	thigh, hipbone, skinny	90%
	Stomach	stomach, flat, everything	80%
	Body Checking	body slip, body check, selfie	90%
Pornography	Pornography	sex, nude, porn	60%
ED Symptoms	Non-specific ED Symptoms	vitamin, fridge, entire	60%
	Weight Loss	weight loss, diet, proana	70%
	Bulimic Symptoms	daily, stay, night	50%
Education and Treatment	Education and Treatment	recovery, therapy, treatment	90%
Media	Media Portrayals	discuss, deadline, behalf	80%
	Social Media	Instagram, retweet, follow	80%
ED Motivation/ aspiration	Self-worth	worth, plan, cry	60%
	Promoting or Discouraging ED	hungry, ill, starve	70%
	Self-punishment	failure, mirror, anything	90%
ED Consequences	Non-specific	damn, bony, under weight	85%
	Negative	sad, anorex, old	65%
	Shame	think, nothing, feel	100%
Food and Drink	Food and Drink	tea, coffee, pizza	50%

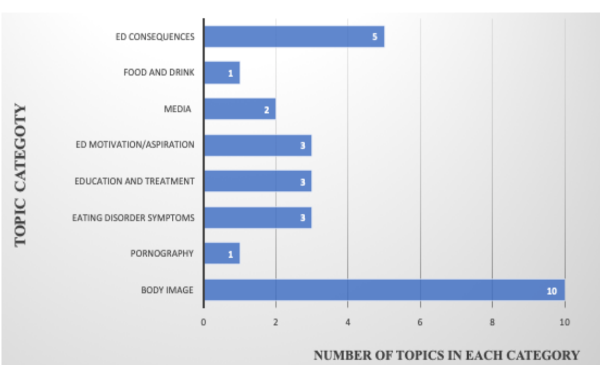

Fig. 4. Topics distribution in different categories.

Selected topics and according representative hashtags and tweets are shown in Table III. After manually reviewed topic 10 tweets assigned for each topic, we have reported the accuracy of topic model for each topic shown in Table II. The average accuracy for all topics is 77.86%. The top accurate topics include shame (100%), thinness, legs/thighs, body checking, treatment and education, self-punishment.

TABLE III. SELECTED TOPICS AND CORRESPONDING HASHTAGES AND TWEET EXAMPLES.

Selected Topics	Representative Hashtags	Tweet Examples
Thinness	#thinspos #skinny #thinspiration #hot	@goalsofperfect: This type of tall, skinny, perfect figure with long slim legs and a narrow top is my goals #thinspo #thinspiration
Fitness	#gainsomeweight #workout #diet #fitness	Your body doesn't control you, you control your body. #AppStore #FitnessMotivation #Thinspiration #Fitness
Legs/ thighs	#skinnyleg #thighgap #bikinibridge	@MyMind_13: #thinspo thigh gap, shame I have thunder thighs, holy shit her legs
Stomach	#thinspo #thinspiration #Anorexia #Ana	Imagine bending over and no stomach rolls of fat, just a flat belly #thinspo #thinspiration
Weight Loss	#diet #ProjectThin #weightloss #eatingdisorder	I'm setting myself a deadline, I will be 130 by march #EDproblems #imdone #givemebackmyoldself #Promise
Education and Treatment	#anorexia #anger #edproblem	If u, a family member or friend have lived with #anorexia nervosa, you can participate in #ANGI study, visit http://t.co/zPaL9sd9Ek.
Social Media	#thinspo #EDfamily #EDproblems #perfect	If you're an ED twitter RT so I can follow you #anafamily #AnaMiaEdFamily #anasisters #Thinspo #EDfamily #EDproblem
Self-worth	#EDproblems #thinspo #EDprobs	I just want someone to Hold me and tell me I'm worth it. But I know I'm not worthy of anything. #failure #selfhate #EDproblems #thinspo
Shame	#AnxietyProbs #PROana #EDprobs #thinspo	Not eating in front of other people because you're scared they'll think you're even fatter. #AnxietyProbs #EDprobs
Food and Drink	#edprobs #pepperoni #pizza #proana	Today I ate:2 slices of pizza (~46)3 tbs of frozen yogurt (idk, 10?)Cereal from the box (110)Popcorn (55)Total: 221UMM NO.#edprobs

We also generated the word clouds for selected topics in Figure 5. We could see majority of the words with higher weights reflect the theme of the topic. For instance, 'fit', 'fitspo' and 'work out' indicate topic 5 'fitness'.

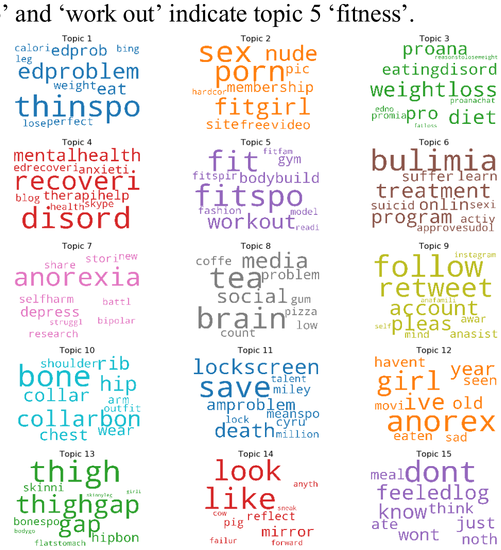

Fig. 5. Word cloud for selected topics.

Comparing with another content analysis study [9], which manually reviewed 4245 tweets during 1 month, we found high consistency on topics, such as body image, body weight, and food. In addition, we found unique topics not previously reported, especially ED consequences, media, treatment/education, and pornography.

IV. DISCUSSION

In this study, we analyzed Twitter data to empirically evaluate the content of ED language in online platforms. We identified 20 unique topics spanning 8 content areas, including body image, ED consequences, ED motivation/aspiration, ED symptoms, education/treatment, media, food and drink, and pornography.

Paralleling prior research in this area [9-10], we found much of the online content to reflect the specific psychopathology of eating disorders, including desire for thinness, eating and weight concerns, body checking, weight loss behaviors, and bulimic symptoms [4]. This suggests that ED behavior online parallels that in the real world. Considered in the context of the heightened risk conferred by consuming pro-ED behavior messages online [9], these findings underscore the need for increased prevention and intervention targeting ED language on social media platforms.

Our analysis identified other novel topic areas that have not been previously described, which provide insight into factors that may contribute to the perpetuation of ED behaviors. For instance, we discovered a latent topic reflecting self-punishment as a means of motivating ED behavior, which corresponds to prior self-report research [15]. Thus, self-criticism may be a fruitful target in future treatment. Further, several topics emerged that highlighted the negative consequences of ED behavior. Given that language reflecting upon the negative consequences of a behavior often precedes behavioral change [16], individuals producing this type of online content may more open to intervention efforts. Finally, topics reflecting ED treatment and education provide encouragement that social media may be used to promote recovery, rather than illness [17].

This study is not without limitations. Due to the nature of the CorEx topic model, each tweet could only be assigned to one topic; whereas, in reality, one tweet might convey information related to several ED topics. In this study, we only included tweets with the hashtags related to the EDs, which makes sure most of the included tweets are relevant to EDs. However, this strategy may have missed some ED related tweets that did not contain these hashtags. In future, it would be more throughout to include tweets with additional keywords that may be related to ED thoughts and behaviors. During manually review, we also found few groups of tweets we could not assign a coherent topic. This is due to the limitation of topic modeling. We would try other topic modeling such as LDA or try semi-supervised machine learning algorithms.

This analysis reflects an important first step towards utilizing data-driven analytics to identify modifiable factors contributing to EDs. Future extensions to further detect and intervene upon ED language online are warranted.

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